The neural and behavioral basis of statistical learning of target facilitation in visual search

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Hao Yu

aus Dalian, Liaoning, China

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Erstgutachter/in: Prof. Dr. Zhuanghua Shi

Zweitgutachter/in: Prof. Dr. Hermann J. Müller

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Table of Contents

1 General Introduction

In our daily lives, the act of searching is a ubiquitous and constant endeavor. Whether it's searching for keys, locating books on the bookshelf, or identifying a specific subway stop, we invest a significant amount of time looking for things in a world full of objects that are not relevant. However, our capacity to process information is very limited. To make effective use of our cognitive resources, the brain prioritizes information relevant to the task at hand and suppresses irrelevant information that might impede performance (e.g., Treisman and Gelade 1980; J. M. Wolfe, Cave, and Franzel 1989; C. L. Folk, Remington, and Johnston 1992).

Traditionally, visual selective attention has been considered to operate under the influence of two types of control signals: when attention is captured - by a salient stimulus, such as a bright flash of light, it is said to be under bottom-up (i.e., stimulus-driven, involuntary mechanisms) control (Jan Theeuwes 2010; Yantis and Egeth 1999); and, when attentional selection is driven by a deliberate act of will and is directed toward task-relevant information, it is considered to be under top-down (i.e., goal-driven,voluntary mechanisms) control (Egeth and Yantis 1997). For example, imagining someone driving with the goal of focusing on the important road signs and traffic signals (current selection goals). However, a flashy roadside billboard or a distracting notification in the car captures attention against the driver's intentions. This unintentional distraction could pose a risk by taking attention away from safe driving.

Although major models of attentional control commonly depict attentional selection as a dichotomy, often referred to as a bottom-up versus a top-down process (J. Duncan and Humphreys 1989; Geng and Witkowski 2019; Jonides and Yantis 1988; Jeremy M. Wolfe and Horowitz 2004; Töllner, Conci, and Müller 2015; H. J. Müller and von Mühlenen 2000). Awh (2012) and other researchers emphasized that attentional selection in many cases is neither solely determined by current behavioral relevance nor exclusively influenced by the stimulus salience (Anderson et al. 2021; Failing and Theeuwes 2018; A. Kristjánsson and Campana 2010; Kadel, Feldmann-Wüstefeld, and Schubö 2017; Hermann J. Müller et al. 2010). Instead, it is shaped by the history of previous attentional deployments, resulting in persistent and enduring selection biases, unrelated to to-down goals or the physical salience of items (see also Failing and Theeuwes 2018; Jan Theeuwes 2019). Currently, three general classes of phenomena related to lingering biases due to selection history have been identified, there are different types of inter-trial priming effects (A. Kristjánsson and Campana 2010; Maljkovic and Nakayama 1994, 1996a; Tipper 1985), which describes how repetition of target- and distractor-defining features across consecutive trials improves performance on the current trial, and contextual cueing (M. M. Chun and Jiang 1998; Marvin M. Chun and Jiang 2003, 1999; Y. Jiang and Chun 2001; Goujon, Didierjean, and Thorpe 2015), i.e., improved target selection that is supported by contextual regularities (spatiotemporal regularities) in the visual context picked up by the observer during the experiment. Also in recent years, increasing evidence has highlighted the significant impact of past rewarding experiences (and punishment) on shaping attention selection in response to stimuli (Chelazzi et al. 2013; Anderson 2013, 2016; Failing and Theeuwes 2018). The last form of selection history effects is statistical learning of target and distractor features or their spatial regularities (Sauter et al. 2021; Dirk van Moorselaar and Slagter 2019; Turk-Browne, Jungé, and Scholl 2005; B. Wang and Theeuwes 2018; Gaspelin, Gaspar, and Luck 2019; Fiser and Aslin 2002; Chen et al. 2022; Zellin et al. 2013; Kerzel et al. 2022). In general, statistical learning refers to the brain's capacity to recognize and leverage environmental regularities through repeated exposures to specific contexts and situations (for a review, see A. Schapiro and Turk-Browne 2015). In the attention domain, statistical learning constitutes a strong determinant of stimulus priority and has been investigated in relation to various kinds of regularities in the spatial distribution of visual elements (typically the target), also known as spatial probability cueing (Druker and Anderson 2010; Geng and Behrmann 2002, 2005; Hoffmann and Kunde 1999; Shaw and Shaw 1977; Walthew and Gilchrist 2006; Y. V. Jiang, Sha, and Remington 2015; Y. V. Jiang, Swallow, and Rosenbaum 2013; Y. V. Jiang et al. 2013; Sha, Remington, and Jiang 2017). For example, when looking for our keys, we often commence searching at the 'usual' places, like the hallway table or the kitchen counter. Likewise, learning to deprioritize the task-irrelevant location where salient distractors appear frequently can also improve search efficiency. Imagine you're a student attending a lecture in a large auditorium and you notice the professor consistently places distracting content in the lower-left corner. Over time, the lower-left corner of the slides may not capture your attention anymore. In the laboratory, such phenomenon has been systematically investigated in terms of so-called spatial 'distractor probability cueing effects' (e.g., Goschy et al. 2014; Sauter et al. 2018; D. van Moorselaar, Daneshtalab, and Slagter 2021; Allenmark et al. 2019).

Many studies investigating probability-cueing effects concluded that spatial statistical learning is not dependent on awareness and thus implicit in nature (e.g., Y. V. Jiang, Swallow, and Rosenbaum 2013; Y. V. Jiang, Won, and Swallow 2014; Won and Jiang 2015). However, more recent studies have used more sophisticated awareness measures to investigate the relationship between explicit awareness and cueing of target locations, challenging the notion that statistic probability cueing is implicit (Huang, Donk, and Theeuwes 2022; Yu et al. 2023; Dirk van Moorselaar and Theeuwes 2023; Golan and Lamy 2023; Vicente-Conesa et al. 2021; Giménez-Fernández et al. 2020). The conflicting findings regarding awareness's role in learning static target regularities may be due to a variety of factors, such as the probability levels used in the various studies, the number of trials, and the method used for measuring awareness (Vadillo et al. 2020). After improved the method of measuring awareness, some studies investigating static probability cueing effect fund that the level of conscious awareness correlates with the magnitude of the attentional bias (e.g., Geyer et al. 2020;

Giménez-Fernández et al. 2020), raising the question whether dynamic target-location regularities depend on participants' awareness of the rule regarding target or distractor-location across trials.

Last but not least, many recent studies have been done to characterize the electrophysiological correlates of statistical learned distractor suppression (e.g., Dirk van Moorselaar et al. 2020; Dirk van Moorselaar and Slagter 2019; Benchi Wang et al. 2019; Qiu et al. 2023). However, we still lack a thorough understanding of the underlying neural mechanisms concerning statistical learned attentional enhancement (both static and dynamic) within the priority map. In the current thesis, we used oculomotor evidence as well as neural markers, such as EEG components associated with visuospatial selection, to address these questions.

The introduction starts with section (1.1) exploring theoretical perspectives on attentional selection. Apart from introducing the bottom-up capture of attention by distractors and the top-down control to minimize interference during visual attention. Additionally, we also emphasize a novel theory, termed "selection history" , that is introduced as an alternative source of influence. The second part of the introduction (1.2) introduces statistical learning effects regarding distractor and target locations. Additionally, we also discuss the latest studies investigating dynamic regularities of target and distractor. The third part of the introduction (1.3) mainly discusses the awareness of target-location probability cueing, which has been studied many years but still controversial. The fourth part (1.4) outlines the neural dynamics underlying statistical learning regarding target and distractor location learning in visual attention. The last subsection of the introduction (1.5) lists the main aims of the doctoral thesis.

Chapter 2 encompasses the three distinct studies that form the core of the cumulative dissertation. Finally, in Chapter 3, the thesis is summarized and comprehensively discussed. As the last chapter, Chapter 3 summarizes three studies-a behavioral study, an eye-tracking study, and an EEG study. In the General Discussion section, a comprehensive conclusion and some recommendations for further research are provided.

1.1 Theory of visual attention

In our daily lives, we constantly engage in visual search activities. For instance, seeking our preferred brand of cereal in a bustling supermarket, identifying a specific car on a busy street, locating a particular book on the shelves, or scanning the luggage carousel for our suitcase at the airport. All those activities impose substantial/considerable demands on the visual system (Horowitz and Wolfe 1998). Selective attention is a mechanism that helps us focus on limited resources and filter out distracting information (Treisman and Gelade 1980; Egeth and Yantis 1997; Marvin M. Chun and

Marois 2002; Jeremy M. Wolfe and Horowitz 2004; Geyer, Müller, and Krummenacher 2006; Mazza et al. 2007; C. L. Folk, Remington, and Johnston 1992). Attention selection has been considered as the result of interaction between top-down (goals of the observer) and bottom-up (the physical properties of the visual environment) mechanisms (Egeth and Yantis 1997; Yantis and Egeth 1999; Orchard-Mills, Alais, and Van der Burg 2013; Jeremy M. Wolfe et al. 2003; C. L. Folk, Remington, and Johnston 1992).

Top-down visual attention is a voluntary process in which a particular location, feature, or object relevant to current behavioral goals is selected internally or focused upon (Katsuki and Constantinidis 2014), which can exert its influence through acts of will (Baluch and Itti 2011). For example, imagine you are planning a vacation to a new city, and you have a list of specific attractions and landmarks you want to visit. Additionally, this voluntary process can occur in response to exogenous or endogenous cues, as well as expectations set by prior knowledge or contingencies of the stimulus (Geng and Behrmann 2002, 2005; Moore and Egeth 1998; Drummond and Shomstein 2010). The *contingent capture hypothesis*, proposed by Folk et al. (1992), suggests that the selection and focus of attention are greatly influenced by the observer's top-down control settings, particularly their current perceptual goals or tasks. However, visual search is not merely driven by the “act of will”, some computational models have highlighted the role of salience (bottom-up) in attentional selection (Parkhurst, Law, and Niebur 2002; Itti and Koch 2001). Evidence supporting bottom-up attentional allocation has been established through diverse attentional capture paradigms, in which participants are engaged in a top-down search and their attention is diverted to the task-irrelevant stimuli, demonstrating that attention is captured by feature singletons (Charles L. Folk, Leber, and Egeth 2002; J. Theeuwes 1991) and abrupt onsets (Yantis and Jonides 1984; J. Theeuwes 1991; Koshino, Warner, and Juola 1992; Juola, Koshino, and Warner 1995).

Rather than considering visual selection as the result of either top-down or bottom-up process, some theories provided critical insights that attentional selection is determined by an interaction of both top-down and bottom-up factors (Yantis and Jonides 1990; J. M. Wolfe and Gray 2007). For instance, *search-mode account,* which assumes that two distinct search strategies are employed while people perform a task (Bacon and Egeth 1994; Leber and Egeth 2006). One is *feature search mode*, which hypothesized that observers can exert top-down selectivity, thereby eliminating capture by salient yet task-irrelevant stimuli that do not align with the current attentional set. In other words, applying top-down control allows for the avoidance of capture by the irrelevant salient singleton. Another attentional strategy is *singleton detection mode*, different from feature search mode, which is entirely salience driven and therefore optimized for detection of salient singletons (Bacon and Egeth 1994). With an additional singleton task, Theeuwes (1992) found the irrelevant distractor singleton interferes with search for the target singleton. In this task, participants need to search for one specific and clearly defined salient singleton (e.g., a diamond among many circles) while another singleton irrelevant for the task (e.g., a red shape among many green shapes) is simultaneously present. Theeuwes (1994) called this mode *a stimulus-driven attentional capture model* in which selection was entirely determined by the features of the items. Another *Signal suppression hypothesis* developed by Gaspelin et al. (2015) also emphasizing that physical salient stimuli can attract attention, but it also correlates with goal-driven theories (Charles L. Folk and Remington 1998; C. L. Folk, Remington, and Johnston 1992) claiming that inhibitory processes can effectively suppress these when top-down control is exerted.

Instead of considering selection as only a result of the interaction between top-down and bottom-up processes, Awh and colleagues (2012) proposed that many instances of selection are driven by previous selection experiences, independent of both goal-driven and stimulus-driven factors, which they termed "selection history" (see also Failing and Theeuwes 2018; Hermann J. Müller et al. 2010). Observers are often unaware that these mechanisms are influencing their attention, making selection-history mechanisms are therefore typically considered to be implicit (Liesefeld et al. 2024). The selection-history phenomena that have been extensively investigated can be categorized into three main groups: statistical learning, inter-trial priming and value learning.

In general, statistical learning refers to the brain's capacity to recognize and leverage environmental regularities through repeated exposures to specific contexts and situations (for a review, see A. Schapiro and Turk-Browne 2015). In the attention domain, statistical learning refers to the finding that statistical regularities with regard to the locations, features or temporal characteristics of targets and distractors influence attentional priority (e.g., Benchi Wang et al. 2019; Geng and Behrmann 2002, 2005; Bacigalupo and Luck 2019). For example, if the target appears at a given location more often than would be expected by chance, observer will respond to the target faster with lower error when the it appears at the high-probability location than other locations (Ferrante et al. 2018; Geng and Behrmann 2002, 2005); if the distractor was presented at a location with high-probability, observers made fewer errors and faster responses relative to low probability, some oculomotor studies validated these findings, revealing that oculomotor capture was less likely when singleton distractors occurred at frequent locations rather than rare locations (Benchi Wang, Samara, and Theeuwes 2019; Di Caro, Theeuwes, and Della Libera 2019; Sauter et al. 2021). Alternatively, people will have greater difficulty selecting the target when it appears at the high-probability distractor location than at other locations (Sauter et al. 2018).

Inter-trial priming, whereby that recent selection of a stimulus biases attention on subsequent stimuli sharing properties with previous stimuli (e.g., Á. Kristjánsson 2006; Maljkovic and Nakayama 1994, 1996a). Depending on the specific properties of the prior stimuli, inter-trial priming could be categorized into feature intertrial priming (involving color or shape, Maljkovic and Nakayama 1994), location intertrial priming (involving location, Maljkovic and Nakayama 1996a), dimension inter-trial priming (involving different dimensions, Found and Müller 1996; Lamy, Bar-Anan, and Egeth 2008).

Finally, value learning refers to the finding that stimuli that are reliably associated with either reward or aversive experience are endowed with higher attentional priority than neutral- value stimuli (Anderson, Laurent, and Yantis 2011). A wealth of researches and reviews (Anderson 2016; Chelazzi et al. 2013; Della Libera, Perlato, and Chelazzi 2011; Anderson 2013; Anderson, Laurent, and Yantis 2011; Della Libera and Chelazzi 2006, 2009; Stanković, Müller, and Shi 2023) over recent years provided evidence that rewarding experience in the past have a large effect on attention selection.

Hence, based on the evidence discussed earlier, attention selection is the result of the interaction between top-down, bottom-up, and previous selection experiences. Priority map is a notion that represents dynamic spatial representation that codes attentional priority at each location (Fecteau and Munoz 2006; Itti and Koch 2001; Zelinsky and Bisley 2015)

1.2 Statistical learning as history effect: location probability cueing effect

To efficiently adapt to the environment with overwhelming amounts of information, utilizing environmental regularities such as the likely location of a ‘target’ object, facilitates the optimal deployment of attention and cognitive resources. For example, when searching for a misplaced document, we instinctively start the search in familiar and likely locations, such as our desk or filing cabinet. In the laboratory, this phenomenon has been systematically investigated in terms of so-called spatial ‘probability cueing effects’, when a task-relevant target occurs with a high probability at one location, our attentional system can acquire this information to enhance search efficiency, facilitating target detection and corresponding response decisions (Druker and Anderson 2010; Geng and Behrmann 2002, 2005; Hoffmann and Kunde 1999; Y. V. Jiang, Swallow, and Rosenbaum 2013; Shaw and Shaw 1977). Some eye-tracking studies also found evidence of probability cueing effect, in terms of an increased frequency and reduced latencies of (early) saccades directed to targets at likely locations (Walthew and Gilchrist 2006; Jones and Kaschak 2012; Y. V. Jiang, Won, and Swallow 2014). To facilitate visual search, prior learning about target location is not enough, it is essential to filter out irrelevant and distracting details simultaneously, which ensures a focused and efficient search.

Thus spatial probability cueing is not limited to prioritizing the target location, many recent studies have shown that people can also learn a high probability of a salient but task-irrelevant distractor appearing at a specific location or in a specific region to de-prioritize the processing of such stimuli – referred as ‘distractor-location probability cueing’ (e.g., Sauter et al. 2018; Goschy et al. 2014; Leber et al. 2016; Ferrante et al. 2018)

It is worth mentioning that most of studies investigating spatial statistical learning, whether involving target or distractor locations, did use some static uneven probability manipulation, such as one location or region being more likely to contain the target, or a distractor, than any other location or region (e.g., Geng and Behrmann 2002, 2005; Shaw and Shaw 1977; Goschy et al. 2014; Sauter et al. 2018). The implicit assumption is that statistical learning can enhance or suppress specific (static) locations on the attentional priority map that governs the allocation of focal-selective attention (for a review, see Steven J. Luck et al. 2021). Nevertheless, the question remains whether or not such a modulation of selection priorities is stationary – accommodating a static spatial distribution of targets and distractors, or dynamic, flexibly adapting to predictable changes in the distribution of targets and distractors.

In recent years, several studies, including our own work, try to investigate the questions mentioned above (Li and Theeuwes 2020; Li, Bogaerts, and Theeuwes 2022; Yu et al. 2023). Accordingly, these studies have demonstrated that attentional selection can successfully adapt to such dynamic, cross-trial regularities in the placement of target items: RTs were faster to target when it occurs at predicted location by the dynamic rule, relative to random locations (Li and Theeuwes 2020; Yu et al. 2023). Notably, Li et al. (2022) found that the presence of a dynamic cueing effect depends on the nature of the search mode. Specifically, in spatially parallel searches (their Experiment 2), a dynamic cueing effect was observed, whereas in serial searches (Experiment 1), no such effect was observed. The task used in Li's study (2022) is known to offer little bottom-up or top-down guidance (e.g., Moran et al. 2013), requiring serial scanning of the search array by focal attention to find and respond to the target item.

More specifically, in Li and Theeuwes's (2020) design, some target locations were predictably coupled across trials; for instance, a target occurring at the left-most (or respectively, the top) display location on trial n would invariably lead to the next target, on trial n+1, occurring at the rightmost (or respectively, the bottom) location (but not vice versa). Although unbeknown to participants, this target regularity nevertheless facilitated search and boosted accuracy, which is in line with our own study (Yu et al. 2023), in which search was facilitated when the target moved predictably across consecutive trials to the neighboring position in either clockwise or anticlockwise (blocked) direction.

In studies involving static (spatially fixed) likely target locations, the ability to learn and predict these targets is observed to be effective under both serial and parallel search conditions. Conversely, when dealing with dynamic target-location regularities, this learning mechanism appears to operate exclusively under parallel search conditions, where simultaneous processing facilitates adaptation to changing target probabilities (Li and Theeuwes 2020; 2022). The question remains: why?

However, it remains controversial whether statistical learning of dynamic distractor location is possible. Wang et al. (2021) examined whether similar flexibility could be found in statistical learning of distractor locations. In their experiment, the 'classical' additional-singleton search paradigm with a circular display arrangement was applied, a salient color distractor 'jumped' by one location in either clockwise or counterclockwise direction across consecutive trials, with 100% predictability. Wang et al. found a reduced distractor interference in "regular" groups relative to "random" and baseline groups. However, the interference between two groups was diminished toward the end of testing, which implies that both groups likely employed a similar, spatially non-specific suppression strategy, particularly towards the end of the experiment. However, in another study deployed both the same design and a modified design, in Chapter 2.1 (Yu et al. 2023), we found that participants could not learn and exploit the dynamic distractor probability, at odds with Wang et al. (2021). Thus, it appears that the ability to benefit from dynamic distractor probability is affected by the experimental design. Therefore, further research is necessary to fully understand the underlying mechanisms of proactive suppression of the predictable distractor location.

1.3 Awareness of target-location probability cueing

Statistical learning is generally assumed to be an implicit process, extracting statistical regularities from input without intent or explicit awareness (Turk-Browne, Jungé, and Scholl 2005; Turk-Browne et al. 2009). As one of main phenomena of statistical learning, contextual cueing demonstrates/illustrates that locating a target is easier when it appears in a previously searched visual layout compared to entirely new layouts that were previously unseen (M. M. Chun and Jiang 1998; Marvin M. Chun and Jiang 2003). The basic finding regarding awareness was that observers could not report which configurations they had seen before, suggesting little awareness of what they had learned (Marvin M. Chun and Jiang 2003; M. M. Chun and Phelps 1999; M. M. Chun and Jiang 1998; Y. Jiang and Chun 2001; for a review, see Goujon, Didierjean, and Thorpe 2015).

In line with this, there are reports indicating that individuals can acquire and apply static regularities regarding the locations of prominent distractors without conscious awareness, namely, most participants were unable, in post-experimental awareness tests, to identify the frequent distractor location, and the cueing effect differed little between those who correctly selected vs. those who failed to select the frequent location (e.g., Failing, Wang, and Theeuwes 2019; Dirk van Moorselaar and Theeuwes 2022; B. Wang and Theeuwes 2018). Additionally, similar findings have been reported regarding the statistical learning of target locations (e.g., Li, Bogaerts, and Theeuwes 2022; Ferrante et al. 2018; Geng and Behrmann 2005).

In experiments in which regularities regarding the target are manipulated, awareness is much higher, with about two-thirds of the participants able to report the high-probability target location (Huang, Donk, and Theeuwes 2022). Note, however, that this all depends on the probabilities used, the number of trials, and the way awareness is assessed.

Nevertheless, with more sophisticated awareness measures used to investigate the relationship between explicit awareness and cueing of target locations, the notion that probability cueing is implicit in nature has been challenged (Huang, Donk, and Theeuwes 2022; Yu et al. 2023; Dirk van Moorselaar and Theeuwes 2023; Golan and Lamy 2023; Vicente-Conesa et al. 2021; Giménez-Fernández et al. 2020). A variety of factors may contribute to the conflicting findings regarding the role of awareness in learning static target regularities, such as the probability levels used in the various studies, the number of trials, when to measure the awareness and the method employed to assess awareness (Vadillo et al. 2020). For instance, participants were asked to rank the possible locations from the most probable to least probable and estimate numerically how many times the target appearing in each quadrant of the display (in a "serial", contextual-cueing paradigm; cf. M. M. Chun and Jiang 1998), Giménez-Fernández et al. (2020) found that many participants were well aware of the uneven (static) spatial distribution of the target. The new approach mentioned above enable us to illustrate that participants exhibit high performance on these measures, thereby revealing awareness of the manipulation (Smyth and Shanks 2008; Vadillo et al. 2022; Vicente-Conesa et al. 2021) and also that the level of conscious awareness correlates with the magnitude of the attentional bias (Geyer et al. 2020; Giménez-Fernández et al. 2020).

In a recent study of dynamic target-location probability cueing in pop-out search Chan (Yu et al. 2023), we likewise found a substantial number of participants to be explicitly aware of the dynamic (cross-trial) target regularity, and we observed the dynamic target-location probability-cueing effect to be significant only in the group of aware participants.Based on these findings, we hypothesize that at least the learning of dynamic target-location regularities in serial search is explicit in nature, dependent on (or correlated with) participants becoming aware of the rule governing the shifts in the target location across trials.

1.4 Neural mechanism of history-based visual attention

As there are many objects competing for your attention in life, the challenge for the brain is to prioritize information relevant to the task at hand and suppress irrelevant information that is unrelated to the current task goals (e.g., Treisman and Gelade 1980; J. M. Wolfe, Cave, and Franzel 1989; Egeth and Yantis 1997; C. L. Folk, Remington, and Johnston 1992).

Priority map is believed as the most generic and theoretically neutral term for describing a map at the top of the hierarchy that serves to prioritize some information over others (Liesefeld et al. 2024). A spatial priority map means a representation of topographic space encoding the priority of individual locations combining signals originating from sensory input (bottom-up), current goal states (top-down or behavioral relevance), and statistical learning (history driven)-determine the weights within the spatial priority map (Jan Theeuwes, Bogaerts, and van Moorselaar 2022). Importantly, the priority map arises from a distributed network involving frontal, parietal, and temporal areas (for a review, Jan Theeuwes and Failing 2020). To be more specific, frontal brain areas, including the anterior cingulate, are presumed to be associated with top-down goals (Katsuki and Constantinidis 2014); while early visual areas and structures such as the superior colliculus contribute to bottom-up salience calculations (Itti and Koch 2000) ; the medial temporal lobe, including the hippocampus system (hippocampus and associated medial temporal lobe structures; MTL) and other subcortical structures such as the basal ganglia (Hikosaka, Takikawa, and Kawagoe 2000), plays an important role in storing and representing selection history or visual statistical learning (e.g., Gaffan 1994; A. C. Schapiro et al. 2016; Holland and Bouton 1999; Rungratsameetaweemana, Squire, and Serences 2019). These three signals converge into the priority map, potentially within the Frontal Eye Fields (FEF), ultimately influencing selection (e.g., Jan Theeuwes 2019)

Statistical learning regarding target and distractor locations have been investigated intensively in studies both at a behavioral level (Druker and Anderson 2010; Geng and Behrmann 2002, 2005; Hoffmann and Kunde 1999; Y. V. Jiang, Swallow, and Rosenbaum 2013; Shaw and Shaw 1977; Sauter et al. 2018; e.g., Goschy et al. 2014; D. van Moorselaar, Daneshtalab, and Slagter 2021) and eye tracking studies (Walthew and Gilchrist 2006; Jones and Kaschak 2012; Y. V. Jiang, Won, and Swallow 2014), surprisingly very little is known about the underlying neural substrates driving learned distractor suppression and target enhancement. ERP studies can provide a direct window into how these processes unfold. Investigations utilizing ERPs to explore the mechanisms involved in both distractor suppression and target enhancement have primarily relied on analyzing the N2pc component, which numerous studies have provided compelling evidence for as a common electrophysiological marker may reflect the allocation of visuospatial attention within multi-stimulus displays (S. J. Luck and Hillyard 1994; M. Eimer 1996; Woodman and Luck 1999; for a review, see Martin Eimer 2014). The N2pc is an enhanced negative-going component of the EEG recorded in the posterior central electrode sites contralateral to the attended target objects in visual search displays, occurring about 200-350 ms after stimulus onset, (Kiss, Van Velzen, and Eimer 2008; Gaspar et al. 2016), which generated in ventral extrastriate visual areas (Hopf et al. 2000). For instance, in a study investigating probability cueing effect regarding target locations, with additional singleton paradigm, recently Duncan et al. (2023) reported that targets located at high probability locations did elicit larger N2pc amplitudes relative to when targets located at low probability locations. However, van

Moorselaar et al. (2021) failed to find any difference in the N2pc elicited by targets occurring at the frequent relative to a rare distractor location. In another study investigating probability cueing effect regarding distractort locations, Sauter et al. (2017) found the distractor-elicited N2pc amplitude was significantly higher for distractors appearing at locations in the frequent than the rare (distractor) region in the midline-target/lateral-distractor condition; and importantly, the target-N2pc was delayed for targets that appeared in the frequent distractor location but not delayed for targets in the rare distractor location, suggesting that a great allocation of attentional resources is necessary to detect a target stimulus in a region that has been proactively suppressed due to learning the location of distractors.

In addition to examining amplitude differences, researchers also extensively explore disparities in latency across diverse experimental conditions to gain deeper insights into the temporal dynamics of statistical learning processes related to target or distractor location. Sauter (2017) found, the target-N2pc was delayed for targets that appeared in the frequent distractor location but not delayed for targets in the rare distractor location, suggesting that a great allocation of attentional resources is necessary to detect a target stimulus in a region that has been proactively suppressed due to learning the location of distractors. While studies examining static distractor probability-cueing effects, comparatively fewer have emphasized differences in latency between likely and unlikely target locations. However, numerous studies focused on statistical learning have successfully demonstrated that a target elicits an N2pc with an earlier onset when its feature, such as shape or color, repeats compared to when it does not (Christie, Livingstone, and McDonald 2015; Becker, Grubert, and Dux 2014; Tay et al. 2019). Yet, in the domain of visual statistical learning about spatial regularities, the relevant literature fails to provide a coherent depiction of N2pc effects, and new evidence will be needed to resolve those inconsistencies.

Many studies have advanced our understanding of the role of endogenous alpha oscillations (8-12 Hz), suggesting their involvement more in the enhancement of relevant or the suppression of irrelevant stimuli (e.g., Foster and Awh 2019; Foxe and Snyder 2011). Traditionally, alpha oscillation is regarded as a neural signature of stimulus processing in attentional processes. Specifically, an increase in alpha-band amplitude, often referred to as alpha synchronization, at electrodes contralateral to a stimulus (relative to the amplitude over the ipsilateral hemisphere) has been proposed to indicate active suppression of that stimulus (e.g., Foxe and Snyder 2011; Jensen and Mazaheri 2010). Conversely, a decrease in lateralized alpha-band amplitude, is known as alpha desynchronization, has been considered a indicator of attentional facilitation of contralateral stimuli (Bacigalupo and Luck 2019; Forschack et al. 2022; Neuper, Wörtz, and Pfurtscheller 2006; Sauseng et al. 2005). However, compelling evidence for an unequivocal role of alpha rhythms in distractor suppression is somewhat limited. Several studies have demonstrated that alpha activity persists in tracking unattended regions even in the absence of distractor stimuli (Noonan et al. 2016; Sauseng et al. 2005; Thut et al. 2006). Others found no increases of posterior alpha power in anticipation of distractors, for example, Dirk et al. (2021) found no increase in anticipatory alpha-band activity was observed over visual regions representing likely distractor location relative to unlikely distractor location. While, in another study investigating anticipatory distractor suppression caused by spatial statistical regularities, Wang et al. (2019) found that participants had learned that the salient distractor is more likely to appear at one specific location, so this location would be suppressed, as there was an increase in alpha power contralateral to this location relative to the ipsilateral location. Contrary to that finding, a recent study showed that distractor suppression was not associated with lateralized alpha power during the pre-stimulus period (Qiu et al. 2023). Furthermore, some studies emphasized the association between attentional facilitation and alpha power, they found a decrease of alpha power contralateral to the target location reappearing relatively late after target onset (Bacigalupo and Luck 2019; van Diepen et al. 2016). Therefore, there is still a debate over whether alpha modulations reflect distractor suppression or a complementary mechanism that promotes target enhancement (Foster and Awh 2019; Noonan et al. 2016; Slagter et al. 2016).

1.5 Aims of the thesis

The goal of the current dissertation is to mainly advance our understanding of the cognitive and the neural dynamics underlying target enhancement induced by spatial statistical learning in visual search, and further to establish how to make use of both static and dynamic across-trial regularities of target locations to facilitate attention. To address these issues, classical behavioral experiments, eye-tracking and EEG techniques are employed.

To begin with, in Chapter 2.1, four psychophysical experiments were performed to investigate whether statistical learning also extends to dynamic regularities governing the placement of targets and distractors on successive trials. To investigate this question, we adopted singleton classic additional-singleton paradigm and introduced cross-trial spatial regularities for the singleton color distractor (Experiment 1a) and, respectively, the singleton shape target (Experiment 1b). The location of the critical item (either the target or the distractor) would move by one location across trials in one direction, either clockwise or counterclockwise (counterbalanced across participants) with a high probability (80%), or the opposite direction with a low probability (10%), or jump randomly to a non-adjacent location (including location repetitions) (10%). To promote statistical learning taking place at the level of the priority map, we randomly swapped the target and the distractor color across trials, which, previous research indicates (Allenmark et al. 2019), limits learning at a level below the priority map (the level of specific features or feature dimensions). Also, by inducing a ‘singleton-detection’ search mode (cf. Bacon and Egeth 1994), random color swapping produces larger distractor-interference effects compared to consistently separable distractor and target colors (Allenmark et al. 2019; D. van Moorselaar, Daneshtalab, and Slagter 2021), thus providing more room for demonstrating statistical learning effects.

Subsequently, in Chapter 2.2, eye tracking technique was used (1) to examine whether participants would learn a simple dynamic (probabilistic) regularity in the positioning of target items across consecutive trials in a *serial* search task; (2) to investigate if such dynamic learning would rely on explicit awareness of the regularity. To achieve this goal, we used the same dynamic, cross-trial regularity as Chapter 2.1 did in a parallel search task. This involved shifting the target location in a circular display arrangement by one position, either clockwise or anticlockwise (blocked per participant) across trials with a probability of 80%, compared to only a 25%-probability in Li and Theeuwes (2020), we assumed a substantial number of participants would extract and utilize this regularity to speed performance even in serial search, which requires (a sequence of) eye movements to detect and respond to the target item. As for behavioral results, in particular, we expected faster task-final RTs if the cross-trial shift of the target location conforms with the rule (‘frequent’) versus when it didn’t (‘infrequent’- and ‘random’-shift trials), evidencing a dynamic target-location probability-cueing effect. We also hypothesize that participants who are 'aware' of the dynamic regularity will demonstrate a significant dynamic target-location probability-cueing effect, whereas those who are 'unaware' are not expected to benefit from the regularity. Additionally, we anticipate a positive correlation between participants' subjective certainty regarding the rule and the magnitude of their cueing effect. As for eye movements, we hypothesize if rule-based guidance is engaged early, aware participants' initial saccade may be predominantly directed towards the dynamically predicted 'frequent' target location compared to infrequent and random locations. Alternatively, if rule-based guidance is delayed, we expect aware participants to employ fewer saccades to locate the target at the frequent location compared to other locations (excluding possibly the repeated one), and fewer saccades overall compared to unaware participants. Additionally, we also check early eye movements in the mixed condition (non-target identities were mixed, swapping randomly across trials) to assess how dynamic rule guidance on a given trial is modulated by preceding trial events conforming that either conforms or breaks the rule (rule-based intertrial priming). Last, by recording eye movements, we are able to examine whether the earliest saccades performed during the serial search are influenced by explicit knowledge of where the new target is likely to be located.

Finally, Chapter 2.3, combining the EEG approach with the serial search task, the dissertation first explores (1) how the statistical learning of target location modulate attentional selection across trials at the neural level, and how plastic changes induced by statistical learning impact later attentional processing, by examining the ERP component N2pc (latency and amplitudes); and (2) whether any prediction occurs because of target location enhancement occurs prior to search display onset, by examining the pre-stimulus alpha activity.

2 Cumulative Thesis

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

2.1 Asymmetric learning of dynamic spatial regularities in visual search: Robust facilitation of predictable target locations, fragile suppression of distractor locations

Hao Yu, Fredrik Allenmark, Hermann J. Müller, Zhuanghua Shi

General and Experimental Psychology, Department of Psychology, LMU Munich, 80802, Germany

CONTRIBUTIONS

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

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

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

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

Author Note

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Asymmetric learning of dynamic spatial regularities in visual search: robust facilitation of predictable target locations, fragile suppression of distractor locations

Hao Yu
General and Experimental Psychology, Department of Psychology, LMU Munich, 80802, Germany

Fredrik Allenmark
General and Experimental Psychology, Department of Psychology, LMU Munich, 80802, Germany

Hermann J. Müller
General and Experimental Psychology, Department of Psychology, LMU Munich, 80802, Germany

Zhuanghua Shi
General and Experimental Psychology, Department of Psychology, LMU Munich, 80802, Germany

Abstract

Static statistical regularities in the placement of targets and salient distractors within the search display can be learned and used to optimize attentional guidance. Whether statistical learning also extends to dynamic regularities governing the placement of targets and distractors on successive trials remains controversial. Here, we applied the same dynamic cross-trial regularity – one-step shift of the critical item in clock-/counterclockwise direction – to either the target or a distractor. In two experiments, we found and replicated robust learning of the predicted target location: processing of the target at this location was facilitated, compared to random target placement. But we found little evidence of proactive suppression of the predictable distractor location – even in a close replication of Wang et al. (2021), who had reported a dynamic distractor suppression effect. Facilitation of the predictable target location was associated with explicit awareness of the dynamic regularity, whereas participants showed no awareness of the distractor regularity. We propose that this asymmetry arises because, owing to the target's central role in the task set, its location is explicitly encoded in working memory, enabling the learning of dynamic regularities. In contrast, the distractor is not explicitly encoded; so, statistical learning of dynamic distractor locations is more precarious.

Keywords: probability cueing, color swapping, feature-based suppression, priority-based suppression

Introduction

Our environment is extremely rich and complex, while our capacity for information processing is limited. The brain must prioritize information relevant to the task at hand, while resisting irrelevant information that might compete for our limited cognitive resources (C. L. Folk, Remington, and Johnston 1992; Charles L. Folk and Remington 1998, 2008; Wolfe, Cave, and Franzel 1989; Egeth and Yantis 1997; Charles L. Folk, Leber, and Egeth 2002). Fortunately, rather than being random, our visual environment is highly structured. Thus, being able to extract and learn critical environmental regularities is useful for encountering and dealing with similar situations in the future. For example, it is easy to find a sushi box in a familiar supermarket without being distracted by other products, given that you know where the sushi boxes are located. In the laboratory, these phenomena have been systematically investigated under the label (spatial) 'probability-cueing effects' (Geng and Behrmann 2002, 2005). When a task-relevant target occurs with a high probability at a particular location, our attentional system can learn and effectively use this information for guiding search, facilitating target detection and response decisions (Druker and Anderson 2010; Geng and Behrmann 2005, 2002; Jiang, Swallow, and Rosenbaum 2013; Hoffmann and Kunde 1999; Shaw and Shaw 1977).

Spatial probability cueing is not limited to prioritizing the target location. Rather, as has been shown in recent studies, people can also learn a high probability of a salient but task-irrelevant distractor appearing at a specific location or in a specific region to de-prioritize the processing of such stimuli (e.g., Ferrante et al. 2018; Goschy et al. 2014; Leber et al. 2016; Sauter et al. 2018; Sauter, Liesefeld, and Müller 2019; B. Wang and Theeuwes 2018a; Zhang et al. 2019). For example, Goschy and colleagues (2014) designed a visual search task that required participants to search for a tilted bar amongst vertical bars and indicate whether the target bar had a gap at the top or the bottom. In half of the trials, a colored bar was shown with a high probability (90%) in one half of the display and with a low probability (10%) in the other half. The 'interference' (i.e., the reaction time, RT, cost) engendered by a salient color distractor was greatly reduced if the distractor was presented in the high-probability (vs. the low-probability) region, indicating that search performance can also be boosted by statistical learning of distractor locations. In a control experiment, Goschy et al. further confirmed that the reduction of interference reduction is not merely owing to repetition of the distractor location across trials (which is more likely for likely distractor locations); rather, long-term statistical learning of likely distractor locations, and attendant proactive spatial suppression processes, contribute to the efficient search guidance.

Collectively, the aforementioned studies have shown that observers can learn/exploit, from experience, the uneven spatial distributions of target and distractor in the search array over time, to minimize the interference generated by distractors and optimize target selection. However, whether statistical learning of target selection and distractor suppression are distinctive processes remains controversial. Some researchers argue that distractor suppression involves distinct processes to target selection (e.g., Noonan et al. 2016), while others suggest that attentional allocation by statistical learning is a result of a unitary mechanism: enhanced and, respectively, suppressed activities on the search-guiding spatial-attentional priority map are just two sides of the same coin (Ferrante et al. 2018).

Of note, the majority of the probability-cueing studies demonstrating spatial statistical learning used a fixed uneven probability manipulation, such as one region/location having a higher occurrence of the target or distractor compared to the other region/locations (e.g., Geng and Behrmann 2002, 2005; Shaw and Shaw 1977; Goschy et al. 2014; Sauter et al. 2018). The implicit assumption is that statistical learning can modulate the activation pattern on the spatial priority map, by enhancing or suppressing specific locations/regions (for a review, see Luck et al. 2021). However, the question remains whether or not such a modulation of selection priorities is stationary – adapting to a static spatial distribution of targets and distractors – or dynamic – adaptive to predictable changes in the distribution of targets and distractors.

In a recent study, Li and Theeuwes (2020) introduced a dynamic cross-trial regularity to explore this question. In their paradigm, some target locations were predictably coupled across trials; for instance, a target occurring at the left-most (or respectively, the top) display location on trial *n* would invariably lead to the next target, on trial *n+1*, occurring at the rightmost (or respectively, the bottom) location (but not vice versa). Although apparently unbeknown to participants, this target regularity nevertheless facilitated search and boosted accuracy. In a more recent study, Wang et al. (2021) further explored whether such flexibility would also characterize statistical learning, and attendant suppression, of distractor locations. In their adaptation of the 'classical' additional-singleton search paradigm with a circular display arrangement, a salient color distractor 'jumped' by one location in either clockwise or counterclockwise direction across consecutive trials, with 100% predictability. Wang et al. found that participants could relatively rapidly learn this cross-trial regularity to facilitate search, compared to a control group performing the task under conditions in which placement of the distractor across trials was random (i.e., the 'regular' group showed a reduced distractor interference relative to the distractor-absent baseline compared to the 'random' group). Note, though, that in their study, the color of the odd-one-out (color-defined) distractor was either fixed (their Exp. 1) or changed randomly between two colors (their Exp. 2), while the distractor color was *never* the color of the (shape-defined) target (white). Thus, according to both feature- and dimension-based accounts of distractor handling (e.g., Liesefeld and Müller 2019; Müller et al. 2009; Won, Kosoyan, and Geng 2019): as long as the color of the distractors is separable from the target color, it would remain possible to (learn to) globally, in spatially non-specific manner, suppress the feature- or feature-contrast signals they generate in the color dimension and so uniformly reduce their weight in the computation of the priority map. Interestingly in this context, in Wang et al. (2021), the difference in interference between their separate 'regular' and 'random' groups was diminished towards the end of testing. Given there was no spatial regularity participants in the 'random' group could possibly learn, this may be taken to suggest that both groups actually operated the same, spatially non-specific suppression strategy, at least towards the end.

In fact, studies examining a static probability manipulation of distractor locations indicate that separability of the distractor and the target color influence the distractor-handling strategy that observers develop: without color swapping between the distractor and target colors, they tend to adopt a feature- or dimension-based suppression strategy; with color swapping, they develop priority-map-based suppression (Zhang et al. 2019; Allenmark et al. 2019).[1] This echoes a similar idea proposed in the contingent-capture hypothesis (C. L. Folk, Remington, and Johnston 1992), namely, that the top-down attentional set for target-defining features determines which items are prioritized for selection: distractors can only be effectively down-weighted if they do not share search-critical-features with the target – where the attentional control set influences signal coding below the level of the priority map, in a spatially non-specific manner.

Thus, given that statistical learning of item locations for attentional prioritization can occur at multiple levels in the functional architecture of search guidance, whether dynamic enhancement and suppression are purely based on the predictive location of the target and, respectively, distractor remains elusive. To systematically investigate this, we devised the same cross-trial transitional probability structure for predictable target locations and, respectively, predictable distractor locations. We hypothesized that if statistical learning of the predictable locations of the target and distractor are the 'two sides of the same coin', we should observe a similar pattern of dynamic spatial learning and attendant signal modulations – though in opposite directions: prioritizing target and suppressing distractor signals – on the attentional priority map. By contrast, if dynamic modulation of spatial priorities by statistical learning is tied to the positive search goal, namely, to find some pre-specified target, we would expect to see a dissociation between dynamically predictable target locations (which should be learnable) and distractor locations (which may not be learned, as they are only part of the negative task set).

Specifically, in Experiment 1, we adopted the classic additional-singleton paradigm and introduced cross-trial spatial regularities for the singleton color distractor (Experiment 1a) and, respectively, the singleton shape target (Experiment 1b, see Figure 1). The location of the critical item (either the target or the distractor) would move by one location across trials in one direction, either clockwise or counterclockwise (counterbalanced across participants) with a high probability (80%), or the opposite direction with a low probability (10%), or jump randomly to a non-adjacent location

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[1] That feature- or dimension-based distractor information is of reduced utility under conditions of color swapping is consistent with other studies. For instance, Graves and Egeth (2015) found greater RT distractor interference when the colors were swapped between target and distractor across trials. Similarly, in eye-movement experiments with color swapping, Gaspelin and colleagues (Gaspelin and Luck 2018; Gaspelin, Gaspar, and Luck 2019) found the first saccade (after display onset) to be more likely to be directed to the singleton distractor than to the average of the other non-target items. Similarly, Becker (2010) found the irrelevant singleton-color distractor to attract an eye movement more frequently compared to non-target items when its defining (color) feature had switched, rather than repeated, from the previous trial.

(including location repetitions) (10%). Note that, in contrast to Wang et al. (2021),this implements a within-participant design (with the same participants performing both the regular and the random, baseline condition), avoiding spurious effects attributable to random group differences. To promote statistical learning taking place at the level of the priority map, we randomly swapped the target and the distractor color across trials, which, previous research (Zhang et al. 2019; Allenmark et al. 2019) indicates, limits learning at a level below the priority map (the level of specific features or feature dimensions). Also, of course, by inducing a 'singleton-detection' search mode (cf. Bacon and Egeth 1994), random color swapping produces larger distractor-interference effects compared to consistently separable distractor and target colors (Allenmark et al. 2019; van Moorselaar, Daneshtalab, and Slagter 2021), thus providing more room for demonstrating statistical learning effects.[2]

What we found was that participants could successfully learn and exploit the dynamic target probability, consistent with Li and Theeuwes (2020); but they did not acquire the dynamic distractor probability, at odds with Wang et al. (2021). Given that our null-result with the dynamic distractor-location manipulation is at variance with the positive finding of Wang et al. (2021), we went on to perform a direct replication of their Experiment 1 (2021). However, even though we implemented the same stimuli (shape size and eccentricity, fixed distractor and target colors) and design (separate groups performing the 'regular' and 'random' conditions) in Experiment 2, we again find no evidence that participants were able to learn and exploit the regular (100% predictable) shift in the distractor location. By contrast, when the same dynamic manipulation was applied to the target location, we replicated (in a between-participant design) the significant facilitation effect observed in Experiment 1.

Together, we take this pattern to point to an asymmetry in the learning of dynamic spatial regularities in visual search: while we can successfully prioritize dynamically predictable target locations, we are less (if at all) able to de-prioritize dynamically predictable distractor locations.

Experiment 1

In Experiment 1, we applied the cross-trial transitional location regularity separately to the distractor (Experiment 1a) and the target (Experiment 1b) in a paradigm requiring search for an odd-one-out target, with Experiment (a vs. b) as a between-subject factor. Note that the design of Experiment 1 was adapted from an unpublished study (carried out in the winter semester 2018/19). Given the importance of methodological issues for demonstrating the learning of dynamic distractor regularities, we report the Method and Results of this 'pilot' study in Appendix A.

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[2] In fact, most statistical distractor-location learning studies of Theeuwes and colleagues, following the seminal paper (Theeuwes 1992), used random color swapping , Wang et al. (2021) being almost an exception.

Methods

Participants

24 healthy university students were recruited for Experiments 1a (mean age ± SD: 27.3 ± 4.2 years; age range: 21–39 years; 13 females) and 1b (mean age ± SD = 26.0 ± 3.2 years; age range: 21–33 years; 9 females) respectively. All participants reported normal or corrected-to-normal visual acuity. And all passed the Ishihara color test (Clark, 1924), ensuring they had normal color perception (especially for red and green). The participants can thus be regarded as representative of the standard population of healthy (young) adults.

The sample size was determined based on previous studies, in particular, Li and Theeuwes (2020), who had implemented a similar design introducing cross-trial regularities (for the target), with an effect size of $f = 0.42$ (average across all experiments). We conducted an a-priori power analysis, with the effect size of $f = 0.42$, $\alpha = .05$, and 98% power ($1\text{-}\beta$), which yielded a minimum sample size of $n = 20$ (G*Power 3.1; Faul et al., 2007). To be on the safe side, we increased the sample size to 24 per tested group – an *n* that had also been used in another study with a similar design (Ferrante et al., 2018). All participants provided written informed consent prior to the experiment and were paid 9 Euro per hour or given correspondent course credit for their participation. This study was approved by the LMU Faculty of Pedagogics & Psychology Ethics Board. All data in Experiment 1 were collected in 2021.

Apparatus and stimuli.

The experiment was conducted in a sound-attenuated and moderately lit test room. Participants sat in front of the CRT display monitor, with a viewing distance of 60 cm. The search stimuli, presented at 1280 × 1024 pixels screen resolution and a refresh rate of 85 Hz, were generated by customized MATLAB R2019b (The Math- Works® Inc) code with Psychophysics Toolbox Version 3 (PTB-3) (Brainard 1997).

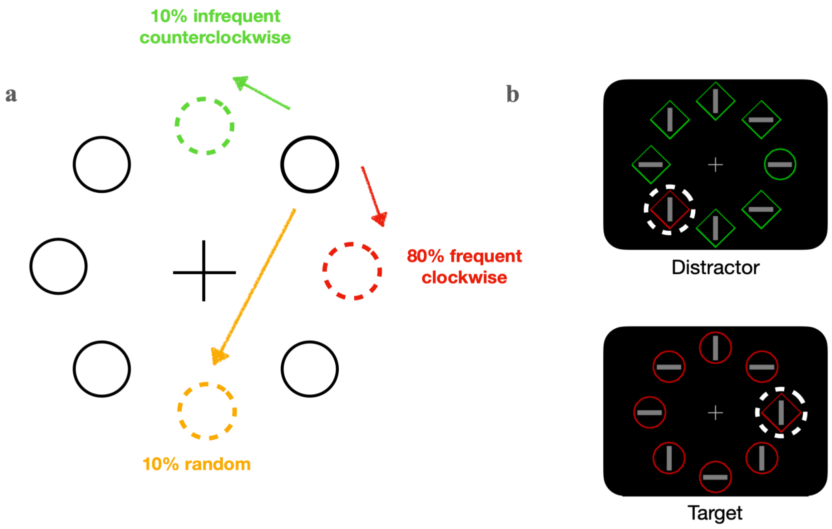

Figure 1. **(a)** Illustration of three cross-trial target- or, respectively, distractor-location transitions in Experiment 1. In each experiment, there were three types of the location change of the critical item (target or distractor) across consecutive trials: with 80% probability, the critical item would move to the adjacent location, either in clockwise or counterclockwise direction (here, indicated by the red dashed circle marking the frequent location). The direction was for a given participant and counterbalanced across participants. With 10% probability, the critical item would shift to the adjacent location in the opposite direction (indicated by the green dashed circle marking the infrequent location). On the remaining 10% of trials, the critical item would move randomly to any of the other locations, including re-appearing at the same location (indicated by the yellow dashed circle marking a random location). **(b)** Schematic illustration of two types of search display in which we implemented the cross-trial transitional regularity of the critical item (marked by white dashed circles, which were not presented in the experiments) to the left. The critical item was a color singleton distractor in Experiment 1a, and the shape-defined target in Experiment 1b.

As illustrated in Figure 1b, a search display was composed of eight items, each consisting of an outline shape (either diamond or circle) and an oriented bar (horizontal or vertical) inside it. The eight items were equidistantly arranged around an imaginary circle (radius 3.6° of visual angle). The diameter of the circle shapes was 1.4° of visual angle, the side length of the diamond shapes 1.9°, and the gray vertical or horizontal line inside the shapes 1.2° × 0.3°. Each display contained one singleton-shape target and seven non-targets. When a singleton distractor was present (replacing one of the non-targets), it differed in color from the seven other shapes, being either green (CIE [Yxy]: [16.8, 0.306, 0.549]) among homogeneous red shapes (CIE [Yxy]: [11.6, 0.605, 0.336]), or red amongst homogeneous green shapes. All search displays were presented on a black screen background (CIE [Yxy]: 1.72, 0.329, 0.265]), with a white fixation cross (0.76° × 0.76°; CIE [Yxy]: 79.7, 0.298, 0.298) in the center.

Design and procedure

A target, which was a shape-defined singleton, either a circle among diamonds or a diamond among circles, equally likely randomly assigned on each trial, was present on all trials. In order to realize a distractor-absent baseline in Experiment 1a without interrupting the structure of the cross-trial transitional probabilities of the distractor, we presented the singleton-distractor present and -absent trials in separate blocks. There were 16 blocks in Experiment 1a, with four singleton-distractor-absent blocks being randomly interleaved with the other, 12 singleton-distractor-present blocks. Each block consisted of 60 trials, yielding a total of 960 trials (240 distractor-absent trials and 720 distractor-present trials). Experiment 1b also consisted of 16 blocks, but without any singleton distractor. In both Experiments 1a and 1b, the target position was overall (across all trials) equally distributed among the eight possible locations, and participants had to respond to the orientation of the line inside the target as fast and accurately as possible.

Importantly, the placement of the critical item – the color-singleton distractor in Experiment 1a, and the shape-singleton target in Experiment 1b – across consecutive trials *n* and *n+1* was made predictable in a probabilistic manner. Specifically, in the majority of trials (80%), the location of the critical (distractor or target) item was shifted to an adjacent position in either clockwise or counterclockwise direction (with the main direction being fixed for a given participant, but counterbalanced across participants); hereafter, this will be referred to as the *frequent* condition. On another 10% of the trials, the position of the singleton distractor was shifted to the adjacent location in the opposite direction to the frequent condition (i.e., if the main direction was clockwise, the shift was counterclockwise, and vice versa) – the *infrequent* condition.[3] And on the remaining 10% of the trials, the position of the critical item was randomly selected among the six remaining alternative locations (including repeated presentation at the same location) – the *random* condition. Of note, the statistical regularities were only assigned to the position of the singleton distractor or, respectively, the singleton target. Its color and shape varied randomly across trials. That is, the colors of the distractor and the target (as well as the other, non-distractor item) could randomly swap across trials – as in previous studies (e.g., Allenmark et al., 2019; Theeuwes, 1992), but different from Wang et al.'s (2021) design, in which the colors of the distractor were never the target color.

A trial started with a fixation cross presented in the center of the screen for 500 ms, followed by the search display (Figure 1b), which was shown until the participant gave a response. Participants were instructed to search for the shape-defined target and discriminate the orientation of the bar inside it by pressing the leftward- ('horizontal') or upward-pointing ('vertical') arrow on the keyboard with their right-hand index or middle fingers, respectively. If participants issued an incorrect response, a feedback display with the word "Error!" in the screen center was presented for 500 ms. The next trial started after an inter-trial interval of 500–750 ms. Between blocks, participants could take a break of a self-determined length.

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[3] This condition was introduced to allow us to compare two conditions with the same inter-trial distance (movement of the critical item by one step) but different probability. With only the 'random' condition for comparison against the 'frequent' condition, we would have had too few 'random' trials on which the critical item moved the same distance as in the 'frequent' condition (but in the opposite direction). Figure 2c, comparing conditions with the equal distance, turned out 'diagnostic' at least in one of the experiments.

At the end of the experiment, participants completed a post-experiment questionnaire in which they had to give two forced-choice responses: First, participants had to indicate whether or not they had noticed any regularity in the way Critical Items (CI: the target or distractor) had moved across trials. Next, they needed to report the specific regularity of the movement, by choosing one of seven options for the most frequent type of movement (CI moved to the opposite end of the circle; CI moved one step clockwise; CI moved one step counterclockwise; CI moved two steps clockwise; CI moved two steps counterclockwise; CI moved three steps clockwise; CI moved three steps counterclockwise.)

Transparency and Openness

The experimental code, raw data, and data analyses of the present study are publicly available at: https://github.com/msenselab/asymmetric_statistical_learning.

Statistical analyses

Analyses of variance (ANOVAs) and associated post-hoc tests were carried out using JASP 0.15 (http://www.jasp-stats.org). All Bayes factors for ANOVA main effects and interactions are inclusion Bayes factors calculated across matched models. Accepting or rejecting the null hypothesis is based on the obtained Bayes factor.

Results

Experiment 1a: transitional regularity of the distractor location

Error rates and Mean RTs

Trials with extreme RTs (slower than 2500 or faster than 200 ms) were excluded from further analysis (4.5% of trials). While the average error rate was overall low (4.7%), more errors occurred on distractor-present vs. -absent trials (5.4% vs. 3.4%), $t(23) = 3.627$, $p = .001$, $d_z = .74$, with the error rates being comparable among the three (the frequent, infrequent, and random) distractor-location transition conditions, $F(2, 46) = 1.002$, $p = .375$, $\eta_p^2 = 0.042$, $BF_{\text{incl}} = .286$.

The mean (correct) RTs for the four distractor conditions (the distractor-absent baseline along with the frequent, infrequent, and random distractor-location transition conditions) are shown in Figure 2. As can be seen, the mean RT was faster in distractor-absent vs. distractor-present blocks, with the interference caused by distractor presence being significant, $t(23) = 6.167$, $p < .001$, $d_z = 1.26$. Similar to the error-rate pattern, the RTs for the three cross-trial distractor-location transition conditions did not differ significantly among each other, $F(2,46) = .168$, $p = .847$, $\eta_p^2 = .007$, $BF_{\text{incl}} = .134$ (note that this Bayes factor argues in favor of the null hypothesis). That is, participants failed to learn the (frequent) cross-trial ‘movement’ of the location of the distractor to reduce its interference. This finding differs from that seen in ‘standard’ distractor-location probability-cueing paradigms, in which a fixed (stationary) frequent location/region of the distractor can be effectively learned to reduce distractor interference (e.g., Ferrante et al. 2018; Goschy et al. 2014; Leber et al. 2016; Sauter et al. 2018; Sauter, Liesefeld, and Müller 2019; B. Wang and Theeuwes 2018a; Zhang et al. 2019).

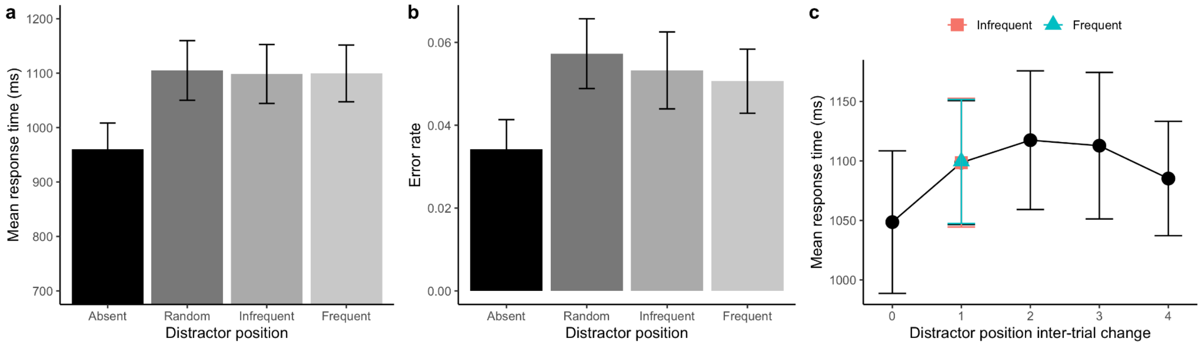

Figure 2. (**a**) Mean RTs and (**b**) Error rates, with associated standard errors, for Experiment 1a, separately for the distractor-absent baseline and the random, infrequent, and frequent cross-trial transitional distractor-location conditions. (**c**) Mean RT as a function of the inter-trial distractor distance (0 indicates the distractor repeated at the same location, while 1 denotes the distractor moved one position to its neighbor, including both the frequent and infrequent directions). Error bars represent one standard error of the mean.

Further analyses, based on or including the random-cross-trial transition condition[4], revealed no evidence of impaired target processing when, on random-distractor-placement trials, the target appeared at the dynamically predicted, ‘frequent’ distractor location: RTs to a target at the ‘frequent’ location (1104 ms) were not significantly longer than those to targets at the ‘infrequent’ (1099 ms) or, respectively, a ‘random’ location (1099 ms), $F(2,46) = 0.579$, $p = .564$, $\eta_p^2 = .025$, $BF_{\text{incl}} = .179$. The absence of a target-location effect is different from standard (static) distractor-location probability-cueing paradigms (e.g., Goschy et al. 2014; B. Wang and Theeuwes 2018a), where it is often found that acquired proactive suppression of likely distractor locations also impacts processing of the target when it occurs at such a location, evidenced by prolonged RTs to targets at likely locations. But the absent target-location effect tallies with the absence of an interference reduction by distractors appearing at dynamically predicted, ‘frequent’ distractor locations (see Figure 2a).

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[4] We acknowledge that analyses based on or including random-distractor-placement conditions are potentially ‘shaky’ given that the respective estimates are based on only a few trials per participant.

On the other hand, there was some evidence of reactive short-term inhibition being placed on the current distractor location: distractor interference was numerically reduced, by 51 ms, when the distractor location repeated on random-distractor-placement trials compared to when the distractor moved one step in the frequent or infrequent direction, $t(23) = -1.922$, $p = .067$, $d_z = -0.392$, $BF_{10} = 1.035$. This is consistent with standard (static) distractor-location probability-cueing paradigms (see, e.g., the Supplementary in Sauter et al., 2018 for a detailed analysis of such effects).

Thus, the picture that emerges from these auxiliary analyses is interesting: it is consistent with the absence of proactive suppression of dynamically predictable distractor locations, while pointing to static reactive suppression of the current distractor location.

Awareness test

Among the 24 participants, only three reported having noticed “a regularity” in the distractor movement. However, only one of the three correctly identified the specific movement direction actually present in the search displays.[5]

Experiment 1b: transitional regularity of the target location

Error rates and Mean RTs

Outliers RTs (slower than 2500 or faster than 200 ms, 6.0%) were again removed prior to further analysis. Similar to Experiment 1a, the error rates were generally low (3.5% of trials) and comparable across the three transitional target location conditions, $F(2, 46) = .320$, $p = .728$, $\eta_p^2 = .014$, $\mathrm{BF}_{\mathrm{incl}} = .162$.

As depicted in Figure 3, the mean (correct) RTs were faster in the frequent cross-trial target-location transition condition relative to the infrequent and random conditions. A one-way repeated-measures ANOVA confirmed a significant Transition main effect, $F(2,46) = 5.643$, $p = .006$, $\eta_p^2 = .197$. Post-host comparisons with Bonferroni-correction revealed the RTs to be faster in the frequent (1094 ms) vs. both the infrequent (1158 ms), $t(23) = 2.970$, $p = .014$, $d_z = 0.606$, and random (1155 ms), $t(23) = 2.845$, $p < .001$, $d_z = 0.581$, transition conditions, with comparable RTs between the latter two conditions, $t(23) = -0.125$, $p = 1.000$, $d_z = -0.009$, $BF_{10} = .219$. This pattern indicates that participants were able to exploit the cross-trial transitional regularity of the target placement to facilitate search performance.

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[5] Recent evidence from the Vadillo lab indicates that the ‘standard procedure to assess *distractor*-related awareness (which we adopted here, in line with almost virtually all extant studies of *distractor*-location probability cueing) likely underestimates the ‘true’ awareness as assessed by more rigorous measures (e.g., Vicente-Conesa et al. 2021). However, since we failed to find a behavioral effect (reduced interference by distractors at dynamically predicted locations), awareness does not have any explanatory value, i.e.: even if our procedure had underestimated the ‘true’ awareness, awareness cannot account for the behavioral null-effect (unless one assumes that awareness somehow interferes with the expression of the effect, rather than promoting it).

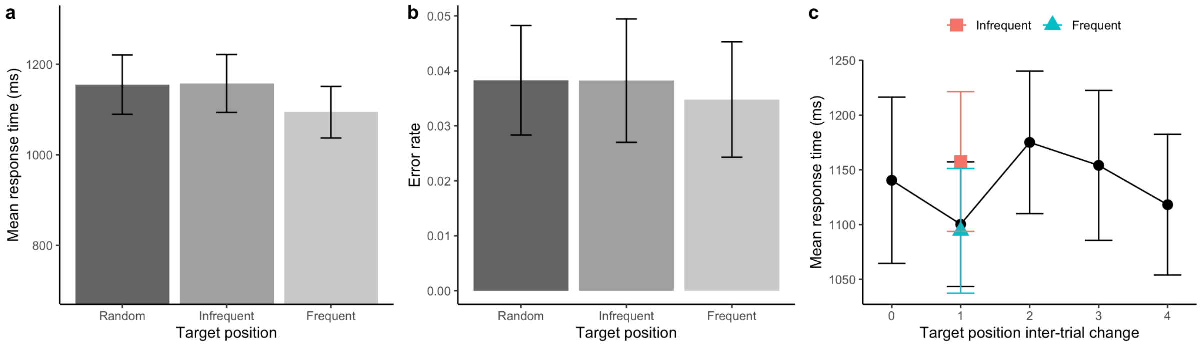

Figure 3. (**a**) Mean RTs and (**b**) Error rates, with associated standard errors, for Experiment 1b, separately for the random, infrequent, and frequent cross-trial transitional target location conditions. (**c**) Mean RT as a function of the inter-trial target distance (0 indicates the target repeated at the same location, while 1 denotes the target moved one position to its neighbor, including both the frequent and infrequent directions). Error bars represent one standard error of the mean.

We also examined for short-term inter-trial positional-priming effects (e.g., Allenmark et al., 2019, 2021; Sauter et al., 2018) by comparing RT performance across the various inter-trial target distances (Figure 3c), but failed to obtain a significant Distance effect, $F(4,92) = 1.753$, $p = .145$, $\eta_p^2 = .071$, $\mathrm{BF}_{\mathrm{incl}} = .329$. The numerical facilitation, of 60 ms, for the inter-trial target distance of 1 vs. the target location repetition (distance 0) largely originated from the frequent cross-trial transition condition (which contributed 8 times more trials than the infrequent condition) (Figure 3a). This suggests that short-term inter-trial target location priming was not as strong as the dynamic, cross-trial probability cueing of the target location.

Awareness test

According to the questionnaire, 16 out of 24 participants reported noticing the regularity of the target movement, and ten of them indicated the right target movement direction. We classified those ten participants as the 'aware' group, and the other 14 participants as the 'unaware' group.

To examine for any differences between the two groups in statistical learning, we estimated the probability-cueing effect in terms of the RT difference between the infrequent and frequent transition conditions for individual participants. A positive probability-cueing effect means that the mean RT is faster to a target appearing at the frequent vs. the infrequent location, while a negative probability-cueing effect indicates a reverse effect. Figure 4 plots the distribution of the probability-cueing effect for the two groups. The mean probability-cueing effects were 116 ms and 25 ms for the aware and unaware groups, respectively – with the effect being robust for the aware group, $t(9) = 2.356$, $p = .043$, $d_z = .745$, but not for the unaware group, $t(13) = 1.480$, $p = .163$, $d_z = .396$, $\mathrm{BF}_{10} = 0.660$. Even though the (numerically large) difference between the two groups only approached significance ($t(22) = 1.970$, $p = .062$, $d_z = .816$, $\mathrm{BF}_{10} = 1.445$), this pattern suggests that becoming aware of the dynamic probabilistic change of the target location across trials helped participants to more effectively deploy visuo-spatial attention to the predicted target location.[6]

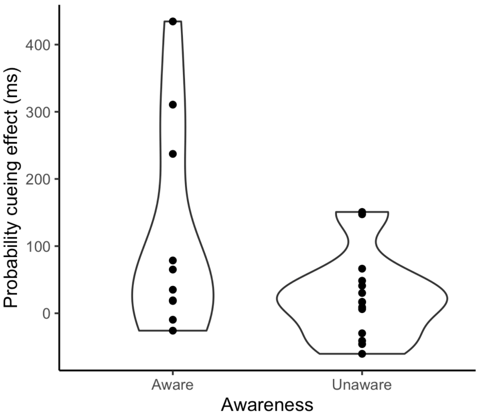

Figure 4. Violin plots of the probability-cueing effect ($RT_{infrequent} - RT_{frequent}$), separately for the aware and unaware groups of participants.

Comparison of probability-cueing effects between Experiments 1a and 1b

An independent-samples *t*-test comparing the probability-cueing effects between Experiment 1a and Experiment 1b (–1.1 ms vs. 63.3 ms) turned out to be significant: $t(46) = -2.480$, $p = .017$ (two-tailed), $d_z = -.716$. In other words, participants could readily pick up the probabilistic change of the target position across trials and utilize it to enhance their search performance, whereas they found it hard to learn the same change of the distractor position across trials.

Discussion

In Experiment 1, we manipulated the cross-trial transitional location probability of the singleton distractor (Experiment 1a) and the singleton target (Experiment 1b) in a standard (additional-) singleton search paradigm. We found that the regularity of the cross-trial transition of the target location could be learned successfully to facilitate target search. In contrast, the dynamic regularity of the cross-trial distractor location had no significant effect on search performance and the Bayesian results supported the null hypothesis, even though the structure of the transitional probability manipulation was exactly the same for both experiments.

The ability to exploit the cross-trial regularity of the target placement to guide search is consistent with Li and Theeuwes (2020). In their study, however, the cross-trial regularity was 100% certain and relatively simple (either from the left- to the rightmost position, or from the top to the

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[6] Again, our ‘standard’ procedure to assess awareness of the dynamic *target* regularity may have underestimated the ‘true’ level as assessed by more rigorous measures (e.g., Giménez-Fernández et al., 2020). However, this would only reinforce our proposal that “that becoming aware of the dynamic probabilistic change of the target location across trials helped participants to more effectively deploy visuo-spatial attention to the predicted target location”.

bottom location for half the participants, and in the reverse direction for the other half). Surprisingly, Li and Theeuwes reported that none of their participants had noticed this simple cross-trial regularity. The present experiment, by contrast, showed that awareness – that is, explicit learning – of the regularity boosted the dynamic target-location probability-cueing effect – suggesting that it reflects largely an endogenous, top-down-driven spatial-attentional orienting process (Posner 1980).

In contrast to the facilitation by the transitional regularity of the target location, we failed to find any significant suppression of the dynamically predictable distractor location in Experiment 1a. This replicates the outcome of two pilot experiments with the same paradigm and a similar design (except that distractor-absent and present trials were presented in randomized order, rather than in mini-blocks, as in the present experiments; see Appendix A for details of the design and results). Although there is ample evidence that the probability of a fixed distractor location/region can be learned to suppress the salient distractor (Goschy et al. 2014; Sauter et al. 2018; B. Wang and Theeuwes 2018b; Allenmark et al. 2019; Zhang et al. 2019), thus far there is only one study, by Wang et al. (2021), reporting that a regular (100% predictable) cross-trial change of the distractor location (clockwise or counterclockwise) could be implicitly (i.e., without awareness) learned to reduce the interference of the upcoming distractor. It should be noted, however, that in Wang et al. (2021), the colors of the distractor (single color in their Experiment 1, and two colors in their Experiment 2) were never the target color (the target was invariably white), and the differential distractor interference between their ‘random’ (baseline) group and their ‘regular’ group almost vanished towards the end of testing. Thus, it remains a possibility that the distractor-suppression strategy developed by their participants might involve dimension-based, or even feature-based, distractor filtering (Liesefeld and Müller 2019), which operates below the level of the priority map. On this account, the cross-trial regularity might increase the rate at which (a spatially unspecific) dimension-based suppression strategy is acquired (compared to the ‘random’ baseline group), rather than fostering spatial learning, and attendant de-prioritization, of the dynamically predicted distractor location. In contrast to Wang et al. (2021), in our design, we randomly swapped the target and distractor colors across trials to make observers adopt a priority-map-based suppression strategy (Allenmark et al. 2019) – and failed to find any robust statistical learning of the cross-trial dynamics. The fact that responses were faster on trials on which the distractor appeared at the same (i.e., an unlikely) vs. the likely location (Figure 2c) suggests that distractor suppression was mainly driven by short-term (inter-trial) reactive inhibition (or ‘negative priming’) of the repeated (fixed) location, rather than the long-term learning of the dynamically predictable location.

Experiment 2

Experiment 1a yielded no evidence that participants could extract and utilize the dynamic spatial regularity regarding the distractor across the trials. This null-result is at variance with Wang et al. (2021), who reported a positive finding, namely, enhanced suppression of dynamically predictable ('regular') versus non-predictable ('random') placement of the salient color distractor. Of note, however, there are major differences between their experiments and our Experiment 1a: in their Experiment 1, the distractor and the target color were fixed (although the distractor color was variable in their Experiment 2, the target color was fixed) – as compared to random color swapping across trials in our Experiment 1a; further, they used separate groups of participants performing the 'regular' and the 'random' (i.e., the baseline) condition – whereas we measured the baseline within participants; finally, the (clockwise/anti-clockwise) shift of the distractor locations on consecutive trials was 100% predictable in their 'regular' condition – whereas it was only 80% predictable in our Experiment 1a (as we wanted to compare a regular shift with non-predictable shifts in the opposite direction, 10%, or a random direction, 10%, within the same task episode). The target shape was fixed, too (rather than randomly varying in our Experiment 1a), effectively allowing for a 'feature-search' mode (cf. Bacon and Egeth 1994). Any of these differences, or combination of differences, might have been critical for our failure to find a dynamic *distractor*-location probability-cueing effect.[7] Given this, we set out to directly replicate Wang et al. (2021), in particular, their Experiment 1, in which, in addition to the target shape being constant, the distractor color was perfectly predictable (and invariably different from the target color) to ascertain whether a dynamic distractor-location cueing effect is replicable under their conditions.

In addition, in Experiment 2b, we implemented an analogous design with 100% dynamic predictability of the *target* location in the 'regular' group and 0% predictability in the 'random' group.

Of note, we conducted Experiment 2 online, whereas Wang et al.'s (2021) Experiment 1 (equivalent to our Experiment 2b) was performed in the laboratory. In this respect, our Experiment 2a is not an exact replication of their Experiment 1.

Method

Participants

48 'valid' healthy participants were recruited via Prolific (Palan & Schitter, 2018) for Experiment 2a (mean age ± SD: 33.73 ± 6.29 years; age range: 20–42 years; 18 females), and 48 for Experiment 2b (mean age ± SD: 25.26 ± 5.53 years; age range: 18–41 years; 12 females). Both

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[7] It is clear, however, that none of these differences did impede our ability to demonstrate a dynamic *target*-location probability-cueing effect in Experiment 1b – in line with the existence of an asymmetry between the two types of statistical learning: statistical learning of dynamic distractor locations, if existent at all, is less robust than the learning of dynamic target locations.

experiments were performed on the online platform Pavlovia. All participants self-reported normal or corrected-to-normal visual acuity and normal color vision, and they were all paid £ 5.80 for their service. For both experiments, the participants were randomly allocated to one of two groups: the 'random' (baseline) group, in which the distractor (Experiment 2a) or, respectively, the target (Experiment 2b) occurred unpredictably at any of the eight display locations, and the 'regular' (experimental) group in which the distractor or, respectively, the target shifted predictably from one trial to the next. In Experiment 2a, four participants who had accuracies lower than 80% (1 in the 'regular' group and 3 in the 'random' group) were excluded from data analysis, and their 'invalid' data sets were replaced by recruiting another 4 participants; in Experiment 2b, 2 participants failed to reach the response-accuracy criterion and were replaced by recruiting another 2 participants. The experiment was approved by the LMU Faculty of Pedagogics & Psychology Ethics Board. Data collection took place in September 2022.

Apparatus and Stimuli

Participants were told to perform the experiment in a quiet, and moderately lit, environment, on full screen (laptop or external monitor). The display monitor was to be placed on a table surface, with the participant being seated on a chair, with their hands comfortably resting on the (response) keyboard in front of them and viewing the monitor at arm's length (i.e., a distance of approximately 60 cm); and the display brightness was to be set to a middle contrast. Since each participant ran the experiment on their own system, the monitor sizes were potentially quite different. In order to ensure comparable physical stimulus size(s) on the various display monitors used by the different participants, we had participants adjust a rectangle on their screen to the standardized size of a credit card at the beginning of the experiment. This way, all stimuli were then scaled according to the respective monitor size, so as to also keep the stimulus size in degrees of visual angle comparable across participants.

The screen background was black (Red-Green-Blue [RGB]: 0, 0, 0). The primary search display contained one outline diamond (subtending 2° × 2° of visual angle), the search target, among seven outline circles (2° in diameter), the non-targets; or, respectively, it contained one circle among seven diamonds. Searching for a diamond or circle was fixed per participant, but counterbalanced across participants per group. The display elements were arranged around a virtual ring, of radius (eccentricity) 4°, with a white fixation cross (0.67° × 0.67°; RGB: 255, 255, 255) in the center, and they all contained a small vertical or horizontal gray line (RGB: 128, 128, 128; 0.3° × 1.5°; the two orientations were equally frequent, but allocated randomly to a given element). In 'distractor' Experiment 2a, on distractor-absent trials (presented in mini-blocks), all display elements were colored in gray (RGB: 128, 128, 128); on distractor-present trials (presented in the other mini-blocks), one of the non-target display elements was colored in red (RGB: 255, 0, 0). In 'target' Experiment 2b (in which there was never a distractor), all display elements were uniformly gray. In both experiments, participants responded to the line orientation in the singleton-shape target by pressing the up-ward or left-ward pointing arrow key on their computer keyboard using their right index and middle fingers, respectively.

The experiment was built using the PsychoPy3 version 2022.2.2 software (Peirce et al., 2019) and run online using the Pavlovia web hosting service (Open Science Tools Limited, Nottingham, UK).

Design and procedure

Our replication 'distractor' Experiment 2a followed essentially the design and procedure of Wang et al.'s (2021) Experiment 1 precisely, with two minor exceptions. First, the instructions were given in English. Second, the questionnaire used to test for awareness of the dynamic regularity was the same as that we had used in Experiment 1.

Analogous adaptations were introduced in 'target' Experiment 2b. One difference to Experiment 2a concerned the 'awareness' test: in Experiment 2b we had participants additionally rate their confidence in their responses (on a scale of 1 = "not confident at all" to 5 = "completely confident"), and, following the question of whether they had noticed a regularity in the cross-trial target placement, all participants in the 'regular' group had to answer a forced-choice question about the direction (clockwise vs. counter-clockwise) and the size (1, 2, or 3 steps) of the target shift.

Experiment 2a consisted of ten blocks, each of one mini-block of 80 distractor-present trials and one of 40 distractor-absent trials. Distractor-absent trials were presented in separate mini-blocks to ensure 100% predictability of the dynamic distractor-location change on distractor-present trials. Half of the participants started with the mini-block of distractor-absent trials, and the other half with the mini-block of distractor-present trials. Experiment 2b also consisted of 10 blocks, each of 80 trials, equating the number of predictable target-shift trials with that of predictable distractor-shift trials in Experiment 2a.

Results

Experiment 2a: transitional regularity of the distractor location

Error rates and Mean RTs

Trials with extreme RTs (slower than 1600 or faster than 200 ms) were excluded from further analysis: 2.6% and 4.1% for the 'random' (baseline) and 'regular' (experimental) distractor-placement groups, respectively. The overall rate of response errors was 4.3% (4.9% and 3.7% for the 'random' and 'regular' groups, respectively), which is comparable to the 2.1% error rate in Wang et al.'s Experiment 1.

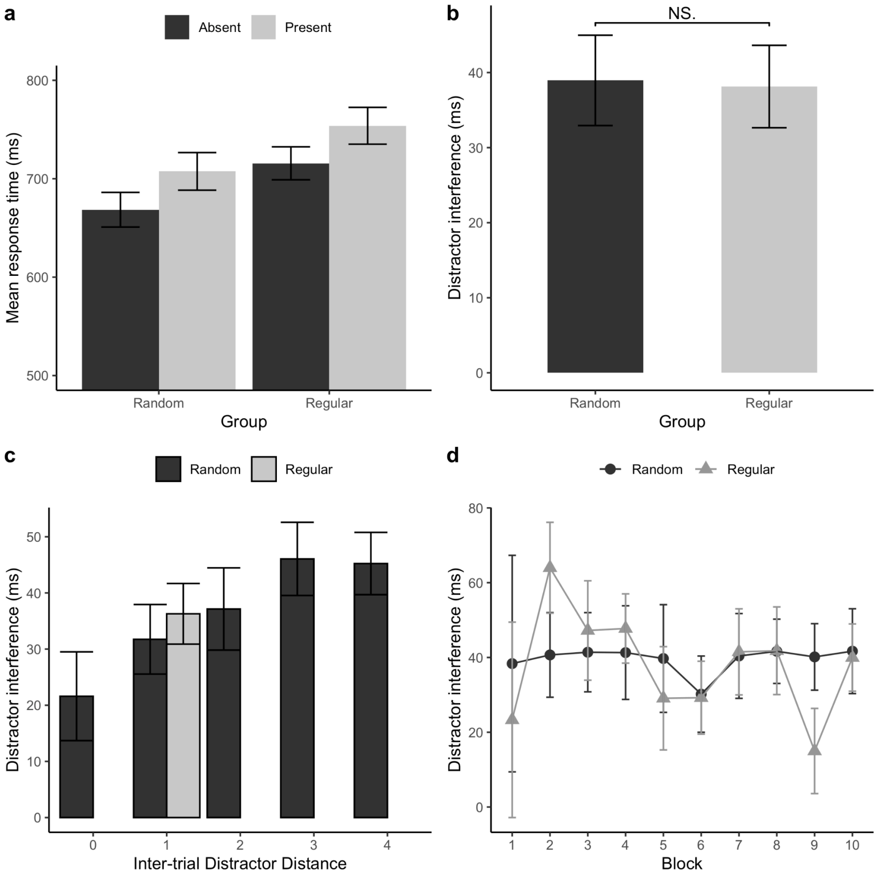

Figure 5. (a) Mean RTs, and associated standard errors, on distractor-present and -absent trials, separately for the 'random' and 'regular' groups in Experiment 2a. (b) Bar chart of the distractor-interference effect ($RT_{\text{distractor-present}} - RT_{\text{distractor-absent}}$), separately for the 'random' and 'regular' groups. (c) Distractor interference as a function of the inter-trial distractor distance (0 indicates that the distractor occurred at the same location, 1 that the distractor moved to a directly adjacent location, etc.; note that for the 'regular' group, the distractor invariably moved to the adjacent location, in either clockwise or counter-clockwise direction). Error bars represent one standard error of the mean. (d) Distractor interference across the experimental trial blocks, separately for the 'random' and 'regular' groups.

Figure 5a presents the mean RTs for the 'random' and 'regular' groups. A mixed ANOVA on mean RTs with the within-subject factor Distractor Condition (distractor-present vs. -absent) and the between-subject factor Group ('random' vs. 'regular' distractor placement) revealed only the main effect of Distractor Condition to be significant, $F(1,46) = 93.511, p < .001, \eta_p^2 = .670$. The absence of a Group main effect, $F(1,46) = 3.074, p = .086, \eta_p^2 = .063$, $BF_{incl} = 0.552$, indicates that the two groups were well balanced in terms of their baseline response speed. Importantly, the Distractor Condition × Group interaction was non-significant, $F(1,46) = 0.011$, $p = .918$, $\eta_p^2 < .001$, $BF_{incl} = 0.258$ (with the Bayes factor arguing in favor of the null-hypothesis), that is: there was no difference in distractor interference between the ‘random’ (baseline) and ‘regular’ (experimental) groups (38.96 ms vs. 38.14 ms; see also Figure 5b).

Figure 5c re-plots the distractor-interference effect as a function of the inter-trial distractor distance (i.e., the distance, in item positions, between the distractor on the preceding trial *n-1* and the current trial *n*) for the ‘random’ (baseline) group, that is, the only group for which this effect could be examined. A repeated-measures ANOVA revealed the main effect of Distance to be significant, $F(4,92) = 7.891$, $p < .001$, $\eta_p^2 = .255$. As can be seen from Figure 5c, this effect reflects an (asymptotic) increase in interference as the inter-trial distractor distance increased. Recall that in the ‘regular’ group, the distractor invariably moved to the adjacent location (consistently in either clockwise or counter-clockwise direction) from one trial to the next (i.e., the distance is invariably 1), the effect of inter-trial distractor distance (established in the ‘random’ group) could be a possible confound for the effect of the ‘regularity’. To rule this out, we compared the distractor interference between the two groups including only those trials in the ‘random’ group on which the distractor had moved to an adjacent location. An independent-samples *t*-test comparing the distractor interference effects for distance 1 revealed no difference between the ‘random’ and ‘regular’ groups, $t(46) = -0.565$, $p = .575$, $d_z = -0.163$, $BF_{10} = 0.327$: the interference was 31.74 in the ‘random’ group and 36.28 in the ‘regular’ group (i.e., if anything, the interference effect was larger in the ‘regular’ group, when successful learning of the regularity would have predicted the effect to be smaller). This null-effect (corroborated by the Bayes factor) suggests that our participants did not learn the dynamic, and 100% predictable, cross-trial regularity in the placement of the distractor in the ‘regular’ group. This differs from the results found in Experiment 1 of Wang et al.’s (2021) as outlined in Appendix B.

Additionally, following Wang et al. (2021), we examined for any differential learning speed between the two groups across the ten blocks of the experiment (Figure 5d): However, a Group × Block ANOVA yielded no significant effects: Group, $F(1, 46) = .039$, $p = .844$, $\eta_p^2 < .001$, $BF_{incl} = .161$; Block, $F(9, 414) = .754$, $p = .659$, $\eta_p^2 = .016$, $BF_{incl} = .005$; interaction, $F(9, 414) = .533$, $p = .851$, $\eta_p^2 = .011$, $BF_{incl} = .011$. The small Bayes factor associated with the interaction indicates that, over the course of the experiment, the ‘regular’ group did not learn faster to deal with the distractor than the ‘random’ group.

Awareness test

Among the 48 participants, three participants in the ‘regular’ group and three in the ‘random’ group immediately reported having noticed a regularity in the cross-trial distractor placement. However, upon being pressed, none of the three participants in the ‘regular’ group correctly identified the specific regularity present in their condition (as there was no regularity in the ‘random’ group, reports of a regularity were necessarily spurious).

Experiment 2b: transitional regularity of the target location

Error rates and Mean RTs

Trials with extreme RTs (slower than 1600 or faster than 200 ms) were excluded from further analysis: 0.9% and 1.0% for the ‘random’ (baseline) and ‘regular’ (experimental) target-placement groups, respectively. The overall rate of response errors was 3.9% (4.4% and 3.3% for the ‘random’ and ‘regular’ groups, respectively), which is comparable to Experiment 2a.

Importantly, as can be seen in Figure 6, participants in the ‘regular’ group benefited from the 100% predictable (1-step clockwise or counter-clockwise) shift of the target location across trials: their RTs were, on average, 72 ms faster than those of the ‘random’ group (575 ms vs. 647 ms, $t(46) = 2.380$, $p = 0.011$, $d_z = 0.687$) – replicating the target-location effect obtained in Experiment 1b.

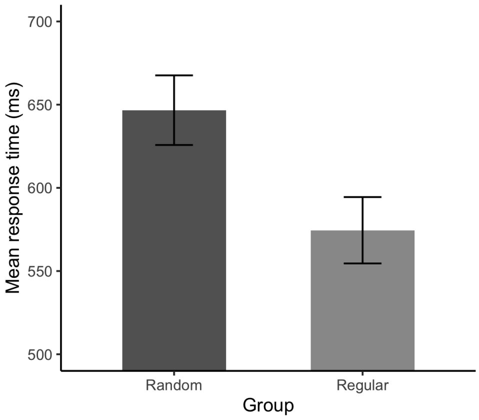

Figure 6. Mean RTs, and associated standard errors, separately for the ‘random’ and ‘regular’ groups, in Experiment 2b.

Awareness test

Of the 24 participants in the ‘regular’ group, 17 reported having noticed a regularity in the cross-trial target placement. 15 of them correctly reported the type of regularity (1-step clockwise or counter-clockwise shift) they had encountered, with near-complete confidence (ratings of 4.67 for the direction and, respectively, 4.47 for the number of steps). One of the two (17 minus 15) remaining participants correctly indicated the shift direction, but not the number of steps; the other selected the wrong direction – both with low confidence. Of the seven participants who first indicated they had not noticed a regularity, all picked the correct type of regularity, also with high confidence (direction and step number: 4.71 and 4.43, respectively). Thus, at least when pressed, 23 of the 24 participants correctly identified the direction of the target shift with high confidence, and in fact, there was no difference in RTs between those who immediately reported having noticed a regularity vs. those who did not and had to be pressed to make a forced-choice decision (suggesting that the latter were simply more reluctant to spontaneously report ‘awareness’). By contrast, in the ‘random’ group, only three participants reported having noticed a (non-existent) regularity (confidence: 2.67).

Omnibus analysis of Experiment 2

To examine whether the critical (‘regular’ vs. ‘random’) between-group effect in Experiment 2b is truly indicative of dynamic target-location learning, we compared this effect against that in Experiment 2a, where the group effect simply reflects a random difference in the baseline response speed between participants assigned to the two groups. A two-way ANOVA of the target-only trials (i.e., in Experiment 2: the distractor-absent trials), with the between-subject factors Experiment (2a, 2b) and Group (‘regular’, ‘random’), revealed the interaction to be significant: $F(1, 92) = 9.01$, $p = .003$, $\eta_p^2 = .089$ – due to a significant Group effect in ‘target’ Experiment 2b, but not in ‘distractor’ Experiment 2a. (The main effect of Experiment was also significant, $F(1, 92) = 16.61$, $p > .001$, $\eta_p^2 = .154$, owing to response speed being overall slower in ‘distractor’ Experiment 2a than in ‘target’ Experiment 2b, as expected.) Coupled with the fact that participants were aware of the dynamic regularity in Experiment 2b, we take this to indicate that the Group effect reflects true facilitation by the regularity, rather than being simply a spurious group difference.

Discussion

Recall that our Experiment 1a had failed to produce any evidence that the participants were able to learn and exploit the (statistically, 80%, predictable) cross-trial shift in the distractor location (whereas the participants in Experiment 1b were able to acquire and utilize the exact-same regularity implemented in the cross-trial *target* shift). As the null-result in Experiment 1a contrasts with the positive findings reported by Wang et al. (2021), in Experiment 2a we conducted a direct replication of their Experiment 1 to examine whether our non-finding was due to the methodological changes we had introduced in our task design compared to the Wang et al. (2021) study, in particular: the reduced (80% vs. 100%) predictability of the positional change in our design and the reduced predictability of the distractor (vs. target) color (50% due to random color-swapping vs. 100% given no swapping). Our replication experiment, however, again provided no evidence of participants (in the ‘regular’ group) being able to exploit the regular, 100% predictable shift of the same-color distractor to reduce the interference it generated (compared to the ‘irregular’ group). And, again, no participants in the ‘regular’ group were able to explicitly tell in which direction the distractor had (invariably) shifted across trials.

In contrast, using an analogous design in Experiment 2b to examine dynamic target-location learning, we found participants in the ‘regular’ group to exhibit robust RT facilitation by the 100% predictable shift of the target location. This effect was coupled with (high-confidence) awareness of the dynamic regularity (in all but one participant).

Thus, consistent with Experiment 1, Experiment 2b confirmed dynamic target-location learning to be a robust phenomenon associated with awareness of the regularity, whereas Experiment 2a provided no evidence of dynamic distractor-location learning even under the same conditions used by Wang et al. (2021).

It should be noted, however, that Wang et al. (2021) performed their Experiment 1 in the laboratory, whereas we conducted our replication Experiment 2a online. Physical stimulus properties are, of course, more difficult to control under online conditions, where much depends on participants’ compliance with the instructions regarding viewing distance, monitor brightness, etc. Within these limits, we at least ensured comparable stimulus dimensions on our participants’ display monitors by having them adjust a rectangle on their screen to the (standard) size of a credit card at the beginning of the experiment and then scaling the stimuli accordingly. Also, the overall performance and data quality in Experiment 2a appeared to be quite comparable to Wang et al. (2021), apart from a somewhat more marked speed-accuracy trade-off: the mean RTs, and associated standard deviations, were 717.6 (175.2) ms in our Experiment 2a vs. 770.2 (180.9) ms in Wang et al.’s (2021) Experiment 1; the corresponding rates of outlier RTs were 3.4% vs. 1.9%, and the rates of response errors 4.3% vs. 2.1%. Most importantly, the baseline distractor-interference effects (in the ‘random’ group) were near-identical: 39 ms in our Experiment 2a vs. 42 ms in Wang et al.’s (2021) Experiment 1 (of course, we found a similar interference effect, of 38 ms, in the ‘regular’ group, whereas Wang et al. reported a reduced effect, of 21 ms). Thus, while we did not conduct an exact, on-site replication of Wang et al. (2021) and so cannot rule out that their pattern of findings would be replicable under the exact-same laboratory conditions, it remains that dynamic *distractor*-location learning is more fragile than dynamic *target*-location learning.

General Discussion

Summary of findings and relation to the extant literature

The present study was designed to investigate whether dynamic target-location enhancement and, respectively, distractor-location suppression purely based on probabilistic cross-trial transitional regularities are possible. Implementing the same cross-trial transitional regularity (80% likely one-step clockwise or counter-clockwise shift) of the critical item, either the search target (Experiment 1b) or a task-irrelevant distractor (Experiment 1a), we found robust dynamic search guidance when the *target* location shifted predictably (vs. randomly) across consecutive trials, but no reduction of distractor interference when the distractor location shifted predictably across trials. The same asymmetry was obtained in Experiment 2, which was modeled after Wang et al. (2021), implementing a 100% predictable distractor shift in Experiment 2a and a 100% predictable target shift in Experiment 2b. Facilitated processing of the target at the predicted location appeared to be associated with conscious awareness of the dynamic regularity: in Experiment 2b, all but one participant had recognized the cross-trial regularity, and in Experiment 1b only those participants who explicitly recognized the regularity exhibited a robust facilitation effect. In contrast, there was no evidence of participants becoming aware of the regular shift of the distractor item.

The statistical learning of the target position that we observed in Experiment 1b is broadly consistent with the probability cueing of the target location reported in the literature (Geng and Behrmann 2002, 2005; Shaw and Shaw 1977). For example, manipulating the likelihood of target presentation unevenly between the left and right sides of the display (80% vs. 20%), Geng and Behrmann (2002) found search to be facilitated when the target actually appeared within the more probable region. Of note, though, most of the previous target-location probability-cueing studies used a stationary (i.e., spatially fixed) uneven probability manipulation (either location- or region-based), finding that search guidance can successfully adapt to these environmental statistics to enhance performance. A recent study, by Li and Theeuwes (2020), showed that this adaptability also extends to dynamic location manipulations: when the target on trial *n-1* (appearing, say, at the leftmost display location) predicted the location of the target on trial *n* (in the example, the right-most location) with 100% certainty, participants were also able to learn this cross-trial regularity to facilitate search performance. Here, we showed that a dynamic cross-trial regularity can also be learned when it is probabilistic (rather than deterministic) in nature. Similar to earlier studies (e.g., Geng and Behrmann 2002), we implemented an uneven cross-trial transitional probability structure (80% for cross-trial frequent, 10% for infrequent, and 10% for random transitions) and showed that participants could learn this probabilistic regularity and use it to facilitate target detection. It is important to note that, in our study, the global probability of the target occurrence remained equal across all possible locations – only the cross-trial transitional probability differed in the direction of the target movement (clockwise or counterclockwise). This suggests that the search-guidance system can learn and adapt to dynamic as well as fixed probability structures that govern where the target appears, and modify the computation of attentional priorities accordingly.

In contrast to robust cross-trial dynamic probability-cueing of the target location, we found no evidence that participants were able to learn the same dynamic probability structure when this was applied to predict the distractor location in Experiment 1a (80% probabilistic manipulation), Experiment 2a (100% deterministic manipulation), and two pilot experiments (with a total of 102 participants). This is different from the many studies with a fixed uneven distribution of the distractor, which have collectively shown that display locations/regions with a high probability of distractor occurrence can be effectively de-prioritized to reduce the interference caused by the irrelevant pop-out stimulus (Ferrante et al. 2018; Goschy et al. 2014; Leber et al. 2016; Sauter et al. 2018; Sauter, Liesefeld, and Müller 2019; B. Wang and Theeuwes 2018a; Zhang et al. 2019; Kerzel, Huynh Cong, and Burra 2021; Luck et al. 2021). For instance, likely distractor locations may be proactively suppressed – that is, some 'no-go' tag may be placed on them – on the attentional priority map (e.g., Ferrante et al. 2018; see also Gaspelin, Leonard, and Luck 2015; Gaspelin and Luck 2018), dampening the build-up of the priority signal at such locations. Support for this also comes from a recent study by Kong et al. (2020) who combined a variation of Gaspelin et al.'s (2015) 'capture-probe' paradigm with a *static* distractor-location probability-cueing paradigm. On a random one-third of trials, a 200-ms search display was directly followed by a 100-ms probe display consisting of oriented line segments. One of the display locations was then probed, that is, participants had to reproduce the orientation of the line previously shown at this location. Examining the distribution of reproduction responses for the precision of the internal representation and the guess rate (using a standard mixture model), Kong et al. (2020) found the guess rate to be increased and the precision to be somewhat decreased following a distractor at the likely vs. an unlikely location. Huang, Donk, and Theeuwes (2022) reported a similar result even when the probe display was not preceded by a search display (i.e., when there was no distractor, however briefly presented, that could initiate reactive processes). These findings are consistent with information uptake from the likely distractor location being proactively suppressed. Thus, while proactive suppression of *fixed* likely distractor locations is a readily available strategy for the search-guidance system to reduce attentional capture, our findings suggest that proactive suppression of *dynamically* predictable distractor locations is much more delicate – at least with the same dynamic probability structure (and the same number of learning trials) that we used for the target location.

Relation to inconsistent findings

Our non-finding in Experiment 1a is at variance with Wang et al. (2021), who reported that a very similar cross-trial transitional regularity of the distractor (clockwise or counter-clockwise shift by one step) did reduce distractor interference. Importantly, however, there are several key differences between their study and our Experiment 1a. First, the regularity they implemented was deterministic (100%), rather than probabilistic (our structure predicted the distractor location with 80% probability). There is evidence from reward-association learning of 'incentive salience' that probabilistic regimens are more effective than deterministic regimens (e.g., Cho and Cho 2021; Sali, Anderson, and Yantis 2014). So this may not (alone) be a critical difference – given also that our participants had no problem learning exactly the same probabilistic structure in relation to the target location.

Another key difference between Wang et al.'s (2021) and our study is that the color of the (color-defined) distractor was distinct from the fixed target color in their experiments (even in their Experiment 2, in which the distractor could appear in two possible colors). In our Experiment 1a, we purposely implemented random swapping, across trials, of the distractor and target (i.e., more generally, the non-distractor) colors to reduce possible dimension- (or feature-based) distractor suppression which operates in a spatially non-specific manner. As shown in our previous studies (Zhang et al. 2019; Allenmark et al. 2019), whether participants adopt dimension-/feature-based or a priority-map-based suppression much depends on the overlapping of the distractor and target features: with color swapping between target and distractor, participants tend to adopt a priority-map-based suppression strategy; without color swapping, they are likely to develop a dimension-based strategy (globally reducing the weight of color signals in priority computations).

Thus, given the perfect separability of the distractor and target (as well as the remaining non-target) colors in Wang et al.'s (2021) study, their participants might have adopted a *global* – that is, spatially unspecific – strategy of suppressing the color dimension, or specific color features, not only in the baseline condition with the 'random' structure, but also condition with the 'regular' structure. Some evidence of this may be gleaned from the fact that, while distractor interference generally (i.e., in both groups) decreased across the ten trial blocks of their experiments, the 'random' group learnt to deal nearly as efficiently with distractors as the 'regular' group by the end of testing. In the 'random' group, this practice-dependent improvement can only be attributed to global learning, as there was no spatial regularity that could be learnt. Accordingly, the on average (i.e, across all trial blocks) reduced interference exhibited by the 'regular' group in Wang et al. (2021) may, at least in part, be owing to expedited global learning when successive distractors appear in a spatially contiguous display region, compared to when they crisscross the display in a haphazard manner. Thus, a faster rate of global learning under 'regular' vs. 'random' conditions might have played a role in the result pattern of Wang et al. (2021).[8]

Alternatively, their result pattern might also be explained by reactive suppression placed post-capture on the distractor location, in order to disengage attention and re-orient it to the target (for oculomotor evidence, see, e.g., Sauter et al., 2021). If reactive suppression is somewhat fuzzy, affecting adjacent locations, and if it is carried over across trials, it would, on average, have a greater impact with the regular movement of the distractor to an adjacent location, as compared to the random placement. Wang et al. (2021) argued against this possibility based on their failure to observe a reliable inter-trial negative priming effect in their 'random' condition (effect of 8 ms, $p = .701$). Recall, though, that in their design, this condition was performed by a different group of participants: they could not examine for such effects directly in the 'regular' group, because the dynamic distractor regularity was deterministic (100% predictability). In contrast, with our probabilistic design in Experiment 1a (80% predictability), in which the 'random' baseline was estimated within (rather than between) participants, we did find evidence of cross-trial carry-over of reactive inhibition placed on the distractor location on a given trial: if the distractor repeated at the same location, its interference

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[8] Recall, though, that we observed no differential reduction of distractor interference between the 'regular' and 'random' groups over the ten trial blocks in our Experiment 2a, but this might have been missed in our *online* experiment.

tended to be reduced compared to when it appeared at a different location (1049 ms vs. 1093 ms, i.e., effect of 44 ms, $p = .039$). However, even though this effect appeared to be spatially relatively precise (focused on the actual distractor location; see Figure 2c), a somewhat more fuzzy inhibition (spreading from the distractor towards adjacent locations) could have contributed to the reduced distractor interference in the ‘regular’ vs. the ‘random’ condition of Wang et al. (2021).

Thus, there are potential alternative mechanisms (i.e., expedited global learning and/or spatially fuzzy negative intertrial priming) which may have been operating besides any genuine learning of the dynamic distractor regularity by participants ‘regular’ group. While the latter is not conclusively ruled out by our unsuccessful attempts to demonstrate dynamic distractor-location learning, our experiments at least show that observers acquire a simple dynamic probabilistic regularity much more readily with regard to the location of *targets*, compared to the location of *distractors*.

Role of explicit awareness in spatial statistical learning?

Thus, the question remains why dynamic suppression of predictable distractor locations is so hard to acquire, whereas dynamic facilitation of predicted target locations is established easily. A clue to answering this question is provided by the ‘awareness’ results. In Experiment 1b (80% predictability of the shifting target location) and, especially, in Experiment 2b (100% predictability), participants became substantially aware of the dynamic target regularity, and those who correctly selected the right regularity in the awareness test in Experiment 1b showed a larger facilitation effect compared to the ‘unaware’ participants. In Experiment 2b, all but one participant were ‘aware’, so the equivalent comparison could not be performed. Note, though, that the general response speed was faster in Experiment 2b (in which the color of the display items was consistent across trials) than in Experiment 1b (in which the items’ color changed randomly across trials). When taking the differential RT levels into account, the facilitation effect in Experiment 2b was relatively larger than that in Experiment 1b[9] – consistent with awareness of the regularity facilitating performance even, or especially, when the target color is certain. This is not to say that the dynamic target regularity cannot be implicitly learned (see, e.g., Li and Theeuwes 2020)[10], but the learning effect appears to be larger for ‘aware’ than ‘unaware’ participants. The fact that explicit awareness greatly boosted the dynamic facilitation effect suggests that participants did develop a dynamic top-down set to prioritize the next target location in the regular (clockwise or counterclockwise) direction (endogenous orienting in

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[9] The 72 ms effect in Experiment 2b corresponds to an 11% decrease of the RT in the baseline (random) condition (647 ms), while the 63 ms effect in Experiment 1b only corresponds to a 5% decrease of the much slower baseline RT (1156 ms, averaged across the infrequent and random conditions) in that experiment.

[10] Recall that Li and Theeuwes (2020) reported that their observers were unaware of their regularity of a target at, say, the rightmost display location being invariably followed by a target at the leftmost location (or vice versa for other observers). Although this shift was 100% predictable, it occurred only on 25% of the trials within a block, i.e.: the remaining 75% of trials involved random placement of the target at other locations and random location shifts across trials. Thus, even though the critical shift was 100% predictable, it was a relatively rare event – which may have hampered participants becoming aware of the regularity.

Posner 1980 terms). Developing such an anticipatory top-down set is likely encouraged by the target being the central item in the task set: observers have to set up a target template in working memory and compare any selected item against this template, and then reject it if there is a mismatch or, alternatively, proceed to extracting the response-relevant feature for the response if there is a match. Given the central place of the target in the task set, even seemingly irrelevant 'features' such as its location may be explicitly encoded, providing the basis for recognizing and exploiting the regularity in the placement/movement of the target across consecutive trials. In contrast, if a distractor is mistakenly selected, it only needs to be rejected as a non-target item, that is, as not matching the target template; in other words, there is no need to process the distractor for, and explicitly represent, any featural information about the distractor, including its location. As a result, there is little, if any, *explicit* learning of higher-order dynamic statistical regularities in the placement of the distractor.

However, with static statistical regularities – that is, with a fixed display location or region being more likely to contain a distractor than other locations –, a plethora of recent studies have reported distractor-location probability-cueing effects in the absence of conscious awareness of a bias in the distractor distribution.[11] We have recently shown that these static cueing effects depend purely on the local distractor probability (Allenmark et al. 2022), and that the frequency with which distractors occur at a particular location modulates the responsivity of neurons in early (i.e., retinotopic) visual cortex areas, from V1 to V4 – with higher frequency rendering a stronger down-modulation (Zhang et al. 2021). Also, we proposed that the 'tuning' signal for the down-modulation of entry-level feature coding is provided by the reactive suppression of a particular location when a selected (distractor) item at this location produced a mismatch decision: the more often this happens for a particular location, the less the responsivity of V1–V4 neurons with corresponding receptive fields. This naturally explains the static distractor-location probability-cueing effect: it reflects an essentially static mechanism (top-down inhibiting the current distractor location, so as to disengage attention and re-deploy it to the target location), which does not require conscious knowledge of the distractor location to work.

In contrast, a dynamically predictable target location can be tracked successfully if the rule is explicitly (consciously) represented in working memory, as part of the task set. This rule can then be applied to flexibly prioritize a likely next target location, perhaps by top-down pre-activating the anticipated location on the attentional priority map. Further, neuroscientific work is necessary to examine the brain mechanisms underlying dynamic target-location prediction, though these are likely to involve the frontoparietal attention network: a richly interconnected network linking the intraparietal sulcus (IPS), the inferior parietal lobe (IPL), and dorsal premotor cortex (PMC), including the frontal eye field (FEF). According to Ptak's (2012) model of this network, the posterior parietal cortex has functional characteristics that point to a central role of this region in the

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[11] We acknowledge, though, that these reports are likely to underestimate to what extent (some) participants were actually aware of the bias, given they used non-optimal procedures to assess awareness (see Vincente-Conesa et al., 2021).

computation of a feature- and dimension-independent attentional-priority map. “Feature maps computed in the sensory cortex and current behavioral goals as well as abstract representations of associated actions (action templates) generated in the prefrontal and premotor cortex (PMC) feed into the parietal priority map. The dorsolateral prefrontal cortex (DLPFC) maintains behavioral goals in working memory and protects them from distracting information. The inferior parietal lobe (IPL) initiates a shift of attention and maintains attention on the relevant stimulus” (Ptak 2012, 512). Given this, it is conceivable that *dynamic* spatial expectations originating in the DLPFC and PMC can also be integrated in the priority map.

Conclusion

The present study investigated statistical learning of the same dynamic, cross-trial probabilistic regularity of the target and (additional-singleton) distractor location in visual search. We found robust facilitation of the dynamically predictable target location, but no suppression of the dynamically predictable location of the distractor (the latter being at variance with another report in the literature). While hardly any participants reported having noticed the cross-trial regularity of the *distractor*, 42% (Experiment 1b) to 96% (Experiment 2b) of the participants correctly selected the cross-trial *target* regularity in a post-search explicit-recognition test; further, awareness of the target regularity greatly enhanced cross-trial cueing of the target location (Experiment 1b). We propose that this asymmetry, in the dynamic cueing and awareness effects, arises because the target occupies a central place in the task and so is explicitly encoded in working memory for template matching and extraction of the response critical feature; as a result, the dynamic cross-trial change in its location is also registered and can be used to top-down prioritize the upcoming target location. In contrast, the distractor is not an explicit part of the task set (e.g., it is not necessary to set up a distractor template in working memory in order to reject distractors that captured attention). Consequently, observers would gain only little, if any, *explicit* awareness of regular distractor-location changes, which could be translated into an anticipatory (top-down) suppression strategy. While not ruling out an element of *implicit* learning, this would limit to what degree dynamic distractor regularities can inform search guidance.

References

Allenmark, Fredrik, Ahu Gokce, Thomas Geyer, Artyom Zinchenko, Hermann J. Müller, and Zhuanghua Shi. 2021. “Inter-Trial Effects in Priming of Pop-out: Comparison of Computational Updating Models.” *PLoS Computational Biology* 17 (9): e1009332.

Allenmark, Fredrik, Bei Zhang, Heinrich René Liesefeld, Zhuanghua Shi, and Hermann J. Müller. 2019. “Probability Cueing of Singleton-Distractor Regions in Visual Search: The Locus of Spatial Distractor Suppression Is Determined by Colour Swapping.” *Visual Cognition*. https://doi.org/10.1080/13506285.2019.1666953.

Allenmark, Fredrik, Bei Zhang, Zhuanghua Shi, and Hermann J. Müller. 2022. “Learning to Suppress

Likely Distractor Locations in Visual Search Is Driven by the Local Distractor Frequency." *Journal of Experimental Psychology. Human Perception and Performance* 48 (11): 1250–78.

Bacon, W. F., and H. E. Egeth. 1994. "Overriding Stimulus-Driven Attentional Capture." *Perception & Psychophysics* 55 (5): 485–96.

Becker, Stefanie I. 2010. "Oculomotor Capture by Colour Singletons Depends on Intertrial Priming." *Vision Research* 50 (21): 2116–26.

Brainard, D. H. 1997. "The Psychophysics Toolbox." *Spatial Vision* 10 (4): 433–36.

Cho, Sang A., and Yang Seok Cho. 2021. "Uncertainty Modulates Value-Driven Attentional Capture." *Attention, Perception & Psychophysics* 83 (1): 142–55.

Clark, J. H. 1924. "The Ishihara Test for Color Blindness." *American Journal of Optometry and Physiological Optics* 5:269–76.

Druker, Michael, and Britt Anderson. 2010. "Spatial Probability AIDS Visual Stimulus Discrimination." *Frontiers in Human Neuroscience* 4 (August). https://doi.org/10.3389/fnhum.2010.00063.

Egeth, H. E., and S. Yantis. 1997. "Visual Attention: Control, Representation, and Time Course." *Annual Review of Psychology* 48:269–97.

Faul, Franz, Edgar Erdfelder, Albert-Georg Lang, and Axel Buchner. 2007. "G*Power 3: A Flexible Statistical Power Analysis Program for the Social, Behavioral, and Biomedical Sciences." *Behavior Research Methods*. https://doi.org/10.3758/bf03193146.

Ferrante, Oscar, Alessia Patacca, Valeria Di Caro, Chiara Della Libera, Elisa Santandrea, and Leonardo Chelazzi. 2018. "Altering Spatial Priority Maps via Statistical Learning of Target Selection and Distractor Filtering." *Cortex; a Journal Devoted to the Study of the Nervous System and Behavior* 102 (May):67–95.

Folk, Charles L., Andrew B. Leber, and Howard E. Egeth. 2002. "Made You Blink! Contingent Attentional Capture Produces a Spatial Blink." *Perception & Psychophysics* 64 (5): 741–53.

Folk, Charles L., and R. Remington. 1998. "Selectivity in Distraction by Irrelevant Featural Singletons: Evidence for Two Forms of Attentional Capture." *Journal of Experimental Psychology. Human Perception and Performance* 24 (3): 847–58.

Folk, Charles L., and Roger W. Remington. 2008. "Bottom-up Priming of Top-down Attentional Control Settings." *Visual Cognition* 16 (2-3): 215–31.

Folk, C. L., R. W. Remington, and J. C. Johnston. 1992. "Involuntary Covert Orienting Is Contingent on Attentional Control Settings." *Journal of Experimental Psychology. Human Perception and Performance* 18 (4): 1030–44.

Gaspelin, Nicholas, John M. Gaspar, and Steven J. Luck. 2019. "Oculomotor Inhibition of Salient Distractors: Voluntary Inhibition Cannot Override Selection History." *Visual Cognition* 27 (3-4): 227–46.

Gaspelin, Nicholas, Carly J. Leonard, and Steven J. Luck. 2015. "Direct Evidence for Active Suppression of Salient-but-Irrelevant Sensory Inputs." *Psychological Science* 26 (11): 1740–50.

Gaspelin, Nicholas, and Steven J. Luck. 2018. "Distinguishing among Potential Mechanisms of Singleton Suppression." *Journal of Experimental Psychology. Human Perception and Performance* 44 (4): 626–44.

Geng, Joy J., and Marlene Behrmann. 2002. "Probability Cuing of Target Location Facilitates Visual Search Implicitly in Normal Participants and Patients with Hemispatial Neglect." *Psychological Science* 13 (6): 520–25.

———. 2005. "Spatial Probability as an Attentional Cue in Visual Search." *Perception & Psychophysics* 67 (7): 1252–68.

Giménez-Fernández, Tamara, David Luque, David R. Shanks, and Miguel A. Vadillo. 2020. "Probabilistic Cuing of Visual Search: Neither Implicit nor Inflexible." *Journal of Experimental Psychology. Human Perception and Performance* 46 (10): 1222–34.

Goschy, Harriet, Sarolta Bakos, Hermann J. Müller, and Michael Zehetleitner. 2014. "Probability Cueing of Distractor Locations: Both Intertrial Facilitation and Statistical Learning Mediate Interference Reduction." *Frontiers in Psychology* 5 (November):1195.

Graves, Tashina, and Howard E. Egeth. 2015. "When Does Feature Search Fail to Protect Against Attentional Capture?" *Visual Cognition* 23 (9-10): 1098–1123.

Hoffmann, Joachim, and Wilfried Kunde. 1999. "Location-Specific Target Expectancies in Visual

Search." *Journal of Experimental Psychology. Human Perception and Performance* 25 (4): 1127–41.

Huang, Changrun, Mieke Donk, and Jan Theeuwes. 2022. "Proactive Enhancement and Suppression Elicited by Statistical Regularities in Visual Search." *Journal of Experimental Psychology. Human Perception and Performance* 48 (5): 443–57.

Jiang, Yuhong V., Khena M. Swallow, and Gail M. Rosenbaum. 2013. "Guidance of Spatial Attention by Incidental Learning and Endogenous Cuing." *Journal of Experimental Psychology. Human Perception and Performance* 39 (1): 285–97.

Kerzel, Dirk, Stanislas Huynh Cong, and Nicolas Burra. 2021. "Do We Need Attentional Suppression?" *Visual Cognition* 29 (9): 580–82.

Kong, Siyang, Xinyu Li, Benchi Wang, and Jan Theeuwes. 2020. "Proactively Location-Based Suppression Elicited by Statistical Learning." *PloS One* 15 (6): e0233544.

Leber, Andrew B., Rachael E. Gwinn, Yoolim Hong, and Ryan J. O'Toole. 2016. "Implicitly Learned Suppression of Irrelevant Spatial Locations." *Psychonomic Bulletin & Review* 23 (6): 1873–81.

Li, Ai-Su, and Jan Theeuwes. 2020. "Statistical Regularities across Trials Bias Attentional Selection." *Journal of Experimental Psychology. Human Perception and Performance* 46 (8): 860–70.

Liesefeld, Heinrich René, and Hermann J. Müller. 2019. "Distractor Handling via Dimension Weighting." *Current Opinion in Psychology* 29 (October):160–67.

Luck, Steven J., Nicholas Gaspelin, Charles L. Folk, Roger W. Remington, and Jan Theeuwes. 2021. "Progress Toward Resolving the Attentional Capture Debate." *Visual Cognition* 29 (1): 1–21.

Moorselaar, D. van, Nasim Daneshtalab, and Heleen A. Slagter. 2021. "Neural Mechanisms Underlying Distractor Inhibition on the Basis of Feature And/or Spatial Expectations." *Cortex; a Journal Devoted to the Study of the Nervous System and Behavior* 137 (April):232–50.

Müller, Hermann J., Thomas Geyer, Michael Zehetleitner, and Joseph Krummenacher. 2009. "Attentional Capture by Salient Color Singleton Distractors Is Modulated by Top-down Dimensional Set." *Journal of Experimental Psychology. Human Perception and Performance* 35 (1): 1–16.

Noonan, Maryann P., Nika Adamian, Alexandra Pike, Frida Printzlau, Ben M. Crittenden, and Mark G. Stokes. 2016. "Distinct Mechanisms for Distractor Suppression and Target Facilitation." *The Journal of Neuroscience: The Official Journal of the Society for Neuroscience* 36 (6): 1797–1807.

Palan, S., and C. Schitter. 2018. "Prolific. Ac—a Subject Pool for Online Experiments. J Behav Exp Financ 17: 22--27."

Peirce, Jonathan, Jeremy R. Gray, Sol Simpson, Michael MacAskill, Richard Höchenberger, Hiroyuki Sogo, Erik Kastman, and Jonas Kristoffer Lindeløv. 2019. "PsychoPy2: Experiments in Behavior Made Easy." *Behavior Research Methods* 51 (1): 195–203.

Posner, M. I. 1980. "Orienting of Attention." *The Quarterly Journal of Experimental Psychology* 32 (1): 3–25.

Ptak, Radek. 2012. "The Frontoparietal Attention Network of the Human Brain: Action, Saliency, and a Priority Map of the Environment." *The Neuroscientist: A Review Journal Bringing Neurobiology, Neurology and Psychiatry* 18 (5): 502–15.

Sali, Anthony W., Brian A. Anderson, and Steven Yantis. 2014. "The Role of Reward Prediction in the Control of Attention." *Journal of Experimental Psychology. Human Perception and Performance* 40 (4): 1654–64.

Sauter, Marian, Nina M. Hanning, Heinrich René Liesefeld, and Hermann J. Müller. 2021. "Post-Capture Processes Contribute to Statistical Learning of Distractor Locations in Visual Search." *Cortex; a Journal Devoted to the Study of the Nervous System and Behavior* 135 (February):108–26.

Sauter, Marian, Heinrich René Liesefeld, and Hermann J. Müller. 2019. "Learning to Suppress Salient Distractors in the Target Dimension: Region-Based Inhibition Is Persistent and Transfers to Distractors in a Nontarget Dimension." *Journal of Experimental Psychology. Learning, Memory, and Cognition*, January. https://doi.org/10.1037/xlm0000691.

Sauter, Marian, Heinrich René Liesefeld, Michael Zehetleitner, and Hermann J. Müller. 2018. "Region-Based Shielding of Visual Search from Salient Distractors: Target Detection Is Impaired with Same- but Not Different-Dimension Distractors." *Attention, Perception & Psychophysics* 80

(3): 622–42.

Shaw, M. L., and P. Shaw. 1977. “Optimal Allocation of Cognitive Resources to Spatial Locations.” *Journal of Experimental Psychology. Human Perception and Performance* 3 (2): 201–11.

Theeuwes, Jan. 1992. “Perceptual Selectivity for Color and Form.” *Perception & Psychophysics* 51 (6): 599–606.

Vicente-Conesa, Francisco, Tamara Giménez-Fernández, David Luque, and Miguel A. Vadillo. 2021. “Learning to Suppress a Distractor May Not Be Unconscious.” https://doi.org/10.31234/osf.io/yekvu.

Wang, Benchi, and Jan Theeuwes. 2018a. “Statistical Regularities Modulate Attentional Capture.” *Journal of Experimental Psychology. Human Perception and Performance* 44 (1): 13–17.

———. 2018b. “Statistical Regularities Modulate Attentional Capture Independent of Search Strategy.” *Attention, Perception & Psychophysics* 80 (7): 1763–74.

Wang, Lishuang, Benchi Wang, and Jan Theeuwes. 2021. “Across-Trial Spatial Suppression in Visual Search.” *Attention, Perception & Psychophysics* 83 (7): 2744–52.

Wolfe, J. M., K. R. Cave, and S. L. Franzel. 1989. “Guided Search: An Alternative to the Feature Integration Model for Visual Search.” *Journal of Experimental Psychology. Human Perception and Performance* 15 (3): 419–33.

Won, Bo-Yeong, Mary Kosoyan, and Joy J. Geng. 2019. “Evidence for Second-Order Singleton Suppression Based on Probabilistic Expectations.” *Journal of Experimental Psychology. Human Perception and Performance* 45 (1): 125–38.

Zhang, Bei, Fredrik Allenmark, Heinrich René Liesefeld, Zhuanghua Shi, and Hermann J. Müller. 2019. “Probability Cueing of Singleton-Distractor Locations in Visual Search: Priority-Map- versus Dimension-Based Inhibition?” *Journal of Experimental Psychology. Human Perception and Performance* 45 (9): 1146–63.

Zhang, Bei, Ralph Weidner, Fredrik Allenmark, Sabine Bertleff, Gereon R. Fink, Zhuanghua Shi, and Hermann J. Müller. 2021. “Statistical Learning of Frequent Distractor Locations in Visual Search Involves Regional Signal Suppression in Early Visual Cortex.” *Cerebral Cortex* , November. https://doi.org/10.1093/cercor/bhab377.

2.2 Learning regular cross-trial shifts of the target location in serial search involves awareness – an eye-tracking study

Hao Yu, Fredrik Allenmark, Hermann J. Müller, Zhuanghua Shi

General and Experimental Psychology, Department of Psychology, LMU Munich, 80802, Germany

CONTRIBUTIONS

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

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

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

Zhuanghua Shi: Funding acquisition, Methodology, Resources, Supervision, Validation, Writing, Review, and Editing.

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Hao Yu
General and Experimental Psychology, Department of Psychology, LMU Munich, 80802, Germany

Fredrik Allenmark
General and Experimental Psychology, Department of Psychology, LMU Munich, 80802, Germany

Hermann J. Müller
General and Experimental Psychology, Department of Psychology, LMU Munich, 80802, Germany

Zhuanghua Shi
General and Experimental Psychology, Department of Psychology, LMU Munich, 80802, Germany

Abstract

People can learn and use both static and dynamic (cross-trial) regularities in the positioning of target items during parallel, ‘pop-out’ visual search. Static target-location learning also works in serial search, however, acquiring dynamic regularities is hindered by the demands of item-by-item scanning. Also, questions have been raised regarding whether explicit awareness is necessary for using dynamic regularities to optimize performance. The present study re-examined if dynamic regularities can be learned in serial search when regular shifts of the target location occur frequently, and if such learning correlates with awareness of the dynamic rule. We adopted the same regularity used by Yu et al. (2023) to demonstrate dynamic learning in parallel search: a cross-trial shift of the target location in a (counter-)clockwise direction within a circular array in 80% of the trials, compared to irregular shifts in the opposite direction (10%) or some other random direction (10%). The results showed that about 70% of participants learned the dynamic regularity, with performance gains correlating with awareness: the more accurately they estimated the likelihood of the target shifting in the frequent direction, the greater their gains. Importantly, part of the gains accrued already early during the search: a large proportion of the very first and short-latency eye movements were directed to the predicted location, regardless of the target appeared there. We discuss whether this rule-driven behavior is causally mediated by conscious control.

Keywords: probability cueing, statistical learning, parallel/serial search, search guidance, eye movements, oculomotor scanning, inter-trial priming, conscious awareness

Introduction

Our visual environment is exceedingly rich and complex, yet our capacity to process information is limited. To make effective use of our cognitive resources, the brain prioritizes information relevant to the task at hand and suppresses irrelevant information that might impede performance (e.g., Egeth & Yantis, 1997; Folk et al., 1992; Treisman & Gelade, 1980; Wolfe et al., 1989). Selection of relevant and de-selection of irrelevant information is aided by the structured nature of our environment, allowing us to extract and learn recurrent patterns and regularities that benefit us in similar future situations. For example, when looking for our keys, we often start searching at the usual places, like the hallway table or the kitchen counter. Using environmental regularities, such as the likely location of a target object, helps us deploy attention and cognitive resources efficiently. Effects such as this, known as spatial 'probability cueing', have been extensively investigated in laboratory settings. When a task-relevant target appears at a likely location, the attentional system can acquire this information to enhance search efficiency, expediting target detection and attendant response decisions (Druker & Anderson, 2010; Geng & Behrmann, 2002, 2005; Hoffmann & Kunde, 1999; Jiang et al., 2013; Shaw & Shaw, 1977). Probability cueing is also evident in oculomotor scanning, with an increased frequency and reduced latencies of early saccades directed to targets at likely locations (Jiang et al., 2014; Jones & Kaschak, 2012; Walthew & Gilchrist, 2006). Recently, research has demonstrated an analogous effect: observers can learn to attentionally suppress likely locations of salient but task-irrelevant distractor items in the search displays – referred to as 'distractor-location probability cueing' (e.g., Allenmark et al., 2019; Goschy et al., 2014; Sauter et al., 2018; van Moorselaar et al., 2021).

It is noteworthy that the majority of studies examining spatial statistical learning, whether of target or distractor locations, have used *static* uneven probability manipulation. For example, one display location or region is more likely to contain the target or a distractor than any other location or region (e.g., Geng & Behrmann, 2002, 2005; Goschy et al., 2014; Sauter et al., 2018; Shaw & Shaw, 1977). The resulting probability-cueing effects are attributed to statistical learning that enhances or suppresses specific *static* locations on the attentional priority map, which governs the allocation of focal-selective attention (for a review, see Luck et al., 2021).

More recently, several studies have extended the study of probability cueing from static target and distractor distributions to dynamic scenarios to ascertain whether statistical learning of selection priorities would also work with predictable *changes* in the likely locations of targets or distractors across trials (Li et al., 2022; Li & Theeuwes, 2020; Yu et al., 2023). Together, these studies showed that attentional selection can successfully adapt to dynamic, cross-trial regularities in *target* placement: reaction times (RTs) were faster to targets appearing at the location predicted by the dynamic rule compared to random locations (Li & Theeuwes, 2020; Yu et al., 2023). Importantly, though, Li et al. (2022) found this statistical learning to critically depend on spatially parallel search, which operates simultaneously across all display items. In their Experiment 2b, parallel search enabled dynamic cueing effects, while serial search, which proceeds item-by-item (their Experiment 1), did not produce such effects. In Li and Theeuwes's (2020) design, certain target locations were predictably coupled across trials. For instance, a target at the left-most location in a circular display array on trial *n* would invariably lead to the next target on trial *n+1* appearing at the right-most location (but not vice versa). When the target was a bottom-up salient shape-singleton item, among differently but homogeneously shaped non-target items, summoning focal attention automatically, participants were able to extract the dynamic target location shift across trials. This was evidenced by facilitated response to targets at the new, predictable location compared to random locations. Yu et al. (2023) also found that search performance improved when the target predictably moved across consecutive trials to a neighboring position, either clockwise or counterclockwise direction (blocked) – a somewhat simpler dynamic regularity compared to that introduced by Li and Theeuwes (2020).[12]

In contrast to Yu's (2023) parallel search condition, Li and Theeuwes (2020) observed no RT facilitation when the task required search for a rotated T-shape target among rotated L-shaped non-targets – a non-finding replicated by Li et al. (2022)[13]. This task, offering little bottom-up or top-down guidance (e.g., Moran et al., 2013), requires serial scanning of the search array with focal attention to find and respond to the target. The findings by Li and colleagues (Li et al., 2022; Li & Theeuwes, 2020) suggest that dynamic, cross-trial regularities in target placement may not be extractable or usable to improve performance under serial search conditions.

Thus, with static (spatially fixed) likely target locations, target-location probability learning works under serial and parallel search conditions (Geng & Behrmann, 2002). However, with dynamic target-location regularities, it seems to work only under parallel conditions, not serial (Li et al., 2022; Li & Theeuwes, 2020). The question is: why?

Why would *dynamic* target-location probability-cueing be dependent on the – parallel vs. serial – search mode?

While Li and colleagues offer little explanation, a possible answer might be related to the complexity of monitoring attention allocations over time, within and across trials. Under parallel search, the target "pops out", meaning it is almost always the first and only item that summons

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[12] In Li and Theeuwes's (2020) design, regular target shifts occurred in 25% of the trials. When a target on trial *n* occurred at either of two critical positions, such as the top or left-most positions, the next (trial *n*+1) target would *always* appear at a specific position on the opposite side of the search display, for instance, moving from the left-most to the right-most position. This rule was *deterministic*, in that a target at a critical position predicted the location of the next target with absolute (100%) certainty. In contrast, Yu et al. (2023) implemented regular target shifts in 80% of the trials, moving the target by one position in a particular – say, clockwise – direction (the regular direction, clockwise or counterclockwise, was counterbalanced across participants). In the remaining 20% of trials, the target shifted irregularly, either by one position counterclockwise or to a random location. Thus, the rule was *probabilistic*, in that it applied only on a proportion (the 80% majority) of trials.

[13] Li et al. (2022) focused solely on a serial search condition. They found no dynamic target-location probability-cueing effect when the target was purely shape-defined throughout the experiment. But when the target was a color singleton (pop-out) item during an initial learning phase, participants acquired a cueing effect, which persisted in a subsequent test phase, even after the color information was removed.

attention. When the target is selected, it is identified as the task-relevant item, and the response-critical information is extracted and search terminated. As a result, the current target location is ‘marked’ by the system as task-critical, enabling a higher-order ‘working-memory’ system, which monitors attention allocations over time (where was attention allocated to and where is it to go next?), to pick up cross-trial dependencies in the positioning of consecutive targets within a regularly structured (circular) display array.

Under serial search, by contrast, search involves attentional inspection of various non-target items before eventually selecting the target, after which the search is terminated. Monitoring attention allocations over time becomes considerably more complex, as the locations of already inspected non-target items need to be marked and remembered to avoid re-visiting them. As a result, the location of the target, once eventually selected, stands out less compared to a pop-out target. In addition, the search on the next trial might again start at a randomly selected location (likely a non-target), making it harder to track dynamic regularities of the target placement across trials. Compared to dynamic regularities, static regularities are easier to pick up even under serial search conditions, as the search almost always ends at the same location. This consistency allows knowledge of fixed target-location probabilities to be gradually accumulated across sequential trial episodes.

Thus, the increased working memory demands in monitoring attention allocations within trials and search-terminating target locations across trials under serial vs. parallel search would particularly impact the acquisition of dynamic regularities in target placement. In contrast, static regularities may be extracted relatively efficiently even in serial search. Nevertheless, we hypothesize – and test in the present study – that, depending on the frequency with which a dynamic rule is invoked and possibly its complexity, participants may be able to extract the regularity even in serial search and use it to optimize performance.

In fact, a large body of evidence shows that people are capable of learning inter-trial statistical dependencies in ‘implicit’ learning tasks, even in visual statistical-learning tasks involving complex (e.g., second-order) dependencies (Turk-Browne et al., 2008) as well as difficult (e.g., dual-target) search tasks (Allenmark et al., 2024). Thus, there is no a-priori reason to expect that dynamic target-location learning would not be feasible in demanding, serial search tasks.

Is (dynamic) target-location probability cueing implicit in nature?

It is widely assumed that statistical learning is implicit in nature, extracting statistical regularities from the input without explicit awareness or intent (Turk-Browne et al., 2005, 2009). Consistent with this, many studies report that individuals can learn and use static regularities related to salient *distractor* locations without awareness, that is: most participants cannot identify the frequent distractor location in post-experimental awareness tests, and the cueing effect differs little between those who correctly select the frequent location and those who do not (e.g., Failing et al., 2019; van

Moorselaar & Theeuwes, 2022; B. Wang & Theeuwes, 2018). Similar findings apply to the statistical learning of *target* locations (Ferrante et al., 2018; Geng & Behrmann, 2005; Li et al., 2022).

However, the idea that probability cueing is implicit in nature has come under scrutiny. Studies using more sophisticated awareness measures to probe the relationship between explicit awareness and the cueing of target locations present conflicting indications regarding the role of awareness in statistical learning (Giménez-Fernández et al., 2020; Golan & Lamy, 2023; Huang et al., 2022; van Moorselaar & Theeuwes, 2023; Vicente-Conesa et al., 2021; Yu et al., 2023). These discrepancies may arise from various factors, such as the probability levels used, the number of learning trials, and the methods for assessing awareness (Theeuwes et al., 2022). For instance, Giménez-Fernández et al. (2020) found that many participants were actually aware of the target's unequal (*static*) spatial distribution when asked to rank the possible locations from most probable to least probable and estimate the number of times the target appeared in each display quadrant (in a "serial", contextual-cueing paradigm; cf. Chun & Jiang, 1998). In a recent study of *dynamic* target-location probability cueing in pop-out search (Yu et al., 2023), many participants were also explicitly aware of the dynamic (cross-trial) target regularity, and the cueing effect was significant only in 'aware' participants.

Based on these findings, we hypothesize that learning *dynamic* target-location regularities in *serial* search is explicit in nature, depending on (or correlating with) participants becoming aware of the rule governing the shifts in the target location across trials.[14]

Role of inter-trial target-identity swapping, positional priming, and rule-based priming

Besides serial search making greater demands on the tracking of attention allocations within trials and target placements across trials, the difficulty increases if the target identities (e.g., shape) change randomly, alternating with the non-target identities, across trials, as opposed to remaining fixed. Note that feature swapping is a standard feature in 'additional-singleton' paradigms (e.g., Theeuwes, 1991), where it promotes a spatially parallel 'singleton-detection' search mode (cf. Bacon & Egeth, 1994). In such paradigms, statistical learning of distractor locations is influenced by whether there is random feature swapping across trials (e.g., Allenmark et al., 2019), likely because further processing is required to establish the dimensional or featural identity of both distractor and target items. Of note, swapping of the color that singled out the target from the color-homogeneous background items was also implemented in Yu et al. (2023). This did not hinder (aware) participants from acquiring the dynamic rule, likely because the target popped out of the search array.

Random swapping of target and non-target features is less common in serial search studies. Conceptually, without swapping, observers can set up a fixed 'target template' to compare any

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[14] This would also be consistent with Li et al. (2022), where only two of a total of 57 participants could be said to have become explicitly aware of the dynamic regularity implemented in their study: failure to become aware of the regularity would predict the absence of a cueing effect.

selected item and make a target/non-target decision. This allows for a top-down bias towards selection of critical features that differentiate the target from non-target items. In contrast, with swapping, observers need to create two templates and determine, for each trial, which is the target and which the non-target template. Establishing this requires inspecting multiple items: if two inspected items share essentially the same features, they are likely non-targets – defining the non-target template. By default, the other description becomes the target template. Typically, under swapping conditions, the search system carries over the template from one trial to the next (Geyer et al., 2006; Kristjánsson et al., 2002; Maljkovic & Nakayama, 1994) – the implicit assumption being that critical task settings stay the same, and additional information is required to change or update the task set, expediting search on no-swap relative to swap trials. Nevertheless, given the added complexity in attention allocations to establish the target template under random swapping, one would expect dynamic target-location learning to be less robust under randomly variable vs. fixed target identity conditions.

Note that two other types of intertrial priming may be at work, especially during serial search. The first is positional intertrial priming (Krummenacher et al., 2009; e.g., Maljkovic & Nakayama, 1996), characterized by raised attentional priority for the target location on a given trial and carry-over of this positional selection bias to the next trial. This type of intertrial priming might be particularly prominent under serial search conditions that provide no other sources of guidance (e.g., feature-based) to the target location. In this situation, the system might strongly prioritize inspection of locations where a target was detected in the previous search episode. Any dynamic rule-based target-location probability-cueing effect would have to compete with this positional priming effect, thus providing an important reference against which to compare the probability-cueing effect.

Finally, assuming a dynamic target-location regularity is acquired as a top-down ‘prior’ predicting the next location, the weight of this prior on a given trial might depend on whether the target placement on the preceding trial was consistent with the rule (rule-conforming) or inconsistent (rule-breaking). Rule-conforming target placements might strengthen the weight of the rule, while rule-breaking placements might weaken it – leading to a *rule-based intertrial-priming* effect. Again, these rule-based priming effects might be particularly prominent under serial search conditions, where there are no, or few, other sources of guidance to the target location.

Objective and rationale of the present study

The present study aimed to examine whether participants would learn a simple dynamic (probabilistic) regularity in target placement across consecutive trials in a *serial* search task, and whether such dynamic learning would rely on explicit awareness of the regularity. We used the same dynamic, cross-trial regularity as Yu et al. (2023) had in a parallel search task. This involved shifting the target location in a circular display arrangement by one position, either clockwise or counterclockwise (blocked per participant), across trials with a probability of 80% (see Figure 1) for a depiction of search displays and the dynamic regularity in the positioning of sequential target items).

With regular shifts occurring in 80% of the trials, compared to only a 25%-probability in Li and Theeuwes (2020), we expected a substantial number of participants to extract and use this regularity to speed up performance even in serial search. In particular, we expected faster task-final RTs on trials on which the cross-trial shift of the target location conformed with the rule ('frequent'-shift trials in Figure 1) vs. trials on which it did not ('infrequent'- and 'random'-shift trials).

Inspired by the findings of Yu et al. (2023), we expected that only participants who, based on a post-experiment awareness test, were 'aware' of the dynamic regularity would exhibit a dynamic target-location probability-cueing effect. 'Unaware' participants, by contrast, were not expected to benefit from the regularity. We also expected a correlation between participants' subjective certainty about the rule and their cueing effect.

In addition to examining the search-final RTs, we also tracked participants' eye movements while they scanned through the search displays for the target. RTs reflect the culmination of various processes contributing to the final response decision. However, without sophisticated methods to decompose RTs, they are limited in revealing which component processes occurred at what time during a trial to produce the required response. Tracking eye movements provides critical data, particularly in complex search tasks requiring the serial allocation of attention, which inherently involves sequential eye movements to find and respond to the target. Accordingly, here, we examined participants' eye movement to gain further insights into the time course of *dynamic target*-location probability cueing (for oculomotor studies of static distractor-location probability cueing, see, e.g., Allenmark, Shi, et al., 2021; Di Caro et al., 2019; Sauter et al., 2021; B. Wang et al., 2019). In fact, our task required participants to expressly fixate the target item and, upon confirming it as the target, execute a simple manual detection response.

Thus, recording participants' eye movements allowed us to examine, in aware participants, at what stage(s) of the search their saccadic behavior would be guided by the acquired rule or regularity "prior," beyond any bottom-up and top-down guidance signals provided by the search task. In particular, if rule-based guidance influences behavior very early, the first saccade (from the initial, central fixation spot) might be directed straight to the dynamically predicted 'frequent' target location, compared to other locations – in particular, an 'infrequent' position in the opposite direction to the rule that shares the same distance from the last target location as the 'frequent' location, or the same location occupied by the target on the last trial (positional intertrial priming). In any case, even if rule-based guidance takes longer than the first eye movement to come into play, we would expect that aware participants would require fewer saccades to locate the target at the frequent location compared to other locations (except possibly the repeated one), and fewer saccades than unaware participants. These oculomotor dynamics would eventually manifest in cueing effects in the search-final RTs.

Additionally, by mixing ‘frequent’ and ‘random’ (baseline) target placements within blocks, rather than segregating them into separate blocks (e.g., L. Wang et al., 2021), we could assess how dynamic rule guidance on a given trial is modulated by preceding trial events that either conform to or break the rule (rule-based intertrial priming). The eye-movement record can trace this influence back to even the earliest saccades executed on a trial.

We also examined the issues outlined above under conditions where the target identity remained constant across trials and, respectively, under conditions where target and non-target identities were mixed, swapping randomly across trials. The latter condition imposes additional task demands, requiring extended serial scanning of several items to determine the target and non-targets on each trial. Simply inspecting the item at the location predicted by the dynamic rule would not be sufficient to confirm its target status. The mixed condition might weaken or interfere with rule application or, conversely, strengthen reliance on the rule, as all relevant information for decision-making would likely be available at the predicted location (the frequent target position) and its vicinity (likely containing a non-target item). Again, early eye movements would provide insights into the (sub-)processes generating the task-final RTs under these conditions.

Finally, in addition to examining whether any probability-cueing effects in the task-final RTs correlate with participants’ awareness of the dynamic regularity, recording eye movements allows us to examine whether already the earliest saccades executed during serial search are informed by explicit knowledge of where the new target is likely to be located.

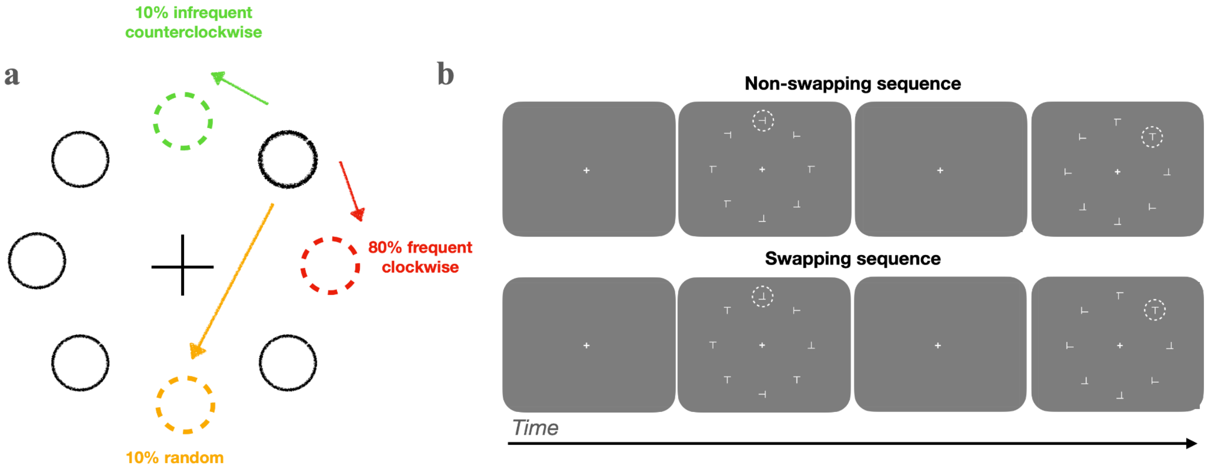

Figure 1. **(a)** Illustration of the three cross-trial target-location transition conditions. There were three types of change of the target location across consecutive trials: With 80% probability, the critical item would move to the adjacent location, in either clockwise or counterclockwise direction (here, indicated by the red dashed circle marking the ‘frequent’ location). The frequent direction was fixed for a given participant and counterbalanced across participants. With 10% probability, the critical item would shift to the adjacent location in the opposite direction (indicated by the green dashed circle marking the ‘infrequent’ location). In the remaining 10% of trials, the critical item would move randomly to any of the other locations, including re-appearing at the same location (indicated by the yellow dashed circle marking a ‘random’ location). **(b)** Examples of sequences from trial blocks with random swapping (mixed) and, respectively, no-swapping (fixed) of the target identity across trials. In the mixed condition, the target identity changes randomly from trial to trial; in the fixed condition, it stays the same.

Methods

Transparency and Openness Statement

Our report details the methodology used to determine the sample size, incorporating both a theoretical comparison and a power analysis. We also fully disclose the criteria for data inclusion and exclusion in pre-processing and all subsequent analyses. Regarding these criteria: no participants were excluded from the study, and all criteria for trial-based inclusion and exclusion were pre-determined prior to data analysis. We report all data manipulations in the study. The experimental code, raw data, and data analyses of the present study are publicly available at: https://github.com/msenselab/learning-in-serial-search. The experiment was conducted in 2022.

Participants

A total of 34 healthy university students from LMU Munich participated in this study (mean age ± SD: 26.32 ± 3.81 years; ranging from 20 to 33 years; 25 females, 9 males). All participants reported normal or corrected-to-normal vision, and passed the Ishihara color test (Clark, 1924), confirming unimpaired red-green color perception.

To ensure robust statistical power for addressing the questions at issue, we estimated our sample size based on previous studies (Li et al., 2022; Li & Theeuwes, 2020; Yu et al., 2023), which employed a similar manipulation of the dynamic (cross-trial) target-location regularity and reported an average effect size of $f = 0.42$ (average across all experiments). An a-priori power analysis, conducted with an effect size of $f = 0.42$, an $\alpha = .05$, and 98% power ($1-\beta$), indicated a minimum sample size of $n = 20$ (G*Power 3.1; Faul et al., 2007). Given that our study introduced a more complex letter-search paradigm, and we were interested in the relation between awareness of the dynamic regularity and the cueing effect, we initially increased the sample size to 24. Then, prompted by an anonymous reviewer, we added another 10 participants during the revision, to potentially increase the number of participants in the subgroup group of observers who failed to become aware of the dynamic target-location regularity (the ‘unaware’ group). The study was approved by the LMU Faculty of Pedagogics & Psychology Ethics Board. All participants provided written informed consent prior to the experiment and received 9.00 Euro per hour or equivalent course credits for their participation.

Apparatus

The experiment was conducted in a sound-attenuated, dimly lit testing chamber. Participants were seated 55 cm away from a 24-inch CRT display monitor that displayed the search stimuli at a screen resolution of 1920 × 1080 pixels and a refresh rate of 120 Hz. We employed PsychoPy (v. 2022.2.2) to control stimulus presentation, manual-response recording, and eye-movement tracking.

Gaze position for the dominant eye was captured using an SR Research EyeLink 1000 desktop-mount eye-tracker (Osgoode, Ontario, Canada), operating at a sampling rate of 1kHz. Participants registered their responses using a QWERTZ keyboard by pressing the space button with either their left- or right-hand index finger.

Stimuli and Design

The search displays (see Figure 1) featured a white fixation cross at the center, set against a gray screen background. Each display contained eight items: a single target shape, either a “T”- or “L”-shaped letter, among seven non-target shapes, “L”- or “T”-shaped letters). When the target was a “T”, the non-targets were all “L”-shaped, and vice versa.

The eight display items, each subtending 1.25° × 1.25° of visual angle (CIE [Yxy]: 70.5, 0.330, 0.326), were equally spaced on a virtual circle, at an eccentricity of 7° (yielding a center-to-center distance of 5.4° between adjacent items). To elevate task difficulty and encourage serial search, the “L”-shaped items featured a slight offset at the line junction, measuring 0.3°. Both “T” and “L” shapes appeared randomly in one of the four orthogonal orientations (0°, 90°,180°, or 270°). A shape-defined target, either a “T” or an “L”, was present on every trial. The target could appear at any of the eight possible display locations, with its location uniformly distributed across all trials. Participants were tasked to locate the target with their eyes (i.e., making a saccade to it and fixating) and then promptly press the spacebar to confirm target identification. Upon their response, a feedback message was shown for 500 ms, indicating either “Correct (response)” in green or “Incorrect (response) ” in red.

Crucially, the positioning of the target within the circular array was probabilistically predictable across consecutive trials *n* and *n+1*. In 80% of the trials, the target shifted to an adjacent location, in a consistent clockwise or counterclockwise direction – we refer to this as the “frequent (target) location”. The primary direction of this shift was constant for each participant, but counterbalanced across participants. In another 10% of the trials, termed “infrequent condition”, the target moved to an adjacent location in the opposite direction to that of the frequent condition. For the remaining 10% – the “random condition” –, the target’s position was chosen randomly among the six remaining alternative locations (including repeated presentation at the same location). Note that upon any irregular shift (including “infrequent” shifts by one position in counter-direction, position repetitions, and any larger “random” shifts), a regular shift (in the “frequent” direction) on the subsequent trial would proceed from the last target location. This is exactly the same dynamic regularity introduced in Yu et al.’s (2023) parallel-search Experiment 1.

The experiment consisted of 16 blocks: 8 “target-fixed” blocks, in which the target remained the same across trials, were randomly interleaved with the other 8 “target-swapping” blocks (in which the target identity changed randomly from trial to trial). Each block consisted of 60 trials, yielding a total of 960 trials for the whole experiment. Of note, the target-swapping condition was manipulated between blocks (but within participants). In blocks with swapping, the shape of the target (as well as that of the other, non-target items) could randomly swap across trials, in line with prior studies (of mainly singleton) search (e.g., Allenmark et al., 2019; Theeuwes, 1992).

Procedure

Each trial began once a stable fixation on the central fixation cross was detected (i.e., fixation within a virtual circle of 2° radius for at least 500 ms). Following a randomized (fixation) duration between 700 and 1000 ms, the circular search array was presented and remained visible until the participant responded.

Participants were instructed to localize the target within the display array by making an eye movement to it and then press the spacebar as fast as possible to confirm that they had actually located the target (rather than a non-target item); they were told that they were free to move their eyes in their search for the target. A trial was marked as 'correct' when participants fixated on the target item (i.e., within a circular region of 2.5° radius centered on the target) during the key-press response. If participants fixated a non-target item or no item at all, the feedback message "Incorrect" appeared at the screen center for 500 ms. Each new trial started with the reappearance of the central fixation cross. Between blocks, participants could take a break of a self-determined length.

To determine participants' awareness regarding the dynamic regularity of the target locations across trials, a post-experimental questionnaire was administered. It consisted of three forced-choice questions: First (Q1), participants had to indicate whether or not they had noticed *any* regularity in the target's placement across trials, selecting from six options (Was there any regularity? – Definitely no; Probably no; Possibly no; Possibly yes; Probably yes; Definitely yes). Second, they had to specify the dominant (regular) direction of the movement, by choosing one of two options for the most frequent type of movement (moved clockwise; moved counterclockwise.) Third (Q3), based on their previous answers, they estimated the frequency, in percentage terms, of the target moving in that direction (from 0% to 100%).

Data Analyses

Eye-data pre-processing

The recorded eye-position data were analyzed offline. Saccades were identified based on their velocity distribution, using a moving average over twenty successive eye-position samples (Engbert & Mergenthaler, 2006). Default settings were used to determine the on- and offset of saccades. A saccade was marked as landing on the target or a non-target if its endpoint fell within 2.5°

from the center of the respective item (see Figure 1b). Trials with response errors (i.e., participants pressing the spacebar while fixating outside the target region) were relatively low (4.9%) and excluded from further analysis.

RT Analyses and Reliability of Probability Cueing

RT analyses were performed on individuals' mean RTs after excluding error trials (i.e., trials in which participants did not fixate within the 2.5° region around the target but gave a manual, spacebar response, which happened in approximately 5.2% of the trials, on average). If necessary, the RT data were examined by ANOVA, followed by post-hoc pairwise t-tests. We report effect sizes (η_p^2 or Cohen's d_z), and for multiple comparisons the adjusted p-values along with the number of comparisons.

Previous studies have shown that using correlation analyses to infer implicit learning depends heavily on the assumption that the measures of awareness and 'contextual cueing' or, respectively, 'priming' are perfectly reliable (Vadillo et al., 2016, 2022). However, a lack of correlation between the awareness scores and the cueing/priming effects may result from the low reliability of both measures, which prevents any meaningful inference to be drawn from the null correlation. To assess the reliability of the dynamic target-location probability-cueing effects in the present study, we adopted the permuted split-half method recommended by Vadillo et al. (2022). Specifically, for each participant and condition, we split trials randomly in half and then calculated the probability-cueing effects separately for each half. We then calculated the correlation of these effects across participants. A high correlation ($r > .5$) between the two halves indicates reliable probability cueing. We repeated this process for 1000 random splits, averaged the results using Fisher's z-transformation, and corrected the correlation using the Spearman-Brown prediction formula (Vadillo et al., 2022).

Results

Awareness test

Given the recent finding (Yu et al., 2023) that awareness plays a – likely critical – role in learning dynamic cross-trial regularities, we first classified participants into an 'aware' and an 'unaware' group. Then, we examined search performance separately for the two groups. Among the 34 participants, 24 both reported having noticed "a regularity" in the cross-trial target movement and correctly identified the specific type of regularity they had encountered in the search displays. These participants were assigned to the aware group. The remaining eight participants could not identify the pattern based on their questionnaire responses and were designated as the unaware group.

Response times

Figure 2 depicts the mean RTs (calculated across individual participants' means) for the three cross-trial Target-Location Transition conditions (frequent, infrequent, random), separately for the two Target-Constancy block types (target identity fixed vs. mixed) and the two groups (aware vs. unaware).

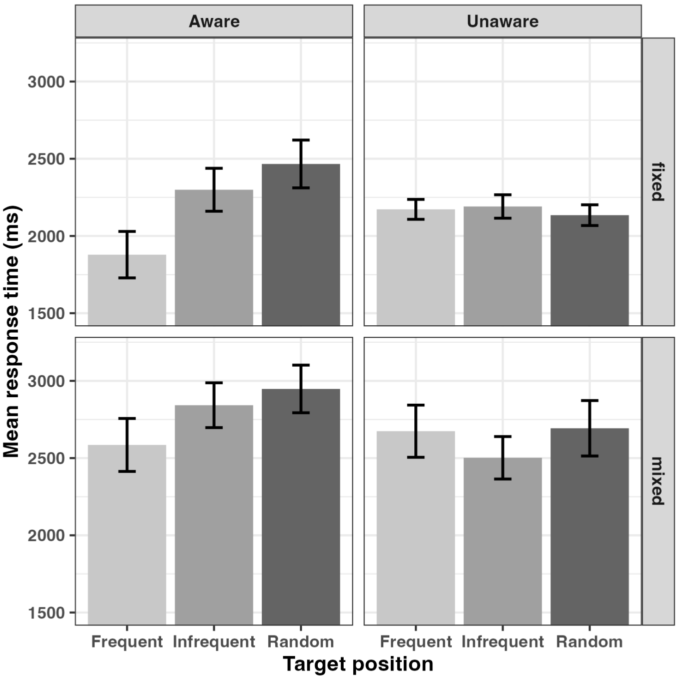

Figure 2. Mean RTs as a function of the cross-trial target-location transition (random, infrequent, frequent transition) and cross-trial target constancy (target identity fixed, mixed per block), separately for the aware and the unaware groups of participants. Error bars represent one standard error.

A mixed-design ANOVA with the within-participant factors cross-trial Target-Location Transition (random, infrequent, frequent) and cross-trial Target Constancy (target identity fixed, mixed per trial block) and the between-participant factor Awareness (aware, unaware) revealed significant main effects of Target Constancy, $F(1,32) = 87.193$, $p < .001$, $\eta_p^2 = 0.732$, and Location Transition, $F(2,64) = 6.737$, $p = .002$, $\eta_p^2 = 0.174$. RTs were faster overall (by > 500 ms) when the target identity was fixed per block compared to when it changed randomly across trials. And RTs were overall faster when the target location shifted by one position in the frequent direction across trials (2345 ms) compared to both a shift by one position in the infrequent (i.e., counter-) direction (2451 ms) or a random shift (2547 ms). Additionally, the Location-Transition × Awareness interaction was significant, $F(2,64) = 9.223$, $p < .001$, $\eta_p^2 = 0.224$, due to only the aware group, but not the unaware group, showing a systematic Location-Transition effect.

To better understand the interaction, we focused on comparing the frequent vs. infrequent locations and calculated the target-location probability-cueing effects (see next section).

Awareness and Dynamic Target-Location Probability Cueing

Figure 3 depicts the target-location probability-cueing effects ($RT_{infrequent} - RT_{frequent}$) in the two Target-Constancy conditions, separately for the aware and the unaware groups. An ANOVA of the cueing effect confirmed a significant main effect of the (between-participant) factor Awareness, $F(1,32) = 10.81$, $p = .002, \eta_p^2 = 0.253$: aware participants exhibited an overall greater probability-cueing effect compared to unaware participants (297 ms vs. -85 ms), and more precisely, the latter was actually significantly negative (-85 ms), $t(9) = -3.708$, $p = .005$. Thus, becoming aware of the dynamic, cross-trial regularity in the placement of the target helped participants optimize their search performance while failing to become aware was detrimental to performance.

One important question concerns how reliable these probability-cueing effects are. To assess reliability, we adopted the permuted split-half method (Vadillo et al., 2022). For the aware group, the probability-cueing effect was highly reliable (fixed target identity: split-half reliability $r = .932$; mixed target identity: $r = .842$). For the unaware group, the reliability was moderate for the mixed target identity ($r = .571$), but relatively low for the fixed target identity ($r = .211$).

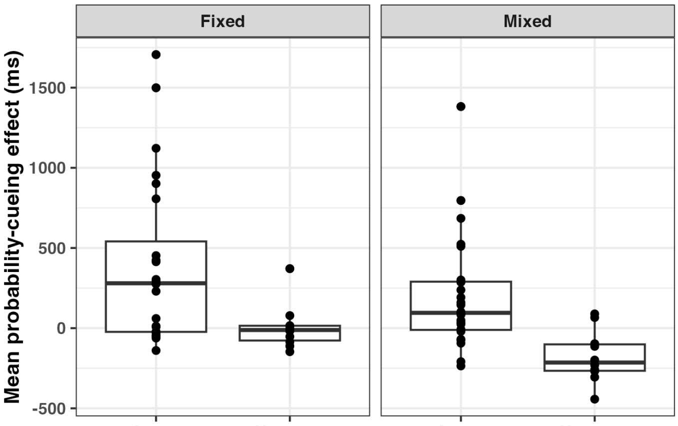

Figure 3. Probability-cueing effect ($RT_{infrequent} - RT_{frequent}$) in the fixed vs. mixed Target-Constancy blocks, separately for the aware and unaware groups of participants.

Positional intertrial priming

Next, we examined for short-term (i.e., inter-trial) positional priming effects (e.g., Allenmark et al., 2019; Allenmark, Gokce, et al., 2021; Sauter et al., 2018) by comparing the mean RTs across the various inter-trial target distances. The results are plotted in Figure 4, where distance 0 means that the target repeated at the exact same location, which could happen in the random transition condition; distance 1 means that the target moved one position to its previous neighbor, including both the frequent and infrequent directions; all other distances are from trials in the random transition conditions. Positional (inter-trial) priming (Krummenacher et al., 2009; Maljkovic & Nakayama, 1996) would predict an RT advantage for cross-trial repetitions of the target location, providing a strict baseline against which to assess any effect of knowing that the target shifts regularly to the adjacent position in a specific direction across trials.

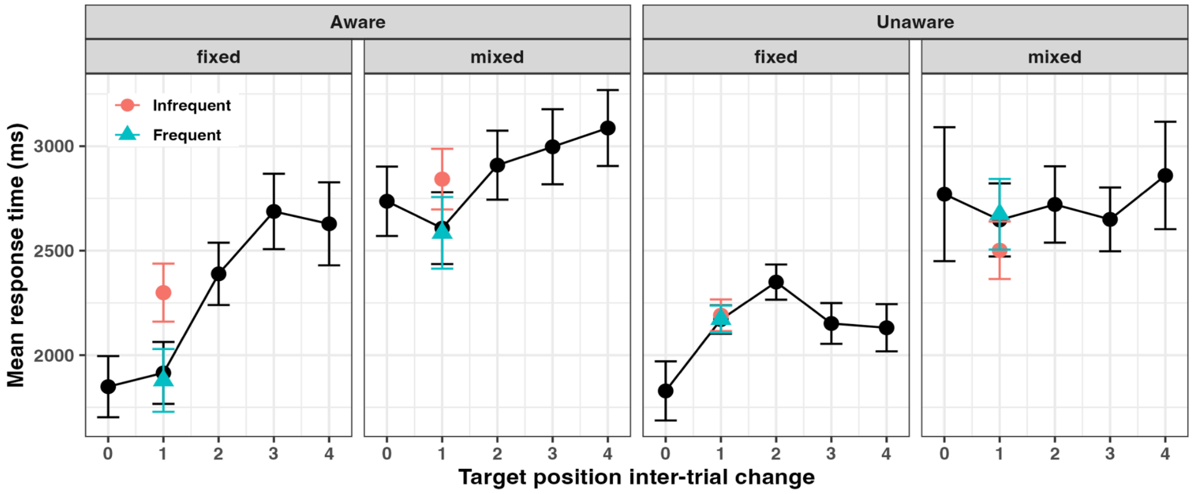

Figure 4. RTs (calculated from individual participants' medians) as a function of the inter-trial target distance (0 indicates the target repeated at the same location, while 1 denotes the target moved one position to its neighbor, including both the frequent and infrequent directions) in the trial blocks with fixed and mixed target identity, separately for the aware and the unaware groups of participants. Data points marked by green triangles and red circles represent frequent and, respectively, infrequent cross-trial shifts. Error bars represent one standard error of the mean.

We conducted a linear mixed-effects model (LMM) with the within-participant factors inter-trial target Distance and Target Constancy (target identity fixed, mixed per block) and the between-participant factor Awareness (aware, unaware), assuming slopes vary across participants. The LMM revealed significant effects of Distance, $F(1,32.3) = 17.42$, $p < .001$, and Target Constancy, $F(1,35.85) = 71.17$, $p < .001$, but no main effect of Awareness, $F(1, 32.01)=.053$, $p = .82$. Of the interactions, that between Distance and Awareness, $F(1,32.3) = 8.0$, $p = .008$, and that between Distance and Target-Constancy, $F(1,76.43) = 9.22$, $p = .003$, were significant; the remaining interactions were non-significant (Fs < 3.55, $p > 0.064$). Following up the Distance × Awareness interaction by post hoc comparisons (with Bonferroni correction) showed that, for the aware group, RTs were significantly faster with both distances 0 and 1 vs. each of the distances 2, 3, and 4, ts(33) $>$ 4.871, p_{bonf}s $< .001$, ds > 0.611 (there was no difference between distances 0 and 1, $t(33) = .148$, $p_{bonf} = 1$, $d_z = 0.019$, and among distances 2, 3, and 4, ts(33) < 1.546, p_{bonf}s $= 1$, d_zs < 0.194). For the unaware group, by contrast, the distance functions were relatively flat; statistically, there were no significant differences between distances 1, 2, 3, and 4; distance 0 showed some RT advantage (minimum advantage: 143 ms, non-significant; average advantage: 200 ms, $t(9) = 1.908$, $p = .089$, $d_z = 0.281$). This overall effect pattern was mainly driven by blocks in which the target identity was fixed, which also allowed generally faster search performance.

Thus, there was an advantage for distance 0 – that is, a *positional repetition-priming* effect – for both the aware and (to a weaker extent) the unaware group, whereas there was an advantage for distance 1 – that is, in this analysis, the combined shift of the target in the frequent and infrequent direction – only for the aware group. This pattern was more prominent in target-fixed blocks of trials, compared to blocks with target identity varying randomly across trials – accounting for the significant three-way interaction.

Of note, however, for the aware group (and collapsed across the two Target-Constancy conditions), the advantage for distance 1 was entirely due to target shifts in the frequent direction; shifts in the infrequent direction caused a performance slowing relative to both shifts in the frequent direction (infrequent 1 vs. frequent 1, $t(23) = 4.027$, $p < .001$, $d_z = 0.822$) and exact-same position repetitions (infrequent 1 vs. distance 0, $t(23) = 5.258$, $p < .001$, $d_z = 1.073$), without a difference between frequent shifts and position repetitions (frequent 1 vs. repetition, $t(23) = -0.434$, $p = .668$, $d_z = -0.089$). Again, this pattern was mainly driven by blocks where the target identity was fixed.

Thus, for the aware group, the positional repetition-priming effect was of a comparable magnitude to the dynamic probability-cueing effect. The latter, however, is a genuine effect, rather than simply representing a spatially fuzzy location repetition effect (spreading from the exact same to the neighboring locations), because targets at the location in the infrequent direction (which had the same separation from the 0-distance, reference position as the frequent location) were associated with an RT cost. Thus, at the very least, one would conclude that the attentional ‘spotlight’ was skewed toward the frequent and away from the infrequent direction.

Inter-trial Priming from Rule-conform (vs. Rule-breaking) Target Shifts

Another possible inter-trial effect might arise from the target on the preceding trial being positioned consistent with the rule (i.e., having moved to the predicted, frequent location) vs. having shifted in a rule-inconsistent manner (e.g., having moved in the opposite direction to the frequent location). Rule-consistent shifts might reinforce the rule (or, respectively, inconsistent shifts might weaken the rule), leading to a rule-based inter-trial priming effect. To look for this, we submitted the probability-cueing effect on a given trial *n* to an ANOVA[15] with the within-participant factors Previous (trial *n–1*) Target Location (target at frequent vs. infrequent location) and cross-trial Target Constancy (fixed vs. variable) and the between-participant factor Awareness (aware vs. unaware). The data are plotted in Figure 5.

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[15] Levene’s homogeneity-of-variance test revealed that one condition (Fixed/Frequent) violated the homogeneity assumption across groups. However, the between-group difference was not the main focus of this analysis.

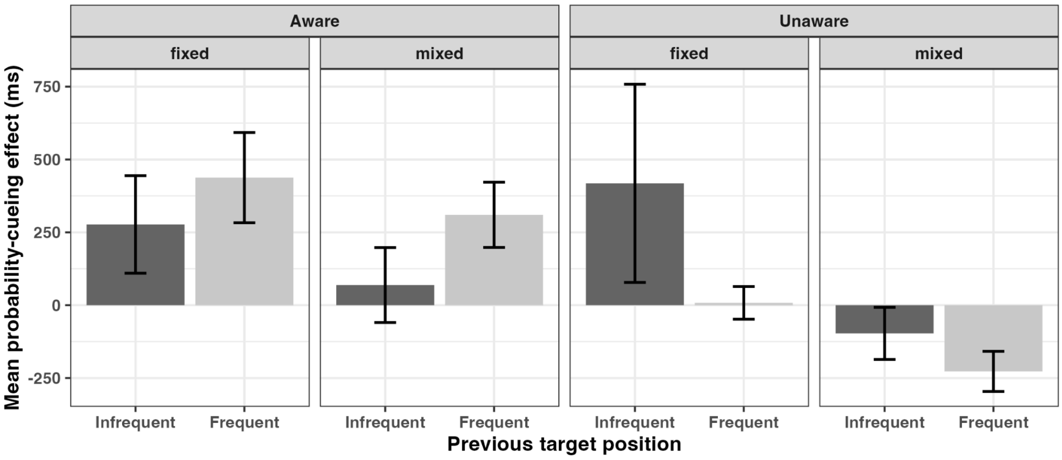

Figure 5. Probability-cueing effect ($RT_{infrequent} - RT_{frequent}$) on a given trial *n* dependent on whether the preceding target (on trial *n–1*) had occurred at the frequent vs. the infrequent location, separately for trial blocks with fixed and mixed target identity and separately for the aware and unaware groups of participants. Error bars represent one standard error of the mean.

There was a main effect of Target Constancy, $F(1,32) = 7.579$, $p = .009$, $\eta_p^2 = 0.188$, with the probability-cueing effect being greater in target-identity fixed (303 ms) vs. mixed (70 ms) trial blocks, and a main effect of Awareness, $F(1,32) = 5.549$, $p = .025$, $\eta_p^2 = 0.148$[16], with the cueing effect being overall positive for the aware group (271ms), but negative for the unaware group (-16 ms). Although the Awareness × Previous-Target-Location interaction was not significant, $F(1,32) = 2.297$, $p = .139$, $\eta_p^2 = 0.067$, the probability-cueing effect was numerically greater when the previous target had occurred at the frequent location (i.e., 312 ms for a rule-consistent shift) compared to an infrequent location (i.e., 221 ms for a rule-breaking shift) (see also a significant pattern which emerged in the eye-movement analysis below, Figure 13). This pattern appeared to be reversed for the unaware group. In other words, for aware participants, consecutive rule-consistent shifts of the target tended to reinforce the effect of the (discovered) regularity (or, respectively, the effect of the regularity was weakened by a preceding rule-breaking shift). This was not the case for unaware participants, who, by definition, had not discovered the rule.

Of note, in the aware group, the probability-cueing effect was still significantly positive even when the target appeared at an infrequent location (i.e., after a rule-breaking shift) on the previous trial, $t(23) = 3.120$, $p = .005$, $d_z = 0.224$. In other words, a rule-breaking shift on the preceding trial just weakened, but did not abolish, the beneficial effect of the regularity.

Correlation Between Awareness and Dynamic Target-Location Probability Cueing

The correlations between the awareness ratings and the probability-cueing effect show differential patterns between the ‘aware’ and ‘unaware’ groups (Figure 6), but the categorization of

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[16] The main effect of awareness turned out significant after adding 10 more participants to the original sample of 24 participants (see Method), pBefore = 0.126 vs. pAfter = 0.025.

the two groups is highly correlated with the ratings. We first checked for multi-collinearity using variance inflation factors (VIFs), finding high collinearity between awareness and Q1 (VIF=17.27) and awareness and Q3 (VIF=14.63). We then opted for the ridge linear regression to obtain more stable and reliable estimates. In the ridge regression, we included the category Awareness (A) as a dummy variable (0: unaware, 1: aware), as well as the awareness rating (Q) and the interaction between the rating and Awareness as predictors to predict the probability-cueing effect (PC).

$$PC = a_0 + a_1 \cdot A + b_1 \cdot Q + b_2 \cdot Q \cdot A.$$

The slope coefficient b is closely related to the correlation coefficient r through the following equation $b = r \cdot \frac{s_y}{s_x}$, where s_y and s_x are the standard deviations of the dependent and independent variables, respectively. This relationship permits us to infer correlations based on the significance of coefficients b_1 and b_2. Specifically, for the unaware group (A=0), b_1 constitutes the main slope coefficient, while for the aware (A=1) group, the sum of b_1 and b_2 (i.e., b_1+b_2) constitutes the main coefficient.

The ridge regression with Awareness and Q1 rating yielded the following results: a_0 = -187.54, a_1 = -79.67 (95% CI [-338.9, 182.3]), b_1 = 35.0 (95% CI [-4.1, 93.8]), and b_2 = 74.87 (95% CI [31.95, 120.4]). Based on the 95% confidence intervals (CIs), the correlation was non-significant for the unaware group (the CI of the slope b_1 includes negative values) but was significant for the aware group (based on the slope b_1+b_2).

Conducting the ridge regression on Awareness, Q3 rating, and their interaction revealed a similar pattern: a_0 =-244.47, a_1 = 11.08 (95% CI [-133.49, 257.96]), b_1 = 3.25 (95% CI [-0.734, 7.884]), and b_2 = 5.1 (95% CI [2.368, 7.5]). The correlation was non-significant for the unaware group but significant for the aware group (see Figure 6).

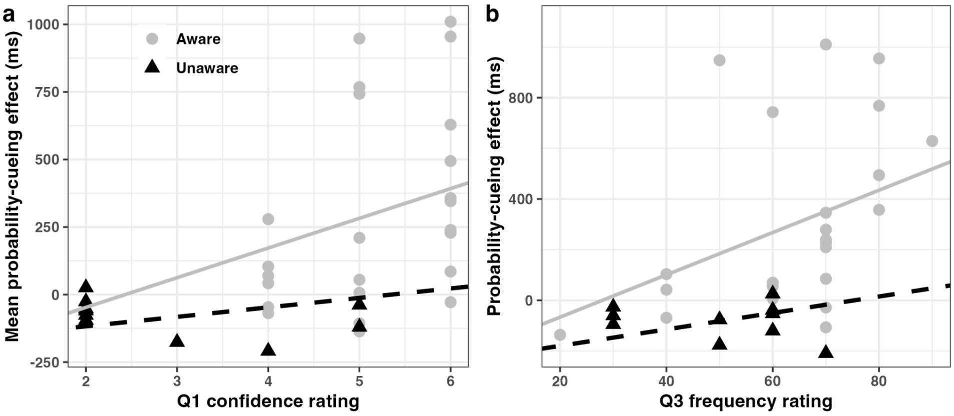

Figure 6. (a) Probability-cueing effect as a function of Q1 confidence rating (1-6), separately for the aware and unaware groups. (**b**) Probability-cueing effect as a function of Q3 frequency rating (0%–100%). The linear fits were obtained through the ridge regression (see the main text).

Eye-movement Results

Due to the absence of a significant (positive) probability-cueing effect for the unaware group in the manual RTs, we focused the analysis of the oculomotor behavior on the the aware group (see Appendix B for the results of the unaware group) – aiming to gain a deeper understanding of the underlying mechanisms driving the dynamic probability-cueing effects in a serial search paradigm.

Number of saccades until reaching the target and dwell-time on the target

We first examined the average *number of saccades required to reach the target* in an ANOVA with the factors of cross-trial Target-Location Transition (frequent, infrequent, random) and cross-trial Target Constancy (fixed, mixed). This ANOVA revealed both main effects to be significant: $F(2,46) = 17.873$, $p < .001$, $\eta_p^2 = 0.437$ and, respectively, $F(1,23) = 15.146$, $p < .001$, $\eta_p^2 = 0.397$. As can be seen from Figure 7a, significantly fewer saccades were required, on average, when the target appeared at the frequent location (4.3 saccades) compared to both the infrequent location (5.6 saccades), $t(23) = 4.554$, $p < .001$, $d_z = 1.163$, and a random location (5.9 saccades), $t(23) = 5.632$, $p < .001$, $d_z = 1.439$, without a difference between the later two conditions, $t(23) = 1.077$, $p = .861$, $d_z = 0.275$. The required number of saccades was also overall lower in fixed target-identity trial blocks compared to randomized blocks, though the difference was not as stark overall (5.0 vs. 5.5 saccades) and of similar magnitude for all Location-Transition conditions (the interaction was non-significant: $F(2,46) = .992$, $p = .378$, $\eta_p^2 = 0.041$). Thus, the Target-Location effect in the RTs – the expedited RTs to targets at the frequent location – is reflected in the savings in the number of fixational eye movements required to reach the target positioned at the frequent location.

Figure 7b presents the *average duration of fixations before reaching the target* in trial blocks with fixed vs. mixed target identity, dependent on the cross-trial Target-Location Transition. A Target-Location Transition × Target-Constancy ANOVA yielded both main effects to be significant: Target-Location Transition ($F(2,46) = 5.978$, $p = .005$, $\eta_p^2 = 0.206$) and Target Constancy, $F(1,23) = 7.066$, $p = .014$, $\eta_p^2 = 0.235$. The pre-target fixation durations were reduced for targets at the frequent vs. the infrequent and random locations (194 ms vs. 201 ms and 200 ms), while being overall, by some 8 ms, increased in blocks with mixed vs. fixed target identity.

An analogous ANOVA of the *total fixation duration on the target* (see Figure 7c) yielded a significant interaction, $F(2,46) = 3.352$, $p = .044$, $\eta_p^2 = 0.127$, besides a main effect of Target Constancy, $F(1,23) = 10.095$, $p = .004$, $\eta_p^2 = 0.305$. The interaction was due to the fixational dwell-time on the target being shorter in the frequent condition, only in the fixed block (frequent vs. infrequent and random combined, 787 ms vs. 825 ms: $t(23) = 2.672$, $p = .014$, $d_z = 0.545$).

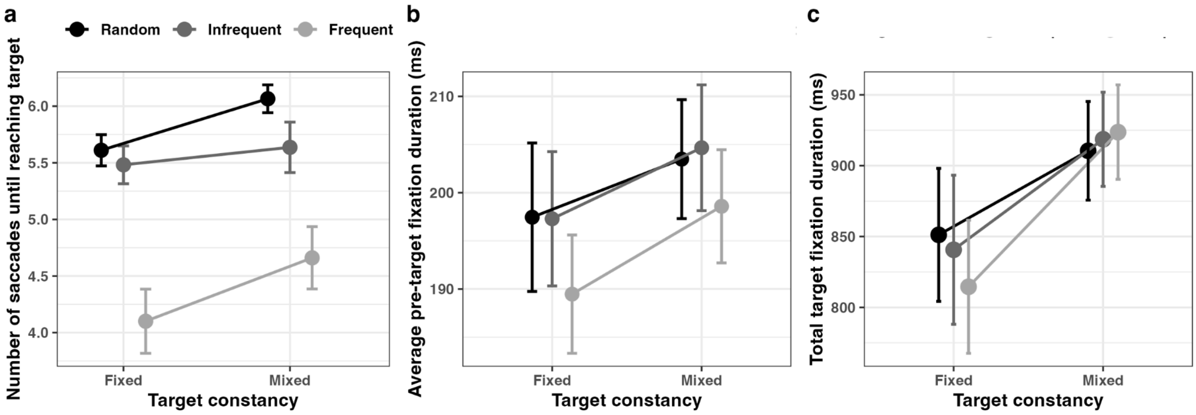

Figure 7. **(a)** Average number of saccades until reaching the target. (**b**) Average duration of the fixations before the first saccade to the target, in trial blocks with fixed vs. mixed target identity (cross-trial Target Constancy), dependent on the cross-trial Target-Location Transition (random, infrequent, frequent). Error bars represent one standard error of the mean. (**c**) Total target fixation duration, in trial blocks with fixed vs. mixed target identity, depending on the cross-trial Target-Location Transition (random, infrequent, frequent). Error bars represent one standard error of the mean.

First fixation locations

One might assume that participants who learned the dynamic cross-trial regularity directed their eyes immediately to the frequent target location on a significant proportion of trials. To corroborate this, for the aware group, we analyzed the locations of the very first fixation, that is, the location to which aware participants made the very first saccade on a trial, directly from the central fixation marker. Figure 8c plots the proportions of first fixations directed to the frequent target location, in comparison with the repeated location and the infrequent location, dependent on the target-location cross-trial transition (frequent, infrequent, random), separately for the target-identity fixed and mixed blocks of trials.

A three-way repeated-measures ANOVA of the proportions of first fixation locations, with Fixated Location (infrequent, frequent), Target Identity (fixed, mixed within blocks), and Target Transition (frequent, infrequent, and random conditions) as within-subject factors, revealed a significant main effect of Fixated Location, $F(2,46) = 8.034$, $p = .001$, $\eta_p^2 = 0.259$. Post-hoc comparisons showed that the frequent location (0.269) was significantly more likely to be the target of the very first saccade than the infrequent location (0.097), $t(33) = 3.304$, $p_{bonf} = .006$ for comparing a family of 3, $d_z = 0.969$, but not compared to the repeated location (0.285), $t(33) = -0.313$, $p_{bonf} = 1$, $d_z = 0.092$. As can be seen from Figure 8c, this difference derives mainly from the fixed target-identity condition – statistically corroborated by a significant Fixated-Location × Target-Constancy interaction, $F(2,46) = 4.914$, $p = .012$, $\eta_p^2 = 0.176$)[17].

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[17] The interaction between Fixated Location and Target Constancy became significant after adding 10 more participants to the original sample of 24 participants (see Method), pBefore = 0.215 vs. pAfter = 0.012.

Of note, the repeated location was prioritized as the target of the first saccade to a similar degree as the frequent location, reflecting positional intertrial priming. However, prioritization of the frequent location is a genuine phenomenon, as the infrequent position (equidistant from the repeated location) was clearly deprioritized.

Furthermore, there was no interaction of Fixated Location with the cross-trial Target-Location Transition ($F(4,92) = 0.310$, $p = .871$, $\eta_p^2 = 0.013$). This is interesting because when the first fixation went to the frequent location and the transition was 'frequent', the target would actually be located at this position. Still, when the transition was 'infrequent' or 'random', the target would not be at the frequent position. The analogous would apply to the other Fixation-Location conditions. Thus, the lack of a Fixated-Location × Target-Transition interaction implies that the increased proportion of first saccades directed to the frequent location was driven by the discovered regularity; in other words, the rule was applied whether or not the target was located there.

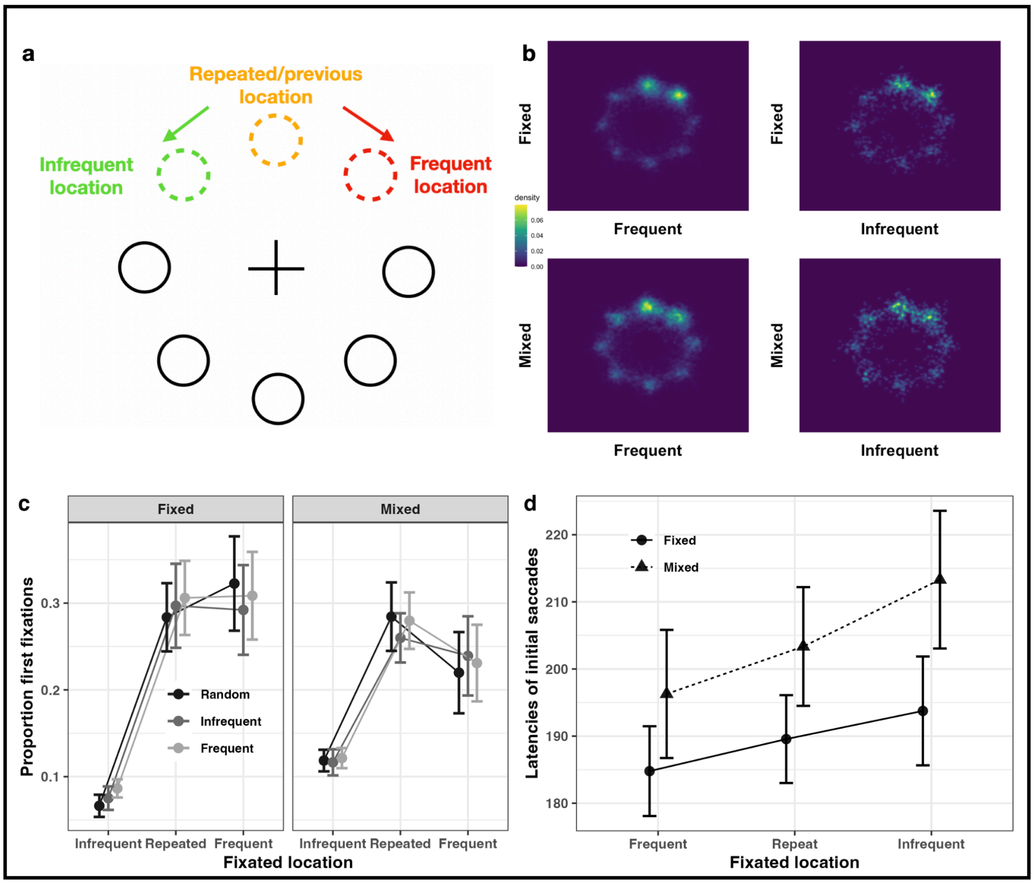

Figure 8. (**a**) illustration of the experimental conditions aligned to the top locations and (**b**) Heatmaps of the landing positions of the first saccade, depending on the cross-trial Target-Location Transition (frequent, infrequent), for blocks with target identity being fixed vs. mixed (i.e., randomly variable) across trials. As illustrated in **(a)**, the fixation locations were rotated such that the target location on trial *n-1* is at the top, and the frequent location that (one position) to the right, and the

infrequent location to the left (i.e., for participants with counterclockwise target shifts, the frequent and infrequent locations were flipped right/left flipped). Gaussian filters with smoothing kernels of 0.3° were used to generate all heat maps. **(b)** Heatmaps for trials on which the target had shifted in the frequent and, respectively, infrequent direction, separately for trial blocks with fixed and mixed target identity. As can be seen, the first saccades were most likely to be directed to the frequent and repeated locations, irrespective of whether the target shifted in the frequent (regular) or the infrequent (irregular) direction; the infrequent location is not more likely to receive a saccade than the random locations (excepting the repeated location). (**c**) and (**d**) proportions and, respectively, latencies of initial saccades directed to the frequent, repeated, and infrequent locations (first fixation location) dependent on the cross-trial target-location transition (frequent, infrequent, random), separately for the target-identity fixed and mixed blocks of trials. Error bars represent one standard error of the mean.

An analogous ANOVA of the *latencies of the first saccade* (depicted in Figure 8d) also revealed (only) a main effect of Fixated Location, $F(2,44) = 5.674$, $p = .006$, $\eta_p^2 = 0.205$. The first saccades were elicited very rapidly upon search display onset, with an average latency of around 200 ms. Post-hoc comparisons revealed the latencies to be significantly shorter for saccades to the frequent vs. the infrequent location (190 ms vs. 204 ms), $t(24) = -3.364$, $p_{bonf} = .005$, $d_z = -0.328$, with a numerical difference for saccades to the frequent vs. the repeated location (190 ms vs. 196 ms). A distribution analysis revealed the difference between the frequent and infrequent locations to be already evident in the very ‘fastest’ time bins (i.e., the first 22%) of the vincentized latency distributions ($\chi^2(1,7305) = 110.32$, $p < .001$), with latencies in the range from between 100 and 150 ms, which would be considered to be too short to be influenced by cognitive control (e.g., Findlay, 1997; Sauter et al., 2021).

Interestingly, also, all first saccades in the general direction of the repeated location (i.e., saccades to the frequent, repeated, and infrequent locations) were elicited faster compared to saccades in the other, random directions, the latencies of the latter averaging 220 ms (random vs. frequent: $t(22) = 6.003$, $p < .001$, $d_z = 0.698$; random vs. repeat: $t(22) = 4.821$, $p < .001$, $d_z = 0.560$; random vs. infrequent: $t(22) = 3.406$, $p = .007$, $d_z = 0.396$[18]).

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[18] The difference between infrequent and random cross-trial shifts of the target location became significant after adding 10 more participants, pBefore = 0.116 vs. pAfter = 0.007.

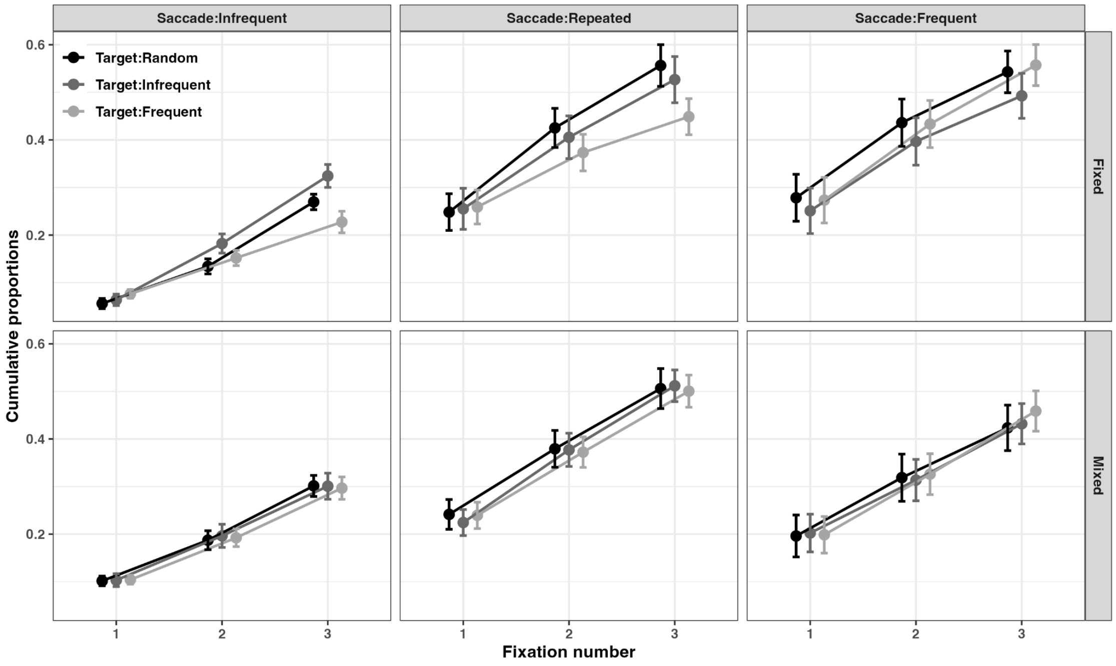

Figure 9. Cumulative probabilities of the first, second, and third fixation falling at a particular location (*Saccade Landing Location*: frequent, repeated, infrequent location) as a function of the cross-trial Target-Location transition (*Target Location*: frequent, random, infrequent), separately for the fixed and the mixed Target-Identity condition (upper and lower rows, respectively). Error bars represent one standard error of the mean.

While the landing positions of the first saccades were little influenced by the actual location of the target, a somewhat different picture emerges when looking at the *second* and, especially, the *third* fixation (see Figure 9) in the condition with *fixed* target identity, where the targets located at the frequent location appear to play a role. Examining the cumulative proportions of the first, second, and third fixations falling at a particular location (frequent, repeated, infrequent) as a function of the cross-trial Target-Location transition (frequent, random, infrequent) shows, first, of all, a similar increase in the proportion for the frequent and repeated locations (and a shallower increase for the random locations); that is, both the frequent and the repeated location stay relatively prioritized. Interestingly, though, when the 2nd and, especially, the 3rd fixation fall at the *frequent* location, the cross-trial transition matters: relatively more fixations fall on the frequent location when the target occurs there (following a ‘frequent’ transition) compared to when it appears at the infrequent location (fixations of *frequent* location: Fixation-Location × Target-Location Transition interaction, $F(2,46) = 6.102$, $p = .004$, $\eta_p^2 = 0.210$; frequent vs. infrequent transition, 3rd fixation: $t(23) = 4.618$, $p < .001$, $d_z = 0.283$). Conversely, for the second and, especially, third fixations at the repeated and, respectively, the infrequent location, fewer fixations land at these locations when the target appears at the frequent location (fixations of *repeated* location: Fixation-Location × Target-Location Transition interaction, $F(2,46) = 4.027$, $p = .024$, $\eta_p^2 = 0.149$; frequent vs. infrequent transition, 3rd fixation: $t(23) = -2.844$, p

= .097, d_z = -0.389; fixations of *infrequent* location: Fixation-Location × Target-Location Transition interaction, $F(2,46) = 22.441$, $p < .001$, $\eta_p^2 = 0.494$; frequent vs. infrequent transition, 3rd fixation: $t(23) = -6.711$, $p < .001$, $d_z = -.1.111$). This means that, while the first saccade directed to the frequent location is largely rule-driven, the second and, especially, the third saccade are also influenced by the identity of the item at the frequent location: a target at the frequent location acts like an attractor (over and above the rule-based prioritization of this location), increasing the likelihood of saccades to the frequent location and reducing the likelihood of saccades to random and infrequent locations. This pattern is seen, however, only in the *fixed* Target-Identity condition (in the mixed condition, there was no consistent pattern of interactions), suggesting that it reflects top-down enhancement of critical target features (at the frequent location) by the fixed target template. Interestingly, though, the enhancement appears to be focused on the frequent location.

In the mixed condition, by contrast, the template valid on a given trial can only be established during the search itself – so, there is no (or relatively little) early search guidance by the target template. This is consistent with an analysis of the saccade patterns following a first saccade to the target at the frequent location. As depicted in Figure 10, when the target identity is fixed, participants show little tendency to go on to inspect one or two further locations in the immediate neighborhood of the frequent location: in some 50% of the trials, they do not check any location, and in about 25% each they check either one or both neighbors. In the mixed condition, by contrast, they are highly likely to check both neighbors (> 60%) or one neighbor (> 30%) and only very rarely neither (< 10%). This differential pattern (statistically evidenced by a significant interaction between Scanning Pattern [inspection of both, one, or neither neighborhood location] and Target Constancy: $F(2,46) = 66.604$, $p < .001$, $\eta_p^2 = 0.743$, besides a main effect of scanning pattern, $F(2,46) = 5.556$, $p = .007$, $\eta_p^2 = 0.195$) indicates that in the mixed target-identity condition, participants continue scanning to establish the target template valid on a given trial. This would likely explain why the required number of saccades (and, consequently, the task-final RT) was increased under mixed-identity conditions and why the dynamic cueing effect was somewhat washed out.

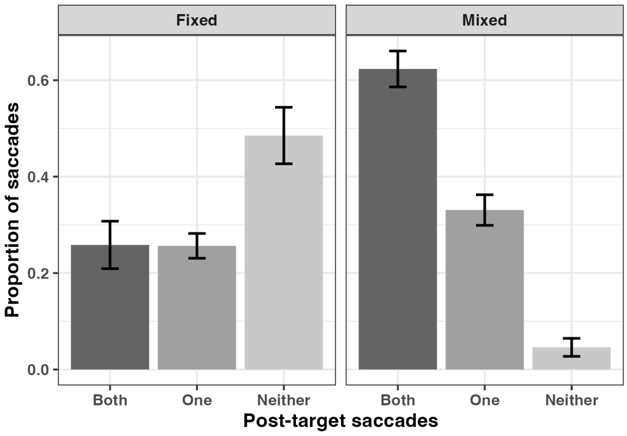

Figure 10. The proportion of saccades directed to one or both neighbors, or neither neighbor, immediately after making the first saccade to the frequent, target-containing location, separately for the fixed and the mixed Target-Identity condition. Error bars represent one standard error of the mean.

Awareness and Dynamic Probability Cueing of the First Eye Movement

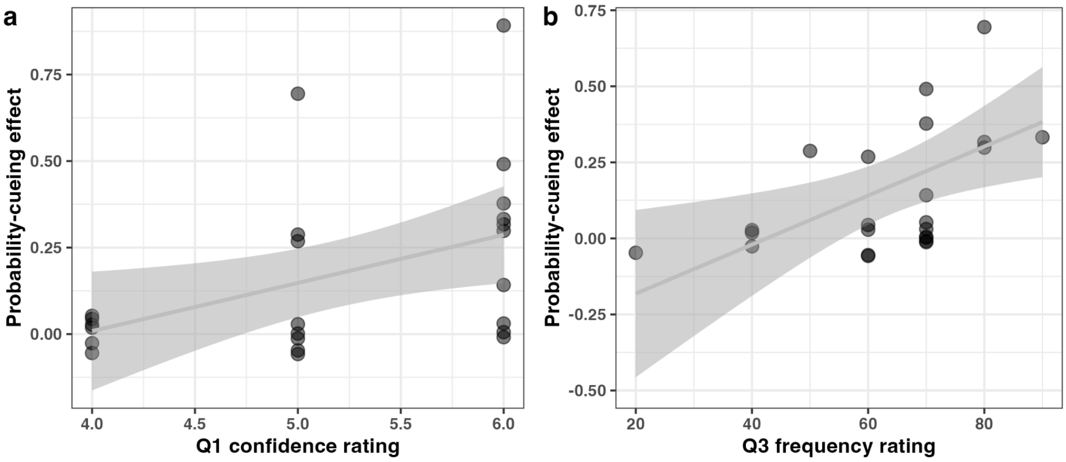

Figure 11. (a) Probability-cueing effect in terms of the first fixation location, as a function of the Q1 confidence rating (1-6), for the group of aware participants. (**b**) Probability-cueing effect in terms of the first fixation location, as a function of the Q3 frequency rating (0%–100%).

Given that the first saccade made by participants in the aware group was more often directed to the frequent than the infrequent location, we went on to ascertain whether this difference was also correlated with our quantitative awareness measures (based on questions Q1 and Q3). Accordingly, we calculated the probability-cueing effect based on the first fixation as the difference in the proportions of first fixations between the frequent and infrequent locations and performed a correlation analysis on effect and the awareness measures. Before the correlation analysis, we assessed (for the *aware* group) the reliability of the probability-cueing effect measured in terms of the differential proportions of first saccades directed to the frequent vs. the infrequent location, separately for the blocks with fixed and mixed target identities. The aware group's reliability was high in both blocks (fixed: r = .94; mixed: r = .911). The analysis revealed the probability-cueing effect to be positively correlated with both Q1 (slope = 0.139, $r = 0.45$, $p = .02$, $R^2 = 0.20$) and Q3 (slope = 0.008, $r = 0.52$, $p = .009$, $R^2 = 0.27$) – see Figure 11 for depictions. In other words, the more accurately participants estimated the frequency and showed confidence in the dynamic regularity, the more likely they were to direct their first saccade to the frequent, compared to the infrequent, location.

Awareness and Dynamic Probability Cueing of the Number of Required Saccades

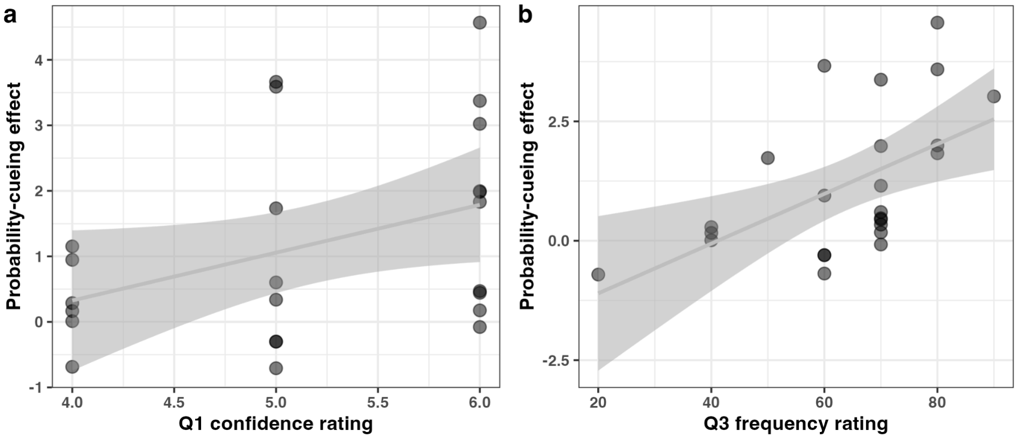

Figure 12. (a) Probability-cueing effect in terms of the number of saccades until reaching the target, as a function of the Q1 confidence rating (1-6), for the group of aware participants. (**b**) Probability-cueing effect regarding the number of saccades until reaching the target as a function of the Q3 frequency rating (0%–100%).

The probability-cueing effects measured in terms of the number of saccades required to reach the target at the frequent vs. the infrequent location were also highly reliable (in the *aware* group), as revealed by permuted split-half tests (fixed target identity: r = .909; mixed target identity: r = .945). The correlation between aware participants' probability-cueing effect (in terms of the required number of saccades) and their Q1 confidence rating of the regularity turned out marginally significant (slope = 0.73, r = 0.39, p = .05, R^2= 0.15), while that with their Q3 rating of the probability with which the rule applied was significant (slope = 0.05, r = 0.55, p = .005, R^2= 0.31) – see Figure 12 for depictions. Thus, the more participants were aware of the dynamic regularity, the fewer saccades they required to find the target at the frequent (compared to the infrequent) location.

Inter-trial Priming of the First Eye Movement from Rule-conform (vs. Rule-breaking) Target Shifts

Figure 13 provides a plot of the probability-cueing effect in terms of the first eye movement (i.e., proportion of saccades to the frequent minus the infrequent location) dependent on the target location on the previous trial (i.e., trial *n–1* target at frequent vs. infrequent location), separately for trial blocks with fixed vs. mixed target identity. An ANOVA of this cueing effect with the factors Previous (trial *n–1*) Target Location and cross-trial Target Constancy revealed the main effect of Previous Target Location to be significant, $F(1,23) = 4.695$, $p = .041$, $\eta_p^2 = 0.170$: the proportion of first saccades directed to the frequent (vs. the infrequent) location was significantly greater after rule-conforming (.179) than after rule-breaking target shifts (.108) on the preceding trial. Of note, though, the cueing effect was significantly greater than zero even in the latter condition ($t(23)$ =

2.829, *p* = .009), consistent with rule violations only weakening, but not abolishing, the effect of the regularity.

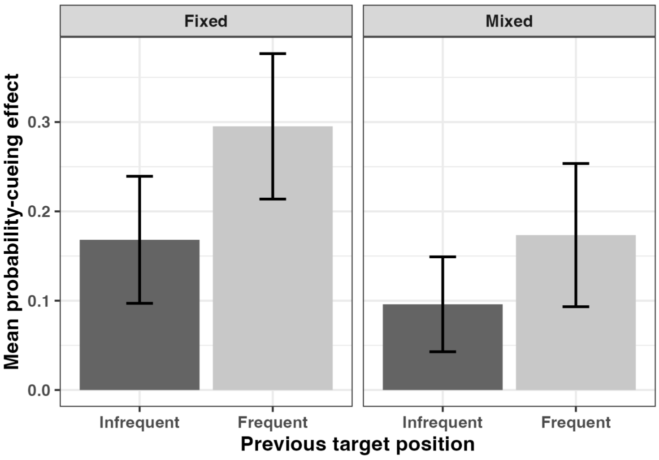

Figure 13. Probability-cueing effect in the first eye movement (proportion of saccades to frequent minus infrequent location) dependent on the target location on the preceding trial (i.e., trial *n–1* target at frequent vs. infrequent location), separately for trial blocks with fixed vs. mixed target identity. Error bars represent one standard error of the mean.

Discussion

The present eye-tracking study aimed to investigate three main questions: (1) whether participants can learn a dynamic, cross-trial statistical regularity regarding the location of the target in a *serial* search task; (2) if so, when the guidance by this regularity would come into play during the search, examined through sequential oculomotor scanning and the task-final RTs for evidence of a dynamic target-location probability-cueing effect; and (3) whether participants' explicit awareness of the regularity would be systematically related to their probability-cueing effect. Additionally, we examined how guidance by the regularity compares to positional intertrial priming, how it is modulated by rule-based (rule-conforming vs. rule-breaking) intertrial priming, and whether it is influenced by the target identity being known in advance (fixed) vs. having to be established during the task.

The main findings were as follows: about 70% of participants successfully learned and utilized the cross-trial statistical regularity in target placement in a serial search task that Yu et al. (2023) had previously shown to be acquired in a parallel, pop-out task. This finding appears to conflict with earlier reports suggesting that the added demands imposed by serial search prevent participants from picking up dynamic regularities (Li et al., 2022; Li & Theeuwes, 2020). Importantly, however, only those who, based on a post-experimental awareness test, were classed as aware of the regularity did exhibit a dynamic probability-cueing effect; unaware participants showed no sign of a (positive) effect. In aware participants, search guidance from the discovered regularity kicked in very early: a large proportion of their very first saccades (from the display center) was already directed to the location predicted by the dynamic rule, in a addition to a bias to saccade to the location that had contained the target on the previous trial; unaware participants displayed only the latter bias. The guidance effect exerted by the dynamic rule in aware participants was modulated by whether the target placement on the previous trial was consistent with the rule. Finally, aware participants were able to use the rule almost as efficiently when the target identity was non-predictable as when it was fixed. In the subsequent sections, we consider these findings in more detail.

Dynamic cross-trial regularities in target placement can be learned even in serial search

The present findings demonstrate that dynamic cross-trial regularities in target placement can be successfully learned and used to optimize performance even in highly demanding *serial* search tasks, not just in simple pop-out tasks that can be performed spatially in parallel. This conclusion applies at least to the regularity implemented here: a shift of the target location within a circular display arrangement by one position in either a clockwise or counterclockwise direction (fixed per participant) – exactly the same regularity as that used by Yu et al. (2023) in a parallel search task. Interestingly, relative to the random-condition baseline, the performance gains from successfully learning the rule were at least as large in the present serial search task as in Yu et al.'s (2023) parallel search task: the gains (infrequent minus frequent transition) here amounted to 339 ms, or 12.5% of the random-baseline RT (2707 ms), compared with a 9.4% gain (116 ms/1236 ms) in parallel search. In other words, the inherent incentive to acquire the rule was comparable between the two types of tasks.

Our finding of a cueing effect appears to be at variance with Li and colleagues (Li et al., 2022; Li & Theeuwes, 2020). They reported that participants could not pick up a different type of dynamic regularity in serial search, but another sample of participants could successfully extract in parallel search (learning phase) and subsequently use it to expedite serial search (test phase). The main difference between Li and colleagues' studies (Li, Bogaerts, and Theeuwes 2022; Li and Theeuwes 2020) and Yu et al. (2023) and the present study lies in the complexity of the regular cross-trial shift and the frequency with which such shifts were encountered during search. In our design, the proportion of trials on which the target moved to the location predicted by the dynamic regularity (80%) was more than three times larger than that in the design of Li and Theeuwes (only 25%). Also, our dynamic target-location shift was relatively simple: either clockwise or counterclockwise, consistent with how participants might 'normally' serially scan a circular search array. In contrast, the shift introduced by Li and Theeuwes was more complex: if the current target was in, say, the left-most array position, the next target would then invariably appear at the right-most location (but not vice versa). Apart from such shifts occurring only relatively rarely (on some 25% of trials), they would also run counter to normal scanning routines. Thus, it might be that both the frequency with which regular dynamic shifts occur and whether or not they fit with routinized scanning procedures (Seitz et al., 2023) might be critical factors determining whether or not a dynamic regularity is successfully acquired in serial scanning.

Based on the present findings, however, we can conclude that serial search does not per se preclude the possibility of extracting and utilizing dynamic regularities to optimize performance.

Dynamic target-location probability cueing acts early during search

Beyond analyzing task-final RTs, our analysis of the oculomotor scanning behavior showed that dynamic target-location probability cueing acts ‘early’ during serial search: already one-third of the very first saccades (from the initial fixation marker in the display center) were directed to the predicted frequent location. Another position receiving almost the same proportion of first saccades was the location that had contained the target on the previous trial, consistent with a positional repetition-priming effect (Krummenacher et al., 2009; Maljkovic & Nakayama, 1996).

Notably, at least under conditions with fixed target identity, a numerically greater proportion of first saccades was directed to the predicted location compared to the repeated location, indicating a tendency for the target-location cueing effect to dominate the repetition-priming effect[19]. Even under conditions of target-identity swapping, the frequent location received a much greater proportion of first saccades than the infrequent location, even though both were equidistant from the repeated position. This shows that the search priorities (or the attentional ‘spotlight’) were systematically biased towards the frequent direction and away from the infrequent direction. Importantly, this early biasing of search was independent of the actual target location, reflecting a genuine rule-based effect.

The early prioritization of the frequent and repeated locations was maintained during further scanning, evidenced by these locations continuing to attract the largest proportions of second and third saccades. However, under conditions of fixed target identity, the second and the third saccade were also affected by whether the target actually appeared at the predicted frequent location: a target appearing at the frequent location increased the proportion of second and third saccades directed to this location, whereas it decreased the proportions of saccades directed to the repeated and infrequent locations. This suggests that by the second and third saccade, the priority of the frequent location was determined not only by the dynamic rule but also increasingly modulated by the fit of the item at the predicted location to the (fixed) target template. This suggests that top-down template-based enhancement of priority signaling is focused on the predicted location, rather than being ‘broadcast’ equally to all locations (e.g., Wiegand et al., 2024). Interestingly, the persistence of the prioritization of the frequent and repeated locations beyond the first few saccades implies that the prioritization is coded in scene-based (environmental), rather than retinal coordinates, with the coordinates dynamically updated across sequential eye movements.

Rule-based intertrial priming

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[19] As can be seen from Figure 14 below, a disadvantage for the frequent vs. repeated conditions developed into advantage by the final ‘epoch’ 4 of the experiment.

While the frequent target location is favored as a result of having acquired the dynamic rule, this rule-based prioritization is itself modulated by short-term trial history: it is stronger on a given trial *n* when the target shift on the preceding trial *n–1* conformed with the rule (i.e., the target moved to the frequent location) and weaker when the shift violated the rule (i.e., the target moved to the infrequent location). This effect is evident in the proportions of first saccades, and there was a trend in the same direction in the task-final RTs. Within a Bayesian framework (e.g., Allenmark et al., 2018; Allenmark, Gokce, et al., 2021), the dynamic rule can be conceived as an acquired long-term 'prior' determining the selection priorities. The weight assigned to this prior on a given trial is modulated by trial history: the current weight is larger following rule-conforming and smaller following rule-breaking target shifts. Importantly, however, intertrial weight changes only modulate the effect of the long-term prior, as shown by the significant cueing of the target location even after rule-violating trials. The weight assigned to the prior is not reduced to zero.

To our knowledge, this rule-based intertrial priming effect is novel and has not been reported before. Of course, there are reports of intertrial priming effects associated with statistical learning of static regularities. For instance, interference caused by a salient distractor increases when the distractor occurs at a previous target location and decreases when it occurs at a previous distractor location; conversely, search is expedited when the target appears at a previous target location and slowed when it appears at a previous distractor location (see, e.g., Sauter et al. 2018). These effects may be modulated by a static 'rule', reflecting how likely the target or distractor is to occur at a particular fixed location. However, these are essentially positional intertrial effects, attributable to some facilitatory or inhibitory 'tags' placed on the respective position as a result of having encountered a target or a distractor there on the previous trial. In contrast, our dynamic scenario, by definition, involves regular changes of the target location on consecutive trials, favoring an account of the priming effect as being genuinely rule-related. Nevertheless, it may exert its influence in location-based coordinates, such as on a common map representing attentional (and oculomotor) priorities.

Dynamic probability-cueing is modulated but not abolished by target-identity swapping

Further of interest, dynamic target-location probability cueing was not abolished by random swapping of the target identity across trials. However, under these conditions, search RTs were overall prolonged, with an increased number of fixations, and the cueing effect was reduced from 420 ms in fixed- to 257 ms in mixed-identity blocks in the aware group. This is not surprising since more fixations were necessary to identify the target and distinguish it from non-targets, especially on identity-swap as compared to identity-repeat trials. Even when the first saccade was directed to the predicted location, further processing steps, including comparisons with (and saccades to) the neighboring items, would have been necessary to ascertain the target identity. This is exacerbated on identity-swap trials, where the 'default' assumption that the target identity stays the same as on the previous trial proves wrong, requiring a change in the “target template.” This effect mirrors feature-based priming effects in pop-out or feature-conjunction search (Geyer et al., 2006; Kristjánsson et al., 2002; Maljkovic & Nakayama, 1994). Interestingly, even though the probability-cueing effect was reduced on identity-swap compared to identity-repeat trials, it remained significantly larger than zero. This suggests that having acquired the dynamic regularity in target placement did facilitate performance even under the most demanding search conditions.

Whether these conditions allow the efficient acquisition of dynamic regularity in the first instance is a different question. Our data are non-conclusive in this regard. For the first four out of the total eight blocks, the cueing effect differed little between aware participants starting with the fixed vs. those starting with the mixed target-identity condition. The latter group, however, showed a numerically nearly doubled effect after switching to the fixed condition, while the former did not exhibit any gain following the switch to the mixed condition. Although the critical interaction was non-significant ($F(1,14) = 0.86$, $p = .369$)[20], this pattern is more consistent with the mixed target-identity condition interfering with the expression of the cueing effect, rather than impeding the acquisition of the dynamic regularity itself. The expression of the effect would be affected due to the need to establish the target template valid on a trial, even if the target at the frequent location target is the first item inspected (see above).

Awareness of the dynamic rule and target-location probability cueing in serial search

Unlike the majority of studies of probability-cueing effects, which conclude that spatial statistical learning is implicit and not dependent on awareness (e.g., Jiang et al., 2013, 2014; Won & Jiang, 2015), we found strong evidence that awareness is involved in the present dynamic target-location cueing effect. First of all, only participants classified as ‘aware’ (70% of participants) based on our post-experimental questionnaire showed a dynamic cueing effect in both the task-final RTs and the earliest eye movements. In contrast, ‘unaware’ participants (30%) showed no cueing effect in either early or later performance indices; they only exhibited a tendency to saccade to the previous target location. Secondly, in ‘aware’ participants, the strength of the cueing effect, even in the proportion of first eye movements directed to the predicted location, correlated significantly with their belief in the rule’s applicability: the more accurately participants estimated the frequency of the target shifting in the regular direction, the larger their cueing effect (uncompromised by low reliability).

Several factors, including reliability, dichotomization, unbalanced groups, could potentially reduce both the effect sizes in group comparisons and correlations. Thus, the significant relationship between dynamic target-probability cueing and awareness of the dynamic regularity suggests a strong

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[20] The degrees of freedom are reduced because one of the aware participants had insufficient trials in one of the conditions and was so excluded from analysis.

link at the latent level.[21] The finding of 'explicitness' aligns with other studies that used sensitive awareness tests (e.g., Giménez-Fernández et al., 2020; Golan & Lamy, 2023), and the study of dynamic target-location cueing in *parallel* search (Yu et al., 2023). In particular, it is in line with the significant correlation reported by Giménez-Fernández et al. (2020), whose measures of awareness we adopted in present study. Interestingly, our study demonstrated the role of awareness in a relatively small sample (24 out of a total of 34 participants) – suggesting that, at least in this dynamic scenario, a large sample size may not be crucial for demonstrating a critical impact of 'awareness' in statistical learning.

What exactly is the role of awareness in the dynamic cueing effect? Our findings indicate that the effect depends on awareness, as only the 'aware' participants benefited, while the 'unaware' group did not. Despite a significant correlation between awareness of the dynamic regularity and the cueing effect, this does not necessarily mean that the effect is 'voluntary' in nature or that participants consciously applied the rule on each trial. Recall that the latencies of the first saccade to the predicted location (some 190 ms) and to the repeated and infrequent locations (somewhat over 200 ms) were shorter compared to random locations (> 220 ms). This pattern suggests that there is an ensuing competition, upon display onset, of the search items at locations in the region of the previous target position, that is, the position to which a saccade had just been executed (on trial *n*-1) and for which activity remains elevated across trials on some (integrative) oculomotor priority map, likely, in the superior colliculus (e.g., Veale et al., 2017). Thus, while the repeated location remains a strong attractor for the first saccade on the new trial (trial *n*), this competition is then resolved in favor of the frequent location, perhaps through a rule-related input injected into the priority representation via frontal-eye-field neurons that represent the dynamically updated, goal-related priority. Given that the display array was not visible during the intertrial interval and there were no placeholders, the updating of the saccade goal likely happened after search-display onset. In this case, latencies below 200 ms may not be sufficient for consciously mediated inputs to influence saccade programing.[22] Accordingly, one would have to assume that rule-based dynamic goal updating, while perhaps initially requiring conscious control to be set up, eventually becomes a rather automatized, 'implicit' process that runs off without 'explicit' cognitive intervention (cf. Schneider and Shiffrin 1977). Thus, it may be premature to conclude from the correlation between awareness of the dynamic regularity and the cueing effect that this effect is causally mediated by awareness on each (or most) trial (s).

Overall, there is no *dynamic target*-location probability-cueing effect in *serial* search without awareness of the regularity. Yu et al. (2023), who implemented the same cross-trial regularity, demonstrated that this also applies to dynamic *target*-location cueing in *parallel* search. They found that the same regularity did *not* produce a cueing effect when it was implemented in a pop-out

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[21] We thank Dr. M. Vadillo for communicating this point to us.

[22] This would also be consistent with Findlay (1997), who concluded from his study of saccade target selection during pop-out and feature-conjunction searches that "the generation of the first saccade is a relatively automatic process, rather than one which is subject to cognitive control" (p. 628).

distractor in *parallel* search, because participants did *not* become aware of the regularity in the cross-trial distractor-location shift – whereas participants became aware of the exact-same shift when implemented in the pop-out target.[23] Thus, we propose that participants' awareness of the regularity (Giménez-Fernández et al., 2020; and, on the part of the experimenter, establishing awareness by sensitive measures; cf. Vadillo et al., 2016, 2020) is crucial for dynamic probability-cueing effects to develop in any type search, whether serial or parallel.

Why do unaware participants show a negative probability-cueing effect?

An intriguing finding is that the unaware participants displayed a significantly *negative* (rather than a positive or no) RT probability-cueing effect (see Figure 3), coupled with their first saccades being somewhat more likely to land at the infrequent than the frequent locations (see Figure 14). Given the small sample size, we can only speculate why this occurs.

One possible reason is that some participants' oculomotor scanning behavior is dominated by a backward-looking 'trial-history' effect, which interferes with acquiring a forward-looking rule-based prediction, thus biasing their selection priorities. Specifically, assume that repetition priming enhances the priority of not just the last target location (trial *n–1*), but also the location on the preceding trial (trial *n–2*), though the enhancement of the latter is reduced due to the longer decay time of the memory trace. This "trial-history" effect would lead to both the repeated (trial *n–1*) location and the infrequent (trial *n–2*) location act as attractors for an eye movement. The decay-dependent gradient from the trial *n–1* to the *n–2* location could produce a scanning bias counter to the direction of the dynamic target shift. Thus, if participants' scanning behavior is strongly influenced by such a 'history' bias, their search would be facilitated for targets located at the infrequent location compared to the frequent location – producing a negative cueing effect. At the same time, this backward scanning bias might also hinder participants from becoming aware of the dynamic regularity, because initial scanning in the 'infrequent' direction would make it harder to relate the location of the current target (established only after multiple fixations on trial *n*) to that of the previous target. In contrast, participants with a weaker history-dependent, backward bias (e.g., due to a fast decay of the trial n–2 memory trace) would be more likely to scan from the repeated to the frequent (rather than the infrequent) target location. As a result, they may become more readily aware of the dynamic regularity, because they find the target rapidly on a significant proportion of trials. Consequently, they would discern the rule and develop a positive probability-cueing effect.

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[23] This would also explain Li and Theeuwes' (2020) non-finding: their participants did not become aware of their (more complex and less likely) dynamic target-location regularity and accordingly exhibited no cueing effect.

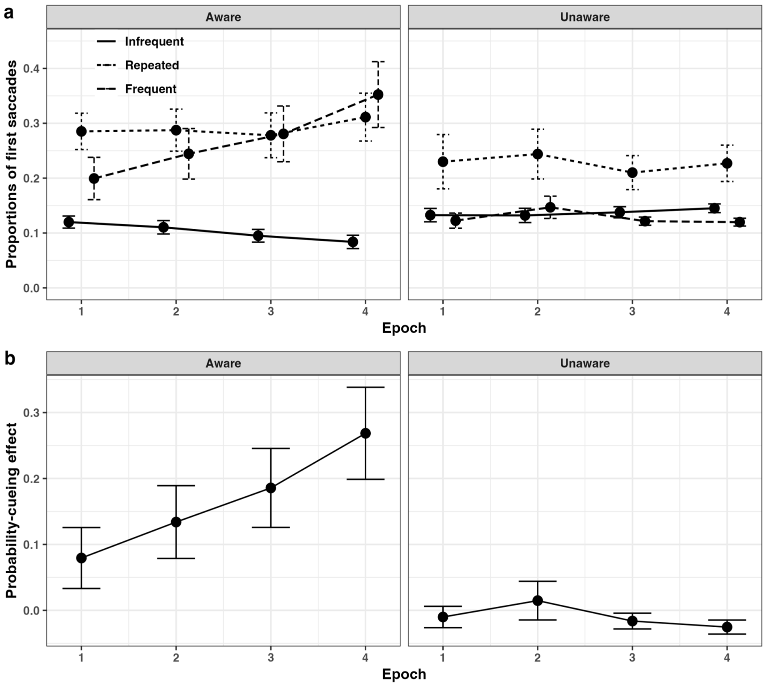

Figure 14. Upper panels: Proportions of first saccades landing on the frequent, repeated, and infrequent locations, respectively, as a function of experimental Epoch (1-4), separately for the aware and unaware groups. **Lower panels:** Probability-cueing effect measured in terms of the landing position of the first saccade (proportion frequent minus infrequent locations). Error bars represent one standard error.

In line with this scenario, Figure 14 shows distinct patterns in the distribution of first saccades between the aware and unaware groups. In the aware group, almost three times as many first saccades (29%) were directed to the repeated location compared to the infrequent location (10%). In contrast, in the unaware group, only some 1.5 times as many first saccades (23%) were directed to the repeated vs. the infrequent location (14%). Overall, both groups made a similar amount of first saccades to the repeated-infrequent region (aware: 19.5%; unaware: 18.5%). This pattern suggests that the repetition bias is more focused on the repeated location in the aware group, whereas it is more distributed across both the repeated and infrequent locations in the unaware group, indicative of an extended 'history' effect. Additionally, Figure 14 shows that learning in the aware group is characterized by a marked increase in first saccades directed to the frequent locations across the four experimental epochs: from 20% in the first block to 35% in the last block. By Epoch 4, saccades to the frequent location dominate saccades to the repeated location, coupled with a decrease in first saccades to the infrequent location (from 12% to 8%) – explaining the cumulative growth of the cueing effect across the experiment. In contrast, the unaware group showed no change in the proportions of first saccades to the frequent location (remaining at 13%), indicating no learning of the dynamic regularity.

Conclusion

Our findings show that, contrary to previous reports, participants *can* extract dynamic regularities in the cross-trial placement of the target even in *serial* search (involving sequential eye movements) and utilize them to improve task performance – at least when the regular cross-trial target shift is relatively simple and occurring frequently. This finding is non-trivial, as the exact-same regularity is not picked up when implemented in a salient, 'pop-out' distractor in parallel search (Yu et al., 2023). Crucially, this dynamic target-location probability-cueing effect is evident even in the proportion and latency of the very first saccade elicited upon search-display onset, driven purely by the learnt rule and not the actual target location. Furthermore, it correlates with participants' awareness of the dynamic regularity. Given how fast the rule-injected bias can operate after display onset (evident in the very fastest first saccades, between 100 and 150 ms post-display onset), the cueing effect itself may not be consciously mediated. In this case, awareness plays a crucial role in acquiring the effect in the first instance. Alternatively, the rule-based biasing may already be prepared during the intertrial interval, allowing the cueing effect to ramp up rapidly after search display onset. More work, including electrophysiological measures, is needed to clarify this. Also, further work is required to map the boundary conditions for observable cueing effects, considering both the complexity of dynamic target regularities and the frequency with which they occur.

Supplementary

Appendix A: Extra RT Analyses

Does target-identity swap influence performance in mixed trial blocks?

To check whether target swapping might affect performance in mixed-block trials, we conducted a 2 × 2 × 3 ANOVA with the within-participant factors cross-trial Target Identity (repetition vs. switch), and cross-trial Target-Location Transition (frequent, infrequent), and the between-participant Awareness (aware vs. unaware). This ANOVA revealed RTs to be overall faster on trials where the target was repeated rather than switched, $F(1,32) = 29.575$, $p < .001$, $\eta_p^2 = 0.480$ (Target-Identity main effect). There was also a significant Awareness × the Target-Location Transition interaction, $F(1,32) = 10.609$, $p = .003$, $\eta_p^2 = 0.249$[24], due to the aware (but not the unaware) participants exhibiting a probability-cueing effect (i.e., faster RTs to targets at frequent vs. infrequent locations). See Figure A1 for a depiction of this effect pattern.

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[24] The interaction between Awareness and Target-Location Transition became significant after adding 10 more participants to the original sample of 24 participants (see Method), $p\text{Before} = 0.064$ vs. $p\text{After} = 0.003$.

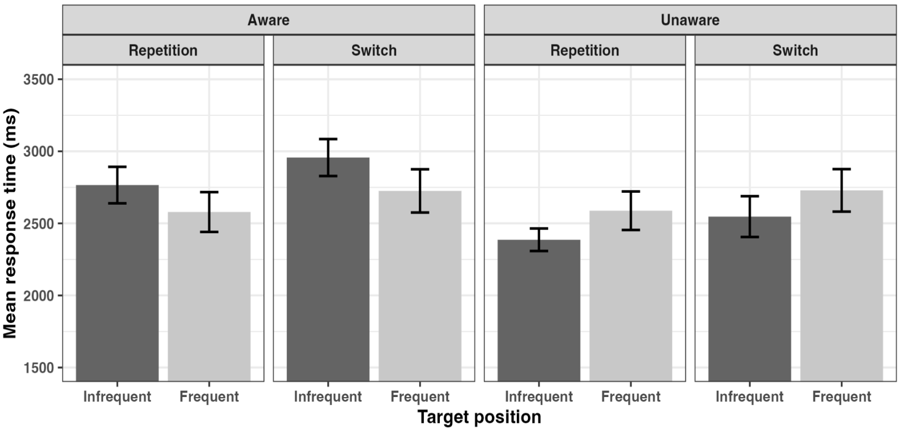

Figure A1. RTs as a function of the cross-trial target-location transition (the frequent, infrequent) for trials *n* in which the target (identity) repeated vs. switched relative to trial *n–1*, separately for the aware and unaware groups of participants. Error bars represent one standard error.

Does the progression of learning differ between the aware and unaware groups?

Figure A2 illustrates the mean probability-cueing effect across the experimental 'epochs' (each comprising four consecutive trial blocks) for the aware and unaware groups. As can be seen, the learning patterns differ between the two groups. Linear mixed-model analysis revealed a main effect of Epoch (β = 84.53, *SE* = 30.28, *t* = 2.792, *p* = .006), and an Epoch× Awareness interaction (β = -118.80, *SE* = 55.83, *t* = -2.128, *p* = .006). Also, statistical learning of the dynamic target-location regularity is evident in, and grows progressively across epochs, in the aware group (being significant already in the first epoch, t(23)=2.167, P=0.041, and effectively doubling by the end of the fourth epoch); in contrast, whereas there is no evidence of positive learning (in any of the epochs, not even the final ones; *t*'s< 0) in the unaware group, and in fact there was a significantly negative probability cueing effect in the third epoch (*t*(9) = -2.84, *p* = .019).

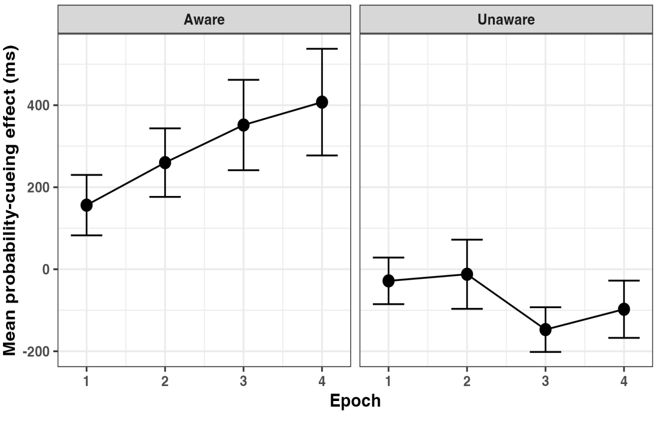

Figure A2. The probability-cueing effect as a function of experimental Epoch (1-4), separately for the aware and unaware groups. Error bars represent one standard error.

RT Analysis Based on Equalized Number of Trials Across Conditions

Our design necessarily involved an imbalance in the number of trials between the frequent and the infrequent, and the random conditions. Consequently, the RT variability might be higher in the latter, rare conditions compared to the frequent conditions, affecting statistical results. To rule this out, we randomly selected an equivalent number of trials (10%) from each condition (i.e., the frequent condition; the infrequent and random conditions already comprised 10% of the total number of trials) and then reanalyzed the RT data. The pattern of results (see Figure A3) remained essentially the same as in the analysis with all trials. A mixed-design ANOVA revealed significant main effects of Location Transition, $F(2,64) = 6.366, p = .003, \eta_p^2 = 0.166$, and Target Constancy, $F(1,32) = 74.886, p < .001, \eta_p^2 = 0.701$. Additionally, the Location-Transition × Awareness interaction ($F(2,64) = 8.400, p < .001, \eta_p^2 = 0.208$) and the Location-Transition × Target-Constancy × Awareness interaction, $F(2,64) = 3.070, p = .053, \eta_p^2 = 0.088$, were significant. Accordingly, the imbalance of the number of trials across conditions in our design does not impact the statistical comparisons.

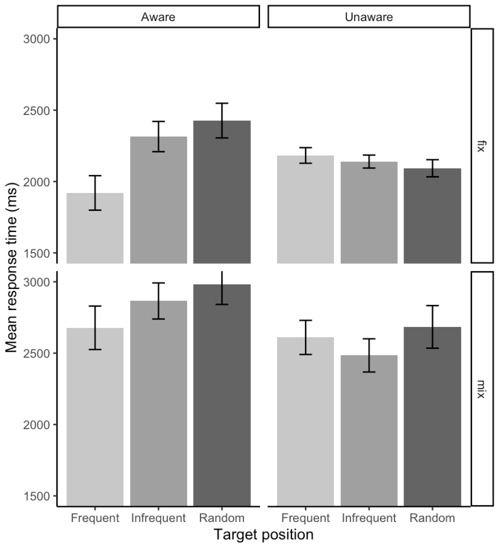

Figure A3. Mean RTs as a function of the cross-trial target-location transition (random, infrequent, frequent transition) and cross-trial target constancy (target identity fixed, mixed per block), separately for the aware and the unaware groups of participants. Error bars represent one standard error.

Appendix B: Analysis of Eye-movements in the Unaware Group

Given that there was no probability cueing effect in the unaware group, we only reported eye-movement analyses in the main text for the aware group. For completeness, we included the eye-movement analyses of the unaware group here.

Figure B1(a) presents the mean number of saccades required to reach the target in trial blocks with fixed vs. mixed (i.e., randomly varying) target identity for the three cross-trial target-location transition conditions (frequent, infrequent, random). An ANOVA revealed the Target-Constancy ×

Target-location Transition interaction to be significant, *F*(2,18) = 5.888, *p* = .011, $\eta_p^2 = 0.395$. Although post hoc tests yielded no significant comparisons, the interaction appears driven by the increased number of saccades in the frequent and random transition conditions vs. the infrequent condition in the mixed block. Importantly, there was no systematic advantage for frequent vs. infrequent and random transitions in either (fixed, mixed) block type.

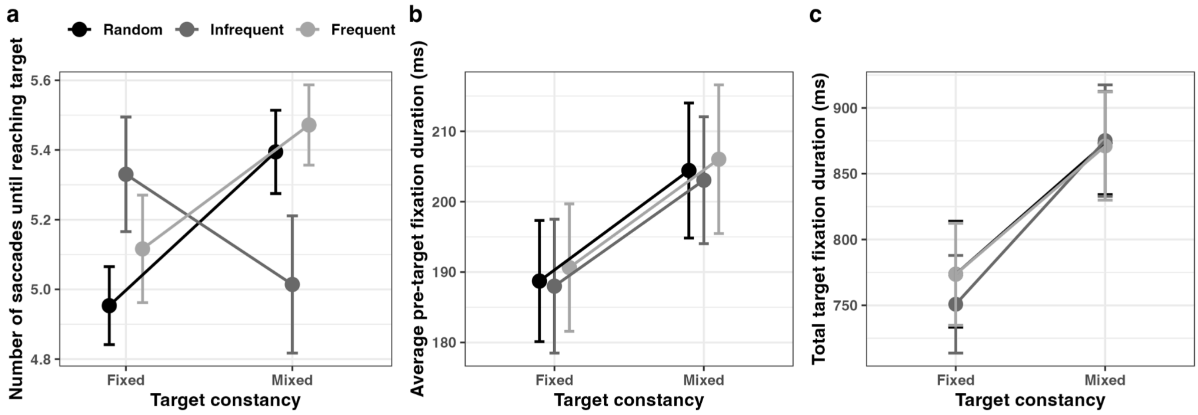

Figure B1 (**a**) Number of saccades until reaching the target under fixed vs. mixed target identities conditions, for the three cross-trial target-location transition conditions (frequent, infrequent, random). Error bars represent one standard error of the mean. (**b**) Average pre-target fixation duration in trial blocks with fixed vs. mixed target identity (cross-trial Target Constancy), dependent on the cross-trial Target-Location Transition (random, infrequent, frequent). Error bars represent one standard error of the mean. (**c**) . Total target fixation duration in trial blocks with fixed vs. mixed target identity (cross-trial Target Constancy), dependent on the cross-trial Target-Location Transition (random, infrequent, frequent) for target transition conditions (the random, infrequent, and frequent). Error bars represent one standard error of the mean.

Figure B1(b) presents the *average pre-target fixation duration* in trial blocks with fixed vs. mixed target identity (cross-trial Target Constancy), dependent on the cross-trial Target-Location Transition (random, infrequent, frequent) for the unaware group. A repeated-measures ANOVA of the *average pre-target fixation duration*, with the factors cross-trial Target-Location Transition (frequent, infrequent, random) and Target Constancy (mixed vs. fixed), yielded only a main effect of Target Constancy, *F*(1,9) = 12.417, *p* = .006, $\eta_p^2 = 0.580$: pre-target fixations were shorter in blocks with fixed vs. randomly varying target identity (189 ms vs. 205 ms).

Figure B1(c) presents the total target fixation duration in trial blocks with fixed vs. mixed target identity for the three cross-trial target-location transition conditions (frequent, infrequent, random). An ANOVA yielded only a main effect of the Target Constancy: *F*(1,9) = 12.706, *p* = .006, $\eta_p^2 = 0.585$, with the fixation duration on the target being shorter in blocks with fixed vs. randomly varying target identity (766 ms vs. 873 ms).

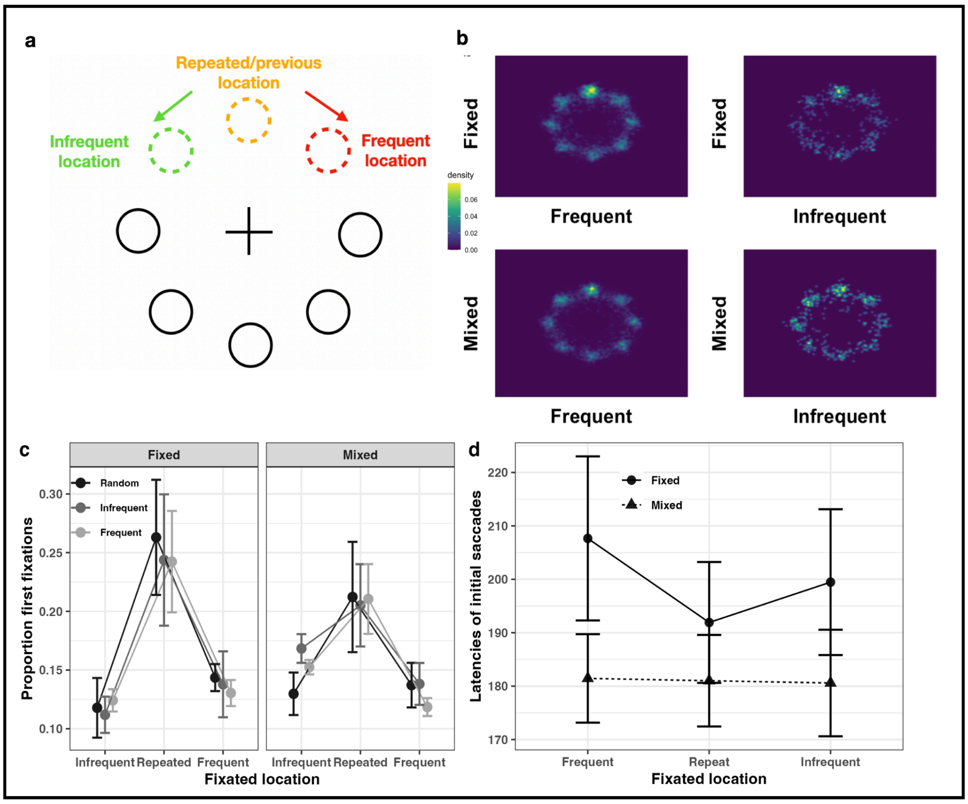

Figure B2. (**a**) and (**b**) Heatmaps of the landing positions of the first saccade, depending on the cross-trial Target-Location Transition (frequent, infrequent), for blocks with target identity being fixed vs. mixed (i.e., randomly variable) across trials. As illustrated in 8a, the fixation locations were rotated such that the target location on trial *n-1* is at the top, and the frequent location one to the right, and the infrequent location to the left (for participants with counterclockwise target shifts, the frequent and infrequent locations were flipped right/left flipped). Gaussian filters with smoothing kernels of 0.3° were used to generate all heat maps. **(b)** Heatmaps for trials on which the target had shifted in the frequent and, respectively, infrequent direction, separately for trial blocks with fixed and mixed target identity. As can be seen, the first saccades were most likely to be directed to the repeated location; the frequent location was *not* more likely to receive a saccade than the infrequent or random locations (excepting the repeated location). (**c**) and (**d**) proportions and, respectively, latencies of initial saccades directed to the frequent, repeated, and infrequent locations (first fixation location) dependent on the cross-trial target-location transition (frequent, infrequent, repeated), separately for the target-identity fixed and mixed blocks of trials. Error bars represent one standard error of the mean.

Awareness and Dynamic Probability Cueing of the First Eye Movement (Unaware)

For the group of unaware participants, there were no significant correlations between the probability-cueing effect in the first fixations and the confidence they associated with their Q1 response (slope = 0.007, r = 0.36, p = .30, R^2 = 0.13) and the rated frequency in their Q3 response (slope = -0.0001, r = –0.10, p = .78, R^2 = 0.01)

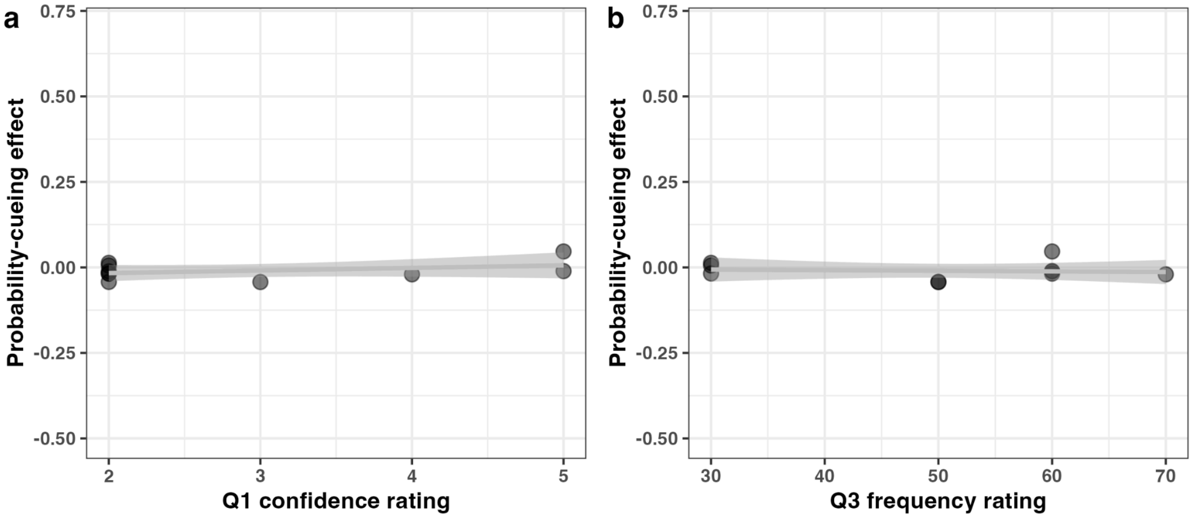

Figure B3. Probability-cueing effect in the first fixation location as a function of the Q1 confidence rating (1-6), for the group of unaware participants. (**b**) Probability-cueing effect in the first fixation location as a function of Q3 frequency rating (0%–100%).

Awareness and Dynamic Probability Cueing of the Number of Required Saccades

For the group of unaware participants, there were no significant correlations between the probability-cueing effect in the first fixations and the confidence they associated with their Q1 response (slope = -0.1, r = -0.31, p = .39, R^2 = 0.09) and the rated frequency in their Q3 response (slope = -0.01, r = –0.40, p = .25, R^2 = 0.16).

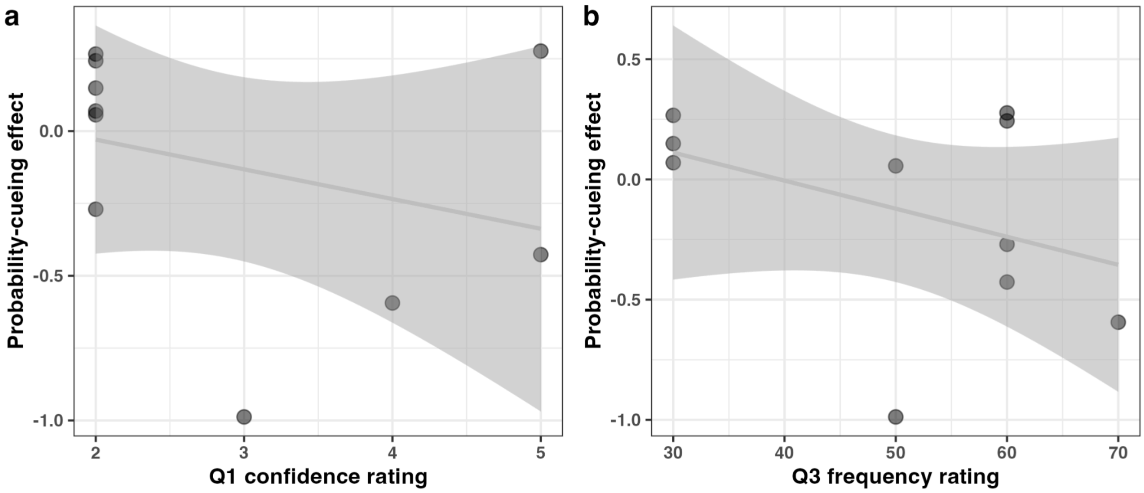

Figure B4. Probability-cueing effect in terms of the number of saccades until reaching the target, as a function of the Q1 confidence rating (1-6), for the group of unaware participants. (**b**) Probability-cueing effect in terms of the number of saccades until reaching the target as a function of Q3 frequency rating (0%–100%).

Inter-trial Priming of the First Eye Movement from Rule-conform (vs. Rule-breaking) Target Shifts (for unaware group)

Figure B5 provides a plot of the probability-cueing effect in terms of the first eye movement (i.e., the proportion of saccades to the frequent minus the infrequent location) dependent on the target location on the previous trial (i.e., trial *n–1* target at frequent vs. infrequent location), separately for trials blocks with fixed vs. mixed target identity. An ANOVA of this cueing effect with the factors Previous (trial *n–1*) Target Location and cross-trial Target Constancy revealed no significant effects. In particular, the main effect of Previous Target Location was non-significant, *F*(1,9) = 0.579, $p = .459$, $\eta_p^2 = 0.062$, that is, the proportion of first saccades directed to the frequent (vs. the infrequent) location was not different following rule-conforming (-0.012) as compared to rule-breaking target shifts (0.007) on the preceding trial.

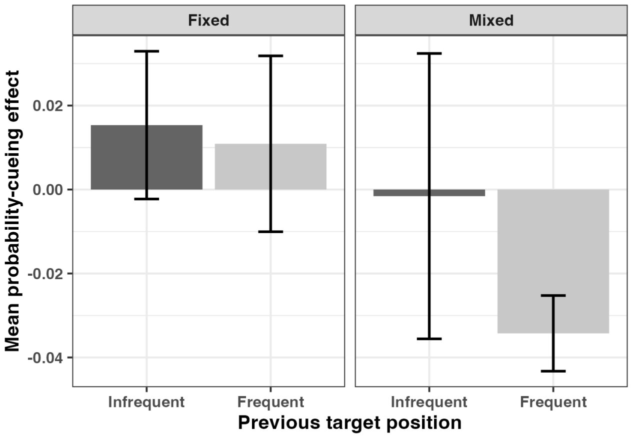

Figure B5. Probability-cueing effect in the first eye movement (proportion of saccades to frequent minus infrequent location) dependent on the target location on the preceding trial (i.e., trial *n–1* target at frequent vs. infrequent location), separately for trial blocks with fixed vs. mixed target identity. Error bars represent one standard error of the mean.

References

Allenmark, Fredrik, Ahu Gokce, Thomas Geyer, Artyom Zinchenko, Hermann J. Müller, and Zhuanghua Shi. 2021. “Inter-Trial Effects in Priming of Pop-out: Comparison of Computational Updating Models.” *PLoS Computational Biology* 17 (9): e1009332.

Allenmark, Fredrik, Hermann J. Müller, and Zhuanghua Shi. 2018. “Inter-Trial Effects in Visual Pop-out Search: Factorial Comparison of Bayesian Updating Models.” *PLoS Computational Biology* 14 (7): e1006328.

Allenmark, Fredrik, Zhuanghua Shi, Rasmus L. Pistorius, Laura A. Theisinger, Nikolaos Koutsouleris, Peter Falkai, Hermann J. Müller, and Christine M. Falter-Wagner. 2021. “Acquisition and Use of ‘Priors’ in Autism: Typical in Deciding Where to Look, Atypical in Deciding What Is There.” *Journal of Autism and Developmental Disorders* 51 (10): 3744–58.

Allenmark, Fredrik, M. Stanković, Hermann J. Müller, and Zhuanghua Shi. 2024. “Dynamic

Suppression of Likely Distractor Locations: Task-Critical Modulation." *Visual Cognition*, August. https://doi.org/10.1080/13506285.2024.2393467.

Allenmark, Fredrik, Bei Zhang, Heinrich René Liesefeld, Zhuanghua Shi, and Hermann J. Müller. 2019. "Probability Cueing of Singleton-Distractor Regions in Visual Search: The Locus of Spatial Distractor Suppression Is Determined by Colour Swapping." *Visual Cognition*. https://doi.org/10.1080/13506285.2019.1666953.

Bacon, W. F., and H. E. Egeth. 1994. "Overriding Stimulus-Driven Attentional Capture." *Perception & Psychophysics* 55 (5): 485–96.

Chun, M. M., and Y. Jiang. 1998. "Contextual Cueing: Implicit Learning and Memory of Visual Context Guides Spatial Attention." *Cognitive Psychology* 36 (1): 28–71.

Clark, J. H. 1924. "The Ishihara Test for Color Blindness." *American Journal of Optometry and Physiological Optics* 5:269–76.

Di Caro, Valeria, Jan Theeuwes, and Chiara Della Libera. 2019. "Suppression History of Distractor Location Biases Attentional and Oculomotor Control." *Visual Cognition* 27 (2): 142–57.

Druker, Michael, and Britt Anderson. 2010. "Spatial Probability AIDS Visual Stimulus Discrimination." *Frontiers in Human Neuroscience* 4 (August). https://doi.org/10.3389/fnhum.2010.00063.

Egeth, H. E., and S. Yantis. 1997. "Visual Attention: Control, Representation, and Time Course." *Annual Review of Psychology* 48:269–97.

Engbert, Ralf, and Konstantin Mergenthaler. 2006. "Microsaccades Are Triggered by Low Retinal Image Slip." *Proceedings of the National Academy of Sciences of the United States of America* 103 (18): 7192–97.

Failing, Michel, Tobias Feldmann-Wüstefeld, Benchi Wang, Christian Olivers, and Jan Theeuwes. 2019. "Statistical Regularities Induce Spatial as Well as Feature-Specific Suppression." *Journal of Experimental Psychology. Human Perception and Performance* 45 (10): 1291–1303.

Faul, Franz, Edgar Erdfelder, Albert-Georg Lang, and Axel Buchner. 2007. "G*Power 3: A Flexible Statistical Power Analysis Program for the Social, Behavioral, and Biomedical Sciences." *Behavior Research Methods*. https://doi.org/10.3758/bf03193146.

Ferrante, Oscar, Alessia Patacca, Valeria Di Caro, Chiara Della Libera, Elisa Santandrea, and Leonardo Chelazzi. 2018. "Altering Spatial Priority Maps via Statistical Learning of Target Selection and Distractor Filtering." *Cortex; a Journal Devoted to the Study of the Nervous System and Behavior* 102 (May):67–95.

Findlay, J. M. 1997. "Saccade Target Selection during Visual Search." *Vision Research* 37 (5): 617–31.

Folk, C. L., R. W. Remington, and J. C. Johnston. 1992. "Involuntary Covert Orienting Is Contingent on Attentional Control Settings." *Journal of Experimental Psychology. Human Perception and Performance* 18 (4): 1030–44.

Geng, Joy J., and Marlene Behrmann. 2002. "Probability Cuing of Target Location Facilitates Visual Search Implicitly in Normal Participants and Patients with Hemispatial Neglect." *Psychological Science* 13 (6): 520–25.

———. 2005. "Spatial Probability as an Attentional Cue in Visual Search." *Perception & Psychophysics* 67 (7): 1252–68.

Geyer, Thomas, Hermann J. Müller, and Joseph Krummenacher. 2006. "Cross-Trial Priming in Visual Search for Singleton Conjunction Targets: Role of Repeated Target and Distractor Features." *Perception & Psychophysics* 68 (5): 736–49.

Giménez-Fernández, Tamara, David Luque, David R. Shanks, and Miguel A. Vadillo. 2020. "Probabilistic Cuing of Visual Search: Neither Implicit nor Inflexible." *Journal of Experimental Psychology. Human Perception and Performance* 46 (10): 1222–34.

Golan, Aidai, and Dominique Lamy. 2023. "Attentional Guidance by Target-Location Probability Cueing Is Largely Inflexible, Long-Lasting, and Distinct from Inter-Trial Priming." *Journal of Experimental Psychology. Learning, Memory, and Cognition*, March. https://doi.org/10.1037/xlm0001220.

Goschy, Harriet, Sarolta Bakos, Hermann J. Müller, and Michael Zehetleitner. 2014. "Probability Cueing of Distractor Locations: Both Intertrial Facilitation and Statistical Learning Mediate Interference Reduction." *Frontiers in Psychology* 5 (November):1195.

Hoffmann, Joachim, and Wilfried Kunde. 1999. “Location-Specific Target Expectancies in Visual Search.” *Journal of Experimental Psychology. Human Perception and Performance* 25 (4): 1127–41.

Huang, Changrun, Mieke Donk, and Jan Theeuwes. 2022. “Proactive Enhancement and Suppression Elicited by Statistical Regularities in Visual Search.” *Journal of Experimental Psychology. Human Perception and Performance* 48 (5): 443–57.

Jiang, Yuhong V., Khena M. Swallow, and Gail M. Rosenbaum. 2013. “Guidance of Spatial Attention by Incidental Learning and Endogenous Cuing.” *Journal of Experimental Psychology. Human Perception and Performance* 39 (1): 285–97.

Jiang, Yuhong V., Bo-Yeong Won, and Khena M. Swallow. 2014. “First Saccadic Eye Movement Reveals Persistent Attentional Guidance by Implicit Learning.” *Journal of Experimental Psychology. Human Perception and Performance* 40 (3): 1161–73.

Jones, John L., and Michael P. Kaschak. 2012. “Global Statistical Learning in a Visual Search Task.” *Journal of Experimental Psychology. Human Perception and Performance* 38 (1): 152–60.

Kristjánsson, Arni, Deliang Wang, and Ken Nakayama. 2002. “The Role of Priming in Conjunctive Visual Search.” *Cognition* 85 (1): 37–52.

Krummenacher, Joseph, Hermann J. Müller, Michael Zehetleitner, and Thomas Geyer. 2009. “Dimension- and Space-Based Intertrial Effects in Visual Pop-out Search: Modulation by Task Demands for Focal-Attentional Processing.” *Psychological Research* 73 (2): 186–97.

Li, Ai-Su, Louisa Bogaerts, and Jan Theeuwes. 2022. “Statistical Learning of across-Trial Regularities during Serial Search.” *Journal of Experimental Psychology. Human Perception and Performance* 48 (3): 262–74.

Li, Ai-Su, and Jan Theeuwes. 2020. “Statistical Regularities across Trials Bias Attentional Selection.” *Journal of Experimental Psychology. Human Perception and Performance* 46 (8): 860–70.

Luck, Steven J., Nicholas Gaspelin, Charles L. Folk, Roger W. Remington, and Jan Theeuwes. 2021. “Progress Toward Resolving the Attentional Capture Debate.” *Visual Cognition* 29 (1): 1–21.

Maljkovic, V., and K. Nakayama. 1994. “Priming of Pop-out: I. Role of Features.” *Memory & Cognition* 22 (6): 657–72.

Maljkovic, V., and Ken Nakayama. 1996. “Priming of Pop-out: II. The Role of Position.” *Perception & Psychophysics*. https://doi.org/10.3758/bf03206826.

Moorselaar, Dirk van, and Jan Theeuwes. 2022. “Spatial Suppression due to Statistical Regularities in a Visual Detection Task.” *Attention, Perception & Psychophysics* 84 (2): 450–58.

———. 2023. “Statistical Learning Within Objects.” *Psychological Science* 34 (4): 501–11.

Moorselaar, D. van, Nasim Daneshtalab, and Heleen A. Slagter. 2021. “Neural Mechanisms Underlying Distractor Inhibition on the Basis of Feature And/or Spatial Expectations.” *Cortex; a Journal Devoted to the Study of the Nervous System and Behavior* 137 (April):232–50.

Moran, Rani, Michael Zehetleitner, Hermann J. Müller, and Marius Usher. 2013. “Competitive Guided Search: Meeting the Challenge of Benchmark RT Distributions.” *Journal of Vision* 13 (8). https://doi.org/10.1167/13.8.24.

Sauter, Marian, Nina M. Hanning, Heinrich R. Liesefeld, and Hermann J. Müller. 2021. “Post-Capture Processes Contribute to Statistical Learning of Distractor Locations in Visual Search.” *Cortex; a Journal Devoted to the Study of the Nervous System and Behavior* 135 (February):108–26.

Sauter, Marian, Heinrich René Liesefeld, Michael Zehetleitner, and Hermann J. Müller. 2018. “Region-Based Shielding of Visual Search from Salient Distractors: Target Detection Is Impaired with Same- but Not Different-Dimension Distractors.” *Attention, Perception & Psychophysics* 80 (3): 622–42.

Schneider, Walter, and Richard M. Shiffrin. 1977. “Controlled and Automatic Human Information Processing: I. Detection, Search, and Attention.” *Psychological Review* 84 (1): 1–66.

Seitz, Werner, Artyom Zinchenko, Hermann J. Müller, and Thomas Geyer. 2023. “Contextual Cueing of Visual Search Reflects the Acquisition of an Optimal, One-for-All Oculomotor Scanning Strategy.” *Communications Psychology* 1 (1): 1–12.

Shaw, M. L., and P. Shaw. 1977. “Optimal Allocation of Cognitive Resources to Spatial Locations.” *Journal of Experimental Psychology. Human Perception and Performance* 3 (2): 201–11.

Theeuwes, J. 1992. “Perceptual Selectivity for Color and Form.” *Perception & Psychophysics* 51 (6): 599–606.

Theeuwes, Jan. 1991. "Cross-Dimensional Perceptual Selectivity." *Perception & Psychophysics* 50 (2): 184–93.

Theeuwes, Jan, Louisa Bogaerts, and Dirk van Moorselaar. 2022. "What to Expect Where and When: How Statistical Learning Drives Visual Selection." *Trends in Cognitive Sciences* 26 (10): 860–72.

Treisman, A. M., and G. Gelade. 1980. "A Feature-Integration Theory of Attention." *Cognitive Psychology* 12 (1): 97–136.

Turk-Browne, Nicholas B., Phillip J. Isola, Brian J. Scholl, and Teresa A. Treat. 2008. "Multidimensional Visual Statistical Learning." *Journal of Experimental Psychology. Learning, Memory, and Cognition* 34 (2): 399–407.

Turk-Browne, Nicholas B., Justin Jungé, and Brian J. Scholl. 2005. "The Automaticity of Visual Statistical Learning." *Journal of Experimental Psychology. General* 134 (4): 552–64.

Turk-Browne, Nicholas B., Brian J. Scholl, Marvin M. Chun, and Marcia K. Johnson. 2009. "Neural Evidence of Statistical Learning: Efficient Detection of Visual Regularities without Awareness." *Journal of Cognitive Neuroscience* 21 (10): 1934–45.

Vadillo, Miguel A., Emmanouil Konstantinidis, and David R. Shanks. 2016. "Underpowered Samples, False Negatives, and Unconscious Learning." *Psychonomic Bulletin & Review* 23 (1): 87–102.

Vadillo, Miguel A., Douglas Linssen, Cristina Orgaz, Stephanie Parsons, and David R. Shanks. 2020. "Unconscious or Underpowered? Probabilistic Cuing of Visual Attention." *Journal of Experimental Psychology. General* 149 (1): 160–81.

Vadillo, Miguel A., Simone Malejka, Daryl Y. H. Lee, Zoltan Dienes, and David R. Shanks. 2022. "Raising Awareness about Measurement Error in Research on Unconscious Mental Processes." *Psychonomic Bulletin & Review* 29 (1): 21–43.

Veale, Richard, Ziad M. Hafed, and Masatoshi Yoshida. 2017. "How Is Visual Salience Computed in the Brain? Insights from Behaviour, Neurobiology and Modelling." *Philosophical Transactions of the Royal Society of London. Series B, Biological Sciences* 372 (1714). https://doi.org/10.1098/rstb.2016.0113.

Vicente-Conesa, Francisco, Tamara Giménez-Fernández, David Luque, and Miguel A. Vadillo. 2021. "Learning to Suppress a Distractor May Not Be Unconscious." https://doi.org/10.31234/osf.io/yekvu.

Walthew, Carol, and Iain D. Gilchrist. 2006. "Target Location Probability Effects in Visual Search: An Effect of Sequential Dependencies." *Journal of Experimental Psychology. Human Perception and Performance* 32 (5): 1294–1301.

Wang, Benchi, Iliana Samara, and Jan Theeuwes. 2019. "Statistical Regularities Bias Overt Attention." *Attention, Perception & Psychophysics* 81 (6): 1813–21.

Wang, Benchi, and Jan Theeuwes. 2018. "Statistical Regularities Modulate Attentional Capture Independent of Search Strategy." *Attention, Perception & Psychophysics* 80 (7): 1763–74.

Wang, Lishuang, Benchi Wang, and Jan Theeuwes. 2021. "Across-Trial Spatial Suppression in Visual Search." *Attention, Perception & Psychophysics* 83 (7): 2744–52.

Wiegand, Iris, Jeremy M. Wolfe, Joseph H. R. Maes, and Roy P. C. Kessels. 2024. "Incidental Learning of Temporal and Spatial Associations in Hybrid Search." *Visual Cognition*, 1–16.

Wolfe, J. M., K. R. Cave, and S. L. Franzel. 1989. "Guided Search: An Alternative to the Feature Integration Model for Visual Search." *Journal of Experimental Psychology. Human Perception and Performance* 15 (3): 419–33.

Won, Bo-Yeong, and Yuhong V. Jiang. 2015. "Spatial Working Memory Interferes with Explicit, but Not Probabilistic Cuing of Spatial Attention." *Journal of Experimental Psychology. Learning, Memory, and Cognition* 41 (3): 787–806.

Yu, Hao, Fredrik Allenmark, Hermann J. Müller, and Zhuanghua Shi. 2023. "Asymmetric Learning of Dynamic Spatial Regularities in Visual Search: Robust Facilitation of Predictable Target Locations, Fragile Suppression of Distractor Locations." *Journal of Experimental Psychology. Human Perception and Performance* 49 (5): 709–24.

2.3 Plastic changes induced by facilitation signals and its impact on attentional processing

Hao Yu, Nan Qiu, Wujiao, Fredrik Allenmark, Hermann J. Müller, Zhuanghua Shi

General and Experimental Psychology, Department of Psychology, LMU Munich, 80802, Germany

CONTRIBUTIONS

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

Nan Qiu: Formal analysis, Methodology, Visualization, Writing – original draft and Editing.

Jiao Wu: Data collection, Analysis, Review

Fredrik Allenmark:, Analysis, Methodology, Review

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

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

Author Note

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Plastic changes induced by target facilitation signals and its impact on attentional processing

Hao Yu
General and Experimental Psychology, Department of Psychology, LMU Munich, 80802, Germany

Nan Qiu
General and Experimental Psychology, Department of Psychology, LMU Munich, 80802, Germany

Jiao Wu
General and Experimental Psychology, Department of Psychology, LMU Munich, 80802, Germany

Fredrik Allenmark
General and Experimental Psychology, Department of Psychology, LMU Munich, 80802, Germany

Hermann J. Müller
General and Experimental Psychology, Department of Psychology, LMU Munich, 80802, Germany

Zhuanghua Shi
General and Experimental Psychology, Department of Psychology, LMU Munich, 80802, Germany

Abstract

Target facilitation can be achieved via spatial statistical learning of the target. Although many behavioral studies have found participants' performance was improved when targets occur at frequent locations relative to infrequent, the electrophysiological correlates of statistically learned target enhancement, however, have not been well studied. Moreover, a recent behavioral study (Turatto and Valsecchi 2022) has proved that the learned distractor suppression could cause long-lasting changes in the priority map, which affects the future computation of target salience at the same location to facilitate attention selection. It remains to be seen whether the learned target enhancement can also cause long-term changes in the priority map. Thus in the current study, the EEG data were collected while participants searched for a target in a serial search task with an unbalanced distribution of targets. N2pc (lateralized event-related potentials) and lateralized alpha (8–12 Hz) power were used to track the temporal dynamics of effects. The experiment consisted of two phases: the probability manipulation of target location was implemented in the training phase; the probability manipulation of target location was removed in the testing phase, and the distractor was also introduced which shared a similar feature as the target. Behaviorally, we found robust learning of predicted target locations in the training phase: processing of the target at frequent locations was facilitated, compared to infrequent target placement. In the testing phase, we found that the long-term learning even persisted when the target in the training phase became the distractor. Electrophysiologically, the learned target enhancement is not associated with lateralized alpha power during the pre-stimulus period. Yet the targets at frequent locations induced larger N2pc amplitude and earlier N2pc latency in the training phase. Thus, we confirm that facilitation resulting from target spatial statistical learning can cause plastic changes on the priority map.

Keywords: target enhancement, spatial statistical learning, N2pc component, alpha power, visual attention

Introduction

The dynamic world demands humans to efficiently adapt to the environment with overwhelming amounts of information. In this case, utilizing environmental regularities such as the likely location of a ‘target’ object, can facilitate an optimal deployment of attention and cognitive resources. For example, when searching for an important document, we often begin our search in familiar and probable locations, like our desk or filing cabinet. In the laboratory, this phenomenon has been systematically investigated in terms of so-called spatial ‘probability cueing effects’, when a task-relevant target occurs with a high probability at one location, our attentional system can acquire this information to enhance search efficiency, facilitating target detection and corresponding response decisions (Druker and Anderson 2010; Geng and Behrmann 2002, 2005; Hoffmann and Kunde 1999; Jiang et al. 2013; Shaw and Shaw 1977). For example, Geng and Behrmann (2002, 2005) manipulated the distribution of the target location in a way that the target appeared with 80% probability in one location and with 20% probability in the other locations. They found that mean reaction times (RTs) were significantly faster when the target was presented in the frequent compared to the infrequent location. Such facilitation effects support the view that statistical learning can bias attention and optimally adjust the weights within an assumed spatial priority map, leading to efficient selection properties (for a review, see Theeuwes, Bogaerts, and van Moorselaar 2022).

This view was also supported by a recent study that examined statistical learning regarding distractor locations (Turatto and Valsecchi 2022; Goschy et al. 2014; Sauter et al. 2018; Zhang et al. 2019). For example, Turatto and Valsecchi (2022) demonstrated that the suppressive signals may not only bias attention but also lead to long-lasting plastic changes in the activation landscape of spatial priority maps, affecting target selection even when the singleton distractor in the training phase became the target in the testing phase (Turatto and Valsecchi 2022). However, the question remains whether or not target enhancement signals can cause such long-lasting plastic changes in the priority map.

While statistical learning regarding target location has been investigated intensively in studies at the behavioral level (Druker and Anderson 2010; Geng and Behrmann 2002, 2005; Goschy et al. 2014; Sauter et al. 2018), knowledge about neural mechanisms underlying this phenomenon is limited. Investigations utilizing ERPs to explore the mechanisms involved in target enhancement have primarily relied on analyzing the N2pc component (Duncan, Theeuwes, and van Moorselaar 2023; Hickey, Di Lollo, and McDonald 2009), which has been demonstrated by numerous studies to be a common electrophysiological marker associated with the rapid assignment of visuospatial attention in multi-stimulus displays (e.g., Luck and Hillyard 1994; M. Eimer 1996; Woodman and Luck 1999; for a review, see Martin Eimer 2014). The N2pc is an enhanced negative-going component of EEG recorded in the posterior central electrode sites contralateral to the attended target objects in visual search displays, occurring about 200-350 ms after stimulus onset (Kiss, Van Velzen, and Eimer 2008; Gaspar et al. 2016), which generated in ventral extrastriate visual areas (Hopf et al. 2000). A recent study reported a close relationship between N2pc and the target locations of the probability cueing effect. By applying an additional singleton paradigm, Duncan et al. (2023) reported that targets located at high probability locations did elicit larger N2pc amplitudes relative to when targets located at low probability locations. Additionally, some studies suggested endogenous alpha oscillations (in the 10 Hz range) are involved in the enhancement of relevant or the suppression of irrelevant stimuli (Foster and Awh 2019; Slagter et al. 2016). Specifically, a decrease in lateralized alpha-band amplitude, known as alpha desynchronization, has been considered an indicator of attentional facilitation of contralateral stimuli (Bacigalupo and Luck 2019; Forschack et al. 2022; Neuper, Wörtz, and Pfurtscheller 2006; Sauseng et al. 2005). One study demonstrated that rapid-response trials were associated with a prediction of target location, as reflected by alpha band (8-12 Hz) laterization (Spaak et al. 2016). However, the prediction caused in that study is not because of target spatial statistical learning. Thus further studies will be needed to address this question regarding the role of alpha oscillation in target spatial statistical learning.

In the present study, we examined the direct impact of statistical learning on selection mechanisms by manipulating the probability that the target would appear at various display locations. EEG signals were also recorded while participants performed the serial search task in order to characterize the neural mechanisms underlying target enhancement caused by target spatial statistical learning. Our hypothesis posited that targets situated in regions with higher probabilities would yield better performance compared to targets located in areas with lower probabilities. Additionally, we were interested in examining whether such learning of likely target locations can also lead to long-lasting plastic changes in the activation landscape of spatial priority maps, facilitating target selection. However, it is not clear if such long-lasting plastic changes, if exist, is bound to the target identity, or the location. If the learned probability cueing is bound to the target identity, the selection and rejection of the target or distractor would be faster. In this case, when the target becomes a distractor during testing, we expect the disengagement from the distractor would be quicker. In contrast, if the learned probability cueing is only associated with the location, attentional guidance towards the learned location would cause great surprise and cost when it is a distractor. This location-based guidance, if exists, would be independent of the target identity, and occurs earlier in the visual processing, likely manifested in the early component N2pc. On this ground, we designed a study with the training and test sessions. In the training session, the target occurrence was uneven. We expect a standard target-location probability cueing effect. However, in the training session, the target and the distractor occurrence was equally likely across display. Moreover, we used the previous target as the distractor to disassociate the learning association is identity-based or location-based. .

Methods

Participants

Twenty-four participants (mean age 24.96 years, age range 19 to 31 years; 15 females) were recruited at Ludwig-Maximilians-University (LMU) Munich for this experiment. All participants were right-handed and had normal or corrected-to-normal visual acuity and (self-reported) normal color vision. Informed consent was obtained from all participants before the experiment. They were paid 9 Euro per hour for their participation or received course credits. The sample size was determined based on the crucial target-location effect reported in the previous study (Yu et al. 2023), which is sufficient to detect effects of size $d_z = 0.65$ and above with a power of 0.8 ($\alpha = 0.05$, one-tailed). The study protocol was approved by the Ethics Committee of the LMU Faculty of Psychology and Pedagogics.

Apparatus and Stimuli

The experiment was performed in a dimly lit, sound-attenuated, and electrically shielded experimental booth. Visual stimuli were generated by PsychoPy (v. 2022.2.2), presented on a 23-inch liquid crystal display monitor (ASUS, Taiwan; refresh rate 60 Hz; display resolution: 1,920 × 1,080 pixels). Participants viewed the stimuli from a distance of 62 cm (eye to screen). They were instructed to sit as relaxed as possible to minimize muscle activity and other ‘noise’ that could impact the quality of the EEG signal during task performance, and maintain fixation on the central fixation while doing the task. They issued manual responses by pressing the keys (“S” and “L” for respectively clockwise and counterclockwise rotation) on the keyboard with their right-hand or left-hand index fingers as fast and as accurately as possible.

The search displays for the training and test phase (see Figure 1) featured a white fixation (1.2° × 1.2°) cross at the center, set against a gray screen background (CIE [Yxy]: 22.4, 0.312, 0.318). Each display contained eight items equidistantly arranged around an imaginary circle (radius: 8.3° of visual angle). For the training phase, one single target shape, either a white “T” or “T”-like shape, among the non-target “L” and “F” shapes. When the target was a “T”, the “T”-like shape was a distractor, and vice versa. All stimuli subtended 1.6° of visual angle in width and height (CIE [Yxy]: 55.4, 0.309, 0.326). To increase task difficulty and encourage serial search, the “T”-like shape featured a slight offset at the line junction, measuring 0.27°. For the testing phase, the search display was identical to that in the training session, except that it consisted of four items. “T”, “T”-like letter, “L” and “F”. Target is either “T” or “T”- like letter. For example, if “T” is the target in the training phase, then the “T”- like letter will be the target in the testing phase. The “F”-shape non-targets were included to increase the difficulty of the task.

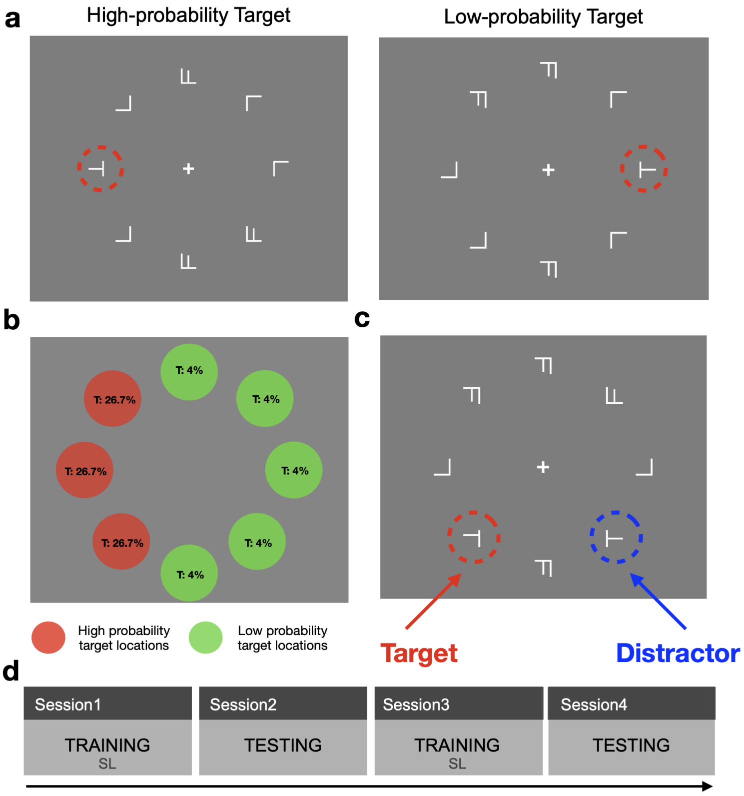

Figure 1. Visual search displays examples of the experiment. **(a)** An example of the search display for the training session of the experiment. The illustration shows different conditions: High-probability target and low-probability target condition and the target is indicated by red dashed circles. Participants had to search for a target (either the letter T or T like letter, the target is balanced across participants). The high-probability region was also balanced across participants. Specifically, for half of the participants, the high-probability target region is located on the right; for the other half, it is located on the left. **(b)** Schematic representation of the spatial and salience regularities of the target. High-probability target locations are shown in red, while low-probability target locations are shown in green. Percentages at each location represent the probabilities of each target type to appear in a given location. The high-probability region was counter-balanced across participants. **(c)** An example search display for the testing session of the experiment. The target is indicated by a red dashed circle and the distractor is indicated by a blue dashed circle. In distractor-present trials, both the target and distractor were equally distributed in the search display. **(d)** Experimental timeline: The experiment was divided into different sessions. During Sessions 1 and 3 (training phases), participants were familiar with the task and uneven target distributions on the display (the regularity regarding target location was unknown to participants). During sessions 2 and 4 (testing phases), participants were tested with a target or a distractor sharing a similar identity to the training target. The phases of training and testing were intertwined.

Design and Procedure

Each trial began with a fixation cross for 500 ms, followed by a search display, the circular search array was presented and remained visible until the participant responded. Participants were tasked to locate the target and then promptly press either the “S” (left-pointing) or the “L” (right-pointing) key to confirm target identification. Upon their response, a feedback message showed for 500 ms, indicating either “Correct (response)” in green or “Incorrect (response) ” in red.

To obtain enough trials for EEG analysis, the experiment included two training phases and two testing phases, which were interleaved. In each training phase (480 trials, divided into 10 blocks with each of 48 trials), the search display consisted of eight shapes with a shape-defined target, either a “T” or T-like letter (counterbalanced among participants). Target was present on every trial and could appear at any of the eight possible display locations, with its location uniformly distributed across all trials. The remaining non-targets were "Ls" and "Fs", oriented randomly in one of two orthogonal directions (90° or 270°). In addition, particular regularities regarding uneven spatial distribution of targets across trials were built in. Specifically, in the majority of trials (80%), the targets appeared in the high-probability location (see Figure 1b). On the remaining 20% of the trials, targets were evenly divided among low-probability locations.

In each testing phase (520 trials, divided in 10 blocks of 520 trials), the distractor was absent in 31% (16 distractor absent-trials in each block) of the trials. In distractor-absent trials, the target was equally likely to appear at each location, whereas in distractor-present trials its location was chosen randomly in each trial among the locations not occupied by the distractor. Moreover, in distractor-present trials, the distractor was the previous trained target, presented together with the new target. Both the target and distractor were equally distributed.

Electrophysiological recording and preprocessing analysis

The electroencephalogram (EEG) was continuously sampled at 1 kHz from 64 Ag/AgCl active electrodes (actiCAP system; Brain Products, Munich, Germany). Electrodes were mounted on an elastic cap (Easy Cap, FMS, Munich, Germany) placed according to the international 10-10 System. To monitor for blinks and eye movements, two electrodes were placed in the superior and inferior orbits and at the outer canthi of the eyes to record electrooculograms. All electrophysiological signals were amplified using BrainAmp amplifiers (Brain Products) with a 0.1-Hz to 250-Hz band-pass filter. During data acquisition, all electrodes were referenced to FCz and re-referenced offline to the average of both mastoids. All electrode impedances were kept below 5 kΩ prior to the experiment.

All EEG data analysis was performed using the Fieldtrip toolbox (Oostenveld et al. 2011), EEGLAB toolbox (Delorme and Makeig 2004), and ERPLAB (Lopez-Calderon and Luck 2014). Firstly, the continuous EEG data were manually inspected to remove apparent noise, such as electromyographic (EMG) bursts or wireless signal interference. Subsequently, the raw data was band-pass filtered using a 0.1-Hz to 30-Hz Butterworth infinite-impulse-response (IIR) filter (24 dB/Oct). Next, an ocular infomax independent-component analysis (ICA) was performed to remove eye blinks and horizontal eye-movement artifacts.

After the preprocessing of the continuous EEG, data were epoched from -200 to 800 ms relative to search display onset and baseline-corrected using the prestimulus interval. Next, incorrect trials and trials with large artifacts, such as any absolute amplitude exceeding ±60 µV, bursts of electromyographic activity as defined by voltage steps larger than 50 µV per sampling point, and activity changes lower than 0.5 µV within an interval length of 500 ms (indicating dead channels), were removed on an individual-channel basis before further ERP averaging.

L-ERP analysis

To examine the three lateralized ERP (L-ERP) components of interest (N2pc) on critical trials, EEG epochs were averaged separately for contralateral and ipsilateral parieto-occipital electrodes (PO7 and PO8) relative to the target location for each condition. These ERPs were then used to calculate the L-ERP components by subtracting the ipsilateral from the contralateral waveforms. We adopted the mean-amplitude approach to provide a metric for the components of interest, as it is less affected by noise (e.g., Larson et al. 2013). To quantify the N2pc, the mean amplitude of the difference waveforms (at the lateral occipital electrodes PO7/PO8) was calculated across the 200-320 ms time window post-stimulus onset, following the criteria used in previous studies (Qiu et al. 2023; van Moorselaar and Slagter 2019; Tay et al. 2019; Mazza, Turatto, and Caramazza 2009). For N2pc component latency estimation, we used fractional area latency (area = 50%). This measurement involved computing the area under the ERP (N2pc) waveform over a given latency range (220-370 ms) and then finding the time point that divides that area into a prespecified fraction (Steven J. Luck 2014; Hansen and Hillyard 1980). Typically the fraction will be in one-half, in which case this would be called a 50% area latency measure, meanwhile, we only choose the negative area to minimize the effect of noise or overlapping components. 50% area latency is considered more reliable than peak latency, due to its less sensitivity to noise than peak latency, and it is also the most reliable way of measuring changes in latency across conditions or groups, leading to the best statistical power (Steven J. Luck 2014; Kiesel et al. 2008).

Time-frequency analysis

To study frequency-specific activity over time, a time-frequency analysis (Mallat 2009) was performed on individual epochs. This was done by transforming epochs into power values using a continuous wavelet transform (CWT) in the time domain (t) to different frequencies (f). The modulated Gaussian sine functions are defined as: $W(t, f) = Ae^{\frac{-t^2}{2\sigma_t^2}} e^{i2\pi f t}$ where W denotes the complex convolution with the wavelet function, t is the time, and f is the frequency which increased from 1 to 30 Hz in 30 logarithmically spaced steps. To keep a good trade-off between temporal and frequency precision, the Morlet parameter c: $c = f_0(2\pi\sigma_t)$, or $c = f_0 / \sigma_f$, represents the number of wavelet cycles which was increased from 3 to 10 cycles in linearly spaced steps to have a good balance between time and frequency resolution. To ensure a reliable analysis with sufficient temporal distance to the stimulus onset and to avoid edge and smearing effects, a 1500-ms long segmentation (i.e., –1500 to 1000 ms relative to the onset) was used for time-frequency decomposition. We assumed that any anticipatory suppression would be detectable within the pre-stimulus time window [-1500, 0 ms]. The resulting power was baseline-corrected using a time window of −1300 to −1000 ms: a time window without any task-related processing and distant from the stimulus onset. The results of the wavelet transformations were then averaged across participants and conditions to obtain a measure of total power (Cohen 2014). Finally, the time-frequency power was quantified as mean power within 8–12 Hz for further statistical analysis.

To investigate whether the presence of a high-probability location on the left or right of the horizontal midline resulted in a lateralization of alpha-power, we first calculated a lateralization index over the broadband frequency range; this was done by taking frequency-band data for all frequency bins calculated over in contralateral sensors across all time points and subtracting them from those calculated over ipsilateral sensors. This matrix was then divided by the value of adding both ipsilateral and contralateral frequency values together (van Moorselaar and Slagter 2020): (*contralateral* − *ipsilateral*) / (*contralateral* + *ipsilateral*), a positive number then would indicate that contralateral power is larger than ipsilateral power, and vice versa for negative numbers. Critically, this index does not require a baseline. Statistical analyses were limited to electrode pairs PO7/8, PO3/4, and O1/2, which were selected on the basis of visual inspection of the topographic distribution of averaged alpha power (8–12 Hz) across the anticipatory time window (-1000 to 0 ms) and also were matched to those used in Wang et al. (Wang et al. 2019) who previously found alpha lateralization following statistical distractor learning. This analysis was further repeated using only the average alpha band frequencies in the total alpha band (8-12 Hz).

Results

Mean RTs

Training phase - Statistical learning of Target location

For the analysis of the correct mean RTs, we excluded the error trials (2.1%) as well as outliers (3.5%), defined as RT outliers if RTs exceed the median absolute deviation from the median or below 0.1 second. Figure 2 shows the mean RTs for the target appeared at the frequent and infrequent regions, respectively. A paired-sample *t*-test between different target conditions (frequent vs. infrequent) showed a significant difference, manifesting the target probability cueing effect, $t(23) = 4.803$, $p < .001$, $d_z = 0.98$. Responses were faster when the target appeared in the frequent region (827.72 ms) compared to that in the infrequent condition (1038.8 ms). The results thus confirmed previous findings (Geng and Behrmann 2002) that visual search was more efficient when the target appeared at frequent (high probability) than at infrequent (low probability) locations.

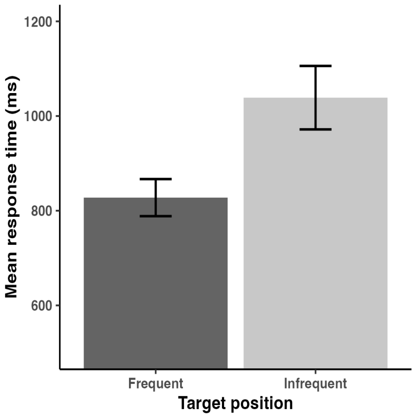

Figure 2. Mean RTs as a function of target-position (frequent and infrequent) condition in the training phase. Error bars represent the standard error.

Testing phase

In the testing phase, the target and distractor appeared equal-likely in all eight possible locations, while the distractor was the previous trained target in the training phase. Given that the target occurrence in the training phase had two regions, we remained to divide the display into two regions: the previous distractor frequent region ('frequent') and the previous distractor infrequent region ('infrequent'). Considering the distractor absence condition, we further divided trials into three categories: The distractor-absent, the distractor-at-frequent, and the distractor-at-infrequent.

The error trials and outliers were relatively low in the testing phase: error rate (5.7%), and outlier rate (3.4%). A repeated measures ANOVA revealed significant difference among three distractor conditions (distractor-absent: 0.011, distractor-frequent: 0.107, distractor-infrequent: 0.102), $F(2,46) = 47.313$, $p < .001$, $\eta_p^2 = .673$, the error rate for the distractor-absent condition is significantly lower than both distractor-frequent ($t(23) = -8.644$, $p < .001$, $d_z = -1.764$) and distractor infrequent conditions ($t(23) = -8.186$, $p < .001$, $d_z = -1.671$).

Testing phase-Statistical learning of Distractor location (or *Distractor probability cueing effect)*

The mean RTs for the distractor-absent, the distractor-at-frequent, and the distractor-at-infrequent conditions were 1140.5, 1401.0, and 1361.8 ms respectively (Figure 3a). A repeated-measures ANOVA for the mean RT revealed a significant difference among distractor conditions, $F(2,46) = 33.139$, $p < .001$, $\eta_p^2 = .590$. A post hoc analysis revealed that the significance was mainly contributed by the fast responses in the absent condition compared to the distractor-present condition (distractor-absent vs distactor-at-frequent: $t(23) = -7.549$, $p < .001$, $d_z = -1.541$; distractor-absent vs distactor-at-infrequent: $t(23) = -6.414$, $p < .001$, $d_z = -1.309$; distactor-at-frequent vs distactor-at-infrequent: $t(23) = 1.135$, $p = .787$, $d_z = 0.232$). Given that we were most interested in the transfer effect of the probability cueing, we computed the difference between the distractor-at-frequent and the distractor-at-infrequent locations (-39.2 ms). As we hypothesized that learning the target-based probability cueing would enhance the guidance toward the previous-defined target (now distractor) identity and expected a cost insurged when the distractor appeared at the frequent location, we applied one-tailed t-test, which yield a significant difference between two regions, $t(23) = 1.86$, $p = .038$ (one-tail), $d_z = 0.380$, evidencing significant distractor interference.

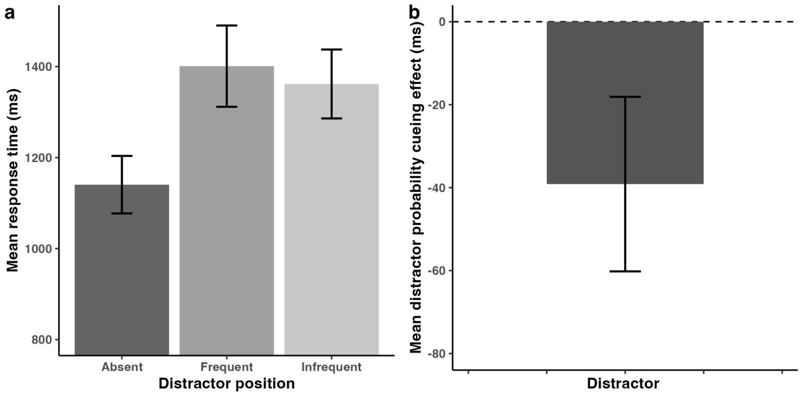

Figure 3. (a) Mean RTs as a function of distractor-location (Absent, frequent and infrequent) in the testing phase. **(b)** Distractor Probability-cueing effect ($RT_{infrequent} - RT_{frequent}$) on a given trial *n* dependent on whether the preceding distractor (on trial *n–1*) had occurred at the frequent vs. infrequent location (depend on target's conditions in the training phase).

Testing phase-Statistical learning of Target location

Figure 4a presents the mean RTs for three different target conditions (frequent, infrequent, and midline). A repeated-measure ANOVA with the within-participant factors target condition (frequent and infrequent) and distractor condition (distractor absent and distractor present (mid)), revealed a significant main effect of target condition (trials were excluded from analysis when target was presented on midline), $F(1,23) = 8.807$, p = .007, $\eta_p^2 = 0.277$, RTs were significantly faster in frequent

(1066.65 ms) condition relative to infrequent (1154.69 ms) condition, with a pattern of RTs consistent with what we found in the training phase. Similar to the training session, the presence of the distractor significantly slowed down responses: distractor present (1231.96 ms) vs. distractor absent (989.38 ms), $F(1,23) = 67.036$, $p < .001$, $\eta_p^2 = 0.745$. There was no significant interaction between target conditions and distractor presence condition, $F(1,23) = 0.047$, $p < .830$, $\eta_p^2 = 0.002$.

Figure 4b provides a bar plot of target probability-cueing ($RT_{infrequent} - RT_{frequent}$) effects for the presence and absence of the salient distractor. They were comparable: the distractor-absent (90.27 ms) and the distractor-present (85.80 ms), $t(23) = 0.217$, $p = .830$, $d_z = 0.044$. Additionally, when distractor was absent, a robust target-cueing effect was found in the testing phase (target probability cueing effect was significantly greater than 0), $t(23) = 2.676$, $p = .0007$, $d_z = 0.546$; when distractor was present (midline), a robust target-cueing effect was also found (target probability cueing effect was significantly greater than 0), $t(23) = 2.971$, $p = .003$, $d_z = 0.606$, suggesting that participants continue to use the learning strategy they had gained during the training phase to guide their visual search during the unbiased testing phase.

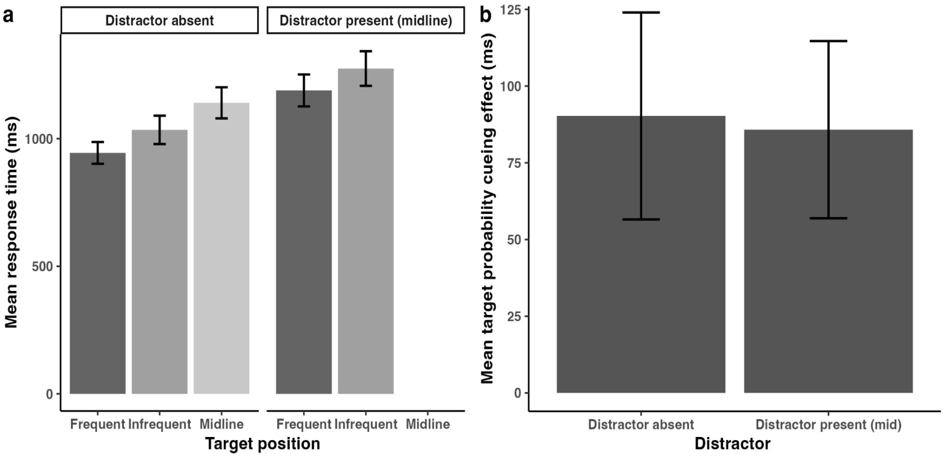

Figure 4. (a) Mean RTs as a function of target-location (frequent, infrequent and midline), separately for distractor absent and distractor present (midline) conditions in the testing phase. **(b)** Target Probability-cueing effect ($RT_{infrequent} - RT_{frequent}$) on a given trial *n* dependent on whether the preceding target (on trial *n–1*) had occurred at the frequent vs. infrequent location, separately for distractor absent and present conditions.

Electrophysiological data

Training phase

Figure 5 shows the lateralied ERPs for the target-only conditions. By visual inspection, all waveforms exhibit a more negative-going deflection in the 200-320 ms time window (N2pc).

Area *Latency (50% percent)* Figure 6a shows the N2pc latency within the time window 220-370 ms showed that N2pc for target-frequent condition (*M* = 287.64-ms) emerged significantly (26.92 ms) earlier than that for target-infrequent condition (*M* = 314.56-ms), *t*(15[25]) = 2.078, *p* = .028, d_z = 0.519 (one tailed).

Peak *mean Amplitude* Figure 6b shows that the mean amplitudes of N2pc in the time window 200-320 m were different across different target conditions. Paired sample *t*-test between the target-frequent condition and the target-infrequent condition revealed that the mean amplitude of N2pc for target-frequent condition (-2.57 µV) is significantly more negative than that for target-infrequent condition (-1.00 µV), *t*(23) = 1.722, *p* = .049, d_z = 0.351 (one-tailed, with the hypothesis that the amplitude of N2PC is greater in infrequent conditions than in frequent conditions), indicating the attention was better guided toward the frequent relative the infrequent location.

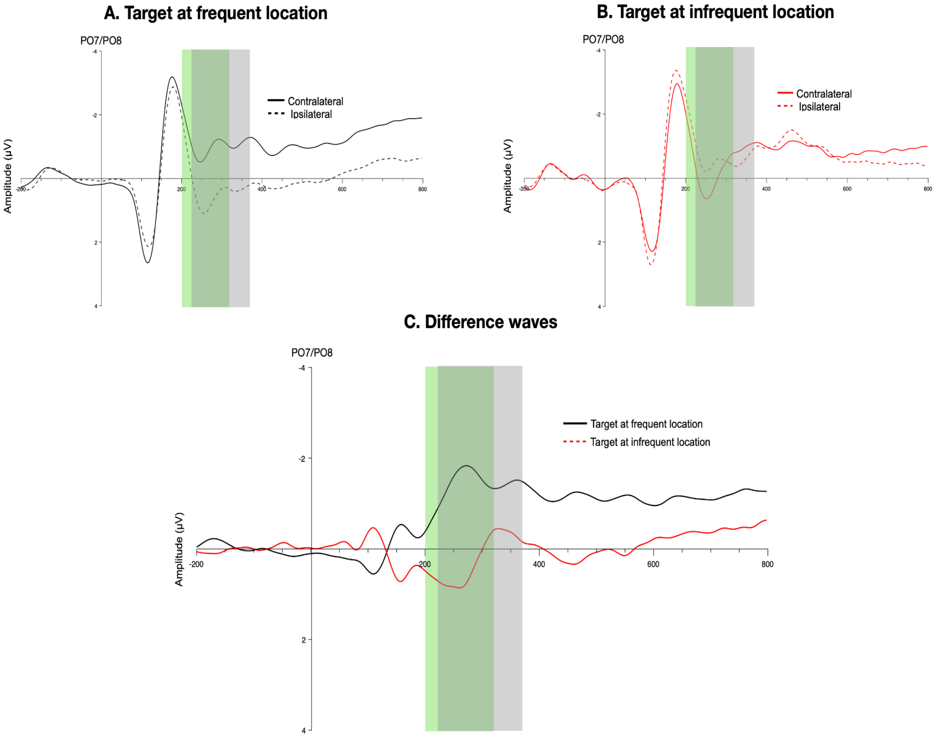

Figure 5. Grand-average ERP waveforms in the training phase. Subpanels A and B show the target-related contra-and ipsilateral waveforms, at electrodes PO7/PO8, from 200 ms pre-stimulus to 800 ms post-stimulus for targets that appeared at the frequent location and infrequent location. (A) The black waveforms indicate the target-frequent condition, where the

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[25] Eight data were excluded from statistical analysis since they failed to show latency. .

target was 80% likely to occur; (B) The red waveforms indicate target-infrequent condition, where the target was 20% likely to occur. The solid lines represent the contralateral waveforms, the dashed lines the ipsilateral waveforms. (C) Panel C shows the difference between contra- and ipsilateral waveforms for the target-frequent and -infrequent locations. The light gray and green areas indicate N2pc latency time window (220-370 ms), and N2pc amplitude time window (20-320 ms).

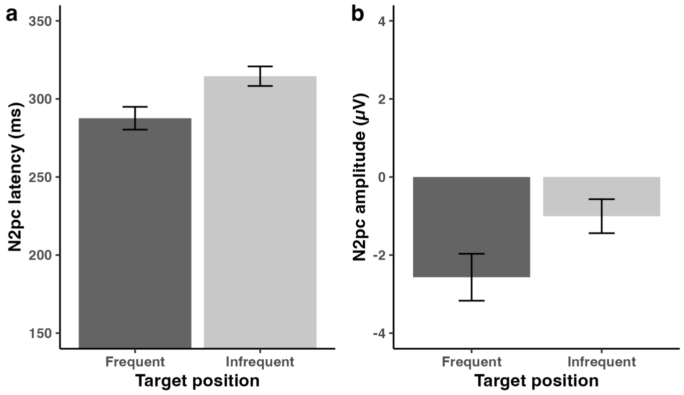

Figure 6. Mean *target-related* N2pc amplitude and latency in the training phase (i.e., left panel (a) and right panel (b), respectively). The *target-related* N2pc amplitude and latency are plotted as a function of the target location (frequent vs. infrequent). Error bars depict the one standard SEMs.

Testing phase

Figure 7 shows the lateralied ERPs for the distractor-present (Target at midline) conditions (Figure 7A,B), distractor-present (Distractor at midline) conditions (Figure 7C,D), target-only conditions (Figure 7E,F). By visual inspection, all waveforms exhibit a more negative-going deflection in the 200-320 ms time window (N2pc).

Target at Midline, Distract at Target-Frequent or Target-Infrequent Region: Examining Disractor cost in Visual Search

Area *Latency (50% percent)* Figure 8a showed that 50% area latency analysis within the time window 220-370 ms were different across distractor conditions, when the target was located at the midline location. Paired sample *t*-test revealed that N2pc for target-frequent condition (M =284.29 ms) was still emerged earlier (20.59 ms) than that for target-infrequent condition (M = 304.88 ms), $t(12) = -1.795, p = .049, d_z = -0.497$[26].

Peak *mean Amplitude* Figure 8b shows that the mean amplitudes of N2pc in the time window 200-320 ms were different across different distractor conditions, with the target located on the midline. Paired- sample *t* test between distractor-frequent condition and -infrequent condition revealed that the mean amplitude of N2pc for distractor-frequent condition (-2.84 µV) is significantly

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[26] Eleven data were excluded from statistical analysis due to failure of detection.

more negative than that for distractor-infrequent condition (-1.06 μV), *t*(23) = 2.036, *p* = .027, d_z = 0.416 (one-tailed, with the hypothesis that the amplitude of N2pc is greater in infrequent conditions than in frequent conditions).

Distractor present (at Midline), Target at Frequent or Infrequent Region: Examining Target facilitation effect in Visual Search

Area *Latency (50% percent)* Figure 8c showed that 50% area latency analysis within the time window 220-370 ms were different across target conditions, when the distractor was located at the midline location. There was no significant difference of the N2pc latencies between the target-frequent condition (293 ms) and the target-infrequent condition (301 ms), *t*(16) = .410, *p* = .344, d_z = 0.100 (one tail t-test)[27].

Peak *mean Amplitude* Figure 8d shows that the mean amplitudes of N2pc in the time window 200-320 m were different across different target conditions, with the distractor located at the midline location. Paired- sample *t*-test between target-frequent condition and target-infrequent condition revealed that the mean amplitude of N2pc for target-frequent condition (-2.62 μV) is significantly more negative than that for target-infrequent condition (-1.18 μV), *t*(23) = 1.724, *p* = .049, d_z = 0.352 (one-tailed, with the hypothesis that the amplitude of N2pc is greater in infrequent conditions than in frequent conditions).

Distractor absent, Target at Frequent or Infrequent Region: Examining Target facilitation effect in Visual Search

Area *Latency (50% percent)* Latency analysis within the time window 220-370 ms showed that N2pc latencies for target-frequent condition (*M* = 298.29-ms) did not significantly differ from target-infrequent condition (*M* = 310.400-ms) (see Figure 8e), *t*(16) = .777, *p* = .224, d_z = 0.188 (one-tailed)[28].

Peak *Mean Amplitude* According to Figure 8f, in terms of visual detection, N2pc amplitudes in the time window 200-320 ms varied across target conditions (frequent vs. infrequent) when the distractor was absent. However, numerically, the paired-sample *t*-test between target-frequent condition and target-infrequent condition revealed that the mean amplitude of N2pc for target-frequent condition (-2.38 μV) is not significantly larger than that for target-infrequent condition (-0.98 μV), *t*(23) = 1.396, *p* = .088, d_z = 0.285(one-tailed, with the hypothesis that the amplitude of N2pc is greater in infrequent conditions than in frequent conditions). This non-significant result may be due to the fact that we do not have enough trials for the distractor-absent condition.

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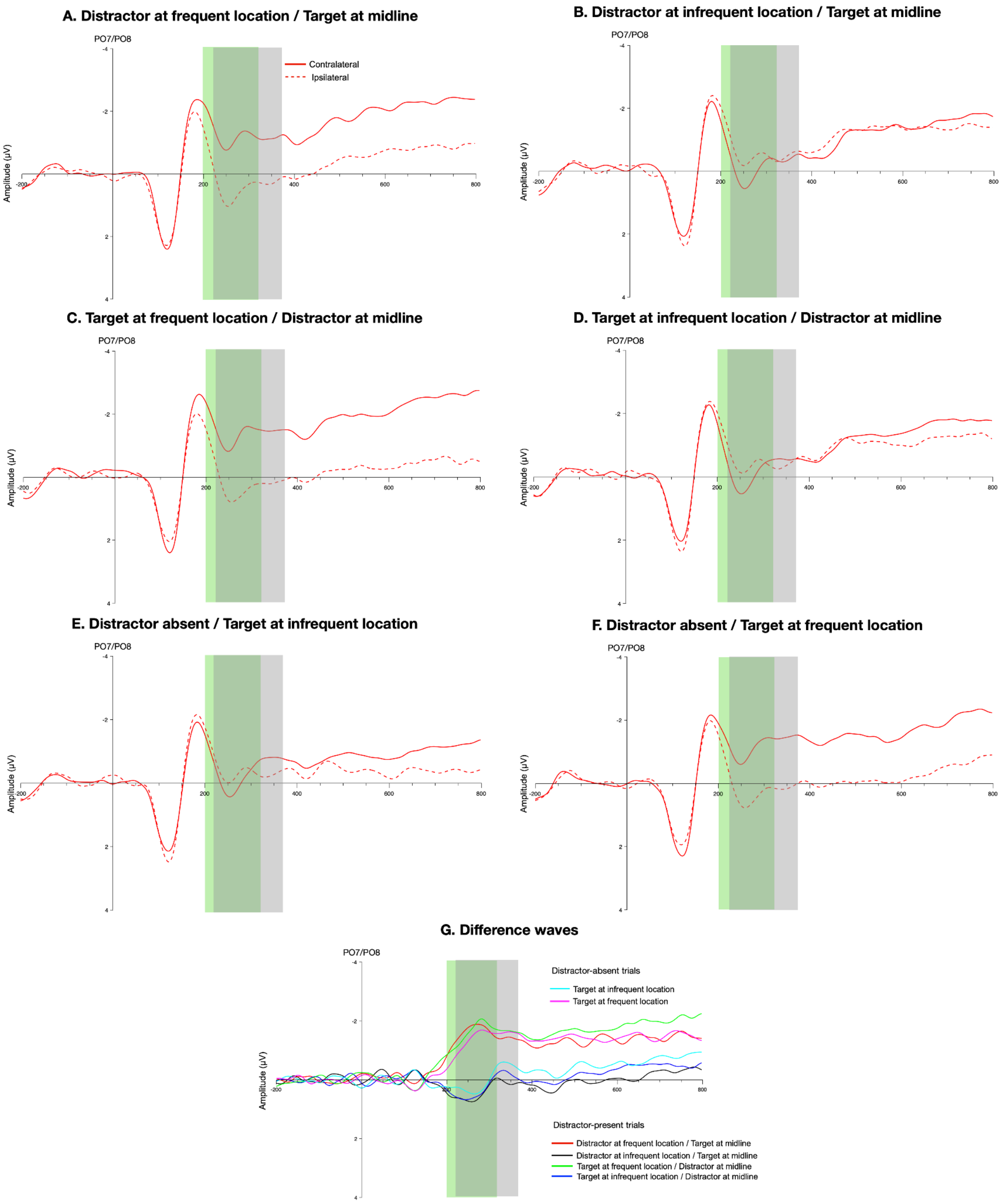
[27] Seven participants' data were excluded from statistical analysis due to failure of detection.

[28] Seven participants' data were excluded from statistical analysis due to failure of detection.



A. Distractor at frequent location / Target at midline

B. Distractor at infrequent location / Target at midline

C. Target at frequent location / Distractor at midline

D. Target at infrequent location / Distractor at midline

E. Distractor absent / Target at infrequent location

F. Distractor absent / Target at frequent location

G. Difference waves

Figure 7. Grand-average ERP waveforms in the testing phase. Subpanels A and B illustrate the distractor-related contra- and ipsilateral waveforms, at electrodes PO7/PO8, from 200 ms pre-stimulus to 800 ms post-stimulus for distractor at the frequent location, with target at the midline location (A); and the distractor at infrequent location with target at the midline location (B). Subpanels C and D illustrate the target-related waveforms for target at the frequent location, with distractor at midline location (C); target at the infrequent location, with distractor at midline location (D). Subpanels E and F present the target-related waveforms for targets located at a frequent and infrequent location, respectively. The red solid lines represent the contralateral waveforms, the red dashed lines the ipsilateral waveforms. Panel (E) illustrates the difference between contra- and ipsilateral waveforms for six experimental conditions. The light gray and green areas indicate the N2pc latency time window (220-370 ms), and the N2pc amplitude time window (20-320 ms).

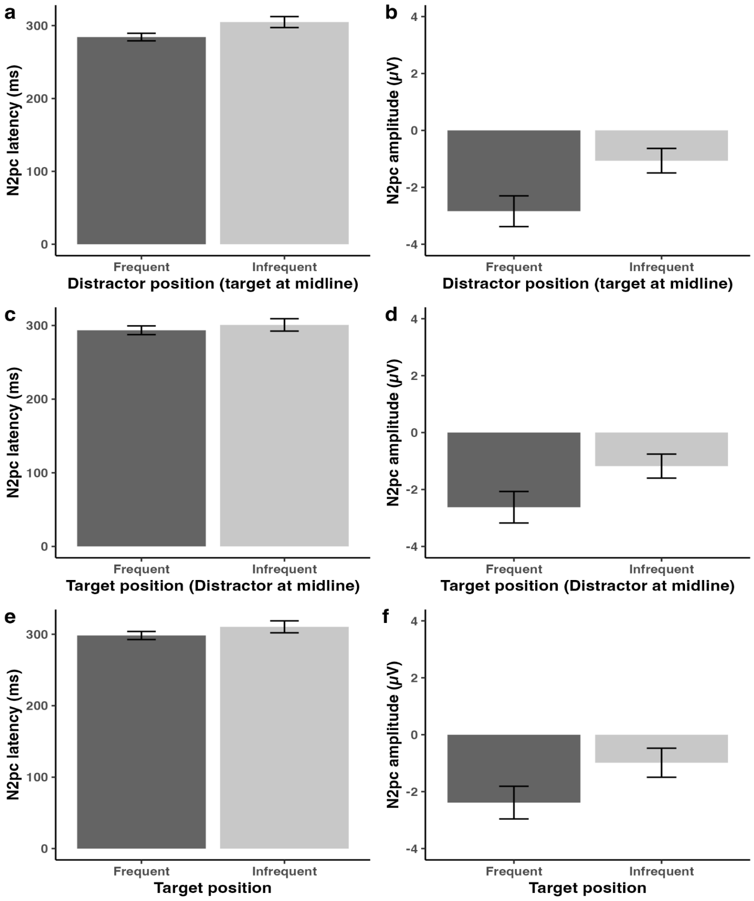


Figure 8. Mean *distractor-related* N2pc amplitude and latency in the testing phase (i.e., left panel and right panel, respectively). (a) and (b) The *distractor-related* N2pc amplitude and latency are plotted as a function of the distractor location (frequent vs. infrequent). (c) and (d) The *Target-related* N2pc amplitude and latency are plotted as a function of the target location (frequent vs. infrequent, distractor was presented at midline location). (e) and (f) *Target-related* N2pc amplitude and latency are plotted as a function of the target location (frequent vs. infrequent, and distractor was absent). Error bars depict the one standard SEMs.

Time-frequency results

As outlined in the Methods section, we further calculated the lateralized alpha-band power during the pre-stimulus period for two conditions (target present at the frequent location, and target present at the rare location) in the training phase, and for four types of conditions (i.e., distractor present at the frequent location meanwhile target at the middle line, distractor present at the rare location meanwhile target at the middle line, target present at the frequent location meanwhile distractor at the middle line, and target present at the rare location meanwhile distractor at the middle line) in the testing phase. Fig. 9 depicts the overall lateralization index alpha-band power (8–12 Hz) for two conditions in the training phase. Fig. 10 depicts the overall lateralization index alpha-band power (8–12 Hz) for two conditions in the testing phase.

The cluster-based permutation tests across the 8–12 Hz frequency band between the contralateral and ipsilateral region over the pre-stimulus interval from -1000 to 0 ms ($p < .05$, cluster-corrected, 1000 iterations). Again, the analysis failed to find any reliable clusters exhibiting enhanced pre-stimulus oscillations between two conditions (target present at the frequent location, and target present at the rare location) in the training phase. In the testing phase, we did not found any significant reliable difference in the lateralizatied alpha-band power between distractor-location conditions (i.e., distractor present at the frequent location meanwhile target at the middle line, distractor present at the rare location meanwhile target at the middle line), nor between target-location conditions (i.e., target present at the frequent location meanwhile distractor at the middle line, target present at the rare location meanwhile distractor at the middle line). To search for potential anticipatory lateralization power between groups in each condition, further the permutation tests on the lateralization index failed to reveal any significant difference between groups in each condition. Taken together, the time-frequency analyses failed to provide any evidence that the proactive alpha lateralization observed prior to the search display. This non-finding is at variance with some reports in the literature (Wang et al. 2019), but consistent with others (van Moorselaar, Daneshtalab, and Slagter 2021).

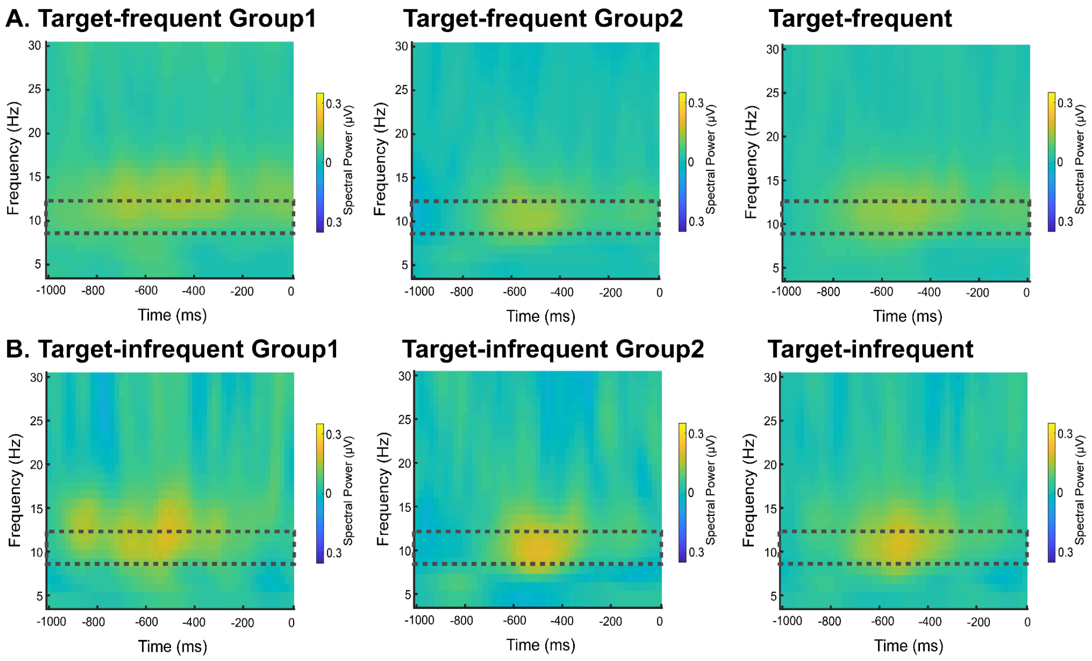


Figure 9. Time-frequency anticipatory lateralization alpha-power in the Training phase. For each condition, the lateralization index was calculated by subtracting contralateral power from ipsilateral and dividing the result by their combined power shows the grand average time-frequency oscillation (time series: -1000 to 0 ms prior to the search-display onset; frequency-band: 1 to 30 Hz) for the lateralization power index which was calculated by subtracting contralateral power from ipsilateral and dividing the result by their combined power across electrodes O1/2, PO3/4, and PO7/8 electrode clusters. **(A)** The left panel presents the lateralization with reference to the training phase when target presented at the frequent location for group1, middle panel with reference to target presented at the frequent location for group2, and the right panel presents the combination of group1 and group2 when target is presented at the frequent location. **(B)** The left panel presents the lateralization with reference to the training phase when target is presented at the infrequent location for group1, middle panel with reference to this condition for group2, and the right panel presents the combination of group1 and group2 when

target is presented at the infrequent location. A cluster permutation test of each of these conditions revealed no significant clusters for the lateralization alpha-power.

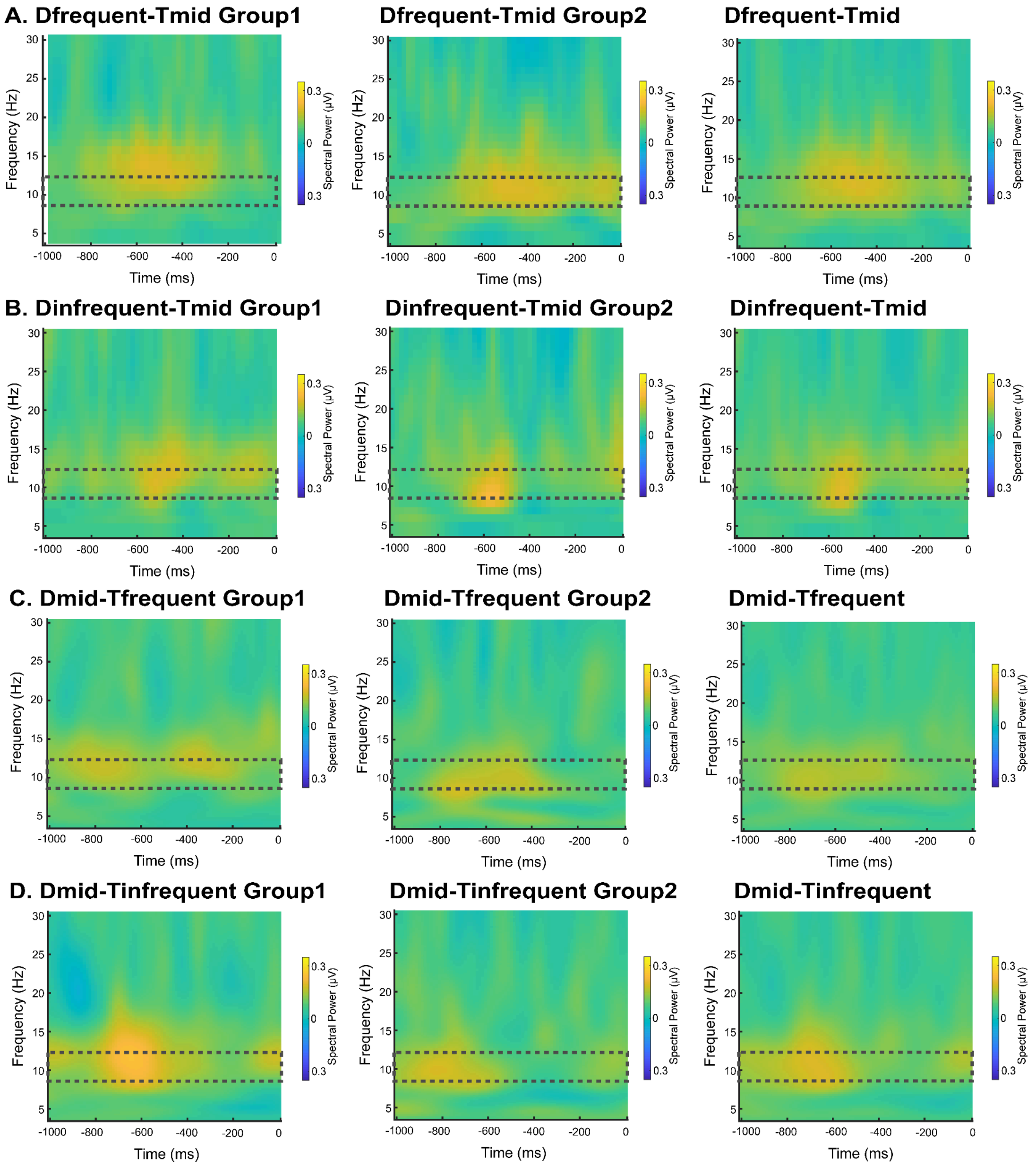


Figure 10. Time-frequency anticipatory lateralization alpha-power in the testing phase**.** For each condition, the lateralization index was calculated by subtracting contralateral power from ipsilateral and dividing the result by their combined power shows the grand average time-frequency oscillation (time series: -1000 to 0 ms prior to the search-display onset; frequency-band: 1 to 30 Hz) for the lateralization power index which was calculated by subtracting contralateral power from ipsilateral and dividing the result by their combined power across electrodes O1/2, PO3/4, and PO7/8 electrode clusters. **(A)** The left panel presents the lateralization with reference to the testing phase when distractor presented at the frequent location but target at the midline location for group1, middle panel with reference to this condition for group2, and right panel presents the combination of group1 and group2 with reference to that distractor presented at the frequent location while target at the midline location. **(B)** The left panel presents the lateralization with reference to the testing phase when distractor presented at the infrequent location but target at the midline location for group1, middle panel with reference to this condition for group2, and right panel presents the combination of group1 and group2 with reference to that distractor

presented at the infrequent location while target at the midline location. **(C)** The left panel presents the lateralization with reference to the testing phase when target presented at the frequent location but distractor at the midline location for group1, middle panel present the same condition for group2, and right panel presents the combination of group1 and group2 with reference to the testing phase when target presented at the frequent location but distractor at the midline location. **(D)** The left panel presents the lateralization index with reference to the testing phase when target presented at the infrequent location but distractor at the midline location for group1, middle panel present the same condition for group2, and right panel presents the combination of group1 and group2 with reference to the testing phase when target presented at the infrequent location but distractor at the midline location. A cluster permutation test of each of these conditions revealed no significant clusters for the lateralization alpha-power.

Discussion

Many previous studies have shown that our attentional system can learn and effectively use spatial probability information for guiding search, facilitating target detection and response decisions (Druker and Anderson 2010; Geng and Behrmann 2005, 2002; Jiang, Swallow, and Rosenbaum 2013; Hoffmann and Kunde 1999; Shaw and Shaw 1977; Ferrante et al. 2018). The current study was designed to investigate the electrophysiological correlates of learned attentional facilitation and whether the learned target enhancement can cause long-term plastic changes on attention selection.

Behaviorally, our study confirmed that target enhancement resulting from spatial statistical learning can cause long-term plastic changes and lead to efficient target selection during visual search. We found the target-location probability cueing effect in the training phase: The mean RTs were significantly faster in target-frequent condition compared to target-infrequent. In the testing phase, we observed that the learning developed during the training phase can be transferred to the testing phase, in which the uneven probability of target location was removed, and target in the training phase became the distractor in the testing phase. However, the target location statistical learning effect diminished from the training (211.08 ms) to the testing phase (88 ms). implying that the long-term plastic changes in response to spatial target learning may be some degree of inflexibility in visual processing - our attention focus can not update accordingly. For example, when we visit a country where traffic travels on the other side of the road, it takes us some time to readjust our attention to the new direction of movement. Furthermore, the interaction between target condition and distractor presence condition was not significant in our study, which is inconsistent with a similar study (Exp1, Ferrante et al. 2018) but used a singleton distractor. It may be due to the fact that the distractor and target share a similarity in our study so that attention would not be captured by pop out singleton which will capture more attention. So when participants were doing tasks their attention bias was mainly from learning (prior knowledge) instead of a pop out distractor.

Electrophysiologically, we found that N2pc latency was earlier for targets appearing in frequent locations than targets appearing in infrequent locations in the training phase. Latency results are consistent with the pattern of RTs observed during the Training. We assume that the optimal performance observed in the frequent condition might be the result from the increased activation on the spatial priority map. Interestingly, with visual inspection for the infrequent condition, the attention was also biased to frequent location first after stimulus onset, and then turned to the opposite side of the visual display. It is noteworthy, however, this learned attentional enhancement was not accompanied by known encephalographic markers of attentional selection - lateralized anticipatory alpha power relative to anticipated target location. Instead, a more negative N2pc amplitude at target-frequent locations relative to target-infrequent locations was observed, indicating enhanced attentional allocation to learned target locations, consistent with the findings in another study (Duncan, Theeuwes, and van Moorselaar 2023) using the singleton paradigm to investigate electrophysiological markers of statistical learned attentional enhancement. Another main finding in the testing phase is that we found that no matter where the target or distractor was located, the N2pc amplitude for frequent conditions was always greater than that for infrequent conditions, confirming the findings of the previous study (Chapter 2.2).

Interestingly, we observed both target location cueing effect and distractor location cueing effect (opposite to target location cueing effect) in the testing phase. Target location cueing effect was expected because attention is biased towards frequent locations due to the training. However, it is unclear as to why the cueing effect for the distractor appears to be opposite that for the target. To quantify the distractor cueing effect, we subtract RTs of the distractor at frequent locations from RTs of distractors at frequent locations. Participants show slower RTs when the distractor appears at frequent locations. This is because attention is initially directed towards these frequent locations regardless of where the target or distractor is, and participants need to disengage attention from frequent locations to focus on the target on the other side, resulting in a time cost. Participants show faster RTs when the distractor appears at infrequent locations. This is because attention is still biased towards the frequent locations, so when the distractor appears at infrequent locations, there's less interference from the pre-existing attentional bias. Importantly, the findings from EEG analysis were consistent with findings from behavioral results. We observed, when target occurred at midline locations, the N2pc latency for distractor-frequent condition start significantly earlier than the N2pc latency for distractor-infrequent condition, meanwhile the N2pc amplitude for distractor-frequent condition was more more negative than that of distractor-infrequent condition, suggesting distrator-frequent location got more attention resource. From other conditions in EEG analysis, it appears that participants always start locating their attention at frequent locations regardless of the real location of the distractor or target. In this regard, it can be inferred that the spatial statistical learning that occurs during the training phase has resulted in long-lasting plastic changes on visual selection, and that its effect is somehow not responsive (flexible) to the new environment.

Furthermore, some studies reported that increasing the salience of targets compared to surrounded distractors leads to a monotonic increase on the N2pc amplitude observed in EEG recordings, which also heightened amplitude reflects enhanced attentional allocation toward the target facilitated by the improved saliency contrast between the targets and distractors (Berggren and Eimer 2020; Zhao et al. 2011; Töllner et al. 2011; Mazza, Turatto, and Caramazza 2009a). However, in our EEG experiment which involving serial search, instead using a singleton target, we used a target who share similarity with distractor item, we found that the amplitude of N2pc for target-frequent location is more significant negative/larger than target- infrequent condition, interestingly, the p value from our training phase is bigger then the p value from another study which involving parallel search (Duncan, Theeuwes, and van Moorselaar 2023). Thus, our findings confirm the idea that the ease of distinguishing targets from background elements contribute to probability cueing effect which is indicated by N2pc amplitude, and providing insights into attentional selection and target processing in visual search tasks.

Alpha power is strongly modulated by the allocation of spatial attention (Sauseng et al. 2005; Thut et al. 2006). Many studies focus on investigating the role of alpha power in statistical learning of distractor suppression (Ferrante et al. 2023; van Moorselaar and Slagter 2019; Qiu et al. 2023). In addition the alpha band is also considered as an important neural signature to understand target enhancement in attentional processes. Some studies emphasized the association between attentional facilitation and alpha power: they found a decrease of alpha power contralateral to the target location reappearing relatively late after target onset (Bacigalupo and Luck 2019; van Diepen et al. 2016). It was reported, however, that limited evidence was provided for the role of pre-stimulus alpha activity in statistical learning of target facilitation. In the current study, no changes in pre-stimulus alpha-band activity were observed as a function of target location condition. In contrast, another study reported that prior knowledge of target location can trigger significant preparatory alphas modulation over visual cortex (Spaak et al. 2016). However, Spaak et al. did not manipulate the probability of target locations through the experiment. Thus, we assume that alpha power can not reflect target spatial statistical learning, consistent with another study that failed to show reliable tuning towards high-probability target location (Duncan, Theeuwes, and van Moorselaar 2023). They also suggested that the prediction result from target spatial statistical learning might not be controlled under the top-down neural mechanism.

Conclusion

In sum, in this study we have demonstrated the mechanisms involved in target spatial statistical learning of target location and long-term plastic changes on the spatial priority map. Behaviorally, we replicated the classical target-location probability cueing effect, showing that participants can statistically learn to facilitate target selection caused by target at frequent locations (vs. infrequent) (Druker and Anderson 2010; Geng and Behrmann 2002, 2005; Hoffmann and Kunde 1999; Jiang et al. 2013; Shaw and Shaw 1977), as well as long-term plastic changes on the spatial priority map - we found target probability cueing effect in both distractor-present and -absent conditions. We also found the spatial learning acquired in the training phase could be transferred to the testing phase, suggesting that long-lasting target-associated spatial statistical learning is somewhat inflexible. Electrophysiologically, statistical learning of the likely target location manifested in an early N2pc post-display onset and bigger N2pc amplitude, suggesting more attention resources were biased to target-frequent location rather than target-infrequent location. However, the target location enhancement was not observed in lateralized alpha power during the pre-stimulus period. The non-finding of alpha power imply that alpha-band was not modulated by uneven probability of target locations across displays, which is in line with other studies investigating neural mechanisms of spatial statistical learning effect (e.g, Qiu et al. 2023; Duncan, Theeuwes, and van Moorselaar 2023).

Declaration of competing interest

The authors declare no competing interests.

Data availability statement

Raw data used for analyses presented within this article will be made available upon request. If you would like to access the raw data and analysis, please email Hao Yu at the following e-mail address: haileyyu527@gmail.com

References

Allenmark, Fredrik, Bei Zhang, Zhuanghua Shi, and Hermann J. Müller. 2022. “Learning to Suppress Likely Distractor Locations in Visual Search Is Driven by the Local Distractor Frequency.” *Journal of Experimental Psychology. Human Perception and Performance* 48 (11): 1250–78.

Bacigalupo, Felix, and Steven J. Luck. 2019. “Lateralized Suppression of Alpha-Band EEG Activity As a Mechanism of Target Processing.” *The Journal of Neuroscience: The Official Journal of the Society for Neuroscience* 39 (5): 900–917.

Berggren, Nick, and Martin Eimer. 2020. “Spatial Filtering Restricts the Attentional Window during Both Singleton and Feature-Based Visual Search.” *Attention, Perception & Psychophysics* 82 (5): 2360–78.

Cohen, M. X. 2014. “Analyzing Neural Time Series Data: Theory and Practice.”

https://books.google.ca/books?hl=en&lr=&id=rDKkAgAAQBAJ&oi=fnd&pg=PR5&ots=g9cguWYVw_&sig=279awkchHZHu941cK6BJ_3Y2hjY.

Delorme, Arnaud, and Scott Makeig. 2004. "EEGLAB: An Open Source Toolbox for Analysis of Single-Trial EEG Dynamics Including Independent Component Analysis." *Journal of Neuroscience Methods* 134 (1): 9–21.

Diepen, Rosanne M. van, Lee M. Miller, Ali Mazaheri, and Joy J. Geng. 2016. "The Role of Alpha Activity in Spatial and Feature-Based Attention." *eNeuro* 3 (5). https://doi.org/10.1523/ENEURO.0204-16.2016.

Druker, Michael, and Britt Anderson. 2010. "Spatial Probability AIDS Visual Stimulus Discrimination." *Frontiers in Human Neuroscience* 4 (August). https://doi.org/10.3389/fnhum.2010.00063.

Duncan, Dock H., Jan Theeuwes, and Dirk van Moorselaar. 2023. "The Electrophysiological Markers of Statistically Learned Attentional Enhancement: Evidence for a Saliency-Based Mechanism." *Journal of Cognitive Neuroscience*, October, 1–16.

Eimer, M. 1996. "The N2pc Component as an Indicator of Attentional Selectivity." *Electroencephalography and Clinical Neurophysiology* 99 (3): 225–34.

Eimer, Martin. 2014. "The Neural Basis of Attentional Control in Visual Search." *Trends in Cognitive Sciences* 18 (10): 526–35.

Ferrante, Oscar, Alessia Patacca, Valeria Di Caro, Chiara Della Libera, Elisa Santandrea, and Leonardo Chelazzi. 2018. "Altering Spatial Priority Maps via Statistical Learning of Target Selection and Distractor Filtering." *Cortex; a Journal Devoted to the Study of the Nervous System and Behavior* 102 (May):67–95.

Ferrante, Oscar, Alexander Zhigalov, Clayton Hickey, and Ole Jensen. 2023. "Statistical Learning of Distractor Suppression Downregulates Prestimulus Neural Excitability in Early Visual Cortex." *The Journal of Neuroscience: The Official Journal of the Society for Neuroscience* 43 (12): 2190–98.

Forschack, Norman, Christopher Gundlach, Steven Hillyard, and Matthias M. Müller. 2022. "Electrophysiological Evidence for Target Facilitation without Distractor Suppression in Two-Stimulus Search Displays." *Cerebral Cortex* 32 (17): 3816–28.

Foster, Joshua J., and Edward Awh. 2019. "The Role of Alpha Oscillations in Spatial Attention: Limited Evidence for a Suppression Account." *Current Opinion in Psychology* 29 (October):34–40.

Geng, Joy J., and Marlene Behrmann. 2002. "Probability Cuing of Target Location Facilitates Visual Search Implicitly in Normal Participants and Patients with Hemispatial Neglect." *Psychological Science* 13 (6): 520–25.

———. 2005. "Spatial Probability as an Attentional Cue in Visual Search." *Perception & Psychophysics* 67 (7): 1252–68.

Goschy, Harriet, Sarolta Bakos, Hermann J. Müller, and Michael Zehetleitner. 2014. "Probability Cueing of Distractor Locations: Both Intertrial Facilitation and Statistical Learning Mediate Interference Reduction." *Frontiers in Psychology* 5 (November):1195.

Hansen, Jonathan C., and Steven A. Hillyard. 1980. "Endogeneous Brain Potentials Associated with Selective Auditory Attention." *Electroencephalography and Clinical Neurophysiology* 49 (3): 277–90.

Hickey, Clayton, Vincent Di Lollo, and John J. McDonald. 2009. "Electrophysiological Indices of Target and Distractor Processing in Visual Search." *Journal of Cognitive Neuroscience* 21 (4): 760–75.

Hoffmann, Joachim, and Wilfried Kunde. 1999. "Location-Specific Target Expectancies in Visual Search." *Journal of Experimental Psychology. Human Perception and Performance* 25 (4): 1127–41.

Jiang, Yuhong V., Khena M. Swallow, and Gail M. Rosenbaum. 2013. "Guidance of Spatial Attention by Incidental Learning and Endogenous Cuing." *Journal of Experimental Psychology. Human Perception and Performance* 39 (1): 285–97.

Jiang, Yuhong V., Khena M. Swallow, Gail M. Rosenbaum, and Chelsey Herzig. 2013. "Rapid Acquisition but Slow Extinction of an Attentional Bias in Space." *Journal of Experimental Psychology. Human Perception and Performance* 39 (1): 87–99.

Kiesel, Andrea, Jeff Miller, Pierre Jolicoeur, and Benoit Brisson. 2008. “Measurement of ERP Latency Differences: A Comparison of Single-Participant and Jackknife-Based Scoring Methods.” *Psychophysiology* 45 (2): 250–74.

Larson, Michael J., Ann Clawson, Peter E. Clayson, and Scott A. Baldwin. 2013. “Cognitive Conflict Adaptation in Generalized Anxiety Disorder.” *Biological Psychology* 94 (2): 408–18.

Lopez-Calderon, Javier, and Steven J. Luck. 2014. “ERPLAB: An Open-Source Toolbox for the Analysis of Event-Related Potentials.” *Frontiers in Human Neuroscience* 8 (April):213.

Luck, S. J., and S. A. Hillyard. 1994. “Electrophysiological Correlates of Feature Analysis during Visual Search.” *Psychophysiology* 31 (3): 291–308.

Luck, Steven J. 2014. *An Introduction to the Event-Related Potential Technique, Second Edition*. MIT Press.

Mallat, Stephane G. 2009. “A Theory for Multiresolution Signal Decomposition: The Wavelet Representation.” In *Fundamental Papers in Wavelet Theory*, 494–513. Princeton: Princeton University Press.

Mazza, Veronica, Massimo Turatto, and Alfonso Caramazza. 2009a. “An Electrophysiological Assessment of Distractor Suppression in Visual Search Tasks.” *Psychophysiology* 46 (4): 771–75.

———. 2009b. “Attention Selection, Distractor Suppression and N2pc.” *Cortex; a Journal Devoted to the Study of the Nervous System and Behavior* 45 (7): 879–90.

Moorselaar, Dirk van, and Heleen A. Slagter. 2019. “Learning What Is Irrelevant or Relevant: Expectations Facilitate Distractor Inhibition and Target Facilitation through Distinct Neural Mechanisms.” *The Journal of Neuroscience: The Official Journal of the Society for Neuroscience* 39 (35): 6953–67.

———. 2020. “Inhibition in Selective Attention.” *Annals of the New York Academy of Sciences* 1464 (1): 204–21.

Moorselaar, D. van, Nasim Daneshtalab, and Heleen A. Slagter. 2021. “Neural Mechanisms Underlying Distractor Inhibition on the Basis of Feature And/or Spatial Expectations.” *Cortex; a Journal Devoted to the Study of the Nervous System and Behavior* 137 (April):232–50.

Neuper, Christa, Michael Wörtz, and Gert Pfurtscheller. 2006. “ERD/ERS Patterns Reflecting Sensorimotor Activation and Deactivation.” *Progress in Brain Research* 159:211–22.

Oostenveld, Robert, Pascal Fries, Eric Maris, and Jan-Mathijs Schoffelen. 2011. “FieldTrip: Open Source Software for Advanced Analysis of MEG, EEG, and Invasive Electrophysiological Data.” *Computational Intelligence and Neuroscience* 2011:156869.

Qiu, Nan, Bei Zhang, Fredrik Allenmark, Jan Nasemann, Shao-Yang Tsai, Hermann J. Müller, and Zhuanghua Shi. 2023. “Long-Term (statistically Learnt) and Short-Term (inter-Trial) Distractor-Location Effects Arise at Different Pre- and Post-Selective Processing Stages.” *Psychophysiology* 60 (10): e14351.

Sauseng, P., W. Klimesch, W. Stadler, M. Schabus, M. Doppelmayr, S. Hanslmayr, W. R. Gruber, and N. Birbaumer. 2005. “A Shift of Visual Spatial Attention Is Selectively Associated with Human EEG Alpha Activity.” *The European Journal of Neuroscience* 22 (11): 2917–26.

Sauter, Marian, Heinrich René Liesefeld, Michael Zehetleitner, and Hermann J. Müller. 2018. “Region-Based Shielding of Visual Search from Salient Distractors: Target Detection Is Impaired with Same- but Not Different-Dimension Distractors.” *Attention, Perception & Psychophysics* 80 (3): 622–42.

Shaw, M. L., and P. Shaw. 1977. “Optimal Allocation of Cognitive Resources to Spatial Locations.” *Journal of Experimental Psychology. Human Perception and Performance* 3 (2): 201–11.

Slagter, H. A., S. Prinssen, L. C. Reteig, and A. Mazaheri. 2016. “Facilitation and Inhibition in Attention: Functional Dissociation of Pre-Stimulus Alpha Activity, P1, and N1 Components.” *NeuroImage* 125 (January):25–35.

Spaak, Eelke, Yvonne Fonken, Ole Jensen, and Floris P. de Lange. 2016. “The Neural Mechanisms of Prediction in Visual Search.” *Cerebral Cortex* 26 (11): 4327–36.

Tay, Daniel, Victoria Harms, Steven A. Hillyard, and John J. McDonald. 2019. “Electrophysiological Correlates of Visual Singleton Detection.” *Psychophysiology* 56 (8): e13375.

Theeuwes, Jan, Louisa Bogaerts, and Dirk van Moorselaar. 2022. “What to Expect Where and When: How Statistical Learning Drives Visual Selection.” *Trends in Cognitive Sciences* 26 (10):

860–72.

Thut, Gregor, Annika Nietzel, Stephan A. Brandt, and Alvaro Pascual-Leone. 2006. "Alpha-Band Electroencephalographic Activity over Occipital Cortex Indexes Visuospatial Attention Bias and Predicts Visual Target Detection." *The Journal of Neuroscience: The Official Journal of the Society for Neuroscience* 26 (37): 9494–9502.

Töllner, Thomas, Michael Zehetleitner, Klaus Gramann, and Hermann J. Müller. 2011. "Stimulus Saliency Modulates Pre-Attentive Processing Speed in Human Visual Cortex." *PloS One* 6 (1): e16276.

Turatto, Massimo, and Matteo Valsecchi. 2022. "Impaired Selection of a Previously Ignored Singleton: Evidence for Salience Map Plastic Changes." *Quarterly Journal of Experimental Psychology* 75 (6): 1114–20.

Wang, Benchi, Joram van Driel, Eduard Ort, and Jan Theeuwes. 2019. "Anticipatory Distractor Suppression Elicited by Statistical Regularities in Visual Search." *Journal of Cognitive Neuroscience* 31 (10): 1535–48.

Woodman, G. F., and S. J. Luck. 1999. "Electrophysiological Measurement of Rapid Shifts of Attention during Visual Search." *Nature* 400 (6747): 867–69.

Yu, Hao, Fredrik Allenmark, Hermann J. Müller, and Zhuanghua Shi. 2023. "Asymmetric Learning of Dynamic Spatial Regularities in Visual Search: Robust Facilitation of Predictable Target Locations, Fragile Suppression of Distractor Locations." *Journal of Experimental Psychology. Human Perception and Performance* 49 (5): 709–24.

———. 2025. "Learning Regular Cross-Trial Shifts of the Target Location in Serial Search Involves Awareness - An Eye-Tracking Study." *Cognition* 254 (105977): 105977.

Zhang, Bei, Fredrik Allenmark, Heinrich René Liesefeld, Zhuanghua Shi, and Hermann J. Müller. 2019. "Probability Cueing of Singleton-Distractor Locations in Visual Search: Priority-Map- versus Dimension-Based Inhibition?" *Journal of Experimental Psychology. Human Perception and Performance* 45 (9): 1146–63.

Zhao, Guang, Qiang Liu, Ye Zhang, Jun Jiao, Qinglin Zhang, Hongjin Sun, and Hong Li. 2011. "The Amplitude of N2pc Reflects the Physical Disparity between Target Item and Distracters." *Neuroscience Letters* 491 (1): 68–72.

3 General Discussion

The present dissertation explores the behavioral and neural mechanisms involved in statistical learning mechanisms of target location and how this location knowledge facilitates visual search. It examines the interplay between dynamic spatial statistical regularities of target locations and our explicit awareness of these patterns, and investigates how our neural responses are shaped by these learned regularities. To do this, we used psychophysics, eye-tracking techniques and electrophysiological methods. In the subsequent sections, I will briefly summarize the key findings from each empirical study and their contribution to our understanding. In the end, I will outline potential future research directions and wrap up with a summary.

3.1 Summary of Results

3.1.1 Learning of dynamic spatial regularities in visual search and the role of explicit awareness in spatial statistical learning

To briefly recap the first study (Chapter 2.1), by adopting the classic additional-singleton paradigm and introducing cross-trial spatial regularities for the singleton color distractor (Experiment 1a) and singleton shape target (Experiment 1b), we found that the regularity of the cross-trial transition of the target location could be learned successfully to facilitate target search. In contrast, the dynamic regularity of the cross-trial distractor location had no significant effect on search performance. Since Experiment 1a failed to yield any evidence that participants could extract and utilize the dynamic spatial regularity regarding the distractor across trials, which is at variance with Wang et al. (2021), we decided to conduct Experiment 2. In Experiment 2a, a direct replication of Wang’s Experiment 1 was conducetd to examine whether our non-finding was due to the methodological changes we had introduced in our task design compared to Wang's (2021) study, and Experiment 2b was designed to examine dynamic target-locations learning with analogous design. However, we observed no evidence of dynamic distractor-location learning but only dynamic target-location learning in the ‘regular’ group. Also, no participants were able to explicitly tell the distractor's movement pattern in Experiment 2a, alternatively, Experiment 2b confirmed dynamic target-location learning to be a robust phenomenon associated with awareness of regularity.

The statistical learning of the target position that we observed in Experiment 1b is broadly consistent with the probability cueing of the target location reported in the literature (Geng and Behrmann 2002, 2005; Shaw and Shaw 1977), which we introduced before (General introduction). For instance, in a study by Geng and Behrmann (2002), where the likelihood of target presentation was manipulated unevenly between the left and right sides of the display (80% vs. 20%), search facilitation was observed when the target appeared within the more probable region. Of note, though, most of the previous target-location probability-cueing studies used a stationary (i.e., spatially fixed) uneven probability manipulation (either location- or region-based), finding that search guidance can successfully adapt to these environmental statistics to enhance performance. A recent study, by Li and Theeuwes (2020), showed that this adaptability also extends to dynamic location manipulations: when the target on trial n-1 (appearing, say, at the leftmost display location) predicted the location of the target on trial n (in the example, the right-most location) with 100% certainty, participants were also able to learn this cross-trial regularity to facilitate search performance. In the current study, we showed that a dynamic cross-trial regularity can also be learned when it is probabilistic (rather than deterministic) in nature. Similar to earlier studies (e.g., Geng and Behrmann 2002), we implemented an uneven cross-trial transitional probability structure (80% for cross-trial frequent, 10% for infrequent, and 10% for random transitions) and showed that participants could learn this probabilistic regularity and use it to facilitate target detection. Importantly, in our study, the global probability of the target occurrence remained equal across all possible locations – only the cross-trial transitional probability differed in the direction of the target movement (clockwise or counterclockwise). This suggests that the search-guidance system can learn and adapt to dynamic as well as fixed probability structures that govern where the target appears, and modify the computation of attentional priorities accordingly

In contrast to robust cross-trial dynamic probability-cueing of the target location, we found no evidence that participants were able to learn the same dynamic probability structure when this was applied to predict the distractor location in Experiment 1a (80% probabilistic manipulation), Experiment 2a (100% deterministic manipulation), which differs from previous studies that have demontrated that display locations/regions with a high probability of distractor occurrence can be effectively de-prioritized to reduce the interference caused by the irrelevant pop-out stimulus (Ferrante et al. 2018; Goschy et al. 2014; Leber et al. 2016; Sauter et al. 2018; Sauter, Liesefeld, and Müller 2019; Benchi Wang and Theeuwes 2018; Zhang et al. 2019; Kerzel, Huynh Cong, and Burra 2021; Steven J. Luck et al. 2021). For example, likely distractor locations may be proactively suppressed by placing a 'no-go' tag on them within the attentional priority map (e.g., Ferrante et al. 2018; see also Gaspelin, Leonard, and Luck 2015; Gaspelin and Luck 2018), thereby dampening the build-up of the priority signal at those locations. Support for this also comes from a recent study by Kong et al. (2020) who combined a variation of Gaspelin et al.'s (2015) 'capture-probe' paradigm with a *static* distractor-location probability-cueing paradigm. And they found that the guess rate to be increased and the precision to be somewhat decreased following a distractor at the likely vs. an unlikely location. Huang, Donk, and Theeuwes (2022) reported a similar result even when the probe display was not preceded by a search display (i.e., when there was no distractor, however briefly presented, that could initiate reactive processes). These findings align with the proactive suppression of information uptake from likely distractor locations. Hence, although proactive suppression of fixed likely distractor locations is a readily available strategy for the search-guidance system to reduce attentional capture, our findings imply that proactive suppression of dynamically predictable distractor locations is considerably more intricate, particularly under the same dynamic probability structure and number of learning trials used for the target location in our study.

While our experiments show that observers acquire a dynamic probabilistic regularity more readily regarding the location of targets compared to distractors, questions persist regarding why it is difficult to acquire dynamic suppression of predictable distractor locations, whereas it is easy to establish dynamic facilitation of predicted target locations. The clue to answering this question is provided by the 'awareness' results.

In both Experiment 1b (80% predictability of the shifting target location) and Experiment 2b (100% predictability), participants became substantially aware of the dynamic target regularity. Additionally, participants who correctly identified the right regularity in the awareness test also showed a larger facilitation effect compared to those who were unaware. Note, though, that the general response speed was faster in Experiment 2b (in which the color of the display items was consistent across trials) than in Experiment 1b (in which the items' color changed randomly across trials), with a higher level of awareness. This is not to say that the dynamic target regularity cannot be implicitly learned (see, e.g., Li and Theeuwes 2020), but the learning effect appears to be larger for 'aware' than 'unaware' participants. In light of the fact that explicit awareness greatly boosted the dynamic facilitation effect, it is reasonable to conclude that participants did develop a dynamic top-down set to prioritize the next target location in the regular (clockwise or counterclockwise) direction (endogenous orienting in Posner 1980 terms). Developing such an anticipatory top-down set is likely encouraged by the central role of the target in the task set: observers compare selected items to a target template in working memory, and then reject them if they are mismatched, or extract the response-relevant feature if they match. As the target occupies a central position in the task set, even seemingly irrelevant features, such as its location, may be explicitly encoded, providing the basis for recognizing and exploiting consistency in the placement and movement of the target between trials. Alternatively, when a distractor is mistakenly selected, the cognitive system only needs to recognize it as a non-target item and reject it based on its deviation from the target template. Unlike target items, there is no necessity to process or explicitly represent detailed features of the distractor, including its location. Consequently, there's minimal explicit learning of higher-order dynamic statistical regularities related to the placement of distractors.

However, a number of studies investigating static statistical regularities have shown that distractor-location probability cueing effects can occur without conscious awareness of a bias in the distractor distribution -that is, with a fixed display location or region being more likely to contain a distractor than other locations. One recent research has demonstrated that static cueing effects are purely dependent on the local distractor probability (Allenmark et al. 2022), and higher frequency of distractor occurrence at a particular location result in stronger down-modulation of neural responsivity in early visual cortex areas (V1–V4) (Zhang et al. 2021). Also, the down-modulation of neural activity in response to frequent distractor occurrence is proposed to be driven by a "tuning" signal. This signal is activated when a selected distractor at this location produces a mismatch decision. The more frequently this mismatch occurs at a particular location, the less the responsiveness of V1–V4 neurons with corresponding receptive fields. This mechanism naturally explains the static distractor-location probability-cueing effect, as it reflects an essentially static process of top-down inhibition of the current distractor location. This inhibition aims to disengage attention from the distractor and redeploy it to the target location, all without the need for conscious knowledge of the distractor location.

In contrast, successfully tracking a dynamically predictable target location hinges on explicit representation of the rule in working memory as part of the task set. And this rule can then be applied to flexibly prioritize an anticipated next target location, perhaps by top-down pre-activating the anticipated location on the attentional priority map. Further, according to Ptak's (2012) model of this network, the posterior parietal cortex plays a central role in a computing feature- and dimension -independent attentional-priority map. This map integrates feature maps computed in the sensory cortex, current behavioral goals and abstract representations of associated actions (action templates) generated in the prefrontal and premotor cortex (PMC). The dorsolateral prefrontal cortex (DLPFC) maintains behavioral goals in working memory, shielding them from distracting information, while the inferior parietal lobe (IPL) initiates and maintains attention on the relevant stimulus" (Ptak 2012, 512). Given this model, it is plausible that dynamic spatial expectations from DLPFC and PMC can also be integrated in the priority map.

3.1.2 Dynamic target spatial learning in serial search involves awareness: from behavioral and oculomotor evidence

In the second study (Chapter 2.2), we concentrated on examining (1) whether, in a serial search task, participants can learn a simple dynamic (probabilistic), cross-trial regularity regarding the location of the target within a search display, and if so, (2) when during the search guidance by the regularity would come into play - the latter by examining (sequential) oculomotor scanning of the displays, as well as the task-final RTs, for evidence of a dynamic target-location probability-cueing effect; further (3) whether dynamic learning would rely on explicit awareness of the regularity. To do this, our second study adopted the same dynamic, cross-trial regularity as Chapter 2.1 did in a parallel search task. This involved shifting the target location in a circular display arrangement by one position, either clockwise or anticlockwise (blocked per participant) across trials with a probability of 80%.

According to study 2 of this dissertation, the following main findings were obtained: First, we found that people can effectively learn and utilize dynamic cross-trial regularities in target placement across trials, even in challenging, sequential search tasks. Such ability is not limited to parallel tasks where items stand out immediately and can be processed simultaneously. This at least applies to the regularity implemented here: a shift of the target location, within a circular display arrangement, by one position in either clockwise or counterclockwise direction (fixed per participant) – exactly the same regularity as that used in Chapter 2.1 in a parallel search task, which allowed for much faster completion times. Interestingly, relative to the random-condition baseline, the performance gains from successfully learning the rule turned out at least as large in the present, serial search task as in the parallel task of Chapter 2.1: the gains (infrequent minus frequent transition) here amounted to 339 ms, that is, 12.5% of the random-baseline RT (2707 ms) – which compares with a 9.4%-gain (116 ms/1236 ms) in parallel search. The intrinsic motivation to grasp the rule was similar in both types of task.

However, this finding appears to be at odds with earlier reports suggesting that the added demands imposed by serial search hinder participants from detecting dynamic regularities (Li and Theeuwes 2020; Li, Bogaerts, and Theeuwes 2022), who reported participants to be unable to pick up different type of regularity in serial search. The main difference between Li and colleagues’ (Li and Theeuwes 2020; Li, Bogaerts, and Theeuwes 2022; Yu et al. 2023) and our study (Chapter 2.2) lies in the complexity of the regular cross-trial shift and the frequency of encountering such shifts during search. More specifically, the proportion of trials on which the target moved to the location predicted by the dynamic regularity (80%) was three times greater in our design than in Li and Theeuwes' (only 25%). Additionally, we used a relatively simple dynamic target-location shift: either clockwise or counterclockwise, similar to how a circular search array might normally be scanned serially by participants. According to Li and Theeuwes, if the current target is in the leftmost array position, the next target will invariably appear at the rightmost position (but not vice versa). In addition to the fact that such shifts occur only relatively rarely (on approximately 25% of trials), they would also contradict the normal scanning routines. Thus, it is possible that the frequency with which regular dynamic shifts occur and the degree to which these shifts are compatible with routine scanning procedures (Seitz et al. 2023) may be critical factors determining whether or not a dynamic regularity is successfully acquired in serial scanning.

On the basis of our current findings, we can conclude that serial search doesn't prevent the extraction and utilization of dynamic regularities to optimize performance.

The second main finding is that we found that dynamic target-location probability cueing can act early during serial search. We found a large number of participants successfully learned to utilize the same cross-trial (statistical) regularity in the placement of the target and optimize performance in a serial search task. In addition to analyzing task-final response times, examination of oculomotor scanning behavior revealed that dynamic target-location probability cueing influences early stages of serial search. Notably, a significant proportion (approximately one-third) of initial saccades were directed towards the predicted, frequent location, suggesting an early engagement of cueing effects. Another position receiving almost the same proportion of first saccades was the location that had previously contained the target, consistent with a positional repetition-priming effect (Maljkovic and Nakayama 1996b; Krummenacher et al. 2009). Interestingly, under conditions of fixed target identity, a greater proportion of initial saccades were directed towards the predicted location compared to the repeated locations, indicating the dominance of the target-location cueing effect over repetition-priming. Moreover, in any case, even under conditions of target-identity swapping, the frequent location received a much greater proportion of first saccades than the infrequent location, even though both were equidistant from the repeated position. This shows that search.

This indicates that the search priorities (or, correspondingly, the attentional spotlight) were systematically biased towards the frequent direction and away from the infrequent direction. Of note, this early biasing of search turned out to be quite independent of where the target was actually located in the display, that is: it reflects a genuine rule-based effect.

The early prioritization of the frequent and repeated locations was maintained during further scanning, evidenced by these locations continuing to attract the largest proportions of second and third saccades. However, when the target identity was fixed, it was found that the second and third saccade were influenced by whether the target actually appeared at the predicted, frequent location. A target appearing at the frequent location increased the proportion of (second and third) saccades directed to this location, whereas it decreased the proportions of saccades directed to the repeated and infrequent locations. That is, the priority of the frequent location on the second and third saccades was not only determined by the dynamic rule but also by the fit of the item at the predicted location to the fixed ‘target template’. This suggests that template-based (top-down) enhancement of priority signaling is focused on specifically the predicted location, rather than being ‘broadcast’ equally to all locations (Wiegand et al. 2024). Interestingly also: the fact that the prioritization of the frequent and repeated locations persisted beyond the first few saccades would imply that the prioritization is coded in scene-based (environmental), rather than retinal, coordinates: the coordinates are dynamically updated across sequential eye movements.

The last but not least point of discussion concerns the role of awareness for the dynamic target-location probability-cueing effect in serial search. In contrast to the majority of studies that explored probability-cueing effects and concluded that spatial statistical learning was not dependent on awareness and was therefore "implicit" in nature (e.g., Y. V. Jiang, Swallow, and Rosenbaum 2013; Y. V. Jiang, Won, and Swallow 2014; Won and Jiang 2015), we found strong evidence of the present, dynamic target-location cueing effect involving awareness. First of all, only participants classed as ‘aware’ (⅔ of participants) based on our post-experimental questionnaire showed a dynamic cueing effect in both the task-final RTs and the earliest eye movements; ‘unaware’ participants (⅓), by contrast showed no sign of a cueing effect in either early or late(r) measures of performance (they only exhibited a tendency to saccade to the previous target location). Second, in ‘aware’ participants, the strength of the cueing effect, even in the proportion of first eye movements directed to the predicted location, strongly correlated significantly with how realistically they believed the rule applied: the more accurately participants estimated the frequency with which the target shifted in the regular direction, the larger their cueing effect. Showing an element of ‘explicitness’ is in line with other studies that used more sensitive awareness tests (e.g., Giménez-Fernández et al. 2020; Golan and Lamy 2023), as well as our experiment of dynamic target-location cueing in *parallel* search (Yu et al. 2023) Chapter 2.1 (Yu et al. 2023). In particular, it is in line with the significant correlation reported by Giménez-Fernández et al. (2020), whose measures of awareness we adopted in present study. Interestingly, however, here a role of awareness was seen in a relatively small sample (in 16 out of a total of 24 participants) – arguing that, at least in the present, dynamic scenario, a large sample size may not be crucial for demonstrating ‘awareness’.

However, exactly what is the role of awareness in the dynamic cueing effect? The effect is, in some way, dependent on awareness, as only the group of ‘aware’ participants showed a benefit, but not the ‘unaware’ group. But, despite a significant correlation between awareness of the dynamic regularity and the cueing effect, does this mean that this effect is a ‘voluntary’ in nature, that is, mediated by participants deliberately applying the rule to guide their search on each (or most) trial(s)? While this is a possibility, recall that the latencies of first saccade to the predicted location were rather short (some 190 ms), as were, in fact, the latencies to the repeated and infrequent locations (somewhat over 200 ms) which were both shorter compared to random locations (> 220 ms). This pattern suggests an ensuing competition, upon display onset, of the search items at locations in the general direction of the previous target position (to which the task had just required a saccade to be executed), for which activity remains elevated across trials on some (integrative) oculomotor priority map, likely, in the superior colliculus (e.g., Veale, Hafed, and Yoshida 2017). Thus, while the repeated location remains a strong attractor for the next eye movement (the first saccade on the new trial), this competition is then resolved in favor of the frequent location, perhaps through a rule-related input injected into the priority representation via frontal-eye-field neurons that represent the dynamically updated, ‘goal’-related priority. Given that the display array was not visible during the intertrial interval (there were no placeholders), the updating of the saccade goal may happen only after search-display onset. In this case, latencies (well) below 200 ms may not be sufficient for consciously mediated inputs to influence saccade programing.[29] Accordingly, one would have to assume that rule-based dynamic goal updating, while perhaps initially requiring conscious control to be set up, eventually becomes a rather automatized, 'implicit' process that runs off without 'explicit' cognitive intervention (cf. Schneider and Shiffrin 1977). Thus, it may be premature to conclude from the correlation between awareness of the dynamic regularity and the cueing effect that this effect is causally mediated by awareness on each (or most) trial(s).

Overall, it remains that there is no *dynamic target*-location probability-cueing effect in *serial* search when there is no awareness of the regularity. In Chapter 2.2, where we implemented the same cross-trial regularity, we argued that this also applies to dynamic *target*-location cueing in *parallel* search. By implication, we attributed our finding that the same regularity did *not* produce a cueing effect when it was implemented in a pop-out *distractor* in *parallel* search to the fact that participants did *not* become of the regularity in the cross-trial distractor-location shift – whereas participants became aware of the exact-same shift when implemented in the pop-out target.[30] Thus, we propose that participants becoming aware of the regularity (and, on the part of the experimenter, establishing awareness by sensitive measures; cf. Vadillo, Konstantinidis, and Shanks 2016; Vadillo et al. 2020; Giménez-Fernández et al. 2020) is crucial for dynamic probability-cueing effects in any type – serial or parallel – of search to develop.

3.1.3 Target spatial statistical learning and its plastic changes on attentional processing: behavioral and electrophysiological evidence

To briefly review the third study (Chapter 2.3), the purpose of the study was to investigate (1) how target spatial statistical learning modulate attentional selection across trials at the neural level, by examining N2pc component; (2) whether the learning spatial regularity can cause long lasting changes affect attention selection when the regularity regarding target locations was removed, and its related electrophysiological evidence; (3) whether any anticipatory facilitation occurs before search display onset, by examining the pre-stimulus alpha activity. A serial search paradigm was employed in the current study, participants need to find and respond to the target (either the letter T or T like letter, the target is balanced across participants) in the training phase, where the probability manipulation of target location was implemented across trials; participants were required to find and respond to the

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[29] This would also be consistent with Findlay (1997), who concluded from his study of saccade target selection during pop-out and feature-conjunction searches that "the generation of the first saccade is a relatively automatic process, rather than one which is subject to cognitive control" (p. 628).

[30] This would also explain Li and Theeuwes' (2020) non-finding: their participants did not become unaware of their (more complex and less likely) dynamic target-location regularity and accordingly exhibited no cueing effect.

target while ignoring a distractor (the distractor was the target in the training phase) which shared similarity with the target in the testing phase.

Behaviorally, our study confirmed that spatial statistical learning enhances target selection during visual search, leading to efficient target selection. In the training phase, participants showed faster reaction times (RTs) in target-frequent conditions compared to target-infrequent conditions, indicating a target-location probability cueing effect. This learning transferred to the testing phase, albeit with diminished effect, suggesting some inflexibility in visual processing. Electrophysiologically, we found that N2pc latency was earlier for targets appearing in frequent locations than targets appearing in infrequent locations in the training phase. Latency results are consistent with the pattern of RTs observed during the Training. We assume that the optimal performance observed in the frequent condition might be the result from the increased activation on the spatial priority map. Interestingly, with visual inspection for the infrequent condition, the attention was also biased to frequent location first after stimulus onset, and then turned to the opposite side of the visual display. It is noteworthy, however, this learned attentional enhancement was not accompanied by known encephalographic markers of attentional selection - lateralized anticipatory alpha power relative to anticipated target location. Instead, a more negative N2pc amplitude at target-frequent locations relative to target-infrequent locations was observed, indicating enhanced attentional allocation to learned target locations, consistent with the findings in another study (D. H. Duncan, Theeuwes, and van Moorselaar 2023) using the singleton paradigm to investigate electrophysiological markers of statistical learned attentional enhancement. Another main finding in the testing phase is that we found that no matter where the target or distractor was located, the N2pc amplitude for frequent conditions was always greater than that for infrequent conditions, confirming the findings of the previous study (Chapter 2.2)

An interesting observation from the testing phase was that both target location cueing effect and distractor location cueing effect (opposite to target location cueing effect) were observed. Target location cueing effect was expected because attention is biased towards frequent locations due to the training. However, it is unclear as to why the cueing effect for the distractor appears to be opposite that for the target. To quantify the distractor cueing effect, we subtract RTs of the distractor at frequent locations from RTs of distractors at frequent locations. Participants show slower RTs when the distractor appears at frequent locations. This is because attention is initially directed towards these frequent locations regardless of where the target or distractor is, and participants need to disengage attention from frequent locations to focus on the target on the other side, resulting in a time cost. Participants show faster RTs when the distractor appears at infrequent locations. This is because attention is still biased towards the frequent locations, so when the distractor appears at infrequent locations, there's less interference from the pre-existing attentional bias. Importantly, the findings from EEG analysis were consistent with findings from behavioral results. We observed, when target occurred at midline locations, the N2pc latency for distractor-frequent condition start significantly earlier than the N2pc latency for distractor-infrequent condition, meanwhile the N2pc amplitude for distractor-frequent condition was more more negative than that of distractor-infrequent condition, suggesting distrator-frequent location got more attention resource. From other conditions in EEG analysis, it appears that participants always start locating their attention at frequent locations regardless of the real location of the distractor or target. In this regard, it can be inferred that the spatial statistical learning that occurs during the training phase has resulted in long-lasting plastic changes on visual selection, and that its effect is somehow not responsive (flexible) to the new environment.

Further of interest, some studies reported that increasing the salience of targets compared to surrounded distractors leads to a monotonic increase on the N2pc amplitude observed in EEG recordings, which also heightened amplitude reflects enhanced attentional allocation toward the target facilitated by the improved saliency contrast between the targets and distractors (Berggren and Eimer 2020; Zhao et al. 2011; Töllner et al. 2011; Mazza, Turatto, and Caramazza 2009). However, in our EEG experiment which involved serial search, instead of using a singleton target, we used a target that shared similarity with the distractor item, we found that the amplitude of N2pc for target-frequent location is significant negative/larger relative to target-infrequent condition, which was also confirmed by another study using a singleton target (D. H. Duncan, Theeuwes, and van Moorselaar 2023). Thus, our findings confirm the idea that the ease of distinguishing targets from background elements contribute to probability cueing effect which is indicated by N2pc amplitude, and providing insights into attentional selection and target processing in visual search tasks.

Many studies focus on investigating the role of alpha power in statistical learning of distractor suppression (Ferrante et al. 2023; Dirk van Moorselaar and Slagter 2019; Qiu et al. 2023). In addition the alpha band is also considered as an important neural signature to understand target enhancement in attentional processes. Some studies emphasized the association between attentional facilitation and alpha power: they found a decrease of alpha power contralateral to the target location reappearing relatively late after target onset (Bacigalupo and Luck 2019; van Diepen et al. 2016). It was reported, however, that limited evidence was provided for the role of pre-stimulus alpha activity in statistical learning of target facilitation. In the current study, no changes in pre-stimulus alpha-band activity were observed as a function of the target location condition. In contrast, an early study reported that prior knowledge of the target location can trigger significant preparatory alphas modulation over the visual cortex (Spaak et al. 2016). However, Spaak et al. did not manipulate the probability of target locations through the experiment. Thus, we assume that alpha power can not reflect target spatial statistical learning, which is consistent with a recent study that also failed to show reliable tuning toward high-probability target location (D. H. Duncan, Theeuwes, and van Moorselaar 2023). They also suggested that the prediction result from target spatial statistical learning might not be controlled under the top-down neural mechanism.

3.2 Future research directions

The findings from this dissertation open up exciting directions for future research. Specifically, Studies 1 and 2 both look into how learning likely target locations are likely to enhance perceptual and decision processes during visual search. We conclude that 1) Predictable target locations can significantly facilitate search in both serial and parallel search modes. 2) Being aware of dynamic regularity of the target is crucial for learning this dynamic probability-cueing, independent of serial or parallel search. Beyond these shared findings, Study 1 reveals that when a dynamically predictable target location is successfully tracked with explicitly (consciously) rules, it allows us to flexibly prioritize a likely next target location, possibly achieved through top-down pre-activation of the anticipated location on the attentional priority map.

Further investigation through neuroscientific research is necessary to better understand the brain mechanisms underlying dynamic target-location prediction. These mechanisms are likely to involve the frontoparietal attention network, a richly interconnected network encompassing regions such as the intraparietal sulcus (IPS), the inferior parietal lobe (IPL), and dorsal premotor cortex (PMC), including the frontal eye field (FEF) (A. Kristjánsson et al. 2007). Also, considering that we observed a significant facilitation effect in the dynamically predictable target location, yet no corresponding suppression effect in the dynamically predictable location of the distractor in Study 1, which suggests potential disparities in cognitive processing between these phenomena. Thus, future studies are also needed to investigate neural processing differences between target enhancement resulting from learning across-trial target locations and distractor suppression resulting from learning across-trial distractor locations. From a clinical perspective, leveraging the dynamic spatial statistical regularities of distractor and target feature/locations can greatly aid cognitive interventions in patients with attention deficit hyperactivity disorder (ADHD) or autism. For instance, therapists can design cognitive training tasks that specifically target attentional control by systematically incorporating these regularities. By repeatedly exposing individuals to distractor and target patterns in a controlled environment, therapy can enhance cognitive flexibility and improve attentional allocation. Additionally, clinicians can develop personalized strategies to help patients actively identify and prioritize relevant information while suppressing distractions in daily life settings, ultimately improving cognitive functioning and quality of life. In Study 2, crucially, the dynamic target-location probability-cueing effect is evident even in (both the proportion and latency of) the very first saccade elicited upon search-display onset, which is purely motivated by the learned rule and not by the actual location of the target in the display. Further, it correlates with participants' awareness of the dynamic regularity. However, given how fast the rule-injected bias can operate after display onset (it is evident already in the very first saccades, elicited between 100 and 150 ms post-display onset), the cueing effect itself may not be consciously mediated. In this case, though, awareness would play a crucial role in acquiring the effect in the first instance. Alternatively, the rule-based biasing may already be ‘prepared’ in the intertrial interval, allowing the cueing effect to ramp up rapidly after search display onset. More work, for instance involving electrophysiological measures, is necessary to clarify this. Also, further work would be required to map the boundary conditions, in terms of both the complexity of dynamic target regularities and the frequency with which they occur, for a cueing effect to be observable.

Study 3 provides strong empirical evidence to understand the neural mechanisms involved in target-location enhancement and long-term plastic changes caused by it. On electrophysiological measures, statistical learning of the likely target location was manifested in a post-display onset N2pc, but not in lateralized alpha power pre-stimulus.

3.3 Conclusions

This dissertation provided strong empirical evidence to understand the behavioral and neuropsychological mechanisms involved in spatial statistical learning effect (both dynamic and static). In a detailed investigation, we found that individuals could significantly improve their search performance by leveraging dynamic cross-trial regularities, while we failed to find similar effects for dynamic distractor regularities in Chapter 2.1. With oculomotor evidence, Chapter 2.2 reveals that participants were able to extract dynamic regularities in target placement during serial search tasks and utilized them to improve search performance. Remarkably, this dynamic learning effect manifests from the very first saccade following the search display onset, implying a pre-attentive adjustment of attentional focus based dynamic rules, allowing the cueing effect to occur fast after search display onset. This cueing effect is tightly linked to participants' awareness of the regularities. Additionally, Chapter 2.3 expands behavioral and electrophysiological evidence of statistical learning in target selection, demonstrating long-lasting spatial prioritization (transferability from the training to the testing phase) of target locations and attentional biasing. The enduring effects on spatial prioritization and attentional guidance are mirrored in the changes of N2pc amplitudes and latencies, though we did not observe any modulation of alpha-band activity.

To conclude, the current thesis not only confirms the pivotal influence of spatial statistical learning on target selection but also deepens our understanding of the underlying perceptual and decision processes that facilitate target selection enhancement. Through rigorous empirical investigation, I’ve illuminated how learning of dynamic and static probability distribution of the target location significantly alters attentional guidance, underscoring the power of selection history through environmental regularities that our brains adapt to and optimize with.

References (General Introduction and General Discussion)

Allenmark, Fredrik, Bei Zhang, Heinrich René Liesefeld, Zhuanghua Shi, and Hermann J. Müller. 2019. “Probability Cueing of Singleton-Distractor Regions in Visual Search: The Locus of Spatial Distractor Suppression Is Determined by Colour Swapping.” *Visual Cognition* 27 (5-8): 576–94.

Allenmark, Fredrik, Bei Zhang, Zhuanghua Shi, and Hermann J. Müller. 2022. “Learning to Suppress Likely Distractor Locations in Visual Search Is Driven by the Local Distractor Frequency.” *Journal of Experimental Psychology. Human Perception and Performance* 48 (11): 1250–78.

Anderson, Brian A. 2013. “A Value-Driven Mechanism of Attentional Selection.” *Journal of Vision* 13 (3). https://doi.org/10.1167/13.3.7.

———. 2016. “The Attention Habit: How Reward Learning Shapes Attentional Selection.” *Annals of the New York Academy of Sciences* 1369 (1): 24–39.

Anderson, Brian A., Haena Kim, Andy J. Kim, Ming-Ray Liao, Lana Mrkonja, Andrew Clement, and Laurent Grégoire. 2021. “The Past, Present, and Future of Selection History.” *Neuroscience and Biobehavioral Reviews* 130 (November):326–50.

Anderson, Brian A., Patryk A. Laurent, and Steven Yantis. 2011. “Value-Driven Attentional Capture.” *Proceedings of the National Academy of Sciences of the United States of America* 108 (25): 10367–71.

Awh, Edward, Artem V. Belopolsky, and Jan Theeuwes. 2012. “Top-down versus Bottom-up Attentional Control: A Failed Theoretical Dichotomy.” *Trends in Cognitive Sciences* 16 (8): 437–43.

Bacigalupo, Felix, and Steven J. Luck. 2019. “Lateralized Suppression of Alpha-Band EEG Activity As a Mechanism of Target Processing.” *The Journal of Neuroscience: The Official Journal of the Society for Neuroscience* 39 (5): 900–917.

Bacon, W. F., and H. E. Egeth. 1994. “Overriding Stimulus-Driven Attentional Capture.” *Perception & Psychophysics* 55 (5): 485–96.

Baluch, Farhan, and Laurent Itti. 2011. “Mechanisms of Top-down Attention.” *Trends in Neurosciences* 34 (4): 210–24.

Becker, Stefanie I., Anna Grubert, and Paul E. Dux. 2014. “Distinct Neural Networks for Target Feature versus Dimension Changes in Visual Search, as Revealed by EEG and fMRI.” *NeuroImage* 102 Pt 2 (November):798–808.

Berggren, Nick, and Martin Eimer. 2020. “Spatial Filtering Restricts the Attentional Window during Both Singleton and Feature-Based Visual Search.” *Attention, Perception & Psychophysics* 82 (5): 2360–78.

Chelazzi, Leonardo, Andrea Perlato, Elisa Santandrea, and Chiara Della Libera. 2013. “Rewards Teach Visual Selective Attention.” *Vision Research* 85 (June):58–72.

Chen, Siyi, Zhuanghua Shi, Artyom Zinchenko, Hermann J. Müller, and Thomas Geyer. 2022. “Cross-Modal Contextual Memory Guides Selective Attention in Visual-Search Tasks.” *Psychophysiology*, February, e14025.

Christie, Gregory J., Ashley C. Livingstone, and John J. McDonald. 2015. “Searching for Inefficiency in Visual Search.” *Journal of Cognitive Neuroscience* 27 (1): 46–56.

Chun, Marvin M., and Yuhong Jiang. 1999. “Top-Down Attentional Guidance Based on Implicit Learning of Visual Covariation.” *Psychological Science* 10 (4): 360–65.

———. 2003. “Implicit, Long-Term Spatial Contextual Memory.” *Journal of Experimental Psychology. Learning, Memory, and Cognition* 29 (2): 224–34.

Chun, Marvin M., and René Marois. 2002. “The Dark Side of Visual Attention.” *Current Opinion in*

Neurobiology 12 (2): 184–89.

Chun, M. M., and Y. Jiang. 1998. “Contextual Cueing: Implicit Learning and Memory of Visual Context Guides Spatial Attention.” *Cognitive Psychology* 36 (1): 28–71.

Chun, M. M., and E. A. Phelps. 1999. “Memory Deficits for Implicit Contextual Information in Amnesic Subjects with Hippocampal Damage.” *Nature Neuroscience* 2 (9): 844–47.

Della Libera, Chiara, and Leonardo Chelazzi. 2006. “Visual Selective Attention and the Effects of Monetary Rewards.” *Psychological Science* 17 (3): 222–27.

———. 2009. “Learning to Attend and to Ignore Is a Matter of Gains and Losses.” *Psychological Science* 20 (6): 778–84.

Della Libera, Chiara, Andrea Perlato, and Leonardo Chelazzi. 2011. “Dissociable Effects of Reward on Attentional Learning: From Passive Associations to Active Monitoring.” *PloS One* 6 (4): e19460.

Di Caro, Valeria, Jan Theeuwes, and Chiara Della Libera. 2019. “Suppression History of Distractor Location Biases Attentional and Oculomotor Control.” *Visual Cognition* 27 (2): 142–57.

Diepen, Rosanne M. van, Lee M. Miller, Ali Mazaheri, and Joy J. Geng. 2016. “The Role of Alpha Activity in Spatial and Feature-Based Attention.” *eNeuro* 3 (5). https://doi.org/10.1523/ENEURO.0204-16.2016.

Druker, Michael, and Britt Anderson. 2010. “Spatial Probability AIDS Visual Stimulus Discrimination.” *Frontiers in Human Neuroscience* 4 (August). https://doi.org/10.3389/fnhum.2010.00063.

Drummond, Leslie, and Sarah Shomstein. 2010. “Object-Based Attention: Shifting or Uncertainty?” *Attention, Perception & Psychophysics* 72 (7): 1743–55.

Duncan, Dock H., Jan Theeuwes, and Dirk van Moorselaar. 2023. “The Electrophysiological Markers of Statistically Learned Attentional Enhancement: Evidence for a Saliency-Based Mechanism.” *Journal of Cognitive Neuroscience*, October, 1–16.

Duncan, J., and G. W. Humphreys. 1989. “Visual Search and Stimulus Similarity.” *Psychological Review* 96 (3): 433–58.

Egeth, H. E., and S. Yantis. 1997. “Visual Attention: Control, Representation, and Time Course.” *Annual Review of Psychology* 48:269–97.

Eimer, M. 1996. “The N2pc Component as an Indicator of Attentional Selectivity.” *Electroencephalography and Clinical Neurophysiology* 99 (3): 225–34.

Eimer, Martin. 2014. “The Neural Basis of Attentional Control in Visual Search.” *Trends in Cognitive Sciences* 18 (10): 526–35.

Failing, Michel, and Jan Theeuwes. 2018. “Selection History: How Reward Modulates Selectivity of Visual Attention.” *Psychonomic Bulletin & Review* 25 (2): 514–38.

Failing, Michel, Benchi Wang, and Jan Theeuwes. 2019. “Spatial Suppression due to Statistical Regularities Is Driven by Distractor Suppression Not by Target Activation.” *Attention, Perception & Psychophysics* 81 (5): 1405–14.

Fecteau, Jillian H., and Douglas P. Munoz. 2006. “Salience, Relevance, and Firing: A Priority Map for Target Selection.” *Trends in Cognitive Sciences* 10 (8): 382–90.

Ferrante, Oscar, Alessia Patacca, Valeria Di Caro, Chiara Della Libera, Elisa Santandrea, and Leonardo Chelazzi. 2018. “Altering Spatial Priority Maps via Statistical Learning of Target Selection and Distractor Filtering.” *Cortex; a Journal Devoted to the Study of the Nervous System and Behavior* 102 (May):67–95.

Ferrante, Oscar, Alexander Zhigalov, Clayton Hickey, and Ole Jensen. 2023. “Statistical Learning of Distractor Suppression Downregulates Prestimulus Neural Excitability in Early Visual Cortex.” *The Journal of Neuroscience: The Official Journal of the Society for Neuroscience* 43 (12): 2190–98.

Findlay, J. M. 1997. “Saccade Target Selection during Visual Search.” *Vision Research* 37 (5): 617–31.

Fiser, József, and Richard N. Aslin. 2002. “Statistical Learning of Higher-Order Temporal Structure from Visual Shape Sequences.” *Journal of Experimental Psychology. Learning, Memory, and Cognition* 28 (3): 458–67.

Folk, Charles L., Andrew B. Leber, and Howard E. Egeth. 2002. “Made You Blink! Contingent Attentional Capture Produces a Spatial Blink.” *Perception & Psychophysics* 64 (5): 741–53.

Folk, Charles L., and R. Remington. 1998. “Selectivity in Distraction by Irrelevant Featural Singletons: Evidence for Two Forms of Attentional Capture.” *Journal of Experimental Psychology. Human Perception and Performance* 24 (3): 847–58.

Folk, C. L., R. W. Remington, and J. C. Johnston. 1992. “Involuntary Covert Orienting Is Contingent on Attentional Control Settings.” *Journal of Experimental Psychology. Human Perception and Performance* 18 (4): 1030–44.

Forschack, Norman, Christopher Gundlach, Steven Hillyard, and Matthias M. Müller. 2022. “Electrophysiological Evidence for Target Facilitation without Distractor Suppression in Two-Stimulus Search Displays.” *Cerebral Cortex* 32 (17): 3816–28.

Foster, Joshua J., and Edward Awh. 2019. “The Role of Alpha Oscillations in Spatial Attention: Limited Evidence for a Suppression Account.” *Current Opinion in Psychology* 29 (October):34–40.

Found, Andrew, and Hermann J. Müller. 1996. “Searching for Unknown Feature Targets on More than One Dimension: Investigating a ‘dimension-Weighting’ Account.” *Perception & Psychophysics* 58 (1): 88–101.

Foxe, John J., and Adam C. Snyder. 2011. “The Role of Alpha-Band Brain Oscillations as a Sensory Suppression Mechanism during Selective Attention.” *Frontiers in Psychology* 2 (July):154.

Gaffan, D. 1994. “Scene-Specific Memory for Objects: A Model of Episodic Memory Impairment in Monkeys with Fornix Transection.” *Journal of Cognitive Neuroscience* 6 (4): 305–20.

Gaspar, John M., Gregory J. Christie, David J. Prime, Pierre Jolicœur, and John J. McDonald. 2016. “Inability to Suppress Salient Distractors Predicts Low Visual Working Memory Capacity.” *Proceedings of the National Academy of Sciences of the United States of America* 113 (13): 3693–98.

Gaspelin, Nicholas, John M. Gaspar, and Steven J. Luck. 2019. “Oculomotor Inhibition of Salient Distractors: Voluntary Inhibition Cannot Override Selection History.” *Visual Cognition* 27 (3-4): 227–46.

Gaspelin, Nicholas, Carly J. Leonard, and Steven J. Luck. 2015. “Direct Evidence for Active Suppression of Salient-but-Irrelevant Sensory Inputs.” *Psychological Science* 26 (11): 1740–50.

Gaspelin, Nicholas, and Steven J. Luck. 2018. “Distinguishing among Potential Mechanisms of Singleton Suppression.” *Journal of Experimental Psychology. Human Perception and Performance* 44 (4): 626–44.

Geng, Joy J., and Marlene Behrmann. 2002. “Probability Cuing of Target Location Facilitates Visual Search Implicitly in Normal Participants and Patients with Hemispatial Neglect.” *Psychological Science* 13 (6): 520–25.

———. 2005. “Spatial Probability as an Attentional Cue in Visual Search.” *Perception & Psychophysics* 67 (7): 1252–68.

Geng, Joy J., and Phillip Witkowski. 2019. “Template-to-Distractor Distinctiveness Regulates Visual Search Efficiency.” *Current Opinion in Psychology* 29 (October):119–25.

Geyer, Thomas, Hermann J. Müller, and Joseph Krummenacher. 2006. “Cross-Trial Priming in Visual Search for Singleton Conjunction Targets: Role of Repeated Target and Distractor Features.” *Perception & Psychophysics* 68 (5): 736–49.

Geyer, Thomas, Pardis Rostami, Lisa Sogerer, Bernhard Schlagbauer, and Hermann J. Müller. 2020. “Task-Based Memory Systems in Contextual-Cueing of Visual Search and Explicit Recognition.” *Scientific Reports* 10 (1): 16527.

Giménez-Fernández, Tamara, David Luque, David R. Shanks, and Miguel A. Vadillo. 2020. “Probabilistic Cuing of Visual Search: Neither Implicit nor Inflexible.” *Journal of Experimental Psychology. Human Perception and Performance* 46 (10): 1222–34.

Golan, Aidai, and Dominique Lamy. 2023. “Attentional Guidance by Target-Location Probability Cueing Is Largely Inflexible, Long-Lasting, and Distinct from Inter-Trial Priming.” *Journal of Experimental Psychology. Learning, Memory, and Cognition*, March. https://doi.org/10.1037/xlm0001220.

Goschy, Harriet, Sarolta Bakos, Hermann J. Müller, and Michael Zehetleitner. 2014. “Probability Cueing of Distractor Locations: Both Intertrial Facilitation and Statistical Learning Mediate Interference Reduction.” *Frontiers in Psychology* 5 (November):1195.

Goujon, Annabelle, André Didierjean, and Simon Thorpe. 2015. “Investigating Implicit Statistical

Learning Mechanisms through Contextual Cueing." *Trends in Cognitive Sciences* 19 (9): 524–33.

Hikosaka, O., Y. Takikawa, and R. Kawagoe. 2000. "Role of the Basal Ganglia in the Control of Purposive Saccadic Eye Movements." *Physiological Reviews* 80 (3): 953–78.

Hoffmann, Joachim, and Wilfried Kunde. 1999. "Location-Specific Target Expectancies in Visual Search." *Journal of Experimental Psychology. Human Perception and Performance* 25 (4): 1127–41.

Holland, P. C., and M. E. Bouton. 1999. "Hippocampus and Context in Classical Conditioning." *Current Opinion in Neurobiology* 9 (2): 195–202.

Hopf, J. M., S. J. Luck, M. Girelli, T. Hagner, G. R. Mangun, H. Scheich, and H. J. Heinze. 2000. "Neural Sources of Focused Attention in Visual Search." *Cerebral Cortex* 10 (12): 1233–41.

Horowitz, T. S., and J. M. Wolfe. 1998. "Visual Search Has No Memory." *Nature* 394 (6693): 575–77.

Huang, Changrun, Mieke Donk, and Jan Theeuwes. 2022. "Proactive Enhancement and Suppression Elicited by Statistical Regularities in Visual Search." *Journal of Experimental Psychology. Human Perception and Performance* 48 (5): 443–57.

Itti, L., and C. Koch. 2000. "A Saliency-Based Search Mechanism for Overt and Covert Shifts of Visual Attention." *Vision Research* 40 (10-12): 1489–1506.

———. 2001. "Computational Modelling of Visual Attention." *Nature Reviews. Neuroscience* 2 (3): 194–203.

Jensen, Ole, and Ali Mazaheri. 2010. "Shaping Functional Architecture by Oscillatory Alpha Activity: Gating by Inhibition." *Frontiers in Human Neuroscience* 4 (November):186.

Jiang, Y., and M. M. Chun. 2001. "Selective Attention Modulates Implicit Learning." *The Quarterly Journal of Experimental Psychology. A, Human Experimental Psychology* 54 (4): 1105–24.

Jiang, Yuhong V., Li Z. Sha, and Roger W. Remington. 2015. "Modulation of Spatial Attention by Goals, Statistical Learning, and Monetary Reward." *Attention, Perception & Psychophysics* 77 (7): 2189–2206.

Jiang, Yuhong V., Khena M. Swallow, and Gail M. Rosenbaum. 2013. "Guidance of Spatial Attention by Incidental Learning and Endogenous Cuing." *Journal of Experimental Psychology. Human Perception and Performance* 39 (1): 285–97.

Jiang, Yuhong V., Khena M. Swallow, Gail M. Rosenbaum, and Chelsey Herzig. 2013. "Rapid Acquisition but Slow Extinction of an Attentional Bias in Space." *Journal of Experimental Psychology. Human Perception and Performance* 39 (1): 87–99.

Jiang, Yuhong V., Bo-Yeong Won, and Khena M. Swallow. 2014. "First Saccadic Eye Movement Reveals Persistent Attentional Guidance by Implicit Learning." *Journal of Experimental Psychology. Human Perception and Performance* 40 (3): 1161–73.

Jones, John L., and Michael P. Kaschak. 2012. "Global Statistical Learning in a Visual Search Task." *Journal of Experimental Psychology. Human Perception and Performance* 38 (1): 152–60.

Jonides, J., and S. Yantis. 1988. "Uniqueness of Abrupt Visual Onset in Capturing Attention." *Perception & Psychophysics* 43 (4): 346–54.

Juola, J. F., H. Koshino, and C. B. Warner. 1995. "Tradeoffs between Attentional Effects of Spatial Cues and Abrupt Onsets." *Perception & Psychophysics* 57 (3): 333–42.

Kadel, Hanna, Tobias Feldmann-Wüstefeld, and Anna Schubö. 2017. "Selection History Alters Attentional Filter Settings Persistently and beyond Top-down Control." *Psychophysiology* 54 (5): 736–54.

Katsuki, Fumi, and Christos Constantinidis. 2014. "Bottom-up and Top-down Attention: Different Processes and Overlapping Neural Systems." *The Neuroscientist: A Review Journal Bringing Neurobiology, Neurology and Psychiatry* 20 (5): 509–21.

Kerzel, Dirk, Chiara Balbiani, Sarah Rosa, and Stanislas Huynh Cong. 2022. "Statistical Learning in Visual Search Reflects Distractor Rarity, Not Only Attentional Suppression." *Psychonomic Bulletin & Review* 29 (5): 1890–97.

Kerzel, Dirk, Stanislas Huynh Cong, and Nicolas Burra. 2021. "Do We Need Attentional Suppression?" *Visual Cognition* 29 (9): 580–82.

Kiss, Monika, José Van Velzen, and Martin Eimer. 2008. "The N2pc Component and Its Links to Attention Shifts and Spatially Selective Visual Processing." *Psychophysiology* 45 (2): 240–49.

Kong, Siyang, Xinyu Li, Benchi Wang, and Jan Theeuwes. 2020. "Proactively Location-Based Suppression Elicited by Statistical Learning." *PloS One* 15 (6): e0233544.

Koshino, H., C. B. Warner, and J. F. Juola. 1992. “Relative Effectiveness of Central, Peripheral, and Abrupt-Onset Cues in Visual Attention.” *The Quarterly Journal of Experimental Psychology. A, Human Experimental Psychology* 45 (4): 609–31.

Kristjánsson, Árni. 2006. “Rapid Learning in Attention Shifts: A Review.” *Visual Cognition* 13 (3): 324–62.

Kristjánsson, Arni, and Gianluca Campana. 2010. “Where Perception Meets Memory: A Review of Repetition Priming in Visual Search Tasks.” *Attention, Perception & Psychophysics* 72 (1): 5–18.

Kristjánsson, Arni, Patrik Vuilleumier, Sophie Schwartz, Emiliano Macaluso, and Jon Driver. 2007. “Neural Basis for Priming of Pop-out during Visual Search Revealed with fMRI.” *Cerebral Cortex* 17 (7): 1612–24.

Krummenacher, Joseph, Hermann J. Müller, Michael Zehetleitner, and Thomas Geyer. 2009. “Dimension- and Space-Based Intertrial Effects in Visual Pop-out Search: Modulation by Task Demands for Focal-Attentional Processing.” *Psychological Research* 73 (2): 186–97.

Lamy, Dominique, Yoav Bar-Anan, and Howard E. Egeth. 2008. “The Role of within-Dimension Singleton Priming in Visual Search.” *Journal of Experimental Psychology. Human Perception and Performance* 34 (2): 268–85.

Leber, Andrew B., and Howard E. Egeth. 2006. “It’s under Control: Top-down Search Strategies Can Override Attentional Capture.” *Psychonomic Bulletin & Review* 13 (1): 132–38.

Leber, Andrew B., Rachael E. Gwinn, Yoolim Hong, and Ryan J. O’Toole. 2016. “Implicitly Learned Suppression of Irrelevant Spatial Locations.” *Psychonomic Bulletin & Review* 23 (6): 1873–81.

Li, Ai-Su, Louisa Bogaerts, and Jan Theeuwes. 2022. “Statistical Learning of across-Trial Regularities during Serial Search.” *Journal of Experimental Psychology. Human Perception and Performance* 48 (3): 262–74.

Li, Ai-Su, and Jan Theeuwes. 2020. “Statistical Regularities across Trials Bias Attentional Selection.” *Journal of Experimental Psychology. Human Perception and Performance* 46 (8): 860–70.

Liesefeld, Heinrich René, Dominique Lamy, Nicholas Gaspelin, Joy J. Geng, Dirk Kerzel, Jeffrey D. Schall, Harriet A. Allen, et al. 2024. “Terms of Debate: Consensus Definitions to Guide the Scientific Discourse on Visual Distraction.” *Attention, Perception & Psychophysics*, January. https://doi.org/10.3758/s13414-023-02820-3.

Luck, S. J., and S. A. Hillyard. 1994. “Electrophysiological Correlates of Feature Analysis during Visual Search.” *Psychophysiology* 31 (3): 291–308.

Luck, Steven J., Nicholas Gaspelin, Charles L. Folk, Roger W. Remington, and Jan Theeuwes. 2021. “Progress Toward Resolving the Attentional Capture Debate.” *Visual Cognition* 29 (1): 1–21.

Maljkovic, V., and K. Nakayama. 1994. “Priming of Pop-out: I. Role of Features.” *Memory & Cognition* 22 (6): 657–72.

———. 1996a. “Priming of Pop-out: II. The Role of Position.” *Perception & Psychophysics* 58 (7): 977–91.

Maljkovic, V., and Ken Nakayama. 1996b. “Priming of Pop-out: II. The Role of Position.” *Perception & Psychophysics*. https://doi.org/10.3758/bf03206826.

Mazza, Veronica, Massimo Turatto, and Alfonso Caramazza. 2009. “Attention Selection, Distractor Suppression and N2pc.” *Cortex; a Journal Devoted to the Study of the Nervous System and Behavior* 45 (7): 879–90.

Mazza, Veronica, Massimo Turatto, Carlo Umiltà, and Martin Eimer. 2007. “Attentional Selection and Identification of Visual Objects Are Reflected by Distinct Electrophysiological Responses.” *Experimental Brain Research. Experimentelle Hirnforschung. Experimentation Cerebrale* 181 (3): 531–36.

Moore, C. M., and H. Egeth. 1998. “How Does Feature-Based Attention Affect Visual Processing?” *Journal of Experimental Psychology. Human Perception and Performance* 24 (4): 1296–1310.

Moorselaar, Dirk van, Eline Lampers, Elisa Cordesius, and Heleen A. Slagter. 2020. “Neural Mechanisms Underlying Expectation-Dependent Inhibition of Distracting Information.” *eLife* 9 (December). https://doi.org/10.7554/eLife.61048.

Moorselaar, Dirk van, and Heleen A. Slagter. 2019. “Learning What Is Irrelevant or Relevant: Expectations Facilitate Distractor Inhibition and Target Facilitation through Distinct Neural Mechanisms.” *The Journal of Neuroscience: The Official Journal of the Society for Neuroscience* 39 (35): 6953–67.

Moorselaar, Dirk van, and Jan Theeuwes. 2022. “Spatial Suppression due to Statistical Regularities in a Visual Detection Task.” *Attention, Perception & Psychophysics* 84 (2): 450–58.

———. 2023. “Statistical Learning Within Objects.” *Psychological Science* 34 (4): 501–11.

Moorselaar, D. van, Nasim Daneshtalab, and Heleen A. Slagter. 2021. “Neural Mechanisms Underlying Distractor Inhibition on the Basis of Feature And/or Spatial Expectations.” *Cortex; a Journal Devoted to the Study of the Nervous System and Behavior* 137 (April):232–50.

Moran, Rani, Michael Zehetleitner, Hermann J. Müller, and Marius Usher. 2013. “Competitive Guided Search: Meeting the Challenge of Benchmark RT Distributions.” *Journal of Vision* 13 (8). https://doi.org/10.1167/13.8.24.

Müller, Hermann J., Thomas Töllner, Michael Zehetleitner, Thomas Geyer, Dragan Rangelov, and Joseph Krummenacher. 2010. “Dimension-Based Attention Modulates Feed-Forward Visual Processing.” *Acta Psychologica* 135 (2): 117–22; discussion 133–39.

Müller, H. J., and A. von Mühlenen. 2000. “Probing Distractor Inhibition in Visual Search: Inhibition of Return.” *Journal of Experimental Psychology. Human Perception and Performance* 26 (5): 1591–1605.

Neuper, Christa, Michael Wörtz, and Gert Pfurtscheller. 2006. “ERD/ERS Patterns Reflecting Sensorimotor Activation and Deactivation.” *Progress in Brain Research* 159:211–22.

Noonan, Maryann P., Nika Adamian, Alexandra Pike, Frida Printzlau, Ben M. Crittenden, and Mark G. Stokes. 2016. “Distinct Mechanisms for Distractor Suppression and Target Facilitation.” *The Journal of Neuroscience: The Official Journal of the Society for Neuroscience* 36 (6): 1797–1807.

Orchard-Mills, Emily, David Alais, and Erik Van der Burg. 2013. “Cross-Modal Associations between Vision, Touch, and Audition Influence Visual Search through Top-down Attention, Not Bottom-up Capture.” *Attention, Perception & Psychophysics* 75 (8): 1892–1905.

Parkhurst, Derrick, Klinton Law, and Ernst Niebur. 2002. “Modeling the Role of Salience in the Allocation of Overt Visual Attention.” *Vision Research* 42 (1): 107–23.

Posner, M. I. 1980. “Orienting of Attention.” *The Quarterly Journal of Experimental Psychology* 32 (1): 3–25.

Ptak, Radek. 2012. “The Frontoparietal Attention Network of the Human Brain: Action, Saliency, and a Priority Map of the Environment.” *The Neuroscientist: A Review Journal Bringing Neurobiology, Neurology and Psychiatry* 18 (5): 502–15.

Qiu, Nan, Bei Zhang, Fredrik Allenmark, Jan Nasemann, Shao-Yang Tsai, Hermann J. Müller, and Zhuanghua Shi. 2023. “Long-Term (statistically Learnt) and Short-Term (inter-Trial) Distractor-Location Effects Arise at Different Pre- and Post-Selective Processing Stages.” *Psychophysiology* 60 (10): e14351.

Rungratsameetaweemana, Nuttida, Larry R. Squire, and John T. Serences. 2019. “Preserved Capacity for Learning Statistical Regularities and Directing Selective Attention after Hippocampal Lesions.” *Proceedings of the National Academy of Sciences of the United States of America* 116 (39): 19705–10.

Sauseng, P., W. Klimesch, W. Stadler, M. Schabus, M. Doppelmayr, S. Hanslmayr, W. R. Gruber, and N. Birbaumer. 2005. “A Shift of Visual Spatial Attention Is Selectively Associated with Human EEG Alpha Activity.” *The European Journal of Neuroscience* 22 (11): 2917–26.

Sauter, Marian, Nina M. Hanning, Heinrich R. Liesefeld, and Hermann J. Müller. 2021. “Post-Capture Processes Contribute to Statistical Learning of Distractor Locations in Visual Search.” *Cortex; a Journal Devoted to the Study of the Nervous System and Behavior* 135 (February):108–26.

Sauter, Marian, Heinrich Liesefeld, and Hermann Müller. 2017. “Learning to Shield Visual Search from Salient Distractors: Evidence from the N2pc Component.” *Journal of Vision* 17 (10): 1137–1137.

Sauter, Marian, Heinrich René Liesefeld, and Hermann J. Müller. 2019. “Learning to Suppress Salient Distractors in the Target Dimension: Region-Based Inhibition Is Persistent and Transfers to Distractors in a Nontarget Dimension.” *Journal of Experimental Psychology. Learning, Memory, and Cognition*, January. https://doi.org/10.1037/xlm0000691.

Sauter, Marian, Heinrich René Liesefeld, Michael Zehetleitner, and Hermann J. Müller. 2018. “Region-Based Shielding of Visual Search from Salient Distractors: Target Detection Is Impaired with Same- but Not Different-Dimension Distractors.” *Attention, Perception & Psychophysics* 80

(3): 622–42.

Schapiro, Anna C., Nicholas B. Turk-Browne, Kenneth A. Norman, and Matthew M. Botvinick. 2016. “Statistical Learning of Temporal Community Structure in the Hippocampus.” *Hippocampus* 26 (1): 3–8.

Schapiro, A., and N. Turk-Browne. 2015. “Statistical Learning.” In *Brain Mapping*, edited by Arthur W. Toga, 501–6. Waltham: Academic Press.

Schneider, Walter, and Richard M. Shiffrin. 1977. “Controlled and Automatic Human Information Processing: I. Detection, Search, and Attention.” *Psychological Review* 84 (1): 1–66.

Seitz, Werner, Artyom Zinchenko, Hermann J. Müller, and Thomas Geyer. 2023. “Contextual Cueing of Visual Search Reflects the Acquisition of an Optimal, One-for-All Oculomotor Scanning Strategy.” *Communications Psychology* 1 (1): 1–12.

Sha, Li Z., Roger W. Remington, and Yuhong V. Jiang. 2017. “Rapid and Selective Updating of the Target Template in Visual Search.” *Journal of Vision* 17 (1): 36.

Shaw, M. L., and P. Shaw. 1977. “Optimal Allocation of Cognitive Resources to Spatial Locations.” *Journal of Experimental Psychology. Human Perception and Performance* 3 (2): 201–11.

Slagter, H. A., S. Prinssen, L. C. Reteig, and A. Mazaheri. 2016. “Facilitation and Inhibition in Attention: Functional Dissociation of Pre-Stimulus Alpha Activity, P1, and N1 Components.” *NeuroImage* 125 (January):25–35.

Smyth, Andrea C., and David R. Shanks. 2008. “Awareness in Contextual Cuing with Extended and Concurrent Explicit Tests.” *Memory & Cognition* 36 (2): 403–15.

Spaak, Eelke, Yvonne Fonken, Ole Jensen, and Floris P. de Lange. 2016. “The Neural Mechanisms of Prediction in Visual Search.” *Cerebral Cortex* 26 (11): 4327–36.

Stanković, Miloš, Hermann J. Müller, and Zhuanghua Shi. 2023. “Task-Irrelevant Valence-Preferred Colors Boost Visual Search for a Singleton-Shape Target.” *Psychological Research*, October. https://doi.org/10.1007/s00426-023-01880-2.

Tay, Daniel, Victoria Harms, Steven A. Hillyard, and John J. McDonald. 2019. “Electrophysiological Correlates of Visual Singleton Detection.” *Psychophysiology* 56 (8): e13375.

Theeuwes, J. 1991. “Exogenous and Endogenous Control of Attention: The Effect of Visual Onsets and Offsets.” *Perception & Psychophysics* 49 (1): 83–90.

———. 1994. “Stimulus-Driven Capture and Attentional Set: Selective Search for Color and Visual Abrupt Onsets.” *Journal of Experimental Psychology. Human Perception and Performance* 20 (4): 799–806.

Theeuwes, Jan. 1992. “Perceptual Selectivity for Color and Form.” *Perception & Psychophysics* 51 (6): 599–606.

———. 2010. “Top–down and Bottom–up Control of Visual Selection.” *Acta Psychologica* 135 (2): 77–99.

———. 2019. “Goal-Driven, Stimulus-Driven, and History-Driven Selection.” *Current Opinion in Psychology* 29 (October):97–101.

Theeuwes, Jan, Louisa Bogaerts, and Dirk van Moorselaar. 2022. “What to Expect Where and When: How Statistical Learning Drives Visual Selection.” *Trends in Cognitive Sciences* 26 (10): 860–72.

Theeuwes, Jan, and Michel Failing. 2020. “Attentional Selection: Top-Down, Bottom-Up and History-Based Biases.” In *Elements in Perception*. Cambridge University Press.

Thut, Gregor, Annika Nietzel, Stephan A. Brandt, and Alvaro Pascual-Leone. 2006. “Alpha-Band Electroencephalographic Activity over Occipital Cortex Indexes Visuospatial Attention Bias and Predicts Visual Target Detection.” *The Journal of Neuroscience: The Official Journal of the Society for Neuroscience* 26 (37): 9494–9502.

Tipper, S. P. 1985. “The Negative Priming Effect: Inhibitory Priming by Ignored Objects.” *The Quarterly Journal of Experimental Psychology. A, Human Experimental Psychology* 37 (4): 571–90.

Töllner, Thomas, Markus Conci, and Hermann J. Müller. 2015. “Predictive Distractor Context Facilitates Attentional Selection of High, but Not Intermediate and Low, Salience Targets.” *Human Brain Mapping* 36 (3): 935–44.

Töllner, Thomas, Michael Zehetleitner, Klaus Gramann, and Hermann J. Müller. 2011. “Stimulus Saliency Modulates Pre-Attentive Processing Speed in Human Visual Cortex.” *PloS One* 6 (1):

e16276.

Treisman, A. M., and G. Gelade. 1980. “A Feature-Integration Theory of Attention.” *Cognitive Psychology* 12 (1): 97–136.

Turk-Browne, Nicholas B., Justin Jungé, and Brian J. Scholl. 2005. “The Automaticity of Visual Statistical Learning.” *Journal of Experimental Psychology. General* 134 (4): 552–64.

Turk-Browne, Nicholas B., Brian J. Scholl, Marvin M. Chun, and Marcia K. Johnson. 2009. “Neural Evidence of Statistical Learning: Efficient Detection of Visual Regularities without Awareness.” *Journal of Cognitive Neuroscience* 21 (10): 1934–45.

Vadillo, Miguel A., Emmanouil Konstantinidis, and David R. Shanks. 2016. “Underpowered Samples, False Negatives, and Unconscious Learning.” *Psychonomic Bulletin & Review* 23 (1): 87–102.

Vadillo, Miguel A., Douglas Linssen, Cristina Orgaz, Stephanie Parsons, and David R. Shanks. 2020. “Unconscious or Underpowered? Probabilistic Cuing of Visual Attention.” *Journal of Experimental Psychology. General* 149 (1): 160–81.

Vadillo, Miguel A., Simone Malejka, Daryl Y. H. Lee, Zoltan Dienes, and David R. Shanks. 2022. “Raising Awareness about Measurement Error in Research on Unconscious Mental Processes.” *Psychonomic Bulletin & Review* 29 (1): 21–43.

Veale, Richard, Ziad M. Hafed, and Masatoshi Yoshida. 2017. “How Is Visual Salience Computed in the Brain? Insights from Behaviour, Neurobiology and Modelling.” *Philosophical Transactions of the Royal Society of London. Series B, Biological Sciences* 372 (1714). https://doi.org/10.1098/rstb.2016.0113.

Vicente-Conesa, Francisco, Tamara Giménez-Fernández, David Luque, and Miguel A. Vadillo. 2021. “Learning to Suppress a Distractor May Not Be Unconscious.” https://doi.org/10.31234/osf.io/yekvu.

Walthew, Carol, and Iain D. Gilchrist. 2006. “Target Location Probability Effects in Visual Search: An Effect of Sequential Dependencies.” *Journal of Experimental Psychology. Human Perception and Performance* 32 (5): 1294–1301.

Wang, Benchi, Joram van Driel, Eduard Ort, and Jan Theeuwes. 2019. “Anticipatory Distractor Suppression Elicited by Statistical Regularities in Visual Search.” *Journal of Cognitive Neuroscience* 31 (10): 1535–48.

Wang, Benchi, Iliana Samara, and Jan Theeuwes. 2019. “Statistical Regularities Bias Overt Attention.” *Attention, Perception & Psychophysics* 81 (6): 1813–21.

Wang, Benchi, and Jan Theeuwes. 2018. “Statistical Regularities Modulate Attentional Capture.” *Journal of Experimental Psychology. Human Perception and Performance* 44 (1): 13–17.

Wang, B., and J. Theeuwes. 2018. “Statistical Regularities Modulate Attentional Capture.” *Journal of Experimental Psychology*. https://psycnet.apa.org/journals/xhp/44/1/13/.

Wang, Lishuang, Benchi Wang, and Jan Theeuwes. 2021. “Across-Trial Spatial Suppression in Visual Search.” *Attention, Perception & Psychophysics* 83 (7): 2744–52.

Wiegand, Iris, Jeremy M. Wolfe, Joseph H. R. Maes, and Roy P. C. Kessels. 2024. “Incidental Learning of Temporal and Spatial Associations in Hybrid Search.” *Visual Cognition*, June, 1–16.

Wolfe, Jeremy M., Serena J. Butcher, Carol Lee, and Megan Hyle. 2003. “Changing Your Mind: On the Contributions of Top-down and Bottom-up Guidance in Visual Search for Feature Singletons.” *Journal of Experimental Psychology. Human Perception and Performance* 29 (2): 483–502.

Wolfe, Jeremy M., and Todd S. Horowitz. 2004. “What Attributes Guide the Deployment of Visual Attention and How Do They Do It?” *Nature Reviews. Neuroscience* 5 (6): 495–501.

Wolfe, J. M., K. R. Cave, and S. L. Franzel. 1989. “Guided Search: An Alternative to the Feature Integration Model for Visual Search.” *Journal of Experimental Psychology. Human Perception and Performance* 15 (3): 419–33.

Wolfe, J. M., and W. Gray. 2007. “Guided Search 4.0. Integrated Models of Cognitive Systems, 99--119.”

Won, Bo-Yeong, and Yuhong V. Jiang. 2015. “Spatial Working Memory Interferes with Explicit, but Not Probabilistic Cuing of Spatial Attention.” *Journal of Experimental Psychology. Learning, Memory, and Cognition* 41 (3): 787–806.

Woodman, G. F., and S. J. Luck. 1999. “Electrophysiological Measurement of Rapid Shifts of Attention during Visual Search.” *Nature* 400 (6747): 867–69.

Yantis, S., and H. E. Egeth. 1999. “On the Distinction between Visual Salience and Stimulus-Driven Attentional Capture.” *Journal of Experimental Psychology. Human Perception and Performance* 25 (3): 661–76.

Yantis, S., and J. Jonides. 1984. “Abrupt Visual Onsets and Selective Attention: Evidence from Visual Search.” *Journal of Experimental Psychology. Human Perception and Performance* 10 (5): 601–21.

———. 1990. “Abrupt Visual Onsets and Selective Attention: Voluntary versus Automatic Allocation.” *Journal of Experimental Psychology. Human Perception and Performance* 16 (1): 121–34.

Yu, Hao, Fredrik Allenmark, Hermann J. Müller, and Zhuanghua Shi. 2023. “Asymmetric Learning of Dynamic Spatial Regularities in Visual Search: Robust Facilitation of Predictable Target Locations, Fragile Suppression of Distractor Locations.” *Journal of Experimental Psychology. Human Perception and Performance* 49 (5): 709–24.

Zelinsky, Gregory J., and James W. Bisley. 2015. “The What, Where, and Why of Priority Maps and Their Interactions with Visual Working Memory.” *Annals of the New York Academy of Sciences* 1339 (March):154–64.

Zellin, Martina, Adrian von Mühlenen, Hermann J. Müller, and Markus Conci. 2013. “Statistical Learning in the Past Modulates Contextual Cueing in the Future.” *Journal of Vision* 13 (3). https://doi.org/10.1167/13.3.19.

Zhang, Bei, Fredrik Allenmark, Heinrich René Liesefeld, Zhuanghua Shi, and Hermann J. Müller. 2019. “Probability Cueing of Singleton-Distractor Locations in Visual Search: Priority-Map- versus Dimension-Based Inhibition?” *Journal of Experimental Psychology. Human Perception and Performance* 45 (9): 1146–63.

Zhang, Bei, Ralph Weidner, Fredrik Allenmark, Sabine Bertleff, Gereon R. Fink, Zhuanghua Shi, and Hermann J. Müller. 2021. “Statistical Learning of Frequent Distractor Locations in Visual Search Involves Regional Signal Suppression in Early Visual Cortex.” *Cerebral Cortex* , November. https://doi.org/10.1093/cercor/bhab377.

Zhao, Guang, Qiang Liu, Ye Zhang, Jun Jiao, Qinglin Zhang, Hongjin Sun, and Hong Li. 2011. “The Amplitude of N2pc Reflects the Physical Disparity between Target Item and Distracters.” *Neuroscience Letters* 491 (1): 68–72.

Deutsche Zusammenfassung

In Kapitel 2.1 wollten wir untersuchen, ob Teilnehmer dynamische Regelmäßigkeiten bei der Platzierung von Zielen und Distraktoren in visuellen Suchaufgaben lernen und nutzen können. Insbesondere wurde untersucht, ob die Teilnehmer ihre Aufmerksamkeitssteuerung auf der Grundlage dynamischer Verschiebungen der Ziel- und Ablenkungspositionen in aufeinanderfolgenden Versuchen anpassen können. Es wurden zwei Experimente mit dem Additional-Singleton-Paradigma durchgeführt. In Experiment 1 wurden versuchsübergreifende räumliche Regelmäßigkeiten für singuläre Farbdistraktoren (Experiment 1a) und singuläre Formziele (Experiment 1b) eingeführt. Die Position des kritischen Objekts (Ziel oder Distraktor) bewegte sich über die Versuche hinweg mit unterschiedlicher Wahrscheinlichkeit in verschiedene Richtungen. Experiment 2 war eine direkte Replikation von Wangs Experiment 1 (2021), bei dem dasselbe Design und dieselben Stimuli verwendet wurden, wobei der Schwerpunkt auf Ablenkungsregularitäten lag. Wir fanden heraus, dass die Teilnehmer dynamische Zielwahrscheinlichkeiten erfolgreich erlernten und ausnutzten, was die Verarbeitung an vorhersehbaren Zielorten erleichterte. Es gab jedoch kaum Hinweise auf eine proaktive Unterdrückung vorhersehbarer Distraktoren, selbst in einer Wiederholung einer früheren Studie, in der solche Effekte berichtet wurden. Die Erleichterung von vorhersagbaren Zielorten war mit einem expliziten Bewusstsein für die dynamische Regelmäßigkeit verbunden, während die Teilnehmer kein Bewusstsein für die Regelmäßigkeit der Distraktoren zeigten. Wir vermuten, dass diese Asymmetrie in den dynamischen Cueing- und Awareness-Effekten dadurch entsteht, dass das Ziel einen zentralen Platz in der Aufgabe einnimmt und daher explizit im Arbeitsgedächtnis für den Template-Matching und die Extraktion des für die Antwort kritischen Merkmals kodiert wird; infolgedessen wird die dynamische, trialübergreifende Veränderung seiner Position ebenfalls registriert und kann zur Top-Down-Priorisierung der bevorstehenden Zielposition verwendet werden. Im Gegensatz dazu ist der Distraktor kein expliziter Teil der Aufgabenstellung (z.B. ist es nicht notwendig, ein Distraktor-Template im Arbeitsgedächtnis anzulegen, um Distraktoren, die die Aufmerksamkeit auf sich gezogen haben, zurückzuweisen). Folglich würden die Beobachter, wenn überhaupt, nur ein geringes explizites Bewusstsein für regelmäßige Änderungen der

Distraktorposition erlangen, was in eine antizipatorische (Top-down) Unterdrückungsstrategie umgesetzt werden könnte. Dies schließt zwar ein Element des impliziten Lernens nicht aus, würde aber das Ausmaß einschränken, in dem dynamische Ablenkungsregelmäßigkeiten die Suchführung beeinflussen können.

Menschen können nicht nur statische, sondern auch dynamische (versuchsübergreifende) Regelmäßigkeiten in der Positionierung von Zielobjekten bei der parallelen visuellen "Pop-out"-Suche lernen und nutzen. Während das Erlernen statischer Zielpositionen auch bei der seriellen Suche funktioniert, scheint das Erlernen dynamischer Regelmäßigkeiten durch die Anforderungen des Item-by-Item-Scannens verhindert zu werden. Außerdem wurde die Frage aufgeworfen, ob das explizite Bewusstsein eine Rolle bei der Nutzung (zumindest) dynamischer Regelmäßigkeiten zur Leistungsoptimierung spielt. In Kapitel 2.2 haben wir daher erneut untersucht, ob dynamische Regelmäßigkeiten bei der seriellen Suche erlernt werden können, wenn regelmäßige Verschiebungen der Zielposition häufig auftreten, und ob ein solches Lernen mit dem Bewusstsein für die dynamische Regel korreliert. Zu diesem Zweck haben wir dieselbe Regelmäßigkeit wie in Kapitel 2.1 verwendet, um das dynamische Lernen bei der parallelen Suche zu demonstrieren: eine versuchsübergreifende Verschiebung des Zielortes z.B. im Uhrzeigersinn innerhalb einer kreisförmigen Anordnung in 80% der Versuche, die mit unregelmäßigen Verschiebungen in die entgegengesetzte (z.B. gegen den Uhrzeigersinn; 10%) oder eine andere, zufällige Richtung (10%) verglichen wurde. Unsere Ergebnisse zeigen, dass Teilnehmer im Gegensatz zu früheren Berichten dynamische Regelmäßigkeiten in der trialübergreifenden Platzierung des Ziels sogar bei der seriellen Suche (mit sequenziellen Augenbewegungen) extrahieren und zur Verbesserung der Aufgabenleistung nutzen können - zumindest wenn die regelmäßige trialübergreifende Zielverschiebung relativ einfach ist und häufig auftritt. Dieser Befund ist nicht trivial, da die gleiche Regelmäßigkeit nicht erkannt wird, wenn sie in einem auffälligen "Pop-out"-Distraktor bei der parallelen Suche umgesetzt wird (Kapitel 2.1). Entscheidend ist, dass dieser dynamische Zielort-Wahrscheinlichkeits-Cueing-Effekt sogar in der allerersten Sakkade (sowohl in der Proportion als auch in der Latenz), die bei Beginn der Suche auf dem Display ausgelöst wird, zu beobachten ist. Außerdem korreliert sie mit dem Bewusstsein der Teilnehmer für die dynamische Regelmäßigkeit. Wenn man jedoch bedenkt, wie schnell die durch die Regel ausgelöste Verzerrung nach Beginn der Anzeige wirken kann (sie zeigt sich bereits bei den schnellsten ersten Sakkaden, die zwischen 100 und 150 ms nach Beginn der Anzeige ausgelöst werden), kann es sein, dass der Cueing-Effekt selbst nicht bewusst vermittelt wird. In diesem Fall würde das Bewusstsein jedoch eine entscheidende Rolle dabei spielen, den Effekt überhaupt erst zu erzielen. Alternativ könnte die regelbasierte Verzerrung bereits im Intertrial-Intervall "vorbereitet" sein, so dass der Cueing-Effekt nach Beginn der Suchanzeige schnell ansteigt. Um dies zu klären, sind weitere Arbeiten, z. B. mit elektrophysiologischen Messungen, erforderlich. Außerdem wären weitere Arbeiten erforderlich, um die Randbedingungen für die Beobachtung eines Cueing-Effekts zu bestimmen, und zwar sowohl in Bezug auf die Komplexität der dynamischen Zielregelmäßigkeiten als auch in Bezug auf die Häufigkeit ihres Auftretens.

Zielerleichterung kann durch räumliches statistisches Lernen des Ziels erreicht werden. Obwohl in vielen Verhaltensstudien festgestellt wurde, dass sich die Leistung der Teilnehmer verbesserte, wenn die Ziele an häufigen Orten im Vergleich zu seltenen Orten auftraten, sind die elektrophysiologischen Korrelate der statistisch erlernten Zielerleichterung noch nicht gut untersucht worden. Darüber hinaus hat eine neuere Verhaltensstudie (Turatto und Valsecchi 2022) gezeigt, dass die erlernte Unterdrückung von Distraktoren lang anhaltende Veränderungen in der Prioritätskarte hervorrufen kann, die sich auf die künftige Berechnung des Zielgedächtnisses an derselben Stelle auswirken und so die Aufmerksamkeitsauswahl erleichtern. Es bleibt abzuwarten, ob erlernte Zielanreicherung ebenfalls langfristige Veränderungen in der Prioritätskarte hervorrufen kann. Daher wurden in Kapitel 2.3 EEG-Daten erhoben, während die Teilnehmer in einer seriellen Suchaufgabe mit einer unausgewogenen Verteilung der Ziele nach einem Ziel suchten. N2pc (lateralisierte ereigniskorrelierte Potenziale) und lateralisierte Alpha-Power (8-12 Hz) wurden verwendet, um die zeitliche Dynamik der Effekte zu verfolgen. Das Experiment bestand aus zwei Phasen: In der Trainingsphase wurde die Wahrscheinlichkeitsmanipulation des Zielortes implementiert; in der Testphase wurde die Wahrscheinlichkeitsmanipulation des Zielortes entfernt und zusätzlich ein Distraktor eingeführt, der eine ähnliche Eigenschaft wie das Ziel hatte. In der Trainingsphase beobachteten wir ein robustes Lernen der vorhergesagten Zielorte: Die Verarbeitung des Ziels an häufigen Orten wurde im Vergleich zu seltenen Zielplatzierungen erleichtert. In der Testphase zeigte sich, dass das langfristige Lernen auch dann anhielt, wenn das Ziel während der Trainingsphase zu einem Distraktor wurde. Elektrophysiologisch ist die erlernte Zielverstärkung nicht mit einer lateralisierten Alpha-Leistung während der Prä-Stimulus-Periode verbunden. Dennoch induzierten Ziele an häufigen Orten eine größere N2pc-Amplitude und eine frühere N2pc-Latenz in der Trainingsphase. Somit bestätigen wir, dass die Erleichterung, die aus dem räumlichen statistischen Lernen von Zielen resultiert, plastische Veränderungen in der vorherigen Karte verursachen kann.

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