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



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ABSTRACT

Keywords: Probability cueing Statistical learning Parallel/serial search Search guidance Eye movements Oculomotor scanning Inter-trial priming Conscious awareness 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 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.

1. 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

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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 rightmost 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 $(2020).^{2}$

In contrast to Yu et al. (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).³ 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, targetlocation probability learning works under serial and parallel search conditions (Geng & Behrmann, 2002). However, with dynamic targetlocation regularities, it seems to work only under parallel conditions, not serial (Li et al., 2022; Li & Theeuwes, 2020). The question is: why?

1.1. 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 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., secondorder) dependencies (Turk-Browne et al., 2008) as well as difficult (e.g., dual-target) search tasks (Allenmark, Stanković, Müller, & Shi, 2024). Thus, there is no a-priori reason to expect that dynamic target-location learning would not be feasible in demanding, serial search tasks.

1.2. 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 &

² 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.

 $^{^3}$ 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.

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.⁴

1.3. 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 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.

1.4. 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 Fig. 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 Fig. 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 targetlocation 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

⁴ 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.



Fig. 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 changed randomly from trial to trial; in the fixed condition, it stayed the same. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

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.

2. Method

2.1. 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 preprocessing and all subsequent analyses. No participants were excluded from the study, and all criteria for trial-based inclusion and exclusion were pre-determined before data analysis. We report all data manipulations in the study.

2.2. Participants

A total of 34 healthy university students from LMU Munich participated in this study (mean age \pm SD: 26.32 \pm 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 $\alpha = 0.05$, 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 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.

2.3. Apparatus

The experiment was conducted in a sound-attenuated, dimly lit testing chamber. Participants were seated 55 cm away from a 24-in. CRT monitor that displayed the search stimuli at a screen resolution of 1920 \times 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 1 kHz. Participants registered their responses using a QWERTZ keyboard by pressing the space button with either their left- or right-hand index finger.

2.4. Stimuli and design

The search displays (see Fig. 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 $1.25^{\circ} \times 1.25^{\circ}$ 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).

2.5. 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 keypress 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 %).

2.6. Data analyses

2.6.1. 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 Fig. 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.

2.6.2. 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 > 0.5) 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).

3. Results

3.1. 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.

3.2. Response times

Fig. 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).

A mixed-design ANOVA with the within-participant factors crosstrial 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)



Fig. 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.

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).

3.3. Awareness and dynamic target-location probability cueing

Fig. 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 probabilitycueing effects are. To assess reliability, we adopted the permuted splithalf method (Vadillo et al., 2022). For the aware group, the probability-cueing effect was highly reliable (fixed target identity: splithalf reliability r = 0.932; mixed target identity: r = 0.842). For the unaware group, the reliability was moderate for the mixed target identity (r = 0.571), but relatively low for the fixed target identity (r =0.211).

3.4. 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 Fig. 4, where distance



Fig. 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.



Fig. 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. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

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.

We conducted a linear mixed-effects model (LMM) with the withinparticipant 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) = 0.053, 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 nonsignificant (Fs < 3.55, p > .064). Following up the Distance \times 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, $p_{bonf}s < 0.001$, ds > 0.611 (there was no difference between distances 0 and 1, t(33) = 0.148, $p_{bonf} = 1$, $d_z = 0.019$, and among distances 2, 3, and 4, ts(33) < 1.546, $p_{bonf}s = 1$, $d_2s < 0.194$). 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 0distance, 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 towards the frequent and away from the infrequent direction.

3.5. 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 ANOVA⁵ with the within-participant factors Previous (trial *n*–1) Target Location (target at frequent vs. infrequent location) and cross-trial Target Constancy (fixed

⁵ 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.



Fig. 5. Probability-cueing effect (*RT*_{infrequent}) 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.

vs. variable) and the between-participant factor Awareness (aware vs. unaware). The data are plotted in Fig. 5.

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, $\eta_p^2 = 0.148$,⁶ with the cueing effect being overall positive for the aware group (271 ms), but negative for the unaware group (-16 ms). Although the Awareness \times 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, Fig. 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.

3.6. Correlation between awareness and dynamic target-location probability cueing

The correlations between the awareness ratings and the probabilitycueing effect show differential patterns between the 'aware' and 'unaware' groups (Fig. 6), but the categorization of 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 $b = r \frac{s_T}{s_x}$, 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 Fig. 6).

3.7. 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.

3.8. 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

⁶ The main effect of awareness turned out significant after adding 10 more participants, *p*Before = 0.126 vs. *p*After = 0.025.



Fig. 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).



Fig. 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.

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 Fig. 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) = 0.992, 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.

Fig. 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 Fig. 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, $d_z = 0.545$).

3.9. First fixation locations

One might assume that participants who learned the dynamic crosstrial regularity directed their eyes immediately to the frequent target



Fig. 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.

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. Fig. 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, $p_{bonf} = 0.006$ 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 Fig. 8c, this difference derives mainly from the fixed target-identity condition – statistically corroborated by a significant Fixated-Location \times Target-Constancy interaction, F(2,46) = 4.914,



Fig. 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.

 $p = .012, \eta_p^2 = 0.176).^7$

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.

An analogous ANOVA of the *latencies of the first saccade* (depicted in Fig. 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, $p_{bonf} = 0.005$, $d_z = -0.328$, 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

 7 The interaction between Fixated Location and Target Constancy became significant after adding 10 more participants, *p*Before = 0.215 vs. *p*After = 0.012.

frequent and infrequent locations to be already evident in the very 'fastest' time bins (i.e., the first 22 %) of the vincentized latency distributions ($\chi^2(17305) = 110.32, p < .001$), 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, $d_z = 0.396^8$).

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 Fig. 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

⁸ The difference between infrequent and random cross-trial shifts of the target location became significant, *p*Before = 0.116 vs. *p*After = 0.007.



Fig. 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.

appears at the infrequent location (fixations of *frequent* location: Fixation-Location \times 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 \times 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 \times 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, $d_z = -0.1.111$). 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 rulebased 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 Fig. 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.

3.10. Awareness and dynamic probability cueing of the first eye movement

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 = 0.94; mixed: r = 0.911). 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 Fig. 11 for depictions. In other words, the more accurately participants



Fig. 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 %).



Fig. 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 %).

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.

3.11. Awareness and dynamic probability cueing of the number of required saccades

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 = 0.909; mixed target identity: r = 0.945). 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 Fig. 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.

3.12. Inter-trial priming of the first eye movement from rule-conform (vs. rule-breaking) target shifts

Fig. 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 (0.179) than after rule-breaking target shifts (0.108) 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.

4. 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*



Fig. 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.

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 targetlocation 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.

4.1. 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 et al., 2022; Li & Theeuwes, 2020) and Yu et al. (2023) and the present study lies in the complexity of the regular crosstrial 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.

4.2. 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.⁹ 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.

4.3. Rule-based intertrial priming

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 nwhen 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

⁹ 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.

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.

4.4. Dynamic probability-cueing is modulated but not abolished by targetidentity 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 featurebased 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 nonconclusive 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),¹⁰ 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).

4.5. 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 link at the latent level.¹¹ 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.¹² 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 & 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)

¹⁰ 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.

¹¹ We thank Dr. M. Vadillo for communicating this point to us.

¹² 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).



Fig. 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.

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 *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.¹³ 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.

4.6. 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 Fig. 3), coupled with their first saccades being somewhat more likely to land at the infrequent than the frequent locations (see

Fig. 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

¹³ 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.

proportion of trials. Consequently, they would discern the rule and develop a positive probability-cueing effect.

In line with this scenario, Fig. 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, Fig. 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.

5. 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 ruleinjected 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.

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CRediT authorship contribution statement

Hao Yu: Writing – review & editing, Writing – original draft, Visualization, Validation, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. Fredrik Allenmark: Writing – review & editing, Validation, Supervision, Methodology, Investigation, Formal analysis, Conceptualization. Hermann J. Müller: Writing – review & editing, Validation, Supervision, Methodology, Funding acquisition. **Zhuanghua Shi:** Validation, Writing – review & editing, Supervision, Resources, Project administration, Funding acquisition.

Data availability

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.

Appendix. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.cognition.2024.105977.

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