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How does color distribution learning affect goal-directed visuomotor behavior?

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ABSTRACT

While the visual world is rich and complex, importantly, it nevertheless contains many statistical regularities. For example, environmental feature distributions tend to remain relatively stable from one moment to the next. Recent findings have shown how observers can learn surprising details of environmental color distributions, even when the colors belong to actively ignored stimuli such as distractors in visual search. Our aim was to determine whether such learning influences orienting in the visual environment, measured with saccadic eye movements. In two visual search experiments, observers had to find an odd-one-out target. Firstly, we tested cases where observers selected targets by fixating them. Secondly, we measured saccadic eye movements when observers made judgments on the target and responded manually. Trials were structured in blocks, containing *learning trials* where distractors came from the same color distribution (uniform or Gaussian) while on subsequent *test trials*, the target was at different distances from the mean of the learning distractor distribution. For both manual and saccadic measures, performance improved throughout the learning trials and was better when the distractor colors came from a Gaussian distribution. Moreover, saccade latencies during test trials depended on the distance between the color of the current target and the distractors on learning trials, replicating results obtained with manual responses. Latencies were slowed when the target color was within the learning distractor color distribution and also revealed that observers learned the difference between uniform and Gaussian distributions. The importance of several variables in predicting saccadic and manual reaction times was studied using random forests, revealing similar rankings for both modalities, although previous distractor color had a higher impact on free eye movements. Overall, our results demonstrate learning of detailed characteristics of environmental color distributions that affects early attentional selection rather than later decisional processes.

1. Introduction

Finding a specific target within the visual environment, for example, your favorite book on a shelf, requires selecting relevant items for further processing while filtering out irrelevant ones. An internal representation of the target, typically called *attentional template,* encompassing task-related features is essential for this (Bundesen, 1990; Carlisle et al., 2011; Desimone & Duncan, 1995; Huynh Cong & Kerzel, 2021; Kristjánsson, 2023; Mehrpour et al., 2020; Oberauer, 2019). The role of attentional templates is to guide visual search by prioritizing sensory information that aligns with the features in the target template (e.g., Eimer, 2014).

Conversely, in certain contexts, *templates for rejection* tuned to non-target items can guide attention away from features, resulting in distractor suppression effects (Carlisle, 2023; Chelazzi et al., 2019; Gaspelin & Luck, 2018; Geng, 2014; Geng et al., 2019). For instance, presenting participants with a pre-cue of a distractor facilitates visual search compared to presenting a neutral cue (Arita et al., 2012; Zhang & Carlisle, 2023). According to Geng et al. (2019), such distractor suppression may arise from explicit strategies, implicitly learned statistical regularities or habituation. What is the nature of such templates, especially when observers interact with ensembles of targets and distractors? In a recent review, Kristjánsson (2023) suggests that tuning attentional templates to a precise feature value would not provide particularly effective guidance. For example, the color of an object can change depending on room lighting or differ among multiple targets in tasks like foraging. To accommodate this variability, encoding templates in a probabilistic manner, to a certain range of values, might offer better

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guidance. Several studies have suggested that the visual system can encode ensembles of objects as summary statistics (mean and variance) for efficient processing and to save resources (e.g., Utochkin, 2015; Whitney & Yamanashi Leib, 2018). Taking this further, recent research demonstrates that the probability distribution of target or distractor features can also be encoded and used during visual exploration (e.g., Chetverikov et al., 2016, 2017, 2020; Hansmann-Roth et al., 2021; Witkowski & Geng, 2022).

An example of probabilistic encoding of distractor colors comes from a visual search study by Chetverikov et al. (2017). The authors employed a method known as Feature Distribution Learning (FDL; Chetverikov et al., 2020) to probe distractor representations. Participants were presented with a visual search display containing 36 heterogeneously colored diamonds, each with one corner cut off. They had to find the diamond with the hue most unlike the others and report which corner was missing. The experiment was divided into blocks, composed of learning trials and test trials. The distractor color distribution was either Gaussian or uniform during learning trials and was kept constant. Response times in test trials as a function of the distance in color space between the color of the target and the mean color of the distractors on learning trials (called Current Target – Previous Distractor distance; CT-PD) reflected the shape of the learning distractor color distribution. When the previous learning distractor distribution was Gaussian, the most probable distractor color (at the mean of the Gaussian distribution), led to the slowest search time in test trials. Less probable distractor colors led to faster search times, and reaction times decreased linearly. In contrast, following a uniform distribution, search times in test trials were similar for targets falling within the range of the previous distractor distribution. This outcome mirrored the properties of the distribution, as distractor colors within the uniform distribution range were equally probable. These results showed how participants had detailed representations of the shape of distractor color distribution. Hansmann-Roth et al. (2021) reached the same conclusion using the FDL method but also showed that in contrast, observers' explicit judgments about appearance were limited to the mean and the variance of the color distributions.

Our aim was to assess how distribution-based information affects oculomotor selection. Most of the studies cited above have explored attentional selection through manual response times (e.g., key press). There is typically a strong correlation between the number of eye movements and manual response times in visual search (Zelinsky & Sheinberg, 1997). However, there are also fundamental differences between eye movements and manual responses. In visual search, eye movements are predominantly employed for exploring the visual display and accumulating evidence regarding the target's location, leading to a subsequent perceptual decision. In contrast, manual responses signify the final perceptual decision made about the target, such as determining the side on which a cut corner is located. Many argue that visual search involves multiple sequential processing stages: target search, decision-making regarding selected candidate targets, and response selection and execution (Huang et al., 2004; Treisman, 1988; Wolfe, 2021). Examining eye movements enables the investigation of effects occurring at the initial attentional stage (target search), distinct from subsequent decisional stages. In contrast, manual response times in our context represent the cumulative processes involved.

Overall, eye movements are linked to spatial exploration in retinotopic space. Moreover, coupled with manual responses, eye movement analyses can yield insights into the search process, as attention and saccades have been considered to be tightly connected (Deubel & Schneider, 1996; see Kowler, 2011, Hoffman, 2016 and Kristjánsson, 2011 for reviews). For example, during feature-based foraging, gaze foraging is associated with a higher number of fixations, larger saccade amplitude, and shorter fixation durations than foraging with mouse cursor selection (Tagu & Kristjánsson, 2022a).

There is still debate concerning whether the programming of eye movements and manual response calls on the same representations or mechanisms. First, there is evidence indicating that the learning of preceding target or distractor features affects oculomotor selection in visual search. Therefore, distractors that have the same color as the target on a previous trial are selected more frequently than distractors with a different color (Becker et al., 2009; Becker, 2010a, 2010b; McPeek et al., 1999; Shurygina et al., 2019; see Kristjánsson & Campana, 2010, and Kristjánsson & Ásgeirsson, 2019 for reviews).

The question of whether similar attentional templates are used to decide where to move the eyes and to make a final search decision was addressed by Eckstein et al. (2007) in the context of search for a bright Gaussian-shaped target. Their results suggested that representations for both perceptual decisions and oculomotor action are similar. Additionally, computational modeling showed that a common target template for perceptual decisions and eye movements was optimal and might be expected to evolve through natural selection (Zhang & Eckstein, 2010). Overall, similar templates for perception and saccadic actions during visual search would not necessarily imply that a single pathway mediates both, rather, visual information could be shared between the two systems due to their large overlap (Eckstein, 2011). In the same sense, in a search for two targets, Navalpakkam et al. (2010) found that decisions expressed through a manual keypress or a saccadic eye movement were influenced similarly by reward value and feature contrast. In contrast, dissimilarities between saccadic and manual responses have sometimes been found, for moving objects (Lisi & Cavanagh, 2015), spatial representations (Greenwood et al., 2017), and inhibition of return (Pratt & Neggers, 2008). For moving objects, motion perception and pursuit eye movements may rely on similar signals although, they may have separate noise sources (Schütz et al., 2011).

Saccadic eye movements are sometimes used as behavioral responses, enabling a direct comparison between saccadic and manual responses. For instance, participants may be instructed to either execute a saccade toward a target or indicate the target's location through key presses (e.g., Bacon-Macé et al., 2007; Bannerman et al., 2009; Bompas et al., 2017). Saccadic latencies are consistently faster than manual responses. Using computational modeling, Bompas et al. (2017) concluded that these latency differences reflect distinct dynamics within the brain areas involved. Faster visual information transmission and quicker output generation for the saccadic system would lead to shorter saccadic latencies, rather than fundamental differences in decision-making processes. Beyond latency disparities, saccadic responses may exhibit greater sensitivity to specific visual signals, such as distractors (Bompas & Sumner, 2008) or emotional facial expressions (Bannerman et al., 2009). This may arise from different dynamics, as computational modeling suggests that exogenous signals, such as distractors, influence the saccadic system earlier than the motor system (Bompas et al., 2017). Overall, it may be important to differentiate between studies where eye movements are used as responses and those where responses are manual, allowing for more natural eye movements. Indeed, Becker et al. (2009) showed that in manual response tasks, saccade latencies are faster, and irrelevant distractors are selected more frequently than in tasks where eye movements are used as a response.

2. Current study

To assess how distribution-based information affects oculomotor selection, we analyzed eye movements during a feature distribution learning task. We used a visual search task where participants needed to find the diamond whose color was the most different from the others. Therefore, the experiment consisted of a sequence of blocks of 3–4 learning trials, followed by one test trial. The distractor color distribution was constant throughout the learning trials of any given block, following either a Gaussian or uniform pattern. We expected that saccadic reaction times (SRTs) —measured as the time between display onset and the initiation of the first saccade reaching the target— would decrease throughout the learning trials. Concurrently, we expected improved accuracy throughout the learning trials. During subsequent test trials, we expected that, like Manual Reaction Times (MRTs), SRTs would mirror the acquired knowledge of the distractor feature distribution. Overall, we expected to find similar patterns in the eye-tracking measurements to the results obtained with manual responses in FDL studies. This hypothesis was based on previous evidence showing priming effects on saccade latencies (e.g., Becker, 2010a, 2010b; Becker et al., 2009; McPeek et al., 1999; Tagu & Kristjánsson, 2022a, 2022b) and similar attentional templates for eye movements and manual responses (e.g., Eckstein et al., 2007; Zhang & Eckstein, 2010).

In Experiment 1, participants were instructed to make a saccade toward the target, so that the saccadic eye movement was also the behavioral response. In Experiment 2, participants were instructed to make a perceptual judgment about the target and respond with keypress (4 alternative forced-choice task), matching the original design of Chetverikov et al. (2017). Eye movements in Experiment 2 were therefore naturally used to explore the display and can be considered as free eye movements, unlike the constrained eye movements in Experiment 1. This dual-experiment approach allows us to assess the relationship between distribution-based learning, oculomotor selection, and manual responses, providing an understanding of how visual information influences eye movements in comparison to traditional manual responses.

In an additional random forest analysis, reaction times obtained with saccadic responses, manual responses, and free eye movements were compared. The goal was to assess the forces that drive the visual search and rank them for each modality. Indeed, attention in visual search is guided by several factors, such as bottom-up salience, top-down feature guidance, scene structure and meaning, and the previous history of search (e.g., Eckstein, 2011; MacInnes et al., 2014; Schütz et al., 2011; Wolfe & Horowitz, 2017). We expected that all these factors would influence search time and explored their relative contribution for each response modality. For this, we performed a variable importance analysis using random forests (Breiman, 2001; see Boulesteix et al., 2012 and Biau & Scornet, 2016 for practical guidance; and Wei et al., 2015 for review).

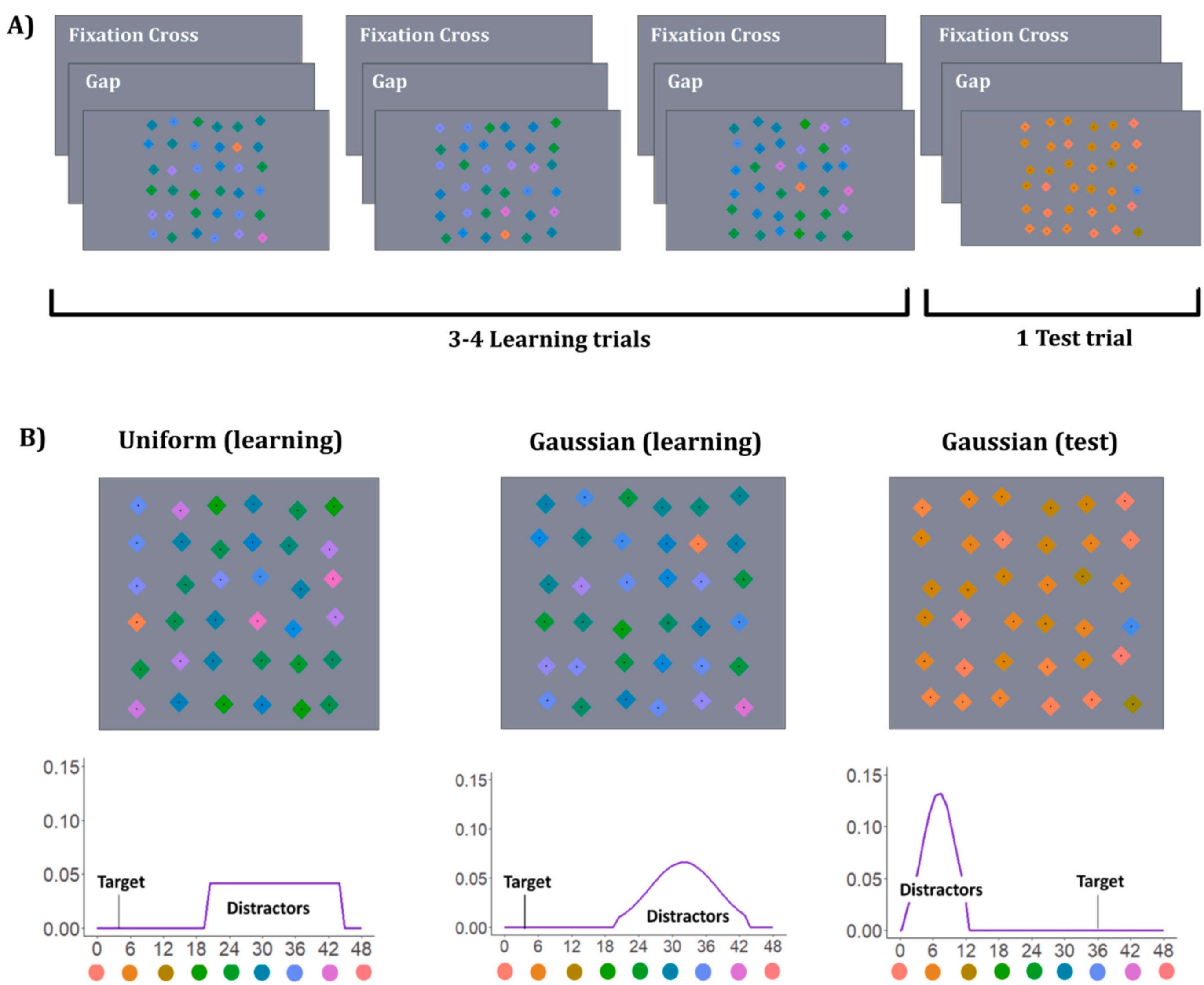

Fig. 1. **(A)** Illustration of a block. Each block included 3–4 learning trials followed by one test trial. Every trial started with the presentation of a fixation cross for 500 to 1000 ms, followed by a 200 ms gap and the visual search display. Participants were asked to make a saccade toward the diamond with the color the most different from the other diamonds. The trial ended when a saccade reached the target or after 1500 ms. **(B)** Examples of visual search displays for learning trials with distractor colors drawn from a uniform (left) or Gaussian (middle) distractor distribution, along with a test-trial example with distractor colors drawn from a Gaussian (right) distractor distribution. Displays are presented above the color distribution their distractors are drawn from. During learning trials, uniform distributions spanned a range of 24 JND, and the standard deviation of the Gaussian distributions was 6 JND. During test trials, the standard deviation of the Gaussian distribution was 3 JND. The distance between target color and the mean of the distractor distribution ranged from 18 to 24 JND.

3. Experiment 1: saccadic responses

3.1. Materials and method

3.1.1. Participants

Sixteen participants (8 females and 8 males; 28.8 ± 4.22 years) were included in this experiment. As there was no previous report of eye-tracking measures in this kind of task, the strength of the expected effects was difficult to estimate. Overall, we decided to recruit a similar number of participants as in previous studies where similar color distribution learning was involved (e.g., 10 participants in Chetverikov et al., 2017; 18 in Hansmann-Roth et al., 2021). All participants gave their informed written consent before participating in the study, which was carried out in accordance with the requirements of the local ethical committee and the declaration of Helsinki for experiments involving humans. Undergraduate psychology students received course credits for participating in the experiment.

3.1.2. Stimuli and procedure

The visual search display consisted of 36 diamonds arranged in a centrally aligned 6 × 6 grid spanning 14 × 14° of visual angle (Fig. 1). Each diamond covered 1.4° of visual angle (the length of the diagonals). Individual diamond positions on the grid were jittered, involving the addition of a random value ranging between +/− 0.5° to both horizontal and vertical coordinates. One diamond was the target, while the remaining 35 were distractors. The target was defined by being the diamond with the color the most different from all the other diamonds. Each diamond had a central dot to encourage participants to fixate the target's center. The colors were drawn from a linear color space featuring 48 isoluminant hues where adjacent hues are separated by one just-noticeable-difference (JND), computed using measurements from Witzel and Gegenfurtner (2013).

The experiment was divided into blocks, each comprising 3 or 4 learning trials followed by one test trial (see Chetverikov et al., 2020). Participants were not aware of the division of the experiment into blocks. In previous FDL studies, participants never reported having any knowledge of the nature of the trial structure (Chetverikov et al., 2020). An illustration of a block is presented in Fig. 1 (A) with examples of learning and test displays in Fig. 1 (B).

Throughout the learning trials, distractor colors were randomly drawn from either a uniform or a Gaussian distribution (constant across each sequence of learning trials). The uniform distribution spanned a range of 24 JND and the Gaussian distribution had a standard deviation of 6 JND and was truncated to exclude color values above or below 2 SD from the mean, to equate the range of the uniform distribution. Within each block, the mean of the distractor distribution for learning trials was chosen randomly. The target color was randomly selected but always with a distance between 18 and 24 JND from the distractor mean. On test trials, distractor colors were randomly drawn from a Gaussian distribution with a standard deviation of 3 JND (excluding values beyond two standard deviations). In these trials, performance as a function of CT-PD is of central interest.

Both learning and test trials started with the presentation of a fixation cross for a pseudo-random duration (500 to 1000 ms). The visual search display appeared following a 200 ms gap. Participants were asked to make an eye movement to the central dot within the diamond with the color most different from the other diamonds. The trial ended when a saccade reached the target (landing within a radius of 1.4° around the center of the target). If, after 1500 ms, no saccade reached the target, an error message briefly appeared. The experiment was divided into 2 sessions, each comprising 272 blocks (one block = training trials with a test trial). Before each session, a 50-block training phase familiarized participants with the task. Each session lasted approximately 1 h. A calibration phase was performed every 70 blocks, and drift correction every 8 blocks (if the drift was larger than 1°, a recalibration was performed). During calibration, participants were asked to fixate nine dots appearing sequentially in a 3 × 3 grid covering the entire screen.

3.1.3. Materials

Stimuli were displayed on a 24-in. LCD monitor with a resolution of 1920 × 1080 and a refresh rate of 144 Hz using Matlab R2017b and Psychtoolbox-3 (Kleiner et al., 2007) on a desktop computer running. Color calibration was performed using a Cambridge Research Systems (Rochester, England) ColorCal MK2 photometer. Participants' heads were stabilized using a chin-rest at a viewing distance of 94 cm. Eye movements were recorded using an Eyelink 1000 plus (SR Research) eye-tracker with a 1000-Hz sampling frequency. Saccades were detected if they had a minimum velocity of 30 degrees/s, a minimum acceleration of 8000 degrees/s^2, and a minimum motion of 0.15 degrees. Blinks were detected when the pupil was partially or totally occluded, and fixations were detected when there was no blink and no saccade in progress. Viewing was binocular, while eye-tracking was monocular, and only the position of the dominant eye was recorded.

3.1.4. Data analysis

Statistical analyses were carried out using the open-source software R 4.2.2 (R Core Team, 2022) with R Studio 2022.7.2.576 (RStudio Team, 2022). Note that a correct trial was defined as a trial with a saccade toward the target. Moreover, both error and post-error trials were excluded from latency analysis (leading to 82.4 % of the learning trials and 87.4 % of the test trial included in latency analysis). Finally, effects were considered significant if *p*-values were below $\alpha = 0.05$.

First, we analyzed performance during learning trials. The proportion of correct trials and the SRT (the time between display onset and the initiation of the saccade reaching the target) were the main dependent variables. We used a paired-samples *t*-test to compare performance between each Distractor Distribution (Gaussian, uniform), and Helmert contrasts comparing performance on each Trial Number Within Learning Sequence (1, 2, 3, 4) with the average performance on subsequent trials. We chose to use *t*-tests and Helmert contrasts independently instead of a more classical ANOVA because we were primarily interested in the main effects of Distractor Distribution and Trial Number, without any hypotheses or interest in studying their interaction. Helmert contrasts are particularly useful for ordinal variables. In this context, we anticipated improved performance throughout the learning trials up to a certain point. Our focus was not on comparing each trial number with another, but rather on comparing each trial number with the subsequent ones to determine whether performance improved after each trial (e.g., 1 vs. 2–3–4, 2 vs. 3–4, 3 vs. 4). However, the results from repeated measures ANOVA that test both main effects and the interaction between Distractor Distribution and Trial Number are included in the Supplementary Materials (S.1.).

Subsequently, we measured SRTs on test trials, comparing the shape of the curve representing the SRT as a function of the CT-PD (in absolute value and sampled in bins of 4 JND; 0, 4, 8, 12, 16, 20, 24) for the two Previous Distractor Distributions (Uniform or Gaussian). Segmented regression analyses were used for this purpose, both at the group level (i.e., approximating the curves obtained aggregating all participants) and individual level (i.e., approximating the curves obtained for each participant). Segmented regression searches for significant breakpoints in the SRT curve at some particular CT-PD. We expected that both uniform and Gaussian SRT curves could be approximated as two segments, as obtained in Chetverikov et al. (2017). Following a uniform distractor distribution, the first segment of the SRT ~ CT-PD function should be flat, and the second should have a negative slope, with a breakpoint around 9 JND (see Fig. 1). Following a Gaussian distribution, the first segment should have a negative slope, and the second should be flat, with a breakpoint around 17 JND (although in another FDL study, there was no significant breakpoint in this case; Chetverikov et al., 2020). We used the segmented package (Muggeo, 2008) to estimate breakpoints. At the group level, a Davies test was used to assess the significance of the difference between a model with 1 breakpoint and a linear model with no breakpoint.

At the individual level, we performed a repeated measures ANOVA on the Slope Coefficient obtained for each participant with Coefficient (β_0, β_1; before and after the range of the distractor distributions) and Previous Distractor Distribution (Uniform or Gaussian) as within-subject factors. We expected an interaction between the Previous Distractor Distribution and the Coefficient, reflecting the difference in slopes between a uniform a Gaussian distribution, within and outside of the distractor distribution range. This analysis was conducted independently of the segmented regression results obtained at the group level, providing insights based on individual data rather than solely on aggregated data. Before the breakpoint, we expected the slope coefficient to be higher (i.e., closer to 0) for the uniform distribution, whereas we expected the opposite after the breakpoint. For the uniform distribution, we expected a higher (closer to zero) slope coefficient before the breakpoint and the opposite for the Gaussian distribution (replicating the pattern observed with a breakpoint at 9 JND in Chetverikov et al., 2017).

Note that test trial analysis throughout the manuscript focused on reaction time measures, which are commonly studied in Feature Distribution Learning paradigms, while accuracy measures often exhibit a ceiling effect. Specifically, accuracy is very high in test trials, and therefore less informative about distractor templates (see Supplementary Materials S.2. for accuracy in test trials).

3.2. Results

3.2.1. Learning trials

Fig. 2 shows mean proportion of correct trials and SRTs during learning trials as a function of trial number within the learning sequence and distractor distribution. The task was easier with distractors drawn from a Gaussian than a uniform color distribution. The proportion of correct trials was higher, $t(15) = 9.71$, $p < .001$, $d = 2.43$, and SRTs faster, $t(15) = -11.2$, $p < .001$, $d = 2.79$, for the Gaussian ($M \pm SD$ for the proportion of correct trials $= 0.92 \pm 0.069$; $M \pm SD$ for the SRT $=$ 328 $\pm$ 32 ms) than the uniform distribution ($M \pm SD$ for the proportion of correct trials $= 0.87 \pm 0.059$; $M \pm SD$ for the SRT $= 358 \pm 27.6$ ms).

Helmert contrasts then revealed that the task became easier over the learning trials with a lower proportion of correct trials, $t(45) = -6.91$, $p < .001$, and slower SRTs, $t(45) = 59.8$, $p < .001$, on the first learning trial than later ones. Moreover, SRTs were also slower on the second trial than on later trials, $t(45) = 13.9$, $p < .001$, demonstrating an attentional priming effect, with easier target detection and faster saccades when target and distractor characteristics are repeated. For the proportion of correct trials, the difference between the second trial and later trials, was not significant, $t(45) = -1.07$, $p = .29$. The difference between the third and the fourth trial was not significant, neither for the proportion of correct trials, $t(45) = -0.59$, $p = .55$, nor for SRTs, $t(45) = 1.63$, $p = .11$.

3.2.2. Test trials

Fig. 3 (A) shows SRTs on test trials as a function of CT-PD and the distractor distribution on learning trials. SRTs were slower when the color of the target was within the range of the previous distractor distribution (i.e., when the CT-PD is below 12 JND; $M \pm SD = 325 \pm 41.5$ ms), than when it was outside this range ($M \pm SD = 277 \pm 42.8$ ms), $t(15) = -13.4$, $p < .001$, $d = 3.35$.

Group-level segmented regression showed that following the uniform learning distribution, SRTs can be described as a two-segment linear function with a breakpoint at 8 JND (95 % CI = [4.75, 11.25]) away from the mean of the learning distribution. The first segment is essentially flat with a slope coefficient of 0.17 (95 % CI = [−1.59, 1.93]; non-significantly different from zero, $p = .84$), while the second segment has a negative slope coefficient of −4.44 (95 % CI = [−5.52, −3.36]; significantly different from zero, $p < .001$). A Davies test comparing this two-line model with a linear model showed that this slope difference was significant, $p < .001$. Following a Gaussian learning distribution, however, the difference between a two-line and a linear model was not significant ($p = .26$).

A repeated measures ANOVA performed on the slope coefficient for each participant before and after 12 JND revealed a marginally significant interaction between the Previous Distractor Distribution and the Coefficient, $F(1,15) = 4.38$, $p = .054$, $\eta_p^2 = 0.23$. Pairwise t-tests showed that following a uniform learning distribution the slope coefficient was higher (i.e., closer to zero) before than after the breakpoint, $p < .001$ ($M \pm SD$ before the breakpoint $= -1.25 \pm 1.94$; $M \pm SD$ after the breakpoint $= -5.05 \pm 2.13$). Following a Gaussian learning distribution, the slope difference was not significant ($M \pm SD$ before the breakpoint $= -2.89 \pm 2.4$; $M \pm SD$ after the breakpoint $= -4.14 \pm 2.08$, $p = .23$). Before the breakpoint, the slope coefficient was significantly higher following a uniform than Gaussian distribution, $p = .03$. Conversely, after the breakpoint, the opposite non-significant pattern was observed ($p = .21$). Fig. 3 (B) displays boxplots obtained from the slope coefficient

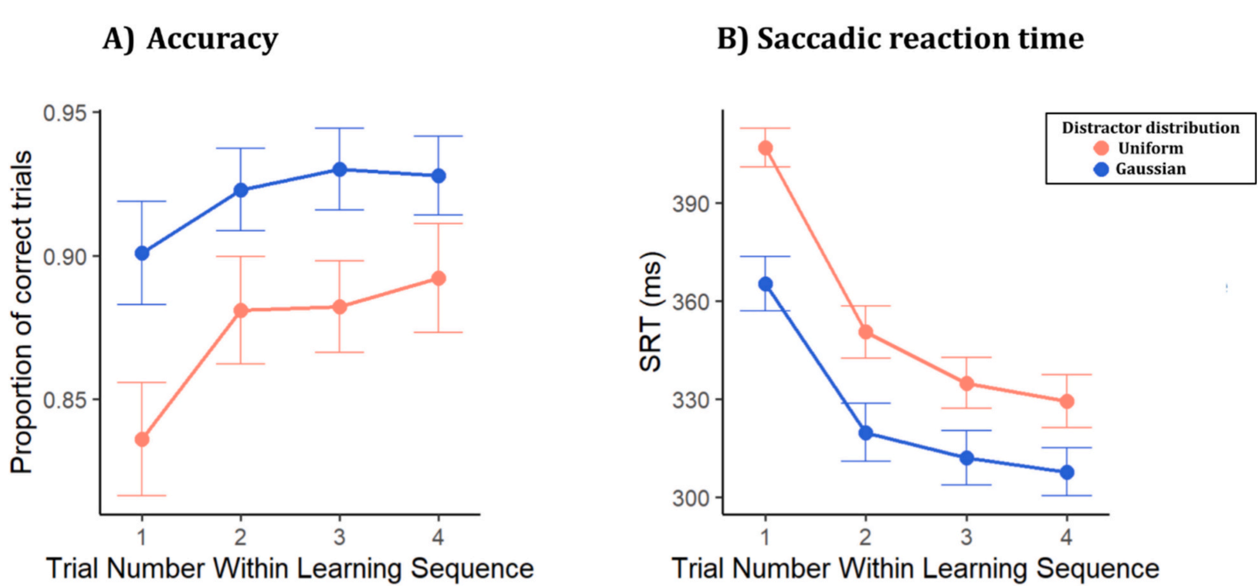

Fig. 2. **(A)** Mean proportion of correct trials, **(B)** Saccadic Reaction Time (SRT) during learning trials, as a function of trial number within learning sequence and distractor distribution. Error bars represent the standard error of the mean.

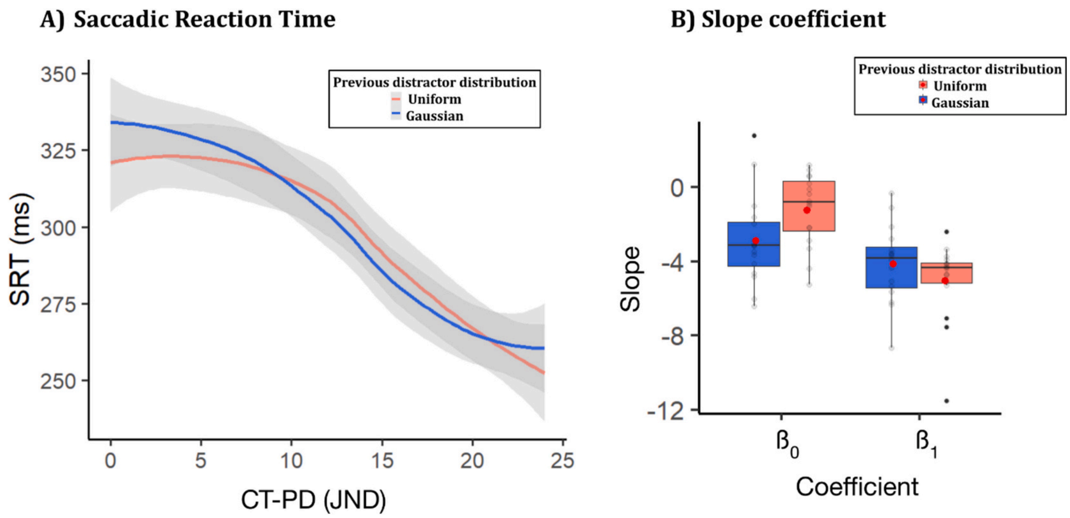

Fig. 3. **(A)** Mean Saccadic Reaction Time (SRT) during test trials as a function of CT-PD (color distance between the target in the test trial and the mean of the distractor distribution on learning trials, in JND) and previous distractor distribution. Curves are smoothed using local polynomial regression, and gray areas represent the 95 % confidence intervals. **(B)** Boxplots obtained from the slope coefficient before (β_0) and after (β_1) the breakpoint (set at 12 JND) for each participant as a function of the previous distractor distribution. Red dots show the mean in each condition. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

before and after the breakpoint for each participant as a function of the previous distractor distribution.

3.3. Discussion

Overall, participants were able to perform the task with high accuracy, although accuracy was lower than in studies with manual responses. Reaction times were shorter here than in previous studies with manual responses, and often, the task was performed with only 1 or 2 saccades (47 % of correct trials were performed with 1 saccade; 35 % with 2 saccades).

The results demonstrated an attentional priming effect on SRT and the proportion of correct saccadic responses, with easier target detection and faster saccades when target and distractor characteristics were repeated. This replicates the results obtained for manual responses in previous studies of color distribution learning (Chetverikov et al., 2017; Hansmann-Roth et al., 2021). Most importantly, test trial analyses revealed that participants learned the previous distractor distribution. First, a breakpoint was found only for the SRT curve following a uniform distribution, with a breakpoint around 8 JND. This value is lower than the real breakpoint (12 JND) but importantly, this aligns with previous results (Chetverikov et al., 2017). Second, the slope before the breakpoint was shallower following the uniform than the Gaussian distribution. Additionally, the slope after the uniform distribution was shallower before than after the breakpoint, which was not the case after the Gaussian distribution. This replicates the results obtained in Chetverikov et al. (2017).

With this experiment, we show that color distribution learning is reflected in saccadic responses. However, eye movements were constrained, and may therefore not optimally reflect natural eye movement behavior. In Experiment 2 we studied the effect of color distribution learning on manual responses and more natural saccadic responses when saccades are not the response modality.

4. Experiment 2: manual responses with eye movement recording

4.1. Method

4.1.1. Participants

There were twenty participants (11 females, 9 males; 28.7 ± 7.1 years), all giving informed written consent before participating. Undergraduate psychology students received course credits for their participation in the experiment. The experiment was carried out in accordance with the requirements of the local ethics committee and declaration of Helsinki for experiments involving humans.

4.1.2. Stimuli and procedure

There were a few minor changes to the visual search display from Experiment 1. Notably, each diamond now had a notch at one corner, and there was no central dot. Additionally, a score was now presented in the top left corner, along with the current and total trial number, to motivate participants. The score was calculated using the same formula as in prior FDL studies (Chetverikov et al., 2020), appearing in green for accurate responses faster than 1 s (denoting increased scores), and in red otherwise (denoting decreased scores).

Now, participants reported (using the keyboard arrows), which corner of the target diamond was missing. Again, the target was the diamond with the color the most different from all the rest. For example, if the right corner of the target was missing, participants should press the right arrow on the keyboard. Target and distractor colors were selected as in Experiment 1 (from the same color distributions, uniform or Gaussian, with the same parameters). Unlike Experiment 1, there was no fixation cross and gap between trials. Therefore, a new trial started right after the previous response was given (see Fig. 4). The experiment was divided into 2 sessions, each with 364 blocks preceded by a training phase of 100 blocks. Each session lasted approximately 1 h. Overall, the experiment design was made to align with Chetverikov et al.'s, 2017 original design. The only differences were a larger number of blocks and the addition of eye-tracking in the present experiment.

4.1.3. Data analysis

Note that a correct trial was defined as a trial with a correct response. Moreover, both error and post-error trials were excluded from latency analysis (leading to 91 % of the learning trials and 94.2 % of the test trials included in latency analysis for MRTs). For SRTs, trials in which there was no saccade to the target were also excluded (leading to 81 % of the learning trials and 86.7 % of the test trials included in the SRT analysis).

We first analyzed manual response and eye movement measures during learning trials. For manual responses, the proportion of correct trials and the reaction times (MRTs), were the dependent variables. For

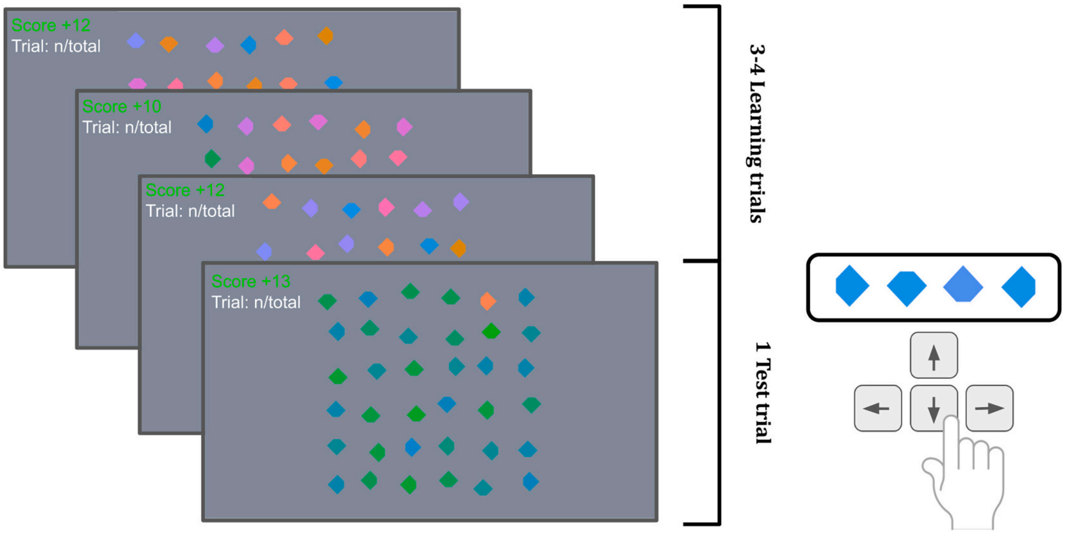

Fig. 4. Illustration of a block. Each block was composed of 3–4 learning trials followed by one test trial. Participants were asked to find the diamond with the most different color from the others and to report the missing corner using the keyboard arrows. Each trial ended upon response.

eye movements, the SRTs were the dependent variable. As in Experiment 1, paired-samples *t*-tests were used to compare performance following Gaussian and uniform learning distributions, and Helmert contrasts were used to compare performance on each Trial Number Within Learning Sequence (1, 2, 3, 4) with the average performance on subsequent trials. We next analyzed MRTs and SRTs during test trials using the same statistical tests as in Experiment 1 (i.e., segmented regressions, both at group and individual levels).

Additionally, in a more exploratory analysis we tested whether specific locations or colors were more likely to attract gaze during the search. On many trials, the target was found with just one saccade. This analysis focused on the remaining trials, in which one or multiple saccades were elicited before fixating the target. It examined the characteristics of the initial saccade landing site, specifically the properties of the distractor closest to the first saccade landing position. Both learning and test trials were included, excluding incorrect and post-error trials. Two repeated measures ANOVA were used with the number of first saccades as a dependent variable. In the first ANOVA, Location (Central; Peripheral) was used as a within-subject factor, determined by whether the fixated diamond was one of the four central diamonds or not. In the second ANOVA, Color Distance (Close; Far) was used as a within-subject factor, determined by whether the target color was close to the mean distractor color (i.e., a distance to the mean of <6 JND) or not. This ANOVA was performed on trials with a uniform distractor color distribution, where all distractor colors had an equal probability of appearing, making the interpretation of the results more straightforward.

4.2. Results

4.2.1. Learning trials

Fig. 5 shows the mean proportion of correct trials, MRTs, and SRTs during learning trials as a function of trial number within learning sequences and distractor distribution on learning trials.

Paired samples *t*-tests revealed that the task was easier with distractors from a Gaussian than uniform distribution. The MRTs were faster, $t(19) = -16.6$, $p < .001$, $d = 3.71$, for the Gaussian (M ± SD = 745 ± 77.3 ms) than the uniform distribution ($M \pm SD = 777 \pm 73.5$ ms). Similarly, SRTs were faster, $t(19) = -13.24$, $p < .001$, $d = 2.96$,

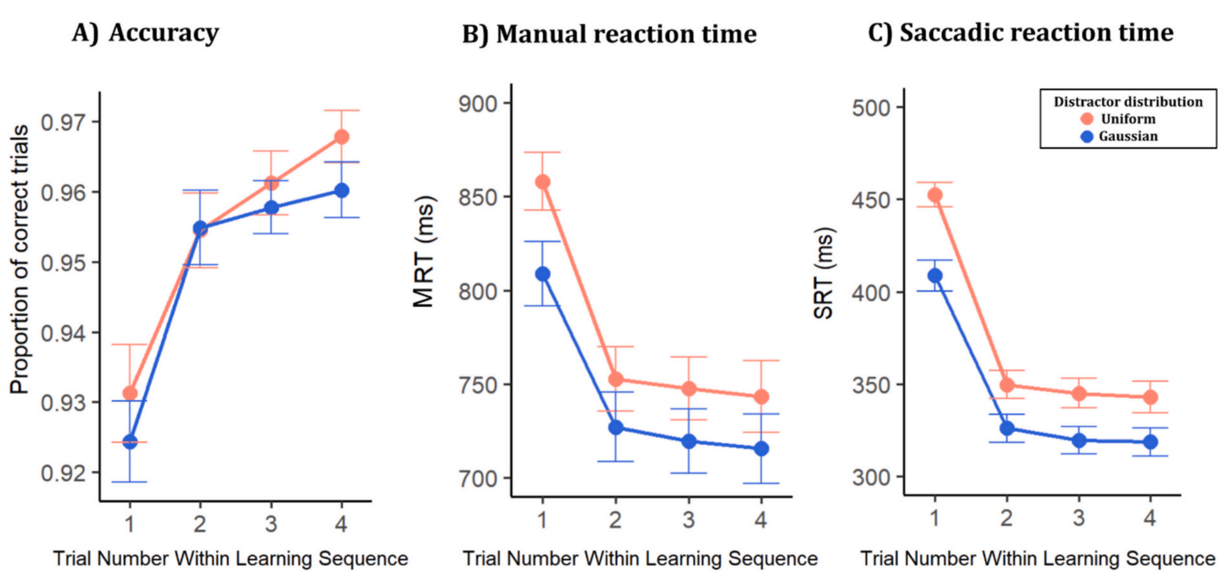

Fig. 5. **(A)** Mean proportion of correct trials, **(B)** Manual Reaction Time (MRT), **(C)** Saccadic Reaction Time (SRT) during learning trials, as a function of the trial number within learning sequence and distractor distribution from Experiment 2. Error bars represent the standard error of the mean.

with a Gaussian ($M \pm SD = 345 \pm 31.8$ ms) than uniform distribution ($M \pm SD = 374 \pm 30.4$ ms). Also, the proportion of correct trials was marginally lower, $t(19) = -1.99$, $p = .06$, $d = 0.45$, with a Gaussian (M ± SD = 0.952 ± 0.019) than a uniform (M ± SD = 0.948 ± 0.021) distribution.

Helmert contrasts revealed that search became easier throughout the learning sequence. The proportion of correct trials was lower, $t(57) = -11.2$, $p < .001$, MRTs were slower, $t(57) = 26.5$, $p < .001$, and SRTs were slower, $t(57) = 28.9$, $p < .001$, on the first than later trials within the learning block. Moreover, the proportion of correct trials was lower, $t(57) = -2.36$, $p = .021$, MRTs were slower, $t(57) = 2.15$, $p = .035$, and SRTs were marginally slower on the second trial compared to later trials, $t(57) = 1.76$, $p = .083$. The difference between the third and the fourth trial was not significant, neither for the proportion of correct trials, $t(57) = 1.31$, $p = .19$, nor for SRTs, $t(57) = 0.35$, $p = .76$, or MRTs, $t(57) = 0.88$, $p = .36$.

4.2.2. *Manual reaction time during test trials*

Fig. 6 (A) shows MRTs during test trials as a function of CT-PD and the previous distractor distribution. Overall, MRTs were slower when target color was within the range of the previous distractor distribution (i.e., when the CT-PD is below 12 JND; $M \pm SD = 817 \pm 112$ ms;), than when it was outside it (M ± SD = 704 ± 99 ms), $t(19) = -14.9$, $p < .001$, $d = 3.34$).

Segmented regression at the group level showed that following the uniform learning distribution, MRTs can be described as a two-segment linear function with a breakpoint at 7.91 JND (95 % CI = [4.95, 10.9]) from the learning distribution mean. The first segment is nearly flat, with a slope coefficient of −0.28 (95 % CI = [−3.97, 3.4]; non-significantly different from zero, $p = .88$), while the second segment has a negative slope coefficient of −8.51 (95 % CI = [−9.32–7.69]; significantly different from zero, $p < .001$). A Davies test confirmed that the difference in slopes was significant, $p < .001$. Following a Gaussian learning distribution, the difference between a two-line and a linear model was also significant, $p = .009$. with a breakpoint at 4.07 JND (95 % CI = [1.51, 6.63]). The first segment was nearly flat with a slope coefficient of −1.02 (95 % CI = [−4.74, 2.71]; non-significantly different from zero, $p = .59$), the second segment had a negative slope coefficient of −7 (95 % CI = [−7.81, −6.17]; significantly different from zero, $p < .001$).

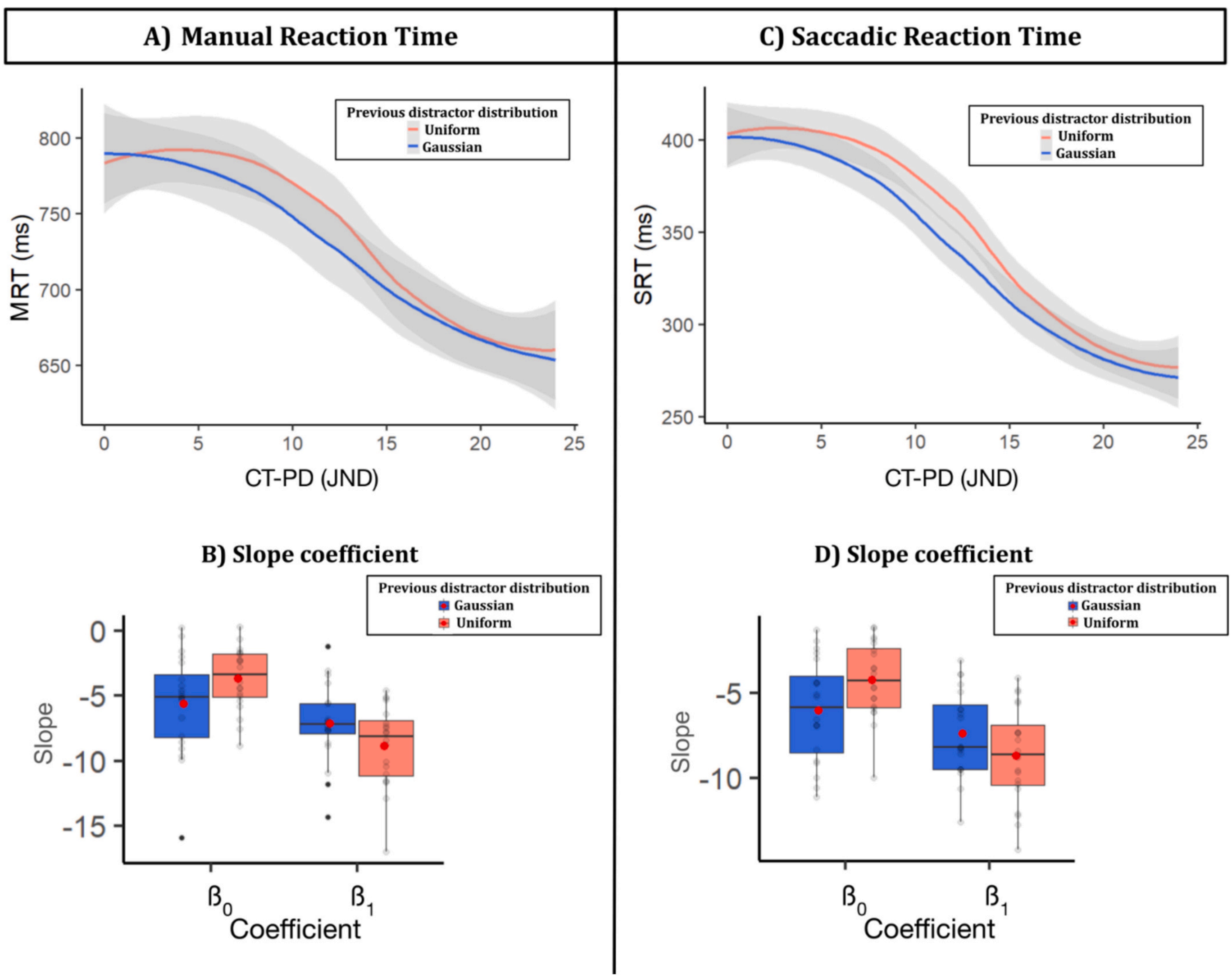

Fig. 6. (A) Mean Manual Reaction Times (MRTs) during test trials as a function of CT-PD (color distance between the target in the test trial and the mean of the distractor distribution on learning trials, in JND) and previous distractor distribution. Curves are smoothed with local polynomial regression and gray areas represent the 95 % confidence intervals. **(B)** Boxplots obtained from the slope coefficient of the MRT curve before (β_0) and after (β_1) the breakpoint (set at 12 JND) for each participant as a function of the previous distractor distribution. Red dots show the mean for each condition. **(C), (D)**, same as (A), (B) but for Saccadic Reaction Times (SRTs) instead of the MRTs. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

A repeated measures ANOVA on the slope coefficients for each participant before and after 12 JND revealed a significant interaction between the learning distribution and Coefficient, $F(1,19) = 8.85$, $p = .008$, $\eta_p^2 = 0.32$. Pairwise *t*-tests showed that following a uniform distribution the slope coefficient was higher (i.e., closer to zero) before than after the breakpoint, $p < .001$ ($M \pm SD$ before the breakpoint $= -3.68 \pm 2.43$; $M \pm SD$ after the breakpoint $= -8.89 \pm 3.14$). Following a Gaussian learning distribution, the slope difference was not significant ($M \pm SD$ before the breakpoint $= -5.62 \pm 3.84$; $M \pm SD$ after the breakpoint $= -7.16 \pm 3.04$; $p = .19$). Before the breakpoint, the slope coefficient was higher (i.e., closer to zero) following a uniform than a Gaussian distribution, $p = .015$. Conversely, after the breakpoint, the opposite pattern was observed, $p = .02$. Fig. 6 (B) shows boxplots for slope coefficients before and after the breakpoint for each participant as a function of the previous distractor distribution.

4.2.3. *Saccadic reaction time on test trials*

Fig. 6 (C) shows SRTs during test trials as a function of CT-PD and the previous distractor distribution. Overall, SRTs were slower when target color was within the range of the previous distractor distribution (i.e., when CT-PD is below 12 JND; $M \pm SD = 403 \pm 47.4$ ms), than when it was outside it ($M \pm SD = 300 \pm 34.4$ ms), $t(19) = -14.4$, $p < .001$, $d = 3.21$.

Group-level segmented regression showed that following the uniform learning distribution, SRTs can be described as a two-segment linear function with a breakpoint at 7.3 JND (95 % CI = [4.65, 10]) away from the mean of the learning distribution. The first segment has a nearly flat slope coefficient of −0.8 (95 % CI = [−4.05, 2.45]; non-significantly different from zero, $p = .63$), the second segment has a negative slope coefficient of −8.24 (95 % CI = [−8.9, −7.52]; significantly different from zero, $p < .001$. Davies test comparing this two-line model with a linear model confirmed that the slope difference was significant, $p < .001$. Following a Gaussian learning distribution, the difference between a two-line and a linear model was also significant, $p = .009$. The estimated two-line model had a breakpoint at 5.08 JND (95 % CI = 2.04, 9.66]). The first segment has a negative slope coefficient of −3.18 (95 % CI = [−6.42, 0.075]; marginally different from zero, $p = .055$), and the second segment has a negative slope coefficient of −7.47 (95 % CI = [−8.19, −6.76]; significantly different from zero, $p < .001$).

A repeated measures ANOVA on the slope coefficients for each participant before and after 12 JND revealed a significant interaction between the Previous Distractor Distribution and Position, $F(1,19) = 7.63$, $p = .012$; $\eta_p^2 = 0.29$. Pairwise *t*-tests showed that following a uniform distribution the slope coefficient was higher (i.e., closer to zero) before than after the breakpoint, $p < .001$ ($M \pm SD$ before the breakpoint $= -4.27 \pm 2.27$; $M \pm SD$ after the breakpoint $= -8.7 \pm 2.88$), while a marginally significant opposite trend followed the Gaussian distribution, $p = .072$ ($M \pm SD$ before the breakpoint $= -6.03 \pm 3$; $M \pm SD$ after the breakpoint $= -7.42 \pm 2.56$). Before the breakpoint, the slope coefficient was higher following a uniform than a Gaussian distribution, $p = .025$. Conversely, after the breakpoint, the opposite trend was observed, $p = .034$. Fig. 6 (D) shows boxplots for slope coefficients before and after the breakpoint for each participant as a function of the previous distractor distribution.

4.2.4. *Search characteristics*

Fig. 7 (A) shows the number of first error saccades per location, and Fig. 7 (B) displays the distribution of the number of first error saccades per color distance between the targeted distractor and mean distractor color. The number of first error saccades was higher for central ($M \pm SD = 169 \pm 73.2$), than peripheral diamonds ($M \pm SD = 39.1 \pm 4.75$; $t(19) = -8$, $p < .001$, $d = 1.79$). Moreover, the number of first error saccades was higher for diamonds whose color was far from the mean of the distractor color ($M \pm SD = 55 \pm 9.62$) than for those close to the mean distractor color ($M \pm SD = 45 \pm 11.3$), $t(19) = 7.85$, $p < .001$, $d = 1.75$).

4.2.5. *Accuracy, MRTs, and SRTs in experiment 1 and 2*

Overall, manual response accuracy in this experiment ($M \pm SD = 0.957 \pm 0.017$) was higher than saccadic response accuracy in Experiment 1 ($M \pm SD = 0.909 \pm 0.056$), $t(18.6) = -3.35$, $p = .003$, $d = 1.18$. Additionally, MRTs in this experiment ($M \pm SD = 725 \pm 0.72.1$ ms) were higher than SRTs in both Experiments 1 ($M \pm SD = 329 \pm 26.9$ ms), $t(24.9) = -22.8$, $p < .001$, $d = 0.6$, and Experiment 2 ($M \pm SD = 348 \pm 36.1$ ms), $t(19) = -32.3$, $p < .001$, $d = 1.18$. SRTs in this experiment were similar to SRTs in Experiment 1 for learning trials, but for test trials SRTs were shorter in Experiment 1 ($M \pm SD = 297 \pm 24.3$ ms) than in Experiment 2 ($M \pm SD = 350 \pm 37.6$ ms), $t(32.9) = -5.17$, $p < .001$, $d = 7.22$. Finally, in Experiment 2, MRTs and SRTs are positively correlated, $r(58198) = -0.54$, $p < .001$.

4.3. *Discussion*

Experiment 2 demonstrated an attentional priming effect on SRTs, MRTs, and the proportion of correct manual responses during learning trials. This followed the same pattern as in Experiment 1. Moreover, test trial analyses revealed that participants can differentiate the shapes of different learning distributions. First, a breakpoint was found at around 8 JND for both the SRT and MRT curves following a uniform distribution. A breakpoint was also found for the SRT and MRT curves following a Gaussian distribution at around 4 JND, which was not expected but

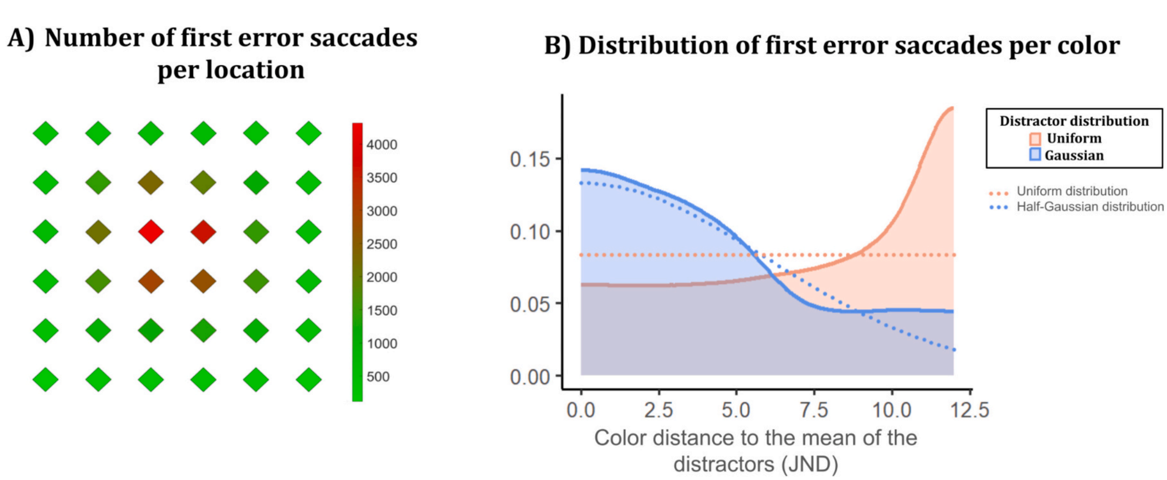

Fig. 7. (A) Number of first error saccades per location and (B) Distribution of the number of first error saccades per color distance between the targeted distractor and the mean of the distractor color. Dotted lines correspond to the distribution that the distractor colors are drawn from.

may reflect noise around the approximation of the mean. We also observed an interaction between the coefficient (before or after the breakpoint) and distractor distribution upon the slope coefficients for both MRT and SRT curves. Overall, very similar patterns were observed for both MRTs and SRTs, suggesting that color distribution learning affects MRTs and SRTs similarly. Note, importantly, that this argues that the color distribution learning observed here affects initial attentional guidance. Further support for this comes from an additional analysis on saccade numbers on each trial in experiments 1 and 2 (see Supplementary Materials S.3.), where we found that the distribution on learning trials influenced how many saccades were needed to locate the target on test trials: Observers made more saccades when the target came from within the preceding distractor distribution than from outside it, supporting the idea that feature distribution learning guides initial attention shifts and saccades.

5. Random forests

In an additional exploratory analysis, we used random forest algorithms to explore the relative predictive contribution of several variables to Manual and Saccadic Reaction Times (MRT and SRT; separately processing the SRT from Experiment 1, where saccades are the response, and Experiment 2, involving manual responses, and saccades were used to freely explore the display). The goal was to assess the influences driving the visual search and rank them for each modality. Random forests are a popular machine-learning algorithm introduced by Breiman (2001), that combines the output of multiple decision trees to reach a single result. Specifically, it can construct a prediction rule for both classification and regression problems. Particularly interesting for us is that it can easily be used to assess and rank measures of a variable's importance, automatically computed for each predictor within the random forest algorithm.

5.1. Method

Both MRTs and SRTs from Experiment 2 and SRTs from Experiment 1 were predicted for each correct trial based on the following variables: First, variables characterizing the current trial: Trial Type (Test, Learning), Distractor Distribution (Uniform, Gaussian), Target Position (1:36), and Distance (in pixels) between eye position at the beginning of the trial and target position. Secondly, variables that characterized the current trial in relation to the other trials: Trial Number within learning sequence (1, 2, 3, 4), Session (1,2), and whether the trial followed an error trial (Post-Error; taking either a value of 1 or 0). Finally, we analyzed color distance between the current target and the current distractor (between 18 and 24 JND) and color distance between the current target and the previous distractor (ranging from 1 to 24). Those variables, referred to as predictors, were chosen based on preceding results that show that they relate to reaction times.

We developed random forest models using the R package *randomForest* (Liaw & Wiener, 2002) and the *randomForest* function. The same procedure was used for each variable to predict MRT and SRT from Experiment 2 and SRT from Experiment 1. First, data were randomly split into a 70 % training set and a 30 % testing set. Then, a random forest algorithm was computed on the training set, using default parameters. Specifically, there were 500 trees and 3 predictors randomly sampled at each split. Variable importance was computed based on the mean decrease in impurity when a variable is included in a tree. The Gini impurity index is used, which translates how well a node splits the data (the lower the Gini, the better the feature is for splitting the data). Measures based on the decrease of impurity are popular because they are simple and fast to compute, but they are biased in favor of variables with many possible split points (e.g., Nembrini et al., 2018; Strobl et al., 2007). This procedure was repeated 10 times for each variable to compute a reliable mean importance value for each predictor (therefore using different training sets).

5.2. Results

Importance rankings from the random forest analyses are displayed in Fig. 8. For all reaction time measures, Distance was the most important variable. Target Position was the second most important variable, followed by the distance between the current target and the previous distractor color. The distance between the current target and the current distractor color was the fourth most important variable, followed by the trial number within the learning sequence. The importance rankings were therefore very similar for all reaction time measures. The only difference may be that for the SRT from Experiment 2, the difference between Target Position and the distance between the current target and the previous distractor color was very small (= 0.0054). Therefore, the distance between the current target and the previous distractor color may be more important for free eye movements.

6. General discussion

We investigated how color distribution learning affects oculomotor selection. We analyzed the effect of color distribution learning on saccadic reaction times in two visual search experiments. In Experiment 1, saccadic eye movements were the behavioral response, while in Experiment 2, participants were instructed to respond with keypress, so eye movements were used to naturally explore the display.

6.1. Probabilistic learning of distractor features affects oculomotor selection

Our key question concerned performance on test trials as a function of the characteristics of the preceding learning distribution. The results showed that participant's search performance reflected whether the learning distribution was Gaussian or uniform. For both SRTs and MRTs, the slope coefficients obtained from the RT ~ CT-PD curve before and after the breakpoint (i.e., 12 JND, based on the range of the learning distribution) according to the previous distractor distribution followed a similar pattern. Before the breakpoint, the slope was shallower following the uniform than the Gaussian distribution, while after the breakpoint, the opposite pattern was observed. Conversely, the slope following the uniform distribution was shallower before, than after the breakpoint, a difference that was not significant following the Gaussian distribution. Notably, this replicates prior findings obtained with manual responses (Chetverikov et al., 2017). Using segmented regression to estimate breakpoints in the aggregated RT ~ CT-PD curve consistently estimated a breakpoint around 8 JND following the uniform distractor color distribution. Following the Gaussian distractor color distribution, no breakpoint was found in Experiment 1, while there was a breakpoint around 4 JND in Experiment 2 (for both MRTs and SRTs). While the estimation of a breakpoint around 8 JND following the uniform distractor color distribution aligns with previous results, the estimation of a breakpoint in Experiment 2 following the Gaussian distractor color distribution was unexpected (Chetverikov et al., 2017).

Following a Gaussian distractor distribution, a monotonically decreasing RT curve was expected within and above the distribution range, while a flat segment within the distribution range followed by a sharp decrease outside that range was anticipated following a uniform distractor distribution, given equal probabilities for all feature values within the range (Chetverikov et al., 2020). Examining the RT ~ CT-PD curves in Experiment 2 following a Gaussian distribution, we observed a slower decline in RT with increasing CT-PD below 4 JND, indicating non-monotonic performance patterns. This might stem from estimation noise in the mean or an overestimation of variance, commonly observed in ensemble perception for various features, such as orientation (Witt, 2019), spread (Witt et al., 2023), or color (Hansmann-Roth et al., 2021). Conducting segmented regression on a half-Gaussian curve with a standard deviation of, for instance, 12 JND would yield a breakpoint around 3.7 JND (see Supplementary Materials S.4.). Overall, despite

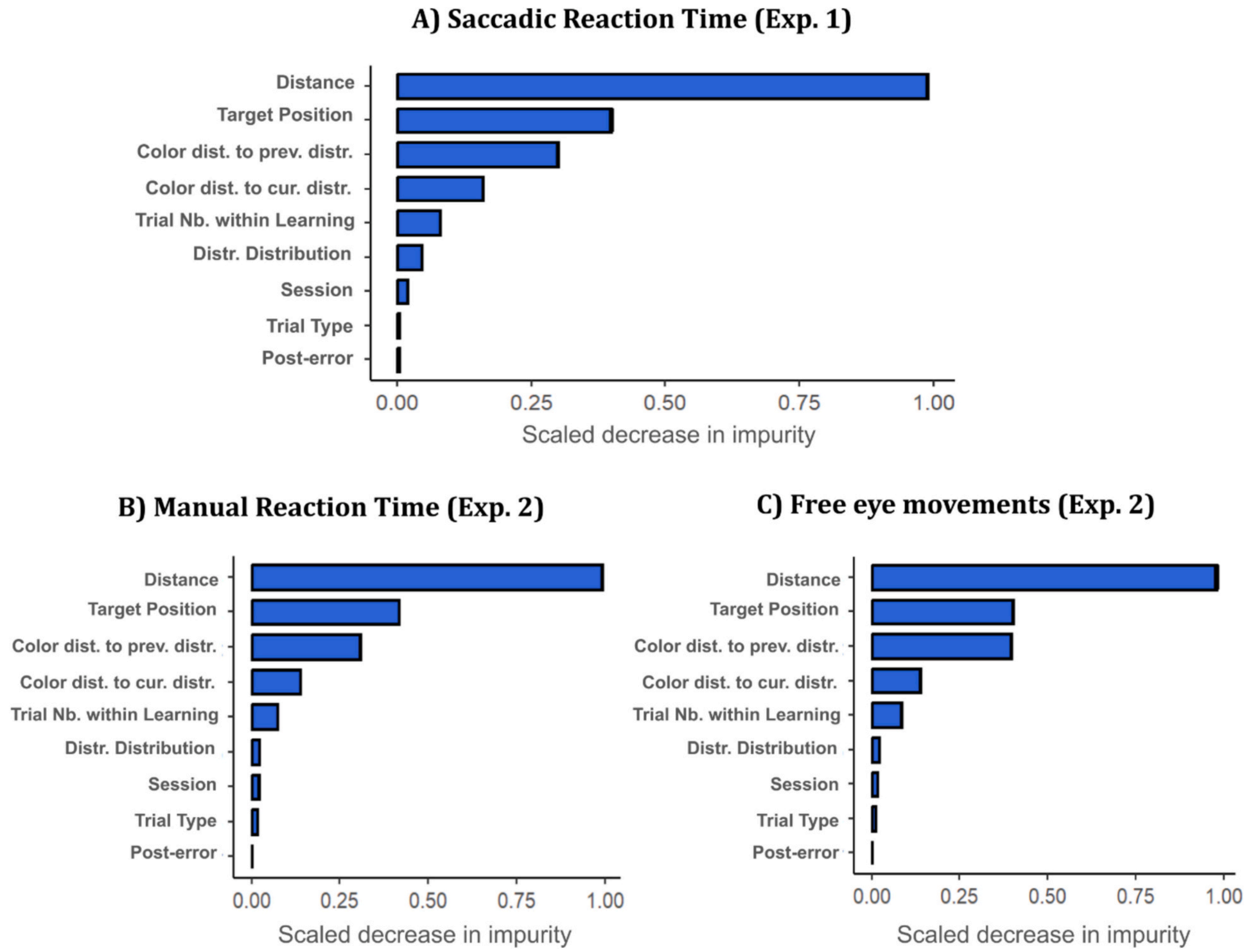

Fig. 8. Importance of selected variables for predicting (A) SRT in Experiment 1, (B) MRT in Experiment 2, and (C) SRT in Experiment 2. Importance is evaluated through the increase in node purity when the variable is included in a split (rescaled between 0 and 1 for the purpose of illustration).

consistent interactions observed in the slope coefficient at the individual level, the estimation obtained with aggregated data appears sensitive to noise. But most importantly, the color distributions of the distractors on learning trials affected oculomotor and manual responses similarly for both MRTs and SRTs.

6.2. Similarities and differences between saccadic responses, manual responses and free eye movements

Indeed, there were only minor differences between results obtained with manual responses, saccadic responses and free eye movements. Although manual response times were generally slower, they mirrored similar effects of color distribution learning. Several studies have already demonstrated a close relationship between target representations for perception and eye movements during visual search (Beutter et al., 2003; Eckstein et al., 2007; Zhang & Eckstein, 2010). This tight coupling between perception and oculomotor selection has also been highlighted in other contexts, such as visual illusions (van Zoest & Hunt, 2011) and microsaccades (White & Rolfs, 2016).

While our findings suggest similar attentional templates for perceptual decisions and eye movement programming, they do not preclude dissociations in other contexts. For instance, Lisi and Cavanagh (2015) demonstrated a dissociation between perception and saccade programming for moving objects. They exploited a visual illusion where a double-drift stimulus causes deviations in apparent motion trajectories (Tse & Hsieh, 2006) showing that saccadic eye movements targeted the real object position rather than the deviated perceived trajectories. Furthermore, there are numerous situations in which eye movements are sensitive to particular visual features that fail to modulate perceptual reports (see Spering & Carrasco, 2015, for a review). In our study, manual responses do not necessarily reflect explicit reports but possibly implicit assessments of distractor color representations. The results might differ (e.g., with more dissimilarities between oculomotor and manual responses) for explicit judgments. Hansmann-Roth et al. (2021) showed that observers' explicit judgments about distractors' color were limited to the summary statistics of color distributions, while implicit assessment revealed encoding of distribution shape.

During learning trials, SRT patterns were similar in Experiment 1 (i.e. for saccadic responses) and Experiment 2 (i.e., for free eye movements). However, on test trials, SRTs were faster in Experiment 1. This difference is particularly noticeable for low CT-PD. This discrepancy may be explained by the fact that, while the overall pattern remains consistent, previous distractor colors may have larger effects on latencies of free eye movements. This observation would align with the results of the Random Forest analysis. Overall, although the ranking was the same, the importance of the previous distractor color was higher for free eye movements than manual or saccadic responses in Experiment 1. This could suggest a potentially greater impact of learning previous distractor colors on free eye movements. However, comparing results from Experiment 1 and Experiment 2 could be misleading due to methodological differences. Notably, the presence of a fixation cross and a gap in Experiment 1 could lead to faster saccades, as gaps have been shown to be associated with shorter latency saccades (e.g., Saslow, 1967). Additionally, starting the search with the gaze near the center of the screen could make the task easier.

Our Random forest analysis showed that the rankings of variable importance were similar for both MRTs and SRTs. Specifically, the distance between initial fixation and the target emerged as the most crucial variable in predicting MRTs and SRTs, followed by target position and previous distractor color. It is important to note that the interpretation of this ranking requires caution. The measure of variable importance that we used is influenced by the number of different values of categorical inputs, with variables having numerous possible values being deemed more important due to their potential for higher prediction precision (e.g., Nembrini et al., 2018; Strobl et al., 2007). The goal was therefore not to analyze the ranking itself but mostly to compare it across different modalities. Overall, although the ranking was the same, the importance of the previous distractor color was higher for eye movements than manual responses in Experiment 2. This suggests a potentially greater impact of learning previous distractor colors on free eye movements. Note that, using an unbiased variable importance measure, the distance between initial fixation and the target still emerged as the most crucial variable, and the importance of the previous distractor color was still higher for eye movements than manual responses in Experiment 2 (see Supplementary Materials S.5).

6.3. Search characteristics

Overall, both manual and saccadic reaction times were faster when the target was close to initial fixation. This is consistent with the literature on the eccentricity effect in visual search where search for targets further away from initial fixation is less efficient (e.g.,Carrasco et al., 1995; Wolfe et al., 1998). Longer reaction times are generally associated with more saccadic eye movements. When the target is far from initial fixation, it is therefore likely that participants will make more than one saccade. Since manual responses only reflect the result of the search, analyzing eye movements within the FDL paradigm offers insights into search characteristics that cannot be gleaned from manual responses alone. In both experiments, the target was often found using only one saccade (47 % of correct trials were performed with 1 saccade in Experiment 1 and 39 % in Experiment 2). But how are fixations selected when they do not land on targets on trials with multiple eye movements?

Experiment 2 showed that first saccades that did not land on the target, were more likely to land on central than peripheral diamonds. When the target location is not immediately apparent, participants may plan fixations to optimize the acquisition of information for subsequent perceptual decisions, maximizing information gain (Ghahghaei & Verghese, 2015; Najemnik & Geisler, 2005; Renninger et al., 2007). According to Schütz et al. (2012), short-latency saccades are primarily influenced by salience, whereas value information influences long-latency saccades. This shift toward a top-down goal is not determined by the time needed to integrate value information into the saccade plan but rather by the time required to inhibit suddenly appearing salient stimuli (Wolf & Lappe, 2020). In our case, the target is always salient due to the odd-one-out search, and even more so when it has been primed, aligning task demands with saliency content. However, especially since in Experiment 2 the initial fixation can occur in one corner, participants may plan subsequent fixations toward the center of the display to gather additional information.

Additionally, in Experiment 2, when distractor colors were equally likely (i.e., with a uniform distribution), first error saccades landed more frequently on distractors that were furthest away from the mean distractor color. Therefore, participants tended to fixate distractors that closely resemble the target color (i.e., those deviating further from the mean of the distractors). This is in line with previous studies showing that distractors that are the most similar to (e.g., Ludwig & Gilchrist, 2002), or differed in the correct direction from the target (in feature space, e.g., Becker, 2010a, 2010b) attract gaze more than other distractors.

6.4. Evidence for early-level priming of color distributions

Finally, attentional priming was found for both manual responses and oculomotor selection. Specifically, repeating target and distractor colors during learning trials resulted in decreased SRTs and MRTs, along with increased accuracy. Importantly, this replicates previous results obtained with manual responses (MRTs and proportion of correct manual responses; Chetverikov et al., 2017; Hansmann-Roth et al., 2021). These results also align with other visual search studies indicating that distractors sharing the same color as the target on preceding trials are more frequently selected than those with a different color (e.g., Becker, 2010a, 2010b; Becker et al., 2009; McPeek et al., 1999; Shurygina et al., 2019). Examining SRTs, defined as the time taken to initiate a saccade to the target, enables the investigation of effects occurring at early stages of search, affecting attentional guidance. In contrast, MRTs reflect both attentional (target search) and decision-making effects (selecting candidate targets, response selection, and execution). In this sense, our results suggest that priming influences attentional allocation during search, not only decisions. The same conclusions were drawn by Becker (2008) who observed that priming effects modulated the precision and time-course of the first saccade but not fixation durations in visual search. Similarly, Sigurdardottir et al. (2008) observed that priming improved target detection but did not facilitate acuity judgments for that specific target (see also Ásgeirsson et al., 2014). Our results go further by showing that priming of not only a single target or distractor color, but a whole distractor color distribution, influences early attentional processes during search, rather than decisions. Our analyses (Supplementary Materials S.3.) that show how the learned distribution influences how many saccades are needed to find the target supports this conclusion, since, for example, more saccades were needed to find the target when it came from the previous distractor distribution.

7. Conclusion

Our study provides important new insights about the interactions between oculomotor behavior and learning of environmental statistics: previous distractor distributions in visual search influence the time it takes to initiate a saccade toward the target. Our results align well with previous studies on the probabilistic nature of attentional templates (Kristjánsson, 2023; Tanrikulu et al., 2021), but they go further by showing how such probabilistic representations can also guide oculomotor selection. This shows that priming of probabilistic attentional templates affects early attentional selection rather than later decisional processes. Additionally, the use of both manual and saccadic responses allowed us to shed light on the similarities and differences between saccadic and manual responses, as well as free eye movements during visual search. The effect of learning history was very similar across modalities, although an exploratory random forest analysis suggests a larger effect of previous distractor characteristics on free eye movements. Overall, our study demonstrates how learning of detailed characteristics of environmental color distributions guides eye-gaze during visual search.

CRediT authorship contribution statement

Léa Entzmann: Writing – original draft, Visualization, Software, Methodology, Investigation, Formal analysis, Conceptualization. **Árni Gunnar Ásgeirsson:** Writing – review & editing, Methodology, Conceptualization. **Árni Kristjánsson:** Writing – review & editing, Methodology, Conceptualization.

Declaration of competing interest

The authors declare no conflict of interest.

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Appendix A. Supplementary data

Supplementary materials, data, and code supporting the findings of this study are available on the Open Science Framework repository at https://osf.io/jgcxf/. Both visual search experiments were pre-registered at this link. Note that some planned analyses were omitted from the main article for conciseness but are provided in the Supplementary Materials (see section S.6). Supplementary data to this article can be found online at [https://doi.org/10.1016/j.cognition.2024.106002].

Data availability

I have shared the link to my data/code at https://osf.io/jgcxf/.

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