Saccade endpoints reflect attentional templates in visual search: Evidence from feature distribution learning

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In visual search, our gaze is guided by mental representations of stimulus features, known as *attentional templates*. These templates are thought to be probabilistic, shaped by environmental regularities. For example, participants can learn to distinguish between the shapes of different distractor color distributions in visual search. The present study assessed whether such subtle differences in distractor color distributions (Gaussian vs. uniform) are reflected in saccade endpoints. We conducted two experiments, each consisting of learning trials, designed to prime a specific distractor color distribution, and test trials, where target color varied in its distance from the mean of previously presented distractor distributions. Saccade endpoint deviations were observed through the global effect, where the saccades tended to land between two nearby stimuli. The experiments differed in difficulty, with test trials in Experiment 2 involving more distractors and colors. During test trials, reaction times and saccade endpoints were affected by target distance from the mean of the preceding distractor distribution. The farther the target color was from this mean, the less the saccade deviated from the target and the lower the reaction times. However, saccade endpoints did not reflect the *shape* of distractor color distributions, an effect that was observed only on reaction times in Experiment 2. Overall, color priming affects both reaction times and saccade deviations, but distractor feature distribution learning depends on search difficulty and response measures, with saccade endpoints less sensitive to subtle differences in the shape of color distributions.

Introduction

The visual world is rich in color; however, these colors are generally not distributed randomly but follow statistical regularities. For example, a blade of grass is usually green, whereas a poppy flower is typically red. Yet, the exact hues of these objects can vary due to differences in lighting conditions or the objects themselves, as not all blades of grass or poppies share identical shades. Given our limited visual capacity, how precisely can we represent the colors within ensembles of objects? Recently, Kristjánsson (2023) argued that, to account for natural variations, templates tuned probabilistically to a broad spectrum of colors would be more effective than those focused on a single color. For example, when picking poppy flowers, our mental representation of a poppy flower would encompass a range of red hues rather than being fixed on a single one.

Feature distribution learning

A substantial body of evidence indicates that humans can rapidly extract statistical summaries of ensembles of similar stimuli, including the average and variability of features (for a review, see Alvarez, 2011; Whitney & Yamanashi Leib, 2018). Recent studies have demonstrated that our perceptual system can learn even more complex aspects of ensembles, such

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as the shape of the probability distribution of visual features (Chetverikov, Campana, & Kristjánsson, 2016; Chetverikov, Campana, & Kristjánsson, 2017; Iakovlev & Utochkin, 2023; Kim & Chong, 2020). In this context, feature ensembles (such as colors) can be encoded as probability distributions, representing the likelihood of specific values from the most to the least probable. Chetverikov et al. (Chetverikov et al., 2016; Chetverikov et al., 2017) used a method referred to as feature distribution learning (FDL) to reveal such probabilistic encoding (for details on the method, see Chetverikov, Hansmann-Roth, Tanrıkulu, & Kristjansson, 2020). FDL takes advantage of priming effects in visual search to assess distractor feature representations. In these studies, participants are asked to identify an odd-one-out target across visual search trials. The feature values of the distractors are drawn from a probability distribution that remains fixed during *learning* trials. Then, in so-called *test* trials, target and distractor features are switched, producing role reversal effects that typically reduce search efficiency (Chetverikov & Kristjánsson, 2015; Kristjánsson & Driver, 2008). Plotting the response time in test trials as a function of the distance between the target feature and the mean of the previous distractor feature distribution (current target – previous distractor distance [CT–PD]) reveals the subject's internal representation of the previous distractor feature distribution.

An example of evidence for probabilistic learning of feature distributions in the context of color ensembles comes from Chetverikov et al. (2017) (see also Entzmann, Ásgeirsson, & Kristjánsson, 2025; Hansmann-Roth, Chetverikov, & Kristjánsson, 2019; Hansmann-Roth, Kristjánsson, Whitney, & Chetverikov, 2021). This study examined how distractor colors are represented during visual search using the FDL method. During learning trials, participants had to find an odd-one-out color diamond among 35 distractors and make a perceptual judgment about the target (report which corner of the diamond was cut off). Distractor colors were drawn from either a Gaussian or a uniform distribution. In test trials, the CT–PD distance was manipulated to probe the participants' internal representation of the learning distractor color distribution. Participants' internal representations mirrored the actual distribution shapes (Gaussian or uniform). When the previous distractor distribution was Gaussian, reaction times in test trials were highest when the target color matched the mean of the previous distractor distribution and decreased linearly as the target color moved away from the mean. When the previous distractor distribution was uniform, reaction times were similar for all possible distractor colors. These findings suggest that color ensembles can be represented with precision, encompassing not only summary statistics but also color distribution shapes.

In a recent study, we demonstrated that FDL extends beyond manual response times, influencing eye movements during visual search (Entzmann et al., 2025). Specifically, learning of color distributions guided eye movements regardless of whether saccades were used as behavioral responses (Experiment 1) or as part of natural exploratory behavior (Experiment 2), underscoring its role in early attentional orienting. In initial FDL studies, manual reaction times reflected the time it takes to make a perceptual judgment on a target. Several studies have already demonstrated a close relationship between perception and eye movements. For example, in an influential study, Kowler, Anderson, Dosher, and Blaser (1995) demonstrated that summoning perceptual attention to a target also facilitates saccades and that perceptual identification is enhanced at the saccadic goal (for related results, see Deubel, Schneider, & Paprotta, 1998; Zhao, Gersch, Schnitzer, Dosher, & Kowler, 2012). Additionally, although some attentional resources could be allocated away from the saccadic goal without cost, excessive diversion impaired saccadic performance. Overall, spatial attention and eye-movements are tightly coupled, but the precise nature of this coupling is debated. The premotor theory of attention suggests that a shift of attention necessarily entails a saccadic plan (Rizzolatti, Riggio, Dascola, & Umiltá, 1987; Sheliga, Riggio, & Rizzolatti, 1994; for reviews, see Kowler, 1999; Kristjánsson, 2011). More recent studies indicate that, although they are linked, there is not a one-to-one relationship between saccades and attention (e.g., Belopolsky & Theeuwes, 2012; Hanning, Szinte, & Deubel, 2019).

Our main goal with the current research was to test whether FDL is reflected in saccade endpoints. Saccade programming is thought to be guided by a retinotopic priority map, where bottom–up and top–down factors are integrated (Belopolsky, 2015; Bisley & Mirpour, 2019; Fecteau & Munoz, 2006; Klink, Jentgens, & Lorteije, 2014; Zelinsky & Bisley, 2015). A priority value (i.e., weight) is assumed to be assigned to each location in a two-dimensional visual scene. The saccadic goal corresponds to the location with the highest weight, and the strength of the competition with other locations plays a large role in determining the time it takes to elicit a saccade to it. We suggest that FDL results in probabilistic weighting in the priority map. Signals from preceding distractors are inhibited, which is reflected in the weights in the priority map. An item with a previous distractor color would have a lower weight, and lower still if this distractor color is one of the most probable (for example, close to the mean of a Gaussian distractor color distribution). We suggest that this weighting influences not only the time it takes to saccade to the target but also the saccade endpoints.

The global effect

In certain contexts, a so-called *global effect* is observed on saccade endpoints. Also known as saccade averaging, the global effect is the finding that, when two elements in a visual scene are in close proximity, a saccade targeted at one of them generally lands in between the two, instead of on one of them (e.g., Findlay, 1982; Van der Stigchel & Nijboer, 2011). Even if the saccade lands in-between the two stimuli, attention has been shown to be directed to the location of the target and distractor, rather than to the exact location where the saccade lands (which is between the target and the distractor) (Van der Stigchel and de Vries, 2015; Wollenberg, Deubel, & Szinte, 2018). This phenomenon is thought to result from overlapping target and distractor signals within priority maps (Findlay & Walker, 1999; Wilimzig, Schneider, & Schöner, 2006). He and Kowler (1989) were among the first to demonstrate that saccade averaging is influenced by top–down processes, challenging the earlier view that it is merely a reflexive response to ambiguous visual signals. Their findings showed that short-latency saccades are guided not only by immediate visual input but also by prior expectations and the probability of target locations. When target discrimination was easy, averaging effects were reduced; when the target appeared alone, saccades were highly accurate. We can hypothesize that the relative strength of the target and distractor signals determines the magnitude of saccade deviation away from the target, with stronger target signals leading to less deviation and stronger distractor signals causing more deviation.

In relation to color priming, previous studies have provided evidence that saccade endpoints measured through the global effect are modulated by primed target and distractor colors in visual search. Priming effects are characterized by improved performance when target and distractor features are repeated (for a review, see Kristjánsson & Ásgeirsson, 2019; Kristjánsson & Campana, 2010). Van der Stigchel and Meeter (2017) investigated whether color priming stemmed from target signal enhancement or distractor signal suppression by analyzing the global effect. Their rationale was as follows: if priming enhances target signals, saccades will land closer to distractors when they match the previous target color. Conversely, if priming suppresses distractor signals, saccades will land farther from targets when they match the previous distractor color. Participants performed a task requiring saccades to a color or shape singleton among distractors, where the target or distractor could share the color of the target or distractor of the previous trial. The results showed that both target enhancement and distractor suppression contributed to priming effects. Interestingly, in another study where only two items were present, there was no evidence of distractor signal suppression (i.e., only target signal enhancement was observed) (Meeter & Van der Stigchel, 2013).

Current study

Whereas studies of priming effects on saccade endpoints have focused on a single specific color value, the objective here was to extend this approach by priming an entire color distribution using FDL. Our participants were trained on classic FDL learning trials to prime a specific distractor color distribution, followed by test trials designed to measure any global effect. The test trials therefore differed from those in previous FDL studies where they typically involved numerous distractors surrounding the target, which complicates isolating the specific contribution of any single distractor to the observed effects. Additionally, the global effect can be observed in specific locations of the visual field, up to 35° in polar angle from the initial fixation (Van der Stigchel & Nijboer, 2013), so it is essential to ensure that both the target and distractor appear in this region, which is not guaranteed with traditional FDL test trials. Overall, our hypothesis was that, similar to reaction times, saccade endpoints will vary, influenced by the CT–PD distance, and reflect the encoding of the shape of the distractor distribution (Gaussian vs. uniform).

In this paper, we present two FDL experiments varying the degree of competition between the target and distractors in test trials (i.e., varying search difficulty). In Experiment 1, there was low competition, with only three distractors, all sharing the same color (the color farthest from the target). In Experiment 2, competition was higher, with five distractors and more variable distractor colors.

Experiment 1: Low competition setting

Materials and methods

Participants

Fifteen participants (nine females and six males; mean age, 25 ± 8.4 years) were recruited for this experiment. Informed written consent was obtained from each individual prior to participation. The study was conducted in accordance with the requirements of the local ethical committee and the tenets of the Declaration of Helsinki for experiments involving humans. Participation was voluntary and unpaid. One participant completed only 90% of the experiment due to time constraints; however, their data were still included in the analysis. As no previous analyses of saccade endpoints in FDL tasks exist, we decided to recruit a similar number of participants as in previous studies related to color distribution learning and saccadic responses (e.g., 16 participants in Entzmann et al., 2025; 13 participants in Van der Stigchel & Meeters, 2017).

Stimuli and procedure

The experiment consisted of two sessions, each lasting approximately 50 minutes. Participants had the option of completing both sessions one after the other or at separate times. There were no differences between the sessions, and dividing participation into two sessions was done to avoid participant fatigue. As in classical FDL studies, trials were structured into blocks. Each block included three or four learning trials followed by one test trial. According to Chetverikov et al. (2020), for simple distributions such as Gaussian or uniform ones, as few as one or two trials may be sufficient for participants to begin learning the distribution shape. However, they recommended using at least three or four learning trials to minimize carryover effects from previous sequences. In our design, the length of the learning streak randomly varied between three and four trials to prevent any predictability in the patterns and prevent participants from anticipating the start or end of a block. At the beginning of the experiment, both the number of trials per learning sequence (three or four) and the distractor distribution type (uniform or Gaussian) were balanced and randomly assigned on a trial-by-trial basis. Each session consisted of 364 blocks. The first session was preceded by a 100-block training phase designed to familiarize participants with the task. The same training was provided before the second session for participants who chose to complete the sessions in different time slots (four participants).

Figure 1A illustrates an example block, showing both learning and test trial displays. During the learning trials, participants were presented with a search display composed of 36 diamonds arranged in a centrally aligned 6×6 grid spanning $14° \times 14°$ of visual angle. Each diamond measured 1.4° of visual angle (diagonal length) and had one of its corners cut. The individual diamond positions of the grid were slightly jittered by adding a random value within $\pm 0.5°$ to both the horizontal and vertical coordinates. One diamond was the target, and the remaining 35 were distractors. For both training and test trials, target position was randomly selected at the beginning of each trial. The target was defined by being the diamond with the color that differed the most from all the other diamonds. Participants were told that the target was the diamond whose color was most different from all the others and were instructed to indicate which corner of the target diamond was missing by pressing the corresponding arrow key on the keyboard. For example, if the upper corner was missing, then the participant would press the up arrow. Thus, unlike in classical global effect paradigms, this experiment did not involve an explicit saccade task, as participants were not required to make an eye movement to the target. However, participants tended to shift their gaze to this location in order to perform the perceptual judgment. No feedback was given for correct responses, and the next trial began following the participant's response. For incorrect responses, an error message was displayed for one second.

Colors were selected from an isoluminant hue circle comprised of 48 distinct hues, with adjacent hues separated by one just noticeable difference (JND). The color space was obtained from Witzel and Gegenfurtner (2013) and was the same as in previous FDL studies using color as a feature (e.g., Chetverikov et al., 2017; Entzmann et al., 2025; Hansmann-Roth et al., 2019; Hansmann-Roth et al., 2021).

For each block of adjacent learning and test trials, the color distribution of the distractors was kept constant within the learning trials, as either a uniform or a Gaussian distribution. The mean of the distractor distribution was randomly selected at the beginning of each block. During each learning trial, distractor colors were randomly sampled from the chosen uniform or Gaussian distribution, which remained consistent throughout the block. The uniform distribution spanned a range of 24 JNDs; the Gaussian distribution had a standard deviation of 6 JNDs and was truncated to exclude color values more than 2 *SD* away from the mean, ensuring that the range matched that of the uniform distribution. The target color was randomly selected from within a range of 18 to 24 JNDs from the mean of the distractor distribution. Figure 1B presents examples of learning trials, showing the color distribution that the distractors are drawn from, along with the target color placed within the color space. Overall, the learning trial display was similar to previous FDL studies using color as a feature (e.g., Chetverikov et al., 2017; Entzmann et al., 2025).

Test trial displays were designed to maximize the chances of detecting any global effect on endpoint deviations resulting from FDL. In most studies on the global effect, a single distractor has been presented close to the target, with its location tightly controlled (for a review, see Van der Stigchel & Nijboer, 2013). In contrast, the learning trials in our study included 35 distractors with jittered positions, many of which were close to the target, making it difficult to isolate the contribution of individual distractors to the global effect. To address this issue, the number of distractors in the test trials was reduced drastically, and the search display consisted of only four diamonds. Two diamonds

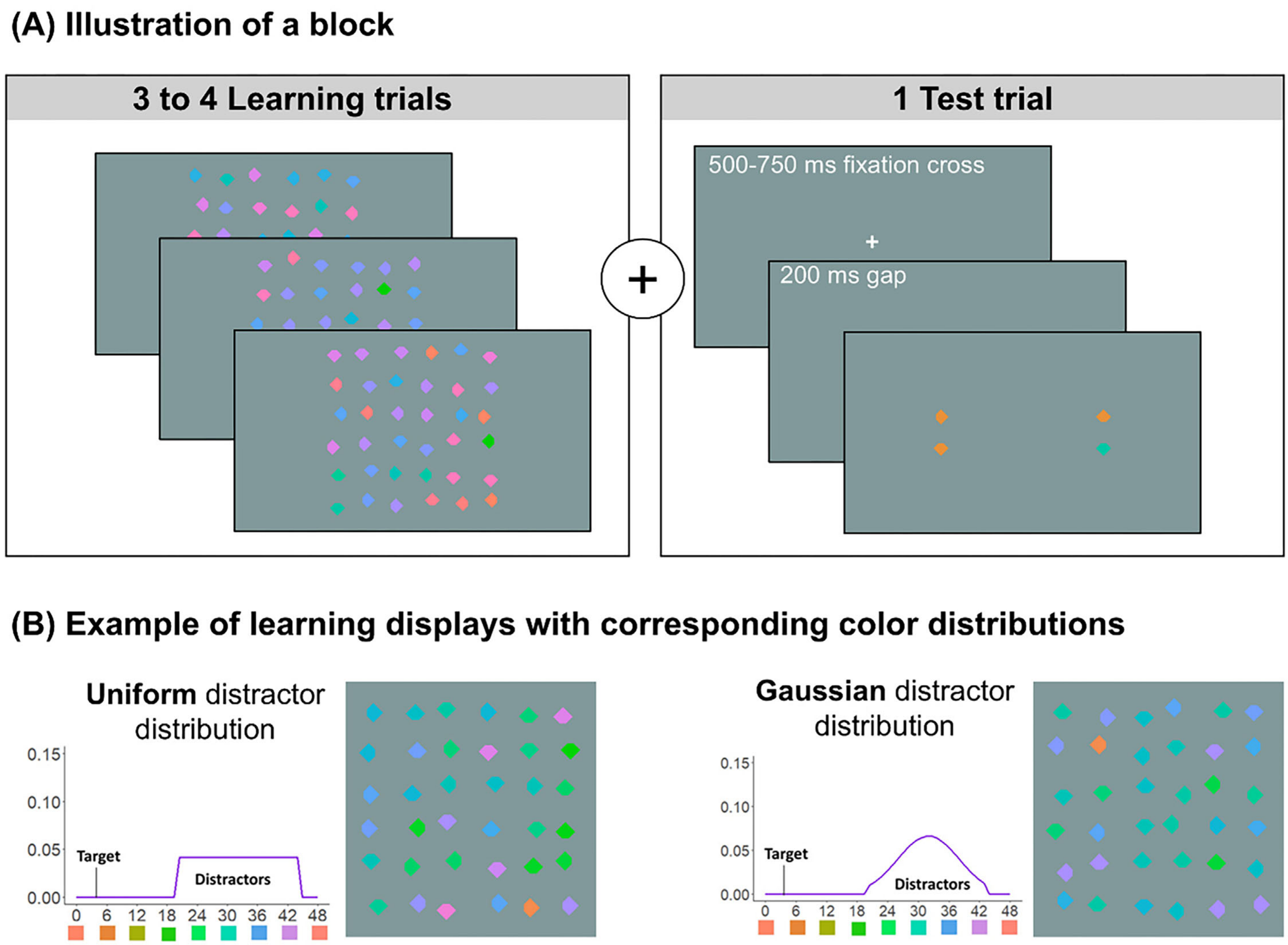

Figure 1. (**A**) Illustration of a block of trials. Each block included three or four learning trials followed by one test trial. (**B**) Examples of visual search displays for learning trials with distractor colors drawn from a uniform (left) or Gaussian (right) distractor distribution. Example displays are presented to the right of the color distribution from which their distractors are drawn.

were positioned along an imaginary circle in each visual field: one located 11° clockwise and the other 11° counterclockwise relative to the horizontal plane. Each diamond was placed 7.7° of visual angle from the center of the screen. The target color was determined based on a balanced CT–PD distance from the mean of the previous distractors, and the distractor color was set as the opposite hue on the color wheel, maintaining a 24 JND distance from the target. A fixation cross was presented before the test display for a pseudo-random duration of 500 to 750 ms, followed by a 200-ms gap before the search displays appeared.

Breaks were scheduled every 100 blocks. A calibration phase was conducted at the start of each session and following every break. During the calibration phase, participants were instructed to fixate on nine dots that appeared sequentially in a 3 × 3 grid spanning the entire screen. Drift correction was performed every eight blocks; if the drift exceeded 0.5°, a calibration was initiated.

Materials

A desktop computer with a 24-inch liquid-crystal display (LCD) monitor was used for the experimental display, with a resolution of 1920 × 1080 and a refresh rate of 144 Hz using MATLAB R2017b (MathWorks, Natick, MA) and Psychtoolbox-3 (Kleiner, Brainard, & Pelli, 2007). Eye movements were recorded using an EyeLink 1000 Plus eye tracker (SR Research, Ottawa, ON, Canada) with a 1000-Hz sampling frequency. Saccades were detected if they had a minimum velocity of 30°/s, a minimum acceleration of 8000°/s^2, and a minimum motion of 0.15°. Blinks were detected when the pupil was partially or totally occluded, and fixations were detected when there was no blink or any saccade in progress. Viewing was binocular but eye tracking was monocular, and only the position of the dominant eye was recorded. During the experiment, the head of each participant was stabilized using a chin-rest at a viewing distance of 94 cm. To correct for screen parameters, color calibration was performed using a ColorCAL MKII photometer (Cambridge Research Systems, Rochester, UK).

Data analysis

Statistical analyses were carried out using R 4.2.2 (R Core Team, 2022) with R Studio 2022.7.2.576 (RStudio Team, 2022), separately for learning and test trials. For each analysis, outliers, defined as values falling outside 1.5 times the interquartile range above the upper quartile or below the lower quartile, were removed. A saccade toward the target was defined as a saccade that landed within a 1.4° visual angle radius around the target. Effects were considered significant if p values were lower than $\alpha = 0.05$.

Learning trials: For the learning trials, three dependent variables were analyzed: the proportion of correct responses; the manual reaction times (MRTs), defined as the time between the start of a trial and the keypress; and the saccadic reaction times (SRTs), defined as the time between the start of a trial and the initiation of a saccade toward the target. For MRTs, incorrect and post-error trials were excluded from the analysis, resulting in 92.2% of trials being included. For SRTs, we also removed trials without a saccade toward the target, resulting in 84.5% of trials being included. We performed pairwise t-tests to compare performance across each distractor distribution (Gaussian or uniform) and used Helmert contrasts to compare performance on each trial number within the learning sequence (1, 2, 3, 4) with the average performance on subsequent trials.

Test trials: For the test trials, MRTs, SRTs, and the endpoint deviations were analyzed. Incorrect and post-error trials were excluded from all test trial analyses, resulting in 95% of trials being included. For SRTs, we also removed trials without a saccade toward the target, resulting in 93.2% of trials being included.

Deviation was calculated from the first saccade performed in the trial, measured as the proportion of angle between the target and the distractor. Only trials in which the first saccade was sufficiently large ($\geq$4° of visual angle) and directed correctly (i.e., not toward the left when the target was on the right, and vice versa) were included. This selection process resulted in 77.7% of the initial number of test trials being retained for the endpoint analysis. More precisely, the deviation was computed as a proportion of angle between the two stimuli, as in Meeter and Van der Stigchel (2013) and Van der Stigchel and Meeter (2017), yielding a value where 0 indicates that the saccade angle matches the target angle, 0.5 indicates a flat saccade, and 1 indicates that the saccade angle corresponds to the distractor angle. Therefore, a higher deviation value indicates a greater deviation *away* from the target or *toward* the distractor. Figure 2 displays a visual representation of the deviation measure for Experiments 1 and 2.

The same analyses were performed on the three dependent variables (i.e., MRT, SRT and deviation). Specifically, we analyzed the relationship between each dependent variable and the CT–PD distance (in absolute values and sampled in bins of four JNDs; 0, 4, 8, 12, 16, 20, 24) for the two previous distractor distributions (uniform and Gaussian).

First, a paired-samples t-test was used to compare each dependent variable across the two sides of the CT–PD values (side: within or outside of the previous distractor distribution, depending on whether the CT–PD was higher or lower than 12 JNDs). To assess how well each observed dependent variable (i.e., MRT, SRT, and deviation) matches the underlying previous distractor distribution, several approaches can be used, including segmented regression and model fitting, as described by Chetverikov et al. (2020). For simple distributions, such as Gaussian or uniform, segmented regression is typically used. Segmented regression involves identifying significant changes in the dependent variable at specific CT–PD distances, referred to as breakpoints. Following a uniform distractor distribution, the curve is expected to exhibit a flat segment within the distribution range (reflecting equal probabilities of all feature values), followed by a sharp decrease beyond the range. In our study and previous ones using the same color set, the estimated breakpoint would theoretically be 12 JNDs, corresponding to the range of the uniform distribution used during learning. Indeed, the uniform distribution spanned 24 JNDs, meaning that the true breakpoint should theoretically occur at $\pm$12 JNDs from the center, as all distractors fall within 12 JNDs of the mean distractor color. In practice, using segmented regression, previous studies have revealed that the breakpoint in the reaction time $\sim$ CT–PD curve following a uniform distribution was below the theoretical value. For example, Chetverikov et al. (2017) reported a breakpoint around nine JNDs, and Entzmann et al. (2025) around eight JNDs.

Segmented regression can be applied at the individual participant level, and statistical comparisons can be made by analyzing the average slope coefficient before and after a predefined breakpoint which would correspond to the uniform distribution range (as in Chetverikov et al., 2017; Entzmann et al., 2025). The rationale is as follows: Following a Gaussian distractor distribution, a monotonic decrease is expected as the CT–PD distance increases, resulting in similar negative slope coefficients before and after the breakpoint. In

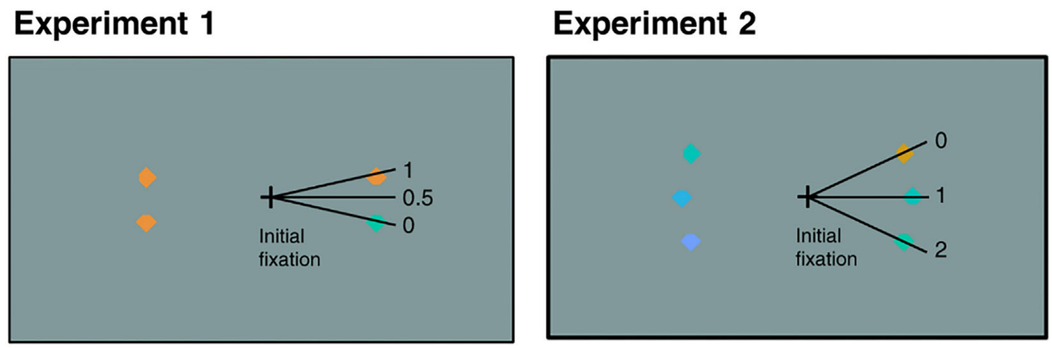

Figure 2. Example of a test trial display and illustration of the saccade endpoint deviation measure in Experiment 1 (left) and 2 (right), calculated based on the first saccade angle, as an angular proportion between the target and the distractor. In Experiment 1, the target and distractor colors (cyan and orange, respectively) were separated by 24 JNDs, corresponding to opposite values on the color wheel. In Experiment 2, distractor colors are drawn from a Gaussian distribution with a standard deviation of three JNDs. The distance between target color (e.g., orange) and the mean of the distractor distribution (e.g., cyan) was 24 JNDs.

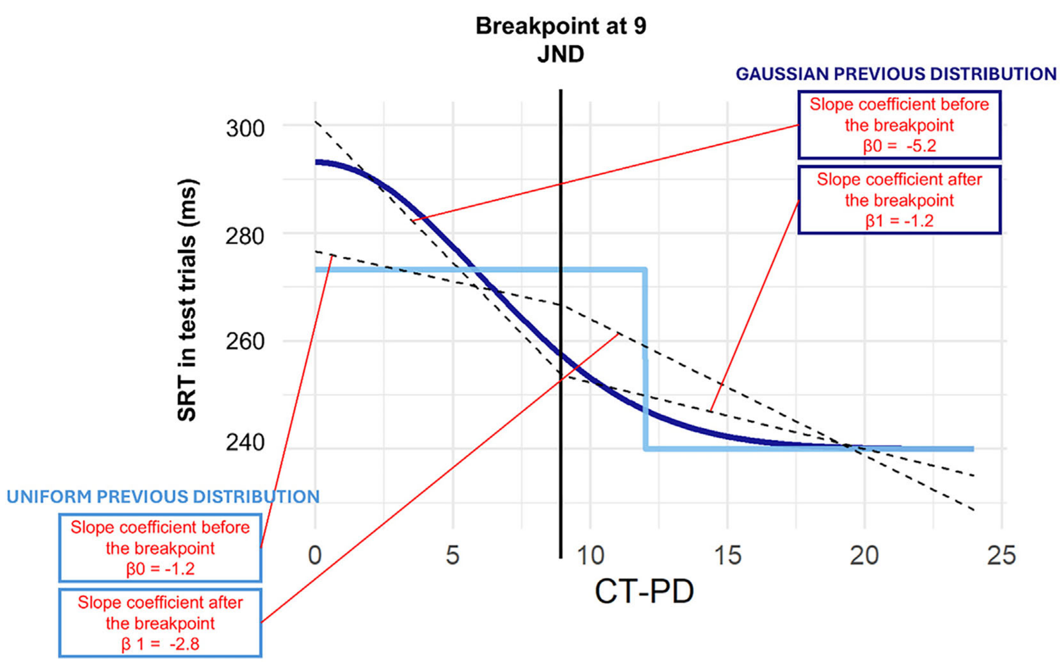

Figure 3. Visualization of the slope coefficient estimation process. Slope coefficients were obtained from MRTs, SRTs, and saccade endpoint deviations in test trials, plotted as a function of CT–PD for each previous distractor distribution. In this example, we present simulated SRT data for a single participant across various CT–PD values (solid lines) for each previous distractor distribution. First, a two-segment model was fitted to each curve, with a breakpoint at nine JNDs (dotted lines). Second, the slope coefficients for the first and second segments were extracted (red boxes) for each distribution.

contrast, following a uniform distractor distribution, the curve is expected to show a flat segment within the distribution range (i.e., a flat slope before the breakpoint), reflecting equal probabilities for all feature values, followed by a negative slope beyond the breakpoint. We used the segmented package (Muggeo, 2008) to estimate slope coefficients using a fixed breakpoint for each participant. We set the breakpoint at nine JNDs, below the true 12 JND breakpoint, to be consistent with underestimations in past FDL studies. In Chetverikov et al. (2017), the slope coefficient analysis was performed using a breakpoint at nine JNDs, whereas in Entzmann et al. (2025), the actual breakpoint was retained. A visual representation of the slope coefficient estimation process is presented in Figure 3.

We then performed a repeated-measures analysis of variance (ANOVA) on the slope coefficient obtained for each participant with CT–PD (β_0, β_1; before and after the breakpoint) and previous distractor distribution (uniform or Gaussian) as within-subject factors. We expected an interaction between the previous distractor distribution and CT–PD, as observed in Chetverikov et al. (2017) and Entzmann et al. (2025). Before the breakpoint, the slope should be flat when the previous distribution is uniform and decrease linearly when the previous distribution is Gaussian. We should, in other words, expect the slope coefficient to be higher (i.e., closer to 0) for the uniform than Gaussian distribution. After the breakpoint, the pattern should be the opposite (see Figure 3). When the previous distribution is uniform, the slope should be flat before the breakpoint followed by a linear decrease; whereas, when it is Gaussian, there should be a linear decrease before the breakpoint but a smaller decrease after it. We then expected a higher (closer to zero) slope coefficient before than after the breakpoint when the previous distribution is uniform and the opposite when it is Gaussian. Only the interaction was tested, not the main effects. When significant, pairwise t-tests were reported. Greenhouse–Geisser corrections were applied when the assumption of sphericity was violated.

In cases where the frequentist repeated-measures ANOVA did not reveal the expected interaction between previous distractor distribution and CT–PD on the slope coefficient (i.e., the expected FDL effect), the null hypothesis (H_0, no interaction) cannot be rejected, and no firm conclusion can be drawn (Hoijtink, Mulder, van Lissa, & Gu, 2019; Wagenmakers, 2007), especially because non-significant interactions may result from insufficient statistical power. Therefore, as an alternative to the frequentist ANOVA, we used Bayes factors (BFs) (Kass & Raftery, 1995). Specifically, we implemented a Bayesian ANOVA to assess the probability of the presence or absence of an interaction between the previous distractor distribution and CT–PD on the slope coefficient for each dependent variable. The Bayesian ANOVA included two within-subjects factors: previous distractor distribution (uniform, Gaussian) and CT–PD (β_0, β_1; before and after the breakpoint), and was implemented using the BayesFactor package (Morey et al., 2015). We report the BFs associated with the interaction effect, as well as a brief interpretation based on the Jeffreys scale (Jeffreys, 1961; see also Wagenmakers, Wetzels, Borsboom, & Van Der Maas, 2011).

Results

Learning trials

Figure 4 shows the mean proportion of correct trials, MRTs, and SRTs during learning trials as a function of trial number within the learning sequence and distractor distribution. MRTs were faster, $t(14) = -5.58$, $p < 0.001$, $d = 1.44$, for the Gaussian distribution ($M \pm SD = 858 \pm 185$ ms) than the uniform distribution ($M \pm SD = 989 \pm 258$ ms). Additionally, SRTs were faster, $t(14) = -9.7$, $p < 0.001$, $d = 2.5$, for the Gaussian distribution ($M \pm SD = 361 \pm 59.8$ ms) than the uniform distribution ($M \pm SD = 404 \pm 70.8$ ms). There was no significant effect of distractor distribution on the proportion of correct responses, $t(14) = -1.48$, $p = 0.16$, $d = 0.38$ (for the Gaussian distribution, $M \pm SD = 0.955 \pm 0.011$; for the uniform distribution, $M \pm SD = 0.958 \pm 0.011$).

Helmert contrasts revealed that task performance improved over the learning trials. Specifically, compared with the later trials, the first learning trial was associated with a lower proportion of correct responses, $t(42) = -9.62$, $p < 0.001$; slower MRT, $t(42) = 13.1$, $p < 0.001$; and slower SRTs, $t(42) = 18.5$, $p < 0.001$.

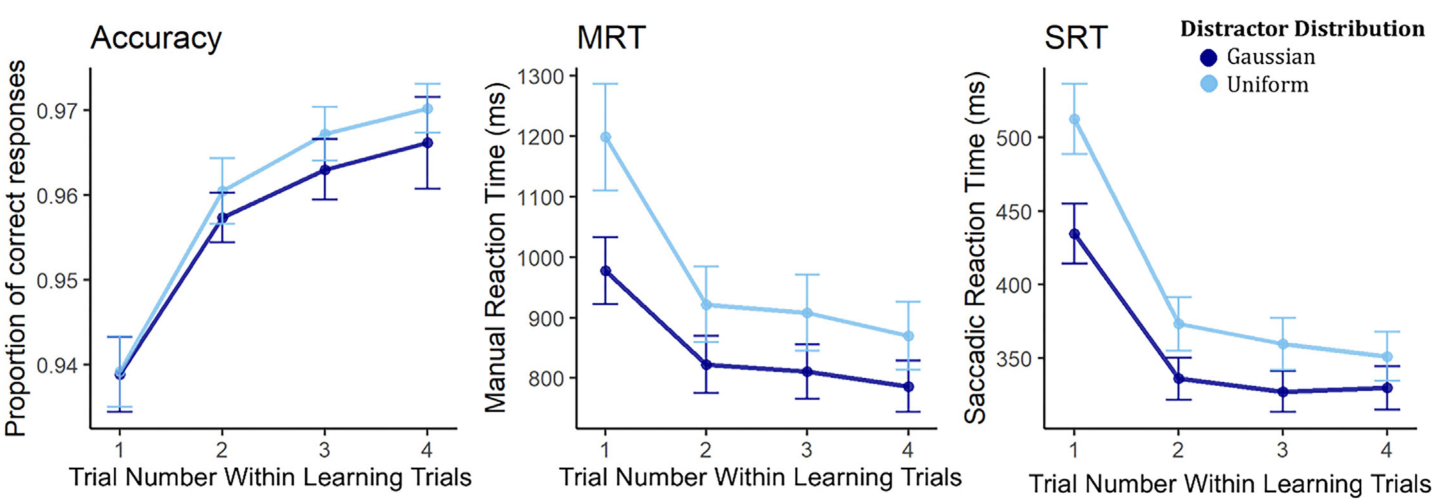

Figure 4. Learning trial results in Experiment 1. Mean proportion of correct trials, MRTs, and SRTs during learning trials, as a function of trial number within learning sequence and distractor distribution. Error bars represent the standard error of the mean.

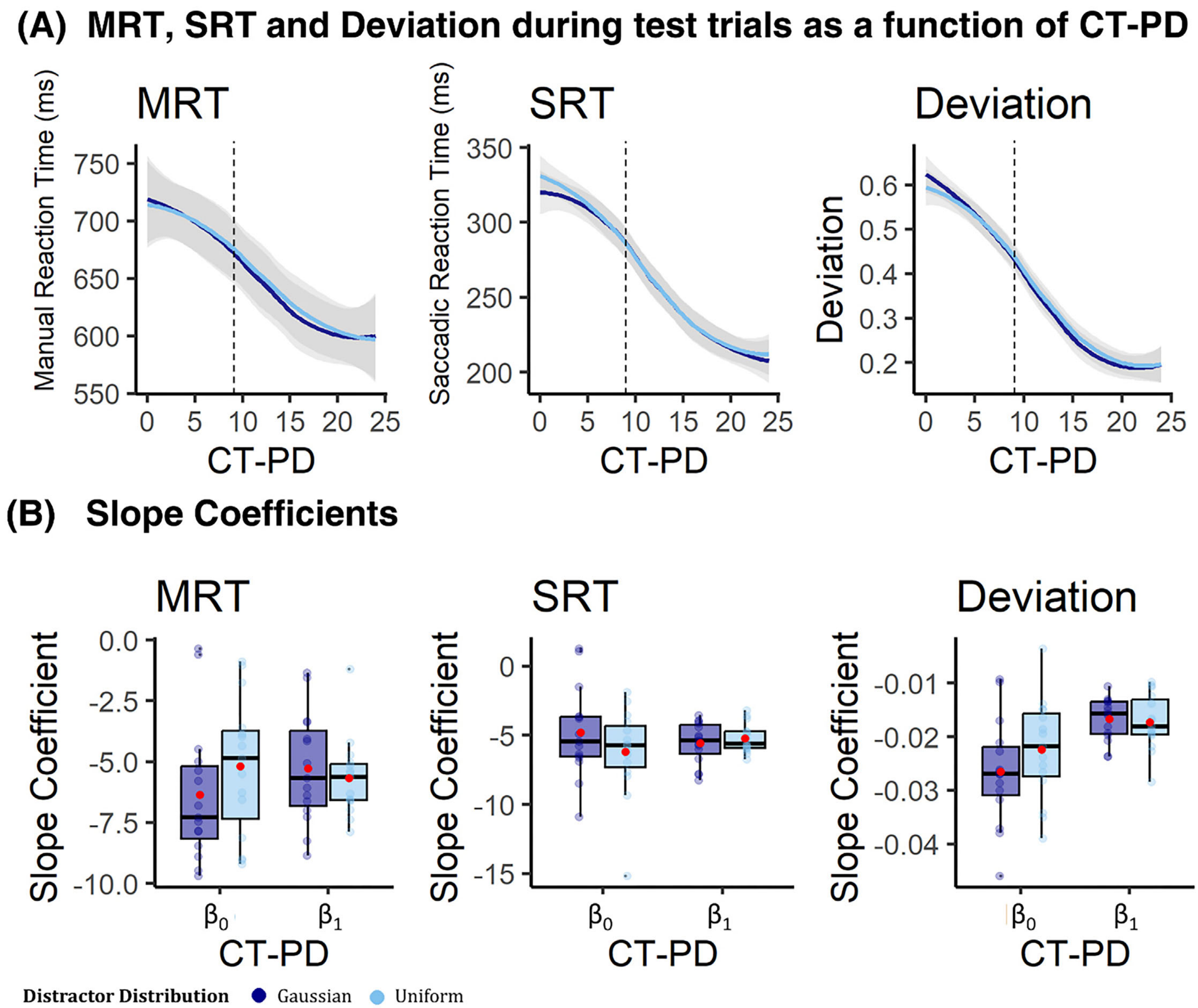

Figure 5. Test trial results in Experiment 1. (**A**) MRTs, SRTs, and deviations during test trials as a function of CT–PD (color distance between the target in the test trial and the mean of the distractor distribution on learning trials, in JNDs) and previous distractor distribution (upper plots). Curves were smoothed using local polynomial regression, and gray areas represent the 95% confidence intervals. The dotted line provides a visual reference for the nine-JND breakpoint that we used to compute β_0 and β_1. (**B**) Boxplots obtained from the slope coefficient before (β_0) and after (β_1) the breakpoint (set at nine JNDs) for each participant as a function of the previous distractor distribution (lower plots). Red dots represent the mean in each condition.

Additionally, the proportion of correct responses was lower on the second trial than on subsequent trials, $t(42) = -2.8$, $p = 0.008$, and SRTs were marginally slower on the second trial than later trials, $t(42) = 1.76$, $p = 0.087$.

Test trials

Figure 5 presents the MRTs, SRTs, and deviations on test trials as a function of CT–PD for each distractor learning distribution (upper plots), along with the slope coefficients calculated before and after the breakpoint (lower plots). MRTs were significantly higher when the target belonged to the previous distractor distribution ($M \pm SD = 695 \pm 68.7$ ms) than when it did not ($M \pm SD = 611 \pm 81.5$ ms), $t(14) = -17.1$, $p < 0.001$, $d = 4.42$. A repeated-measures ANOVA performed on slope coefficients before and after nine JNDs revealed no significant interaction between the previous distractor distribution and CT–PD, $F(1, 14) = 1.64$, $p = 0.22$,

$\eta_p^2 = 0.1$. For MRTs, the BF for the interaction was 0.7 (i.e., there was anecdotal evidence for the absence of an interaction).

Similarly, SRTs were significantly higher when the target belonged to the previous distractor distribution ($M \pm SD = 301 \pm 21.9$ ms) than when it did not ($M \pm SD = 223 \pm 22.3$ ms), $t(14) = -22$, $p < 0.001$, $d = 5.67$. The repeated-measures ANOVA performed on slope coefficients before and after nine JNDs revealed no significant interaction between the previous distractor distribution and CT–PD, $F(1, 14) = 1.26$, $p = 0.28$, $\eta_p^2 = 0.08$. For SRTs, the BF for the interaction was 1.03 (i.e., there was anecdotal evidence for an interaction[1]).

Most notably, for our current purposes, endpoint deviations were significantly larger when the target belonged to the previous distractor distribution ($M \pm SD = 0.51 \pm 0.07$) than when it did not ($M \pm SD = 0.22 \pm 0.07$), $t(14) = -19.35$, $p < 0.001$, $d = 5$. As with MRTs and SRTs, the repeated-measures ANOVA conducted on slope coefficients before and after nine JNDs revealed no significant interaction between the previous distractor distribution and CT–PD, $F(1, 14) = 1.04$, $p = 0.32$, $\eta_p^2 = 0.07$. For deviation, the BF for the interaction was 0.77 (i.e., there was anecdotal evidence for the absence of an interaction).

Discussion

Experiment 1 combined standard FDL learning trials with test trials designed to elicit a global effect. As expected, in learning trials we observed classic FDL outcomes, including priming effects on accuracy, MRTs, and SRTs. On test trials, the CT–PD distance influenced MRTs, SRTs, and, most interestingly, saccade endpoint deviation. Specifically, targets closer in color to the mean of the distractor distribution on the learning trials resulted in endpoints deviating further toward the adjacent distractor; therefore, colored target weighting depends on previous distractor colors, or previous target colors. As the CT–PD correlates with previous target distance and no FDL effect emerged, observed effects can emerge from previous target color. Targets resembling average distractor colors or differing strongly from the previous target received lower weights. Analogous results were recorded for the MRT and SRT measure, where response times were negatively associated with CT–PD. However, the precise shape of the previous distractor distribution (Gaussian or uniform) had no effect on MRTs, SRTs, or endpoints. Unlike most FDL studies, there was a distinct difference between the learning and test conditions in this experiment, potentially limiting the influence of FDL on the test trial measures. In Experiment 2, we adjusted the test trials to increase target discrimination difficulty by introducing greater variability in distractor colors and increasing the number of distractors (five instead of three). These changes served two purposes. First, they reduced the disparity between learning and test environments, and, second, they heightened competition between the target and distractors, making the test trials more challenging.

Experiment 2: High competition setting

Materials and methods

Participants

Seventeen participants (13 females and four males; mean age, 36 ± 12.4 years) were recruited for this experiment. Informed written consent was obtained from each individual prior to participation. The study was conducted in accordance with the requirements of the local ethical committee and the tenets of the Declaration of Helsinki for experiments involving humans. Participation in the research was voluntary and unpaid.

Stimuli and procedure

Experiment 2 closely resembled Experiment 1, except for one major modification to the test trial display. Instead of four diamonds, the test display now consisted of six diamonds. For each visual field, three diamonds were arranged on an imaginary circle: one positioned 22° clockwise, another 22° counterclockwise, and the third directly on the horizontal plane. Therefore, the angular distance between two adjacent diamonds was 22°, corresponding to the angular distance between the distractor and the target in Experiment 1. All diamonds were placed at a distance of 7.7° of visual angle from the center of the screen. The distractor colors were drawn from a Gaussian distribution with a standard deviation of three JNDs, excluding values beyond 2 *SD*. The mean of the distractor distribution was set 24 JNDs away from the target color (i.e., the opposite color on the color wheel). Trials where the target appeared on the horizontal plane were excluded from deviation analyses, as the endpoints in these trials cannot be meaningfully interpreted in terms of deviation toward or away from other elements. To compensate for data loss, additional blocks were introduced, resulting in the experiment being divided into 812 blocks, split into two sessions of 406 blocks each.

Data analysis

We used the same statistical analyses as on the data from Experiment 1. The key difference was that,

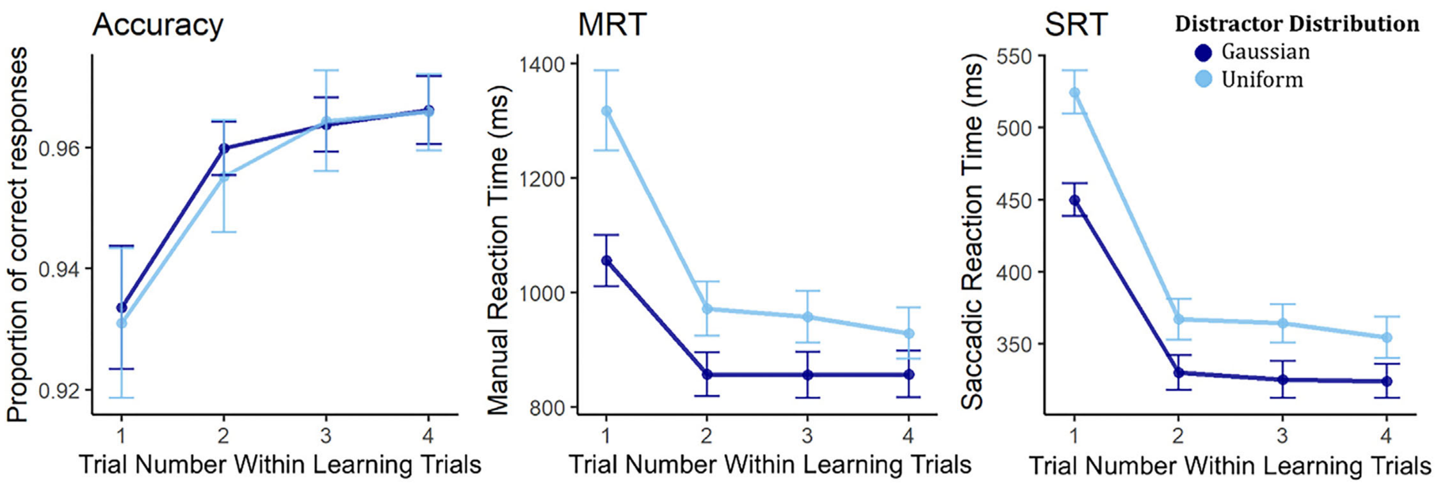

Figure 6. Learning trial results in Experiment 2. Mean proportion of correct trials, MRTs, and SRTs during learning trials in Experiment 2, as a function of trial number within learning sequence and distractor distribution. Error bars represent the standard error of the mean.

in addition to the previous criteria, trials where the target appeared in the horizontal plane from fixation were excluded from the deviation analyses. Figure 2 provides a visual representation of a test trial display alongside the deviation measure used in Experiment 2. For the learning trial analysis, 91% and 82% of the initial trials were included in the MRT analyses (after excluding incorrect and post-error trials) and SRT analyses (additionally excluding trials with no saccade to the target), respectively. For the test trial analysis, 92%, 83%, and 56% of the initial trials were included in the MRT (after filtering out incorrect and post-error trials), SRT (additionally excluding trials with no saccade to the target), and deviation analyses (additionally excluding trials where the target was on the horizontal plane or where the first saccade was either too small or not in the correct direction), respectively.

Results

Learning trials

Figure 6 presents the mean proportions of correct trials, MRTs, and SRTs during the learning trials as a function of trial number within the learning sequence and distractor distribution. MRTs were significantly faster for the Gaussian distribution ($M \pm SD = 913 \pm 163$ ms) than the uniform distribution ($M \pm SD = 1058 \pm 206$ ms), $t(16) = -7.41$, $p < 0.001$, $d = 1.79$. Similarly, SRTs were faster for the Gaussian distribution ($M \pm SD = 360 \pm 45$ ms) than for the uniform distribution ($M \pm SD = 407 \pm 54$ ms), $t(16) = -11.7$, $p < 0.001$, $d = 2.83$. There was no significant effect of distractor distribution on the proportion of correct responses, $t(16) = 0.61$, $p = 0.62$, $d = 0.12$ (for the Gaussian distribution, $M \pm SD = 0.954 \pm 0.024$; for the uniform distribution, $M \pm SD = 0.952 \pm 0.038$).

Helmert contrasts revealed improvements in task performance over the course of the learning trials. Specifically, participants were less accurate, $t(48) = -8.78$, $p < 0.001$, and their MRTs, $t(48) = 15.8$, $p < 0.001$), and SRTs, $t(48) = 23.5$, $p < 0.001$, were slower on the first learning trial than on subsequent ones. Additionally, response accuracy was significantly lower on the second learning trial than later trials, $t(42) = -2.04$, $p = 0.047$.

Test trials

Figure 7 shows, for each distractor learning distribution, the MRTs, SRTs, and deviation on test trials as a function of CT–PD (upper plots), along with the slope coefficients calculated before and after the breakpoint (lower plot). MRTs were significantly slower when the target belonged to the previous distractor distribution ($M \pm SD = 893 \pm 95$ ms) than when it did not ($M \pm SD = 738 \pm 97$ ms), $t(16) = -18.2$, $p < 0.001$, $d = 4.4$. A repeated-measures ANOVA performed on the slope coefficients before and after nine JNDs revealed a significant interaction between the previous distractor distribution and the CT–PD, $F(1, 16) = 16.2$, $p = 0.022$, $\eta_p^2 = 0.29$. Pairwise t-tests showed that the slope coefficient was higher before than after the breakpoint for both the uniform ($M \pm SD$ before the breakpoint $= -1.81 \pm 4.2$ ms; $M \pm SD$ after the breakpoint $= -14.8 \pm 3$ ms) and Gaussian distributions ($M \pm SD$ before the breakpoint $= -4.26$

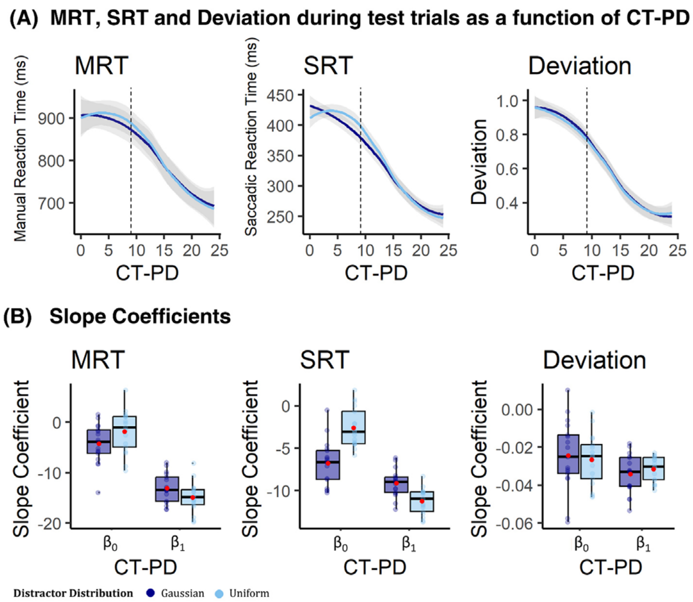

Figure 7. Test trial results in Experiment 2. (**A**) MRTs, SRTs, and deviations during test trials as a function of CT–PD (color distance between the target in the test trial and the mean of the distractor distribution on learning trials, in JNDs) and previous distractor distribution (upper plots). Curves were smoothed using local polynomial regression, and gray areas represent the 95% confidence intervals. The dotted line provides a visual reference for the nine-JND breakpoint that we used to compute β_0 and β_1. (**B**) Boxplots obtained from the slope coefficient before (β_0) and after (β_1) the breakpoint (set at nine JNDs) for each participant as a function of the previous distractor distribution (lower plots).

$\pm$ 3.93 ms; $M \pm SD$ after the breakpoint $= -13 \pm 2.93$ ms; $p < 0.001$). Before the breakpoint, the slope coefficient was significantly higher after the uniform distribution ($p = 0.048$), but, after the breakpoint, the pattern was the opposite ($p = 0.042$). For MRTs, the BF for the interaction was 7.41 (i.e., there was substantial evidence for an interaction).

SRTs were significantly higher when the target belonged to the previous distractor distribution ($M \pm SD = 407 \pm 34.4$ ms) than when it did not ($M \pm SD = 280 \pm 28$ ms), $t(16) = -37.3$, $p < 0.001$, $d = 9$. A repeated-measures ANOVA performed on the slope coefficients revealed a significant interaction between the previous distractor distribution and the CT–PD, $F(1, 16) = 24.6$, $p = 0.001$, $\eta_p{}^2 = 0.62$. Pairwise t-tests showed that the slope coefficient was higher before than after the breakpoint for the uniform distributions ($M \pm SD$ before the breakpoint $= -2.59. \pm 2.47$ ms; $M \pm SD$ after the breakpoint $= -11.2 \pm 1.48$ ms; $p < 0.001$) and Gaussian distributions ($M \pm SD$ before the breakpoint $= -6.74 \pm 2.7$ ms; $M \pm SD$ after the breakpoint $= -9.1 \pm 1.62$ ms; $p = 0.02$). Before the breakpoint, the slope coefficient was higher following the uniform distribution ($p = 0.001$), whereas, after the breakpoint, the pattern was the reverse ($p < 0.001$). For SRTs, the BF for the interaction was 9492 (i.e., there was extreme evidence for an interaction).

Finally, there were significantly higher deviations when the target belonged to the previous distractor distribution ($M \pm SD = 0.87 \pm 0.11$) than when it did not ($M \pm SD = 0.4 \pm 0.09$), $t(16) = -28.8$, $p < 0.001$, $d = 7$. However, a repeated-measures ANOVA performed on the slope coefficients did not show a significant interaction between the previous distractor distribution and the CT–PD, $F(1, 16) = 1.66$, $p = 0.22$, $\eta_p^2 = 0.094$. For deviations, the BF for the interaction was 0.86 (i.e., there was anecdotal evidence for the absence of an interaction).

FDL modulation across measures

We conducted a post hoc analysis to test whether the FDL effect differed across the dependent variables (MRT, SRT, and deviation). The FDL effect is reflected in the interaction between the CT–PD and the previous distractor distribution. To assess how this effect varies across measures, we ran a repeated-measures ANOVA on the slope coefficients, with CT–PD (β_0 and β_1), previous distractor distribution (uniform or Gaussian), and measure (MRT, SRT, or deviation) as within-subject factors. For Experiment 2, we specifically expected a three-way interaction among previous distractor distribution, CT–PD, and measure, as we anticipated the FDL effect to emerge only for SRT and MRT. We used the same dataset as in the test-trial analyses conducted for each measure. No additional pairwise comparisons were performed, as they would be redundant with those already reported in the main analyses.

This three-way interaction was significant, $F(2, 32) = 6.46$, $p = 0.009$, $\eta_p^2 = 0.29$, in Experiment 2. In Experiment 1, this interaction was not significant. The emergence of FDL in Experiment 2 therefore depended on the measure.

FDL modulation across experiments

To test for FDL effects across experiments, we ran an ANOVA on the slope coefficients with CT–PD (β_0 and β_1) and previous distractor distribution (uniform or Gaussian) as within-subject factors, and Experiments 1 and 2 as between-subject factors. We expected a three-way interaction among previous distractor distribution, CT–PD, and experiment, specifically for MRT and SRT, as the FDL effect was expected to emerge only in Experiment 2 for these two measures.

Notably, for MRT and deviation, this three-way interaction was not significant, but it was significant for SRTs, $F(1, 30) = 12.74$, $p = 0.001$, $\eta_p^2 = 0.30$. This

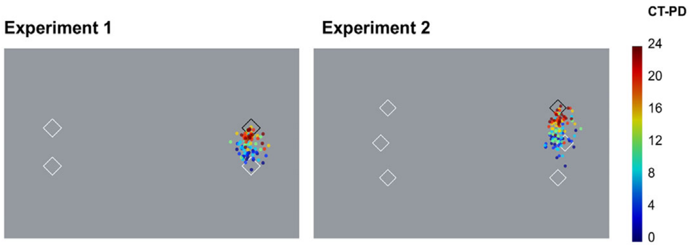

Figure 8. Mean *X* and *Y* endpoint coordinates during test trials in Experiments 1 and 2 when the target was located in the top-right position. Coordinates are averaged across participants and CT–PD values; therefore, each data point represents a participant's average fixation location for a given CT–PD value. The color gradient represents the CT–PD value, with blue indicating trials where the target color closely matched the previous distractor mean color and red indicating trials where the target color was furthest from it.

means that the emergence of FDL effects upon SRT depended on the experiment and consequently the task difficulty.

Discussion

In Experiment 2, the difficulty of the test trials was increased by adding more distractors and varying their colors. As in Experiment 1, the CT–PD distance significantly influenced MRTs, SRTs, and saccade endpoint deviation. Specifically, targets closer in color to previous distractors led to greater endpoint deviations (see Figure 8 for a visual representation of saccade endpoints in Experiments 1 and 2) and longer MRTs and SRTs. Although Experiment 1 provided no evidence that the shape of the previous distractor distribution (Gaussian or uniform) guided attention during test trials, Experiment 2 revealed that the distribution shape influenced MRTs and SRTs. However, saccade endpoint deviations were unaffected by the distribution shape.

General discussion

We investigated how learning of distractor color distributions influences saccade endpoints to odd-one-out colored targets in two visual search experiments. Following the FDL method (Chetverikov et al., 2016; Chetverikov et al., 2020), the experiments were structured into blocks containing learning and test trials. During the learning trials, the distractor color distribution remained constant (uniform or Gaussian). We analyzed SRTs, MRTs, and saccade endpoints in the subsequent test trials as a function of the color distance between the test trial target and the mean color of the previous distractor distribution. The two experiments differed in the level of competition between the target and distractors during the test trials.

Across both experiments, results from the learning trials revealed classical priming effects on accuracy, MRTs, and SRTs, indicating that participants successfully learned target or distractor color features. In test trials, the CT–PD distance significantly influenced MRTs, SRTs, and saccade endpoint deviations. Specifically, targets in test trials that were more similar in color to the previous distractor mean color led to higher endpoint deviations (i.e., endpoints were further away from the target), MRTs, and SRTs. Our main hypothesis was that the shape of the previous distractor distribution (Gaussian or uniform) would guide attention and eye movements during test trials, affecting MRTs, SRTs, and saccade endpoints. However, in Experiment 1, we found no evidence that the precise distribution shape influenced any of these measures. In Experiment 2, on the other hand, distribution shape affected MRTs and SRTs (as in previous FDL studies), but saccade endpoint deviations were unaffected.

Distractor FDL effects depend on search difficulty

Although CT–PD distance influenced all measures (SRTs, MRTs, and deviations) in both experiments, only Experiment 2 provided evidence of the learning of distractor distribution details. This was evidenced by Gaussian- and uniform-shaped patterns in MRTs and SRTs during test trials as a function of CT–PD distance, reflecting the underlying learning distribution, an effect not observed in Experiment 1. Specifically, when distractors followed a Gaussian distribution, MRTs and SRTs decreased monotonically both within and beyond the distribution range. In contrast, a uniform distractor distribution produced a flatter segment within the distribution range, followed by a sharp decrease outside that range, consistent with the equal probability of all feature values within the uniform distribution (replicating previous FDL effects) (Chetverikov et al., 2016; Chetverikov et al., 2020; Entzmann et al., 2025). Although this effect was not observed on saccade endpoint deviation, its presence on MRTs and SRTs suggests that participants successfully learned and utilized the precise distractor color distribution in Experiment 2.

A key question is why FDL emerged in Experiment 2 but not in Experiment 1. We speculated previously that in the test trials in Experiment 1 the target and distractor discrimination may have been too easy. Trying to increase the task difficulty, we added more distractors and varied their colors in Experiment 2, creating a display more similar to the learning trials. Such manipulations also increase minimum target–distractor differences and are known to increase search difficulty (Duncan & Humphreys, 1989; Mihali & Ma, 2020; Nagy, Neriani, & Young, 2005; Rosenholtz, 2001). The ease of the test trials in Experiment 1 is reflected in the reaction times measures. For example, on average, SRTs were shorter in Experiment 1 (261 ms) than in Experiment 2 (368 ms) and in Experiment 1 than previous experiments presented in Entzmann et al. (2025), where SRTs averaged 290 ms and 320 ms in Experiments 1 and 2, respectively. This falls in line with some previous evidence. For example, He and Kowler (1989) demonstrated that, although saccade endpoints are influenced by prior target locations, this effect diminishes as target–distractor discrimination becomes easier. Therefore, with the simpler discrimination, participants may not have needed to rely on learned information about the likely target location.

A similar question arose in the study by Van der Stigchel and Meeter (2017) on color priming effects on saccade endpoint deviation. They found evidence for priming of distractor colors on saccade endpoints (experiment 1), whereas, in an earlier study, the same authors reported no such evidence (Meeter & Van der Stigchel, 2013). Initially, the absence of distractor color priming was attributed to the irrelevance of the repeated feature or to spatial uncertainty. However, Van der Stigchel and Meeter (2017, experiment 2) demonstrated that priming of distractor colors still occurred even when the feature was irrelevant and under conditions of spatial uncertainty. The remaining difference between studies was the number of distractors: a single distractor in Meeter and Van der Stigchel (2013) versus two (experiment 2) or five (experiment 1) in Van der Stigchel and Meeter (2017). The authors proposed that the priming of distractor features is only observed when multiple distractors result in either strong inhibition of distractor features, or strong adaptation to them.

This is consistent with other studies showing how priming is modulated by ambiguity. Meeter and Olivers (2006) (see also Olivers & Meeter, 2006) proposed an *ambiguity account* of priming effects, arguing that intertrial priming helps resolve uncertainty in stimulus selection. They suggested that, when the identity of the target is ambiguous, selection relies more on previous trials. In this sense, Lamy, Zivony, and Yashar (2011) also demonstrated that increasing search difficulty, by reducing target–distractor discriminability, enhances the selection-based component of priming. When search is difficult, attentional engagement with the target is slower, making it more susceptible to feature repetition priming. Olivers and Meeter (2012) provided further evidence that priming effects are stronger when competition is high, and they investigated several accounts of this. Interestingly, they found no evidence that competition strengthens learning itself. Instead, they argued that ambiguity does not increase the strength of priming but makes subsequent trials more sensitive to its effects. In other words, the priming mechanism remains consistent across trials, but ambiguous trials amplify its benefits.

According to this view, the FDL in Experiments 1 and 2 in our study may be similar in terms of what is learned, but the observed benefits differ because of the test trial configuration. Overall, color priming occurs (whether reflected to target or distractor features) in both experiments and is reflected in all measures, as shown by the effect of the CT–PD distance. However, the shape of the distractor color distribution is not consistently reflected in test trial performance, which may depend on test trial difficulty. One important conclusion from this is that future research on FDL should consider search difficulty when deviating from the original paradigm.

The FDL method is typically used to reveal distractor suppression by uncovering attentional templates for distractors. Classic effects (i.e., reaction times reflecting the shape of the previous distractor distribution) suggest learning of distractor features, as this effect is inherently tied to the distractors itself. However, target features can also be learned, as the target consistently appeared 18 to 24 JNDs from the distractor mean, covering a specific hue range. Van der Stigchel and Meeter (2017) found in a similar setting as in Experiment 2 (six items, an odd-one-out color target) that both target signal enhancement and distractor suppression occurred. But, in simpler settings, only target signal enhancement occurred (two items) (Meeter & Van der Stigchel, 2013). Thus, target-related priming likely occurred alongside distractor learning. In Experiment 1, no evidence of distractor feature learning emerged, as SRTs, MRTs, and saccade deviation did not reflect the distractor distribution shape. The observed priming effect, where performance varied with target distance from the distractor mean, may reflect target-related learning, given that greater distractor distance suggests proximity to previous target colors. Participants could have learned the target mean, its variance, or recent target colors. In Experiment 2, distractor suppression was observed through FDL effects on reaction times. Yet, saccade endpoint effects could still stem from target enhancement. The use of distractor information seems to occur only during difficult trials, whereas the use of target information appears to be present regardless of task difficulty for MRTs, SRTs, and deviation.

No evidence of distractor FDL effects on saccade deviation

Examining the test results from Experiments 1 and 2, the MRT, SRT, and deviation measures appear overall quite similar, showing a general decrease as the CT–PD distance increased. In Experiment 2, the most notable difference was that the shape of the previous distractor color distribution (Gaussian or uniform) was reflected in MRT and SRT measures but not in saccade endpoint deviation. However, if FDL occurs, why is it then not reflected in saccade endpoints?

One explanation could relate to the data exclusion criteria we applied. A substantial number of trials were removed from the saccade endpoint analysis, particularly those in which the first saccade landed on the incorrect side of the screen. These excluded trials may reflect instances of high competition, where strong distractor interference led to erroneous saccades. By removing them, we may have unintentionally biased the dataset toward easier trials, thereby diminishing observable priming effects. This issue also ties into the challenge of studying the global effect in contexts with few distractors, which are not ideal for investigating learning of distributions. Specifically, because our analysis focused on the first saccade, participants had to be able to reach the target in a single saccade during the test trials, a condition that is typically not met in standard FDL paradigms. To assess the influence of trial selection on our experimental results, we conducted a supplementary analysis of MRTs, SRTs, and deviation using the same subset of test trials (see Supplementary Material S1). Using the trial set used in MRT or SRT analyses is problematic for deviations, as it would involve trials where saccades landed in the wrong hemifield or far from the target. In such cases, deviation is not meaningful, because, by definition, the global effect only applies when the saccade is intended to reach the target. Therefore, we restricted our supplementary analyses to the trial subset used for the saccade endpoint analysis. Results showed that the FDL effect on SRT and MRT remained significant, although the effect size of the FDL was reduced, especially for SRT. Overall, exclusion criteria cannot account for the differences among the three measures, as the emergence of the FDL still varied depending on the response measure, even when using an identical trial set.

Another explanation could be that the difference between the uniform and Gaussian distributions is subtle and interacts with multiple factors driving attention and eye movements. The relative importance of these factors may vary across different measures, with endpoint deviations potentially being influenced by stronger competing factors. Indeed, SRT and endpoint measures reflect different processes in saccade generation, with SRT reflecting the time it takes to reach a threshold and the global effect the overlap in the weight within the saccade map. In a supplementary analysis (Supplementary Material S2), we present a random forest analysis (Breiman, 2001; for a review, see Wei, Lu, & Song, 2015) based on the results of Experiments 1 and 2. The goal was to rank the factors influencing MRTs, SRTs, and saccade endpoint deviations (e.g., target location, target color relative to the previous target or distractor color), providing insights into their contributions to different measures. In Entzmann et al. (2025) we conducted a similar analysis, comparing factor rankings for SRTs and MRTs. In that study, saccadic reaction times were measured in two contexts: one where saccades served as a behavioral response and another where saccades were used naturally, without any instruction, to explore the visual search display. The results showed similar rankings, although previous distractor color had a larger impact on natural eye movements. Replicating these findings, our analyses showed that CT–PD was a stronger predictor of SRT than MRT, likely because SRT reflects less individual variability. The main difference among MRTs, SRTs, and deviation is that target position has a stronger influence on deviation than on MRTs or SRTs.

The effect of target position, both in absolute terms and relative to the previous target quadrant, on SRT, MRT, and deviation was further analyzed in another supplementary analysis (Supplementary Material S3). Overall, target position influenced only deviation, with greater deviations observed for targets presented in the upper visual field. Because saccades tend to follow a descending trajectory on average, deviations away from the target are greater when the target is positioned at the top. This is consistent with studies that have found that upward saccades tend to undershoot the target, whereas downward saccades are more likely to overshoot it (Bonnet et al., 2013; Jagla, Zikmund, Mashonkina, & Yakimoff, 1992; Yang & Kapoula, 2008). Concerning target position relative to the previous target quadrant, we found an effect of the previous target position only on SRTs and deviation in Experiment 2. More precisely, SRTs were shorter when the target reappeared in the same quadrant as on the previous trial, compared with when it appeared in the opposite quadrant, hemifield, or vertical position. But, saccade deviations were smaller when the target appeared in the opposite quadrant or along the same vertical axis. Although this is speculative, it could suggest that shifting to a new spatial location, particularly across hemifields, may engage stronger top–down control and reduce the global effect. We also tested the hypothesis that SRTs and deviation in the more difficult trials (i.e., those for which the hemifield was not primed) would be more likely to reveal an FDL effect. There was no evidence for such an interaction, although, for SRTs, the effect size for FDL was higher for more difficult trials.

Finally, FDL effects on saccade endpoints may be restricted to short-latency trials. Previous studies have shown that the global effect is more pronounced for saccades with short latencies which are thought to be less influenced by top–down control (Findlay, 1982). Notably, Ottes, Van Gisbergen, and Eggermont (1985) demonstrated that the global effect could be avoided by delaying saccade initiation by 300 ms. Meeter and Van der Stigchel (2013) examined the influence of priming on the global effect across different saccade latency bins, each bin comprising 20% of trials. These latency bins ranged approximately from 125 ms (fastest) to 220 ms (slowest). Although the global effect was present across all bins, its magnitude decreased with increasing saccade latency. In a supplementary analysis (Supplementary Materials S4), we split the test trials by median saccade latency to examine whether color priming and the FDL effects on endpoint deviation varied with latency. Contrary to previous findings, we found that the global effect was greater for high-latency saccades. But, this is likely because the high-latency saccade group contained more low CT–PD trials and the low-latency saccade group contains more high CT–PD trials. Color priming was observed across both latency groups in Experiments 1 and 2, indicating that deviation was higher when the target color was within the previous distractor distribution. There was no significant evidence of an FDL effect on saccade deviation for either high- or low-latency saccades across both experiments.[2] However, this result should be interpreted with caution, as the analysis involved a low number of trials, unevenly distributed across CT–PD values.

Conclusions

This study sheds light on (1) how FDL of an ensemble of distractors guides saccade endpoints in comparison with manual and saccadic reaction times, and (2) the extent to which FDL can be observed in active visual search. First, although previous studies have shown that a single primed color can influence the global effect, we primed an entire color distribution. Our results show a consistent relationship between target color in relation to previous distractors and saccade endpoint deviation, measured through the global effect, such that the deviation becomes more pronounced as the target approaches the mean color of the previously learned distractor distribution. However, the shape of the previous distractor distributions (Gaussian vs. uniform) did not significantly influence the deviation. Second, we found that task difficulty modulated the influence of previously learned distractor information: more difficult test trials led to greater reliance on the learned distribution. Notably, this effect was only reflected in reaction time measures (SRTs and MRTs), not in saccade endpoint deviations. In conclusion, our findings demonstrate that learning the statistical properties of target or distractor features guides oculomotor behavior, influencing both saccade deviation and the speed of target fixation. However, the expression of distractor FDL varies across measures and depends on task difficulty.

Keywords: visual search, feature distribution learning, ensemble perception, eye movements, global effect

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Footnotes

[1]Note that anecdotal results from a BF analysis are barely worth mentioning (Jeffreys, 1961), and the means are not in the expected direction; therefore, this will not be further discussed.

[2]Note that, in Experiment 1, for short-latency saccades, a marginal effect was observed on the slope coefficient in the expected direction, suggesting a potential FDL effect on saccade endpoint for short-latency saccades. But, dividing the data into latency groups resulted in fewer trials per condition. Moreover, because the short-latency group consisted mainly of trials with high CT–PD values and the high-latency group primarily included trials with low CT–PD values, the distribution of trials across CT–PD values was unbalanced. Because this effect was not reflected in MRTs or SRTs in Experiment 1, nor in deviation in Experiment 2, and given the limited number of trials per condition, we refrain from interpreting this result further.

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