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Attentional Capture Alters Feature Perception

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We live in a dynamic, distracting world. When distracting information captures attention, what are the consequences for perception? Previous literature has focused on effects such as reaction time (RT) slowing, accuracy decrements, and oculomotor capture by distractors. In the current study, we asked whether attentional capture by distractors can also more fundamentally alter target feature representations, and if so, whether participants are aware of such errors. Using a continuous report task and novel confidence range report paradigm, we discovered 2 types of feature-binding errors when a distractor was presented along with the target: First, when attention is strongly captured by the distractor, participants commit swapping errors (misreporting the color at the distractor location instead of the target color), which remarkably seem to occur without awareness. Second, when participants successfully resist capture, they tend to exhibit repulsion (perceptual distortion away from the color at the distractor location). Thus, we found that capture not only induces a spatial shift of attention, it also alters feature perception in striking ways.

Public Significance Statement

We live in a dynamic world full of distractions. When spatial attention gets captured by a distractor object, people often respond slower to their target and make more errors. The current study suggests that being captured by a distractor can also change how people perceive a target object. When attention is strongly captured by the distractor, people sometimes misreport the distractor color as the target, and are not even aware of their errors. Even when successfully resisting capture, people tend to report a color distorted by the distractor color.

Keywords: visual attention, feature binding, attentional capture, feature perception, probabilistic mixture modeling

We live in a dynamic world, and the environment presents more information than our visual system can fully process at a time. To select the relevant and ignore the irrelevant information according to the current task, our visual system must dynamically shift its focus or split resources between multiple objects. For example, when we are driving along the highway, our attention never stays in a fixed location: we are constantly monitoring our environment, shifting attention back and forth from the dashboard to the road, and splitting attention to multiple cars and signs around us. Moreover, besides dynamically shifting or splitting attention based on task goals, we are also constantly encountering distractions—for example, a cell phone ringing or a colorful billboard—which further tax our attentional resources. It is crucial to study attention and perception under these dynamic circumstances. This is because not only does attention help facilitate visual processing, but spatial attention is also thought to play an essential role in feature-binding (Reynolds & Desimone, 1999; Treisman & Gelade, 1980), and recent evidence has shown that unstable attention under dynamic circumstances can lead to complex feature-binding errors (Dowd & Golomb, 2019; Golomb, 2015; Golomb, L'Heureux, & Kanwisher, 2014).

In the current study, we ask whether and how feature perception might be altered during dynamic conditions of distraction; that is, when a distracting stimulus captures spatial attention away from a target object. Although the topic of attentional capture has been intensively studied for the last several decades, these studies have focused almost exclusively on the mechanics of involuntarily moving spatial attention to the distractor, disengaging, and returning to the target. Therefore, researchers have focused on dependent measures such as reaction time (RT) slowing, accuracy decrements, and saccades to the distractor (Folk, Leber, & Egeth, 2002; Folk, Remington, & Johnston, 1992; Theeuwes, 1992; Theeuwes,

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Kramer, Hahn, & Irwin, 1998; Yantis & Jonides, 1984). Other studies have explored the neural mechanisms of attentional capture using functional MRI (fMRI) and event-related potentials (ERPs), generally focusing on costs associated with distractor processing. For example, the involuntary shift of spatial attention caused by attentional capture has been associated with greater fMRI activation in extrastriate visual cortex, temporo-parietal junction and ventral frontal cortex (Serences et al., 2005), as well as greater contralateral activation of the N2pc ERP component (Leblanc, Prime, & Jolicoeur, 2008). Additional work has revealed neural signatures associated with distractor suppression, for instance via the distractor positivity (P_D) ERP component (Sawaki & Luck, 2010).

The previous research has gone a long way toward characterizing the impact of distracting information on performance. However, we still do not fully understand the effect of distractors in the attentional capture process, especially the effect of the distractor on target representations. For example, when a distracting stimulus captures attention, does this just result in a slowing of target processing (or potentially missing the target in rapid presentations), or is the perception of the target itself altered? In other words, do these rapid spatial shifts and/or splits of attention that occur during attentional capture influence the perception of target features? As noted in the preceding text, spatial attention has long been thought to play an essential role in feature binding, with spatial attention acting as the "glue" that binds an object's features together (Reynolds & Desimone, 1999; Treisman, 1996; Treisman & Gelade, 1980). When attention is diluted, binding errors can occur (Treisman & Schmidt, 1982). Dynamic shifting or splitting of goal-directed spatial attention can also cause distinct types of feature-binding errors (Dowd & Golomb, 2019; Golomb et al., 2014). For example, when attention is dynamically shifted from one cued location to the target location briefly before the target color appears, participants tend to make swapping errors (misreporting the color in the previously cued location); when attention is simultaneously split between the target location and another location, participants tend to experience feature distortions (the reported target color is systematically biased toward or away from the other color); and during saccadic remapping of attention, both types of errors are present (Golomb, 2015; Golomb et al., 2014).

In the current study, we explore the effect of distractors on target feature representations by adopting a continuous color report and probabilistic modeling approach (Bays, Catalao, & Husain, 2009; Golomb et al., 2014; Wilken & Ma, 2004; Zhang & Luck, 2008). Participants were briefly presented with four colored squares—one target and three nontargets. The target was highlighted with a white border, and participants were instructed to report the target's color by clicking on a color wheel. To manipulate attentional capture, a distractor cue (four white dots) was sometimes presented surrounding either the target item or one of the adjacent nontarget colored items (Folk et al., 1992). For our participants to efficiently find the target, we expected them to enter a feature-based processing mode, or attentional control setting, that was tuned to prioritizing white stimuli. Attentional capture has been shown to be greatest—and most difficult to override—when distractors match the participants' attentional control settings (i.e., contingent attentional capture; Folk et al., 1992, 2002; Folk & Remington, 1998). Therefore, we expected the white dots to produce robust attentional capture. By using continuous report, we tested whether and how the reported target color was influenced by the color of the item at the location surrounded by the distractor cue (heretofore referred to as the "distractor item" or "distractor location"). In Experiment 2 we also supplemented the standard continuous-report task with a confidence report, in which participants subsequently selected a flexible range of error around their "best-guess" on the color wheel. This addition allowed us to not only probe feature errors that may result as an effect of attentional capture disrupting the binding process, but also ask to what extent participants are aware that they may be making these errors.

We predicted that feature-binding errors might occur if the distractor item's features interfere with the target representation, and that this might depend on the degree of attentional capture. When attention is fully captured by the distractor, spatial attention may be diverted to the distractor location. If the stimulus array is presented while spatial attention is at the distractor location, we predict swap errors could happen: Participants could mis-bind the distractor item's features with the target location. If this happens, the participant's response should be close to the color of the item at the distractor location and may even be reported with high confidence (i.e., participants may not be aware of their error). On the other hand, if the distractor is successfully ignored, we predict the response should be accurately centered around the target color, with high confidence. However, because the degree of attentional capture can vary from trial to trial (Leber, 2010; Leber, Lechak, & Tower-Richardi, 2013), it is possible that attention may sometimes be only partially captured by the distractor. In this case, it is possible that spatial attention might be shared between the target and distractor locations simultaneously, or that participants might be actively trying to inhibit the distractor location's feature (see Moher, Lakshmanan, Egeth, & Ewen, 2014). Here we might predict a subtler feature-binding error (e.g., feature distortion; Golomb, 2015; Golomb et al., 2014), where participants report the target color as perhaps biased slightly toward or away from the color at the distractor location. Finally, it is possible that the distractors might capture attention but not actually alter the target feature representations themselves. In this case we may expect to see accurate target color responses preserved (i.e., no feature-binding errors), but solely generic effects of distraction such as decreased precision, an increase in random guessing, or a decrease in confidence. By using the continuous report approach, we can fit the target report errors with a probabilistic mixture model accounting for these different types of errors and their relative proportions during attentional capture.

Method

Participants

Twenty-six participants (five male, 21 female; *M* age = 18.62) participated in Experiment 1, and 27 participants (12 male, 15 female; *M* age = 19.11) participated in Experiment 2. All participants reported having normal or corrected-to-normal color vision and visual acuity. A power analysis was conducted in advance of data collection based on Experiments 3 and 4 of Golomb et al. (2014); using these prior effect sizes, we used G*Power (Faul, Erdfelder, Lang, & Buchner, 2007) to calculate the a priori sample size for detecting a similar effect in a two-tailed *t* test. The analysis showed that 26 participants were needed for a power of 80%. Extra participants were recruited for each experiment in anticipation of participant no-shows and exclusions. Additional participants were excluded for the following reasons: One participant in each experiment was excluded for poor task performance (a priori criteria of >50% guessing rate in the neutral condition; see Golomb et al., 2014), and one participant in Experiment 2 reported only the distractor item colors and never the target. In addition, eight participants in Experiment 2 did not report the confidence range properly, reporting either a zero-degree confidence range (clicking the wheel without moving the mouse) or reporting a confidence range that did not contain the reported color (e.g., moving the mouse in only one direction) on the majority of trials; these participants were replaced (note that these errors occurred on less than 10% of trials for included participants). Study protocols were approved by The Ohio State University Behavioral and Social Sciences Institutional Review Board.

Experimental Setup

All stimuli were generated using MATLAB (MathWorks, Natick, MA) and the Psychophysics Toolbox (Brainard, 1997; Kleiner, Brainard, & Pelli, 2007; Pelli, 1997) on an Apple Mac Mini. Participants were seated in front of a 21-in. CRT monitor (resolution: 1280 × 1024; refresh rate: 85 Hz). The viewing distance was 61 cm. Participants' eye position was monitored and recorded using an Eyelink 1000 system (SR Research, Ontario, Canada). A chin rest was used to stabilize the head position. The monitor was color calibrated with a Minolta CS-100 (Minolta, Osaka, Japan) colorimeter.

Procedure

Experiment 1. Each trial began with a black fixation mark (a plus sign) presented at the center of the screen (background luminance: 35.2 cd/m^2) and four empty placeholders (light gray outlined squares), presented at the upper left, upper right, lower left, and lower right of the fixation mark (each sized 2 degrees × 2 degrees; stroke = 0.08 degrees, centered at an eccentricity of 4 degrees; Figure 1A). After participants continuously maintained fixation for 300 ms, four colored squares briefly filled the placeholders for 50 ms. The colors were selected from a set of 180 color values evenly distributed along a color wheel in $L^*a^*b^*$ color space. The colored squares and gray background were equiluminant. The color wheel was centered at ($L^* = 70$, $a^* = 20$, $b^* = 38$) with a radius of 60. These color values are thought to maximize the discriminability of the colors while maintaining constant luminance and are commonly used in studies using this continuous color report paradigm (e.g., Zhang & Luck, 2008). Further, by keeping the same luminance, we can minimize the potential confound that a color with greater luminance may capture attention faster (Brisson, Robitaille, & Jolicoeur, 2007; Töllner, Zehetleitner, Gramann, & Müller, 2011).

The target item was designated at the same time the colored squares appeared; one of the squares was highlighted with a thicker white border (stroke = 0.2 degrees; RGB value: 255, 255, 255; luminance: 96.75cd/m^2). The color of the item at this target location was randomly selected out of the 180 color values. The color of one of the adjacent nontarget squares was selected to be 90 degrees clockwise along the color wheel, whereas the other adja-

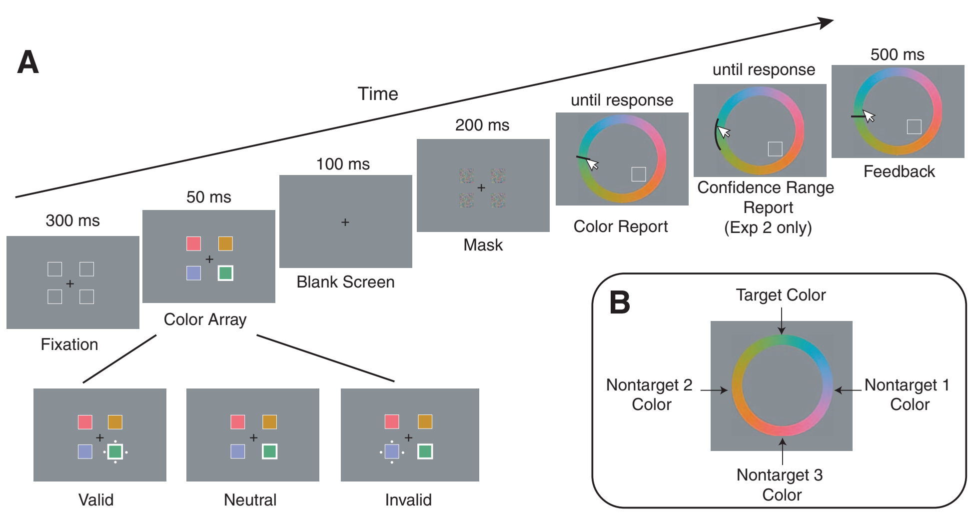

Figure 1. Panel A: Example trial sequence. After participants continuously maintained fixation for 300 ms, four different colored squares briefly filled the placeholders for 50 ms. A distractor cue (white dots) could appear during the color array presentation, simultaneously with the target cue (white outline). The distractor could be displayed at the same location as the target ("valid"), at an adjacent location ("invalid"), or be absent ("neutral"). Participants were instructed to ignore the distractor and report the target color by clicking on a continuous color wheel. In Experiment 2 only, participants were also instructed to select a range that they were confident the correct target color fell within. Panel B: The target color was randomly chosen from anywhere on the color wheel on each trial. The color of one adjacent nontarget square was 90 degrees clockwise along the color wheel, whereas the other adjacent nontarget was 90 degrees counterclockwise (the respective directions were determined randomly from trial to trial). The nontarget color at the diagonal location was 180 degrees away from the target on the color wheel. See the online article for the color version of this figure.

cent nontarget square color was 90 degrees counterclockwise (the respective directions were determined randomly from trial to trial). The color at the diagonal nontarget location was 180 degrees away from the target color on the color wheel. After the 50-ms stimulus presentation, there was a 100-ms blank screen interval, and then the four squares were masked with random colored pixels for 200 ms. Participants were then asked to report the color of the target item by clicking on a color wheel presented at the center of the screen (diameter: 7 degrees). A postcue (one empty placeholder) was also presented on the screen during the response to remind participants of the target location. A feedback line on the color wheel was displayed at the end of the trial to inform participants of the correct target color.

To manipulate attentional capture, a distractor cue (a set of four white dots surrounding one of the colored squares; cf. Folk et al., 1992) was presented on some trials during the color array presentation, simultaneous with the target cue. The color and the luminance of the distractor dots were chosen to be the same as the target cue, to match the participants' attentional control settings and increase likelihood of capture (contingent attentional capture paradigm: Folk et al., 1992, 2002; Folk & Remington, 1998). Specifically, we compared target color reports on invalid trials where the distractor cue highlighted a nontarget location (adjacent to the target), valid trials where the distractor cue appeared at the target location, and neutral trials where no distractor cue was presented. All three conditions were equally likely and intermixed. Invalid trials were evenly split between clockwise and counterclockwise stimulus locations (distractors could not appear at the location diagonal to the target).

Each block had 96 trials (32 trials for each condition), and there were up to 10 blocks in total per participant. Participants completed as many blocks as possible in the time allowed, and participants who completed at least six blocks (192 trials per condition) were included in the analysis. Before the main experiment, each participant completed 40 practice trials.

If a participant's eye position deviated more than 1.5 degrees from the fixation location while the color and mask appeared on the screen, the trial was aborted immediately and repeated at a random position later in the block.

Experiment 2. The experiment setup and procedure were the same as in Experiment 1, except we added a confidence range report after the color report. After reporting the target color as before (single click on the color wheel for their best guess), participants then reported their confidence range for that trial by making two additional clicks on the color wheel, marking the portion of the color wheel that they were confident the correct target color fell within. In other words, if they were highly confident about their initial report, they would select a narrow error margin on both sides of that guess, whereas if they were less certain about the exact target color, they would mark a larger portion of the color wheel. The confidence range could be asymmetrical around their target report, and the angular distance between the two end points could range from 0 degrees to 360 degrees (entire color wheel). Participants were instructed to choose the smallest range they thought was likely to contain the correct target color. They were also told they could select the entire color wheel or a very large range if they did not see the target color and were simply guessing.

Analysis

Color report error and probabilistic mixture modeling. The difference between the correct target color and the reported color on each trial was calculated and recorded as the "report error." For illustration purposes, we aligned the direction of the errors for the invalid trials during the analysis so that a positive-signed error means the response was toward the color of the item at the distractor location and a negative-signed error means away from the color at the distractor location (in figures, the distractor item color is thus always shown in the clockwise direction along the color wheel; i.e., +90 degrees from the target color). On valid and neutral trials where neither of the adjacent items had the distractor cue, the data were mock aligned (i.e., 50% of trials were reversed in error sign) to match the invalid analysis.

The distribution of report errors was then fit with a probabilistic mixture model accounting for four different sources of errors (Formula 1): one von Mises distribution (ϕ) corresponding to the probability of correctly reporting the target, with a flexible mean (bias) μ and concentration κ; two additional von Mises distributions centered around the adjacent nontarget colors (90 degrees and -90 degrees), accounting for the probabilities (β_1 and β_2) of misreporting; and a uniform distribution accounting for the probability γ of random guessing. As noted in the preceding text, in the invalid condition, error sign was aligned such that β_1 corresponds to the probability of misreporting the color of the item at the distractor location, and β_2 the probability of misreporting the control item. In valid and neutral conditions both β_1 and β_2 correspond to control items.

$$p(\theta) = (1 - \beta_1 - \beta_2 - \gamma)\phi_{\mu,\kappa} + \beta_1\,\phi_{90^\circ,\kappa} + \beta_2\,\phi_{-90^\circ,\kappa} + \gamma\left(\frac{1}{2\pi}\right). \tag{1}$$

For each participant and each condition, we fit the model by applying Markov chain Monte Carlo using MemToolbox (Suchow, Brady, Fougnie, & Alvarez, 2013). We also ran Kolmogorov–Smirnov tests to ensure the all model fittings were not significantly different from the raw data ($ps > 0.1$). The best-fitting parameters (maximum likelihood estimates) for each participant and condition were submitted to repeated measures analyses of variance (ANOVAs) and paired two-tailed t tests. Swapping errors specific to the distractor were determined by comparing β_1 to β_2, and feature distortion was tested by comparing whether μ was significantly different from zero. Effect sizes are reported Cohen's d or partial η^2.

Confidence range analyses. In Experiment 2, we analyzed the confidence range reports as follows. We defined the confidence range size as the angular distance between the start and the end point of the confidence report. The confidence size could thus range from 0 degrees to 360 degrees (full wheel). A small confidence range size means participants were more certain about their target report, a larger confidence range size means participants were less confident about the target color and selecting the full wheel (360 degrees) would indicate that participants were randomly guessing. We measured the correlations between the confidence range size and absolute color report errors. We also compared the size of the confidence range across attention conditions.

To probe if the confidence reports reflected some awareness of feature errors, we performed a median split for each participant dividing trials into low confidence and high confidence trials, separately for each attention condition. The distributions of color report errors for high and low confidence trials were then fit separately with the same probabilistic mixture model as discussed earlier, and we compared the parameter fits using within-subjects ANOVAs and paired two-tailed *t* tests.

To further analyze the relationship between confidence range size and swapping errors, we also fit the confidence range size in a mixed-effects model with single random effects (Singmann & Kellen, 2018). We first defined the report type of each trial as follows: If the participant reported a color within ±45 degrees of the correct target color (i.e., the report error was [−45 degrees, 45 degrees]), we defined the trial as a "target trial" for this analysis. If the report color was within ±45 degrees of one of the two neighboring colors, this trial was classified as a "swap to nontarget trial" for this analysis. For invalid trials, we specifically focused on "swap to distractor trials," where the reported color centered on the color of the item at the distractor location. We combined valid and neutral conditions together (and across all nontarget swaps) to increase the power. Note that we did not attempt to separate out random guessing trials for this analysis because they were not many of them, and, by definition, they should be evenly distributed across the whole color space. We fit these data with a mixed-effects regression model using lme4 package in R (Bates, Machler, Bolker, & Walker, 2015), with attention condition and report type as fixed factors. We used the mixed-effects model instead of ANOVA because the mixed-effects model is more accurate in the case when each participant contributes different number of trials in each condition; to account for between-participants variability, the mixed model assumes random intercepts and slopes for each fixed factor for each participant. Because we were interested in the interactions between attention condition and report type, we also compared the confidence range size of "target trials" and "swap trials" in valid/neutral condition and invalid condition using emmeans package in R.

Results

Color Report Error

We first compared the color report error distributions and model fits for the valid, neutral, and invalid conditions to access whether participants made feature errors when captured by distractors in the invalid condition. Figure 2 shows the report error distributions across all participants for the three attention conditions. To quantify the probabilities of different types of errors, we fit the error distributions for each participant, for each condition, using a probabilistic mixture model described in formula 1. The mean model fitting results are shown in Figure 3.

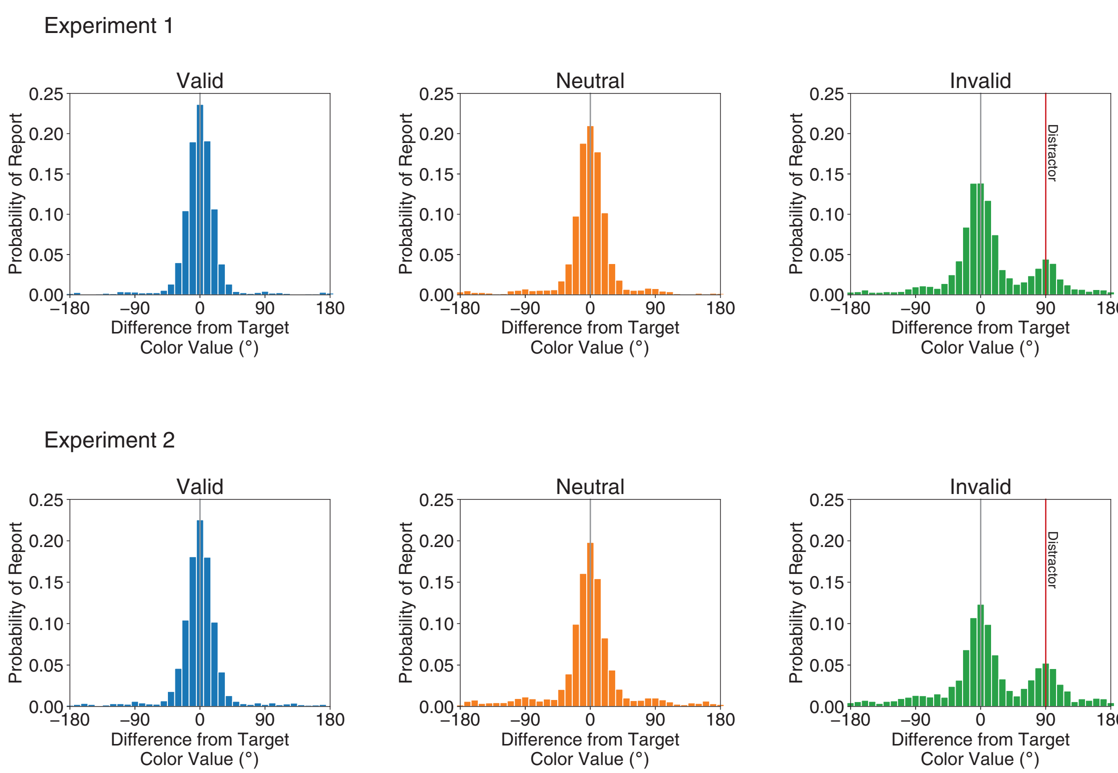

Figure 2. Response distributions for valid, neutral, and invalid conditions. Data are plotted as the differences in color values (error) between the response and the correct target color (aggregated across all participants). Zero error means a perfect response. Note that we aligned the direction of the errors for the invalid trials during the analysis so that the distractor item color was always represented as +90 degrees from the target color, shown by the red vertical line in the figure. In the real experiment, however, the distractor item color could be located in either direction along the color wheel (+90 degrees or −90 degrees from the target color). See the online article for the color version of this figure.

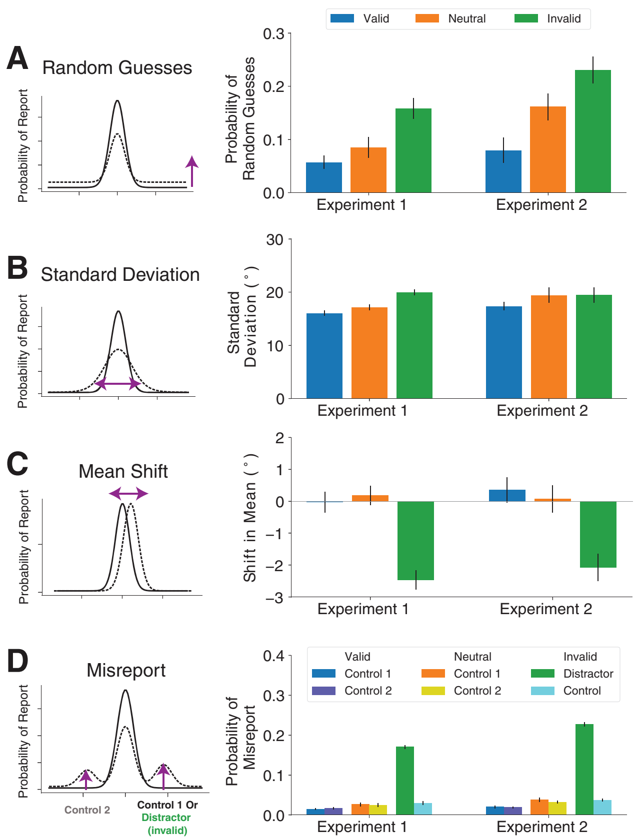

Figure 3. Probabilistic model fits for the color report data in Experiment 1 and 2. From top to bottom, each row represents one parameter: random guesses (γ); standard deviation ($\sqrt{1/\kappa}$; misreports (swap to one of the nontarget colors; β_1 and β_2); mean shift (μ; negative is repulsion away from color of the distractor item). Models were fit separately for each participant and each condition. Error bars show ± 1 standard error of the mean (*SEM*). See the online article for the color version of this figure.

Across the two experiments, the attention cue influenced performance, impacting both the precision (standard deviation) of target color reports (Experiment 1: $F(2, 50) = 22.43$, $p < .001$, $\eta^2 = 0.473$; Experiment 2: $F(2, 52) = 3.243$, $p = .047$, $\eta^2 = 0.111$) and the random guessing rate (Experiment 1: $F(2, 50) = 19.42$, $p < .001$, $\eta^2 = 0.437$; Experiment 2: $F(2, 52) = 18.20$, $p < .001$, $\eta^2 = 0.412$), reflecting that performance on both measures was improved in the valid condition and impaired in the invalid condition compared with the neutral condition (see Figure 3, Panels A and B). These general performance measures confirm that our attentional manipulation was successful, and attention was captured by the distractor cue.

We next explored whether attentional capture in the invalid condition induced specific types of feature-binding errors when participants attempted to report the target color. We considered two types of feature errors previously reported following manipulations of goal-directed attention (Golomb et al., 2014): swapping errors (misreporting the color at the distractor location instead of the target color), and feature distortions (reporting the target color in a systematically distorted way; either blended toward or repulsed away from the color at the distractor location).

Figure 3C shows the probability of swapping errors for the two neighboring nontarget items. We ran a two-way repeated measures ANOVA comparing the factors of Attention Condition (valid, neutral, invalid) $\times$ Misreported Item (β_1, β_2). In Experiment 1, there was a significant main effect of attention condition, $F(2, 50) = 26.5$, $p < .001$, $\eta^2 = 0.515$, with participants making more overall swapping errors in invalid trials than neutral trials and less swapping errors in valid trials compared with neutral trials. There was also a significant main effect of misreported item, $F(1, 25) = 15.11$, $p < .001$, $\eta^2 = 0.377$, which, critically, was qualified by a significant Condition $\times$ Misreported item interaction, $F(2, 50) = 16.45$, $p < .001$, $\eta^2 = 0.397$, indicating a specific influence of the distractor on swapping errors. For valid and neutral conditions, the two neighboring nontarget items should have been equally likely (or unlikely) to produce interference; accordingly, the probability of misreporting them did not significantly differ (*ts*<0.86, *ps* > 0.40). However, for the invalid condition, the probability of misreporting the distractor item's color was significantly larger than the control item's color, $t(25) = 4.03$, $p < .001$, Cohen's $d = 0.455$. We replicated this finding in Experiment 2. The two-way repeated measures ANOVA again revealed significant main effects of attention condition, $F(2, 52) = 25.93$, $p < .001$, $\eta^2 = 0.499$, and misreported item, $F(1, 26) = 19.73$, $p < .001$, $\eta^2 = 0.431$, as well as a significant condition x misreported item interaction, $F(2, 52) = 17.74$, $p < .001$, $\eta^2 = 0.406$. Participants had a significantly higher probability to misreport the distractor item's color than the control nontarget's color in invalid trials, $t(26) = 4.317$, $p < .001$, Cohen's $d = 0.831$, but not in valid or neutral trials (*ts* < 1.003, *ps* > 0.325).

Next, we tested if there was any evidence for feature distortion (shift in the mean of the target distribution) by analyzing the mu parameter in the model (see Figure 3D). There was no evidence for distortion in the valid and neutral conditions: mu was not significantly different from zero (*ts* <1.29, *ps* >0.21). However, for the invalid condition, mu was significantly different from zero, $t(25) = 3.47$, $p = .002$, Cohen's $d = 0.695$, with participants' reports shifted in the negative direction (away from the color of the item at the distractor location). A one-way repeated-measures ANOVA revealed a significant main effect of attention condition, $F(2, 50) = 10.3$, $p < .001$, $\eta^2 = 0.292$. We also replicated these findings in Experiment 2. The ANOVA again revealed a significant main effect of attention condition, $F(2, 52) = 3.538$, $p = .036$, $\eta^2 = 0.120$, and for the invalid condition, mu was significantly different than zero, $t(26) = 2.123$, $p = .043$, Cohen's $d = 0.408$, replicating the finding that participants made feature repulsion errors when reporting the target color with a distractor presented at the same time.

Confidence Range Analysis

In the preceding text we demonstrated that participants make both swapping and repulsion errors when attention is captured by a distractor. We asked a further question in Experiment 2: How aware are participants when they make these feature binding errors? We addressed this question by measuring participants' confidence: If participants were aware that they were making errors in those trials, they should have been less confident about their answer. On the contrary, if participants were not aware that they were making errors, their confidence level should have been comparable to trials with correct responses. As described in the Methods, to measure participants' confidence level, we supplemented the standard continuous-report task with a confidence report in Experiment 2, in which participants subsequently selected a flexible range of error around their best guess on the color wheel. Overall, confidence range size and absolute error were correlated on a single trial level, with smaller confidence ranges (higher confidence) associated with smaller errors (r = .157, p < .001).

To explore how confidence interacted with the different types of feature errors, for each participant and each condition, we separated trials into "high confidence trials" and "low confidence trials" based on a median split of the confidence range size. For high and low confidence trials separately, we fit the target color report errors using the same probabilistic model as discussed earlier. The results are shown in Figure 4A. For standard deviation and guessing rate, in addition to the overall main effect of attention condition described in the preceding text, these measures also varied with confidence; high confidence reports tended to accompany more precise target reports with less random guessing, compared with lower confidence reports. A two-way repeated-measures ANOVA comparing the standard deviation measure as a function of different attentional condition (valid, neutral, invalid) and confidence level (low vs. high) revealed significant main effects of attention condition, $F(2, 52) = 14.206$, $p < .001$, $\eta^2 = 0.353$, and confidence level, $F(1, 26) = 17.988$, $p < .001$, $\eta^2 = 0.409$. A post hoc t test confirmed that high confidence trials had higher precision than low confidence trials, $t(26) = 4.241$, $p < .001$, Cohen's $d = 0.816$. We also ran the same two-way repeated

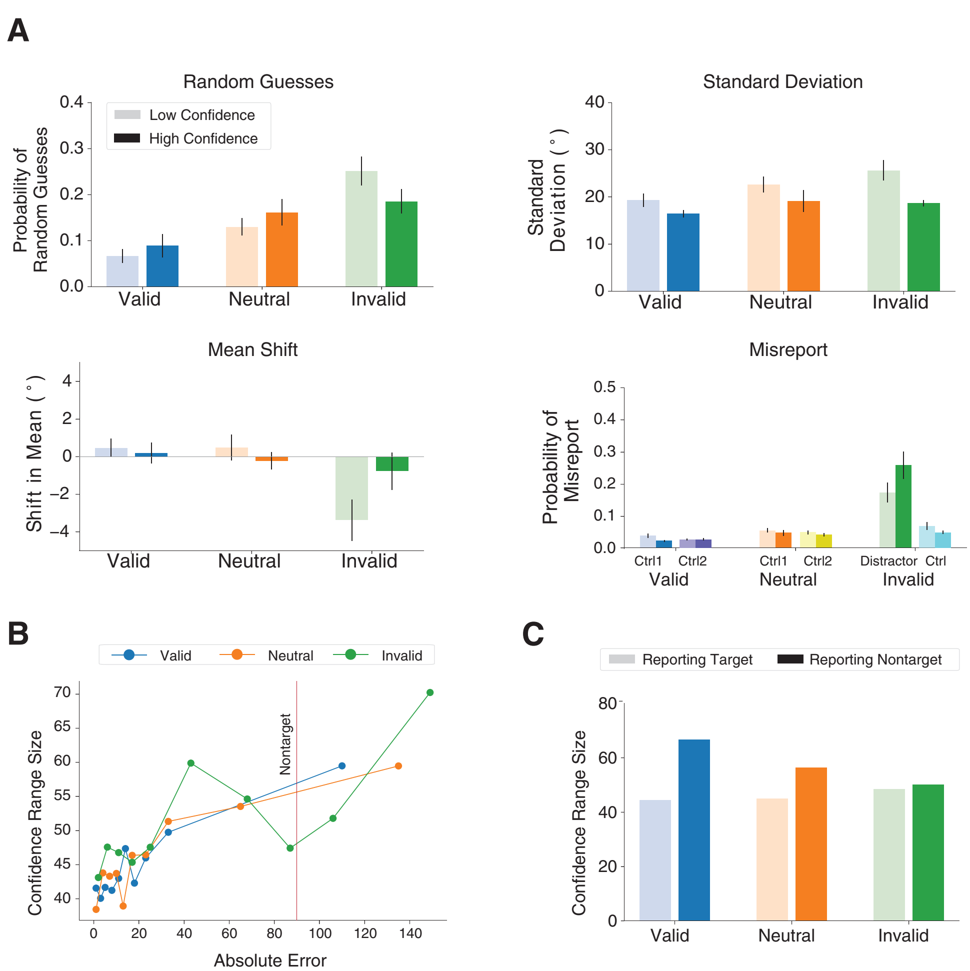

Figure 4. Panel A: Probabilistic model fits for the color report data performed separately for low confidence (lighter bars) and high confidence (darker bars) trials in Experiment 2. Models were fit separately for each participant and each condition. Error bars show ± 1 standard error of the mean (*SEM*). Panel B: Confidence range size as a function of absolute error for each attention condition, plotted in 10 quantile bins. Overall, as the absolute error increased, the confidence range size also increased. However, the confidence range size dips in invalid trials when the absolute error was around 90 degrees (corresponding to misreports of the distractor item's color). Panel C: Mean confidence range size for trials categorized as target reports or nontarget swaps for the linear mixed effects model analysis. The invalid nontarget reports are restricted to the nontarget at the distractor location. Data in Panel C are shown aggregated across participants. See the online article for the color version of this figure.

ANOVA on the probability of random guessing and found a significant main effect of attention condition, $F(2, 52) = 21.923$, $p < .001$, $\eta^2 = 0.457$, and an attention condition x confidence level interaction, $F(2, 52) = 5.093$, $p = .010$, $\eta^2 = 0.164$. Post hoc tests revealed that in invalid trials only, high confidence trials had lower guessing rate, $t(26) = 1.925$, $p = .065$, Cohen's $d = 0.371$; for valid and neutral trials there was no significant effect of confidence (valid: $t(26) = 1.016$, $p = .319$; neutral: $t(26) = 1.581$, $p = .126$).

Repulsion errors are associated with lower confidence. Next, we examined confidence reports for the repulsion and swap errors. Recall that repulsion errors (shift in mean as measured by mu parameter) were only found on invalid trials (see Figure 3); in Figure 4A we again see repulsion errors for the invalid condition only, and it appears that these repulsion errors were primarily on low confidence trials. A two-way repeated-measures ANOVA on the mu parameter, with attention conditions (valid/neutral/invalid) and confidence level (low/high) as factors, revealed a marginal interaction, $F(2, 52) = 2.981$, $p = .059$, $\eta^2 = 0.103$. In the invalid condition, there was a weak but nonsignificant difference between the mean shift of high confidence versus low confidence trials ($t = 1.843$, $p = .077$, Cohen's $d = 0.355$). Further tests revealed that for low confidence trials, the mean shift was significantly negative ($t = 2.781$, $p = .010$, Cohen's $d = 0.535$), but for high confidence trials it did not significantly differ from zero ($t = 0.257$, $p = .799$, Cohen's $d = 0.050$). These results suggest the repulsion errors tend to be associated more with low confidence trials, although the statistics are not entirely conclusive.

Participants may not be aware of swapping errors during attentional capture. For all of the measures reported in the preceding text, the general tendency was for high confidence trials to be associated with better performance. Is this also the case for the swapping errors? One of our key primary findings was that participants were susceptible to selective swapping errors on invalid trials, misreporting the color of the item at the distractor location instead of the target item's color on a substantial proportion of trials. When they make these large errors, are participants aware they might be reporting the entirely wrong item? If participants have an accurate internal sense of performance, we should expect these large errors to be accompanied by lower confidence reports. However, if attention was so completely captured by the distractor cue that participants believed that they were reporting the target item's color when in fact they were misreporting the distractor item's color, then we might expect a high degree of confidence on these error trials.

We ran a three-way repeated-measures ANOVA comparing the probability of swapping errors (see Figure 4A) as a function of Misreported Item (β_1, β_2) × Confidence Level (low, high) × Attention Condition (valid, neutral, invalid), followed by post hoc two-way ANOVAs on each attention condition. The three-way interaction was significant, $F(2, 52) = 9.048$, $p < .001$, $\eta^2 = 0.258$. For both valid and neutral conditions, there was a significant main effect of confidence level ($F_{\text{valid}}(1, 26) = 5.302$, $p = .030$, $\eta^2 = 0.169$; $F_{\text{neutral}}(1, 26) = 7.191$, $p = .013$, $\eta^2 = 0.217$), but no Confidence × Misreported item interaction, $F(1, 26) = 0.151$, $p = .701$, $\eta^2 = 0.006$. For both of these conditions, swapping errors were equally likely for both neighboring nontargets, and were more likely to occur on trials when participants subsequently reported lower confidence in their reports. However, for the invalid condition, we found a different pattern, with significant main effects of confidence level and misreported item ($F_{\text{invalid}}(1, 26) = 6.896$, $p = .014$, $\eta^2 = 0.210$), along with a significant two-way interaction, $F(1, 26) = 9.774$, $p = .004$, $\eta^2 = 0.273$. Post hoc paired t tests revealed that swapping errors for the control nontarget followed a similar confidence pattern as for the valid trials; control nontarget swaps tended to be more likely on lower confidence trials ($t_{\text{control}}(26) = 1.934$, $p = .064$, Cohen's $d = 0.372$). However, swapping errors for the distractor item followed the opposite pattern—they were significantly more likely to be accompanied by high rather than low confidence reports ($t_{\text{distractor}}(26) = 3.142$, $p = .004$, Cohen's $d = 0.605$). These results suggest that when attention is captured by the distractor cue and participants report the color of the item at this location instead of the correct target color, they may make these errors without awareness, with high confidence that they are reporting the correct target color.

A similar pattern can be visualized in Figure 4B, where we separated the absolute error into 10 quantile bins for each attention condition and calculated the mean of confidence range size in each bin. For the most part, as the absolute error increased, the confidence range size also increased, consistent with the idea that a decrease in confidence accompanied the overall reduction in performance. However, for the invalid condition, a dip in confidence range size (relative increase in confidence) can be seen around errors of magnitude 90 degrees, that is, the distractor item's color.

As a final way to examine confidence, we directly asked: were participants were equally confident when they were making swapping errors reporting the color at the distractor location, compared with trials when they were correctly reporting the target color? To answer this question while accounting for other potential sources of variance, we split the data according to report type (coarsely dividing trials according to whether participants reported the correct target feature or a swapped nontarget feature), and fit a mixed-effects model to the confidence range size for "swapping trials" versus "target trials," in valid/neutral (collapsed for power) versus invalid conditions (see Method section). Figure 4C shows the average confidence ratings for these report types and conditions. The mixed-effects model revealed a significant interaction between report type and condition, $t(31.02) = 2.431$, $p = .021$, even after considering all the random factors. In valid/neutral conditions, "target trials" had a smaller confidence range size than "swap trials," $t(28.91) = 2.842$, $p = .008$. On the contrary, in invalid trials, the confidence range size of "target trials" and "swap trials" were not significantly different, $t(28.18) = 0.274$, $p = .786$. The data suggest that participants were significantly more confident when they correctly reported the target's color compared with a nontarget's color in valid/neutral conditions, but they were equally confident when they selected the distractor item's color as the correct target's color in invalid trials.

Discussion

Most attentional capture studies have focused on RT, accuracy effects, and oculomotor capture induced by distractors, showing that when captured by the distractor, attention is briefly allocated to the distractor location (Folk et al., 1992; Hickey, Di Lollo, & McDonald, 2009; Serences et al., 2005). In the current study, we investigated the effect of a distractor on the target representation:

particularly, do distractors alter the target feature representations during involuntary attentional capture? There has been some evidence in the literature of distractor-target compatibility effects: for instance, faster RTs have been observed when a distractor's shape is compatible with the target's reported feature versus when it is incompatible (Lavie & Cox, 1997; Remington, Folk, & McLean, 2001; Theeuwes, Atchley, & Kramer, 2000). Yet, such effects could reflect motor/response interference and not altered perception of the target. Also, the performance cost induced by the incompatible distractor has been typically measured as longer RTs and/or higher error rates of the target report (Theeuwes, 1996; Theeuwes & Burger, 1998), but not from a direct measurement of target representation. Folk et al. (2002; Experiments 3 and 4) did use a method that may have revealed altered target perception by distractors. Participants had to find a color-defined target, embedded in an RSVP stream, and enter the letter into a keyboard. Peripheral distractors, appearing just prior to the target onset, also contained letters, and on error trials, participants reported the identity of the distractor letter at rates well above chance, which bears resemblance to the swap errors observed in the current study. Nevertheless, the authors could not measure more subtle effects on target representations, such as feature distortion, nor could they assess whether participants thought the distractor letter was the target or were just knowingly entering the peripheral item because they missed the target.

In the current study, we further explored how distractors might more fundamentally influence the representation of target features. On invalid trials, participants reported the color of a target item, while a distractor cue appeared simultaneously at a nontarget's location. On most trials, participants were able to report the correct target color rather accurately, indicating that they successfully maintained attention at the target location and bound the target color and location correctly on those trials. But this was not always the case: Critically, we found that participants were susceptible to two unique types of feature errors on trials when attention was captured by the irrelevant distractor. In both of our experiments, we found that participants had a higher probability of misreporting the color of the item at the distractor location than the color of the control nontarget (swapping error). We also found that for those invalid trials when participants successfully reported a color close to the target color, they tended to report a color shifted slightly in color space, away from the color of the item at the distractor location (repulsion error). The results from Experiment 2 suggest that participants were generally less confident when they reported a color further away from the correct target color. However, this was not true when participants were captured by the distractors in invalid trials. Here when they were fully captured and made swapping errors, they were equally confident as when they reported the correct target color.

The results suggest that swapping errors occur when spatial attention is strongly captured by the distractor and involuntarily shifted to the distractor location. These swapping errors may reflect the perceptual consequences of unstable spatial attention, as has also been reported during shifts of goal-directed attention from one location to another (Dowd & Golomb, 2019; Golomb et al., 2014). In the current study, even when we minimized location uncertainty by presenting a postcue, participants still made swapping errors. What is particularly remarkable is that these swapping errors seemed to occur without participants' awareness. This is consistent with early illusory conjunction studies which suggested that there was little difference in subjective confidence when making illusory conjunctions versus reporting the correct items (Treisman, 1998; Treisman & Schmidt, 1982), though in these earlier studies confidence was measured by simply asking participants to categorize their response as doubtful or not. The current study used a novel approach taking advantage of the robustness of the continuous report technique to provide a quantitative measurement of participants' confidence levels.

The confidence report in Experiment 2 was also designed to test some alternative explanations of swapping and repulsion errors. For example, one could argue that swapping errors could be simply due to guessing, if the distractor location color was the only color participants saw during the task when they were captured by the distractor. This is unlikely to be a good strategy because we presented a postcue at the target location to remind participants the location of the target during the response; thus if participants only saw the color of the distractor item and were aware that it was in the wrong location, the better guessing strategy would have been to select a color from a different part of the color wheel. But even if they did use that strategy, it should have resulted in low confidence reports for those trials, similar to the lower confidence levels associated with random guesses.

Another alternative explanation is that participants simply mistook the distractor cue for the target box because both shared the defining white feature. Contingent capture scenarios limit the scope of possible top-down strategies participants could use to avoid distraction, so this manipulation was intended to evoke maximal involuntary capture of attention (Folk et al., 1992, 2002). That said, we do not believe that participants confused the target and distractor cues. Although participants may have been more likely to be distracted by the white dots because they were searching for the white-outlined target, that does not mean they mistook the white dots for the target box. However, it is possible that participants may have been less certain about the target location when they were captured by the distractor. For instance, Dowd and Golomb (2019) showed that when attention is lingering at a wrong location, participants can make correlated swapping errors (reporting the wrong color and orientation at the wrong location). Importantly, even on trials where there was only a single spatial cue, participants sometimes experienced lapses of spatial attention, where they reported the wrong features and location, presumably because spatial attention was focused on the nontarget location when the stimuli appeared (Dowd & Golomb, 2019). To reduce this location uncertainty in our task, we presented the postcue reindicating the correct target location during the color report. We also tested for this uncertainty with the confidence range report in Experiment 2: If participants were confused on invalid trials and thought the distractor cue was the target cue, then when the postcue appeared in a different location, they should be aware of that mismatch, and the confidence reports should reflect this uncertainty. In general participants did show this awareness: on valid/neutral trials where they made swap errors and misreported the color of a control item in the display, or even on invalid trials where they misreported the control item or randomly guessed, they did so with lower confidence. Thus, the high confidence when swapping the color at the distractor location—even with a postcue reminding participants of the target location—argues against this alternative account.

In terms of the repulsion errors, these offer insight into another aspect of distractor influence. Whether participants made one or the other type of feature error could possibly depend on the degree of capture (i.e., the degree to which the participant processed the distractor on that trial). Capture can vary from trial to trial for a variety of reasons (e.g., Leber, 2010; Leber et al., 2013); in a contingent capture paradigm, this could plausibly result from factors such as random variation in attentional allocation and/or noisy signal processing in visual cortex (Newsome, Britten, & Movshon, 1989). On trials where the capture was strong, because the target display duration was very short, participants may not have had enough time to disengage from the distractor and relocate attention to the correct feature, resulting in the swapping errors. By the same rationale, on other trials where participants were able to resist capture, one might assume that they should correctly report the target feature. However, the repulsion errors show that the target feature representation is not perfectly accurate but instead is biased away from the color of the distractor item. These repulsion errors suggest that even on trials when the distractor was more successfully ignored, the distractor might still be distorting target feature perception in more subtle ways. One possibility is that attention may be only partially captured by the distractor on these trials. In this case, it is possible that spatial attention might be shared between the distractor and target locations simultaneously (Golomb, 2015; Golomb et al., 2014) or participants might be actively trying to inhibit the distractor item's representation.

One might argue that the repulsion errors could instead be due to an explicit strategy: reflecting a response-level "not-the-distractor-item-color" report. That is, when participants were captured by the distractor, they might only see one color but know it was not the target, so pick a color distinct from the distractor in color space. However, this strategy is hard to reconcile with the current results because we would have also expected a large percentage of trials selecting other control colors, and/or a noisier and larger magnitude repulsion effect. Also, if participants were using this strategy, we would have expected more "anything-but-the-distractor" confidence reports in Experiment 2 (e.g., participants highlighting large 270-degree sections of the color wheel during the confidence report). Our results thus argue against an explicit strategy, and support that participants were being influenced more subtly (or unconsciously) by the distractor item's color. Previous literature has shown that subliminal stimuli can capture attention (Jiang, Costello, Fang, Huang, & He, 2006; McCormick, 1997) and there has been evidence for the dissociation between attentional capture and conscious perception (Lamy, Alon, Carmel, & Shalev, 2015).

The relational representation model (Bae & Luck, 2017) may also provide some insight to explain the repulsion effect. The model assumes that an individual item is represented in relation to the other items, with each item serving as a reference for the other items. Perceptual representation tends to bias away from the reference point (Bae & Luck, 2017; Gibson & Rander, 1937; Huttenlocher, Hedges, & Duncan, 1991; Pratte, Park, Rademaker, & Tong, 2017; Wei & Stocker, 2015). Among all the reference points, the attended item is given most weight. In the current study, on invalid trials, even if attention is not fully captured by the distractor, the color at this location may be attended or processed more than the other nontargets. Therefore, the distractor item could serve as the most salient reference point, making the target report bias away from this color.

Previous publications reporting a feature bias introduced by a nontarget stimulus have generally reported that the direction of the bias depends on the differences of the two stimuli in the feature space. When the two features are close in the feature space, it tends to show a repulsion effect, whereas when they are far away in the feature space, it tends to show an attraction (mixing) effect (e.g., Bae & Luck, 2017; Golomb, 2015). But it is controversial where is the turning point between repulsion and attraction. For example, in Bae and Luck (2017), the repulsion effect was found when the feature differences were smaller than 90 degrees, and attraction was found when the feature difference were larger than 90 degrees. They did not find any feature bias when two features were 90 degrees apart. However, they used orientation as the feature and the 90 degrees in orientation could be a particular case. In Golomb et al. (2014) and Golomb (2015), feature attraction was instead found when the two colors were 90 degrees apart in color space (with repulsion only at smaller, e.g., 30-degree distances; Golomb, 2015). Here we used colors 90 degrees apart and found repulsion. However, the discrepancy may stem from the different task and design in the current study. In Golomb et al. (2014) and Golomb (2015), participants were instructed to split attention to two items and after they disappeared, a post cue was displayed indicating which was the target item. Participants thus needed to encode two colors, since either of them could potentially be the target. However, in the current study, because the single target was highlighted when the colored items appeared, participants only needed to encode one color, and ignore the others. Therefore, it is possible that the current task involved more active suppression, which caused the report to be repulsed away from the distractor even with the larger distance in color space. It would be interesting for the future studies to further explore if the direction of the capture-induced bias depends on the feature relations between the target and distractor.

Besides the theoretical contributions, our study also makes methodological contributions by implementing the continuous feature report and novel asymmetric continuous confidence report. Compared with the traditional alternative forced choice task, the continuous feature report helps us get access to the internal representation of the target in a fine scale. In some previous attentional capture studies, letters were used as the target and distractors (e.g., Folk et al., 2002). One can still analyze the error responses from the letters, but it fails to discover any systematic effect of distractors unless it is misreporting the target. The continuous report and the probabilistic mixture model fitting make it possible to also identify any subtle errors participants made during the experiment. Recently there has been discussion about the limitations of the traditional probabilistic mixture model, especially since the parameters of guessing rate and precision have been found to be correlated (Schurgin, Wixted, & Brady, 2018), making those parameter estimations less reliable (Ma, 2018). However, in our experiment, we did not draw any main conclusions based on guessing and precision. Our primary conclusions are based on the parameters of swapping error (B1) and repulsion (μ), which we confirmed were not correlated (combined across both experiments [$N = 53$], correlation between B1 and mu in invalid condition: $r = -0.100$, $p = .476$).

We further showed that by applying a flexible continuous confidence report, we are able to gain more information than the commonly used Likert-type scale (confidence rating, e.g., Rademaker, Tredway, & Tong, 2012). Unlike other studies using similar methods (e.g., Honig, Ma, & Fougnie, 2018), the confidence report in the current study could be asymmetric, and therefore the selected arc in the color wheel during the confidence report can better reflect participants' internal representation of the target feature. Our novel asymmetric continuous confidence report reveals that participants can make pretty dramatic errors and still remain highly confident about their performance, which opens up a variety of possibilities for how this approach might be used to investigate questions related to the topics of consciousness and cognition, for example, how these "confident errors" could affect other aspects of perception and decision making.

Future research may investigate how target feature perception is altered under different types of attentional capture scenarios. Here, we used a contingent capture manipulation, in which the distractor matched the observers' attentional control settings and thus could not be easily ignored. It is possible that other forms of capture would contribute additional insights. For instance, had we chosen a distractor based on its physical salience (e.g., unique color; Theeuwes, 1992), observers would have had the possibility of implementing a proactive suppression strategy to ignore it (Gaspelin, Leonard, & Luck, 2015; Gaspelin & Luck, 2018; Vatterott & Vecera, 2012). How such forms of suppression interact with target feature perception represents an intriguing avenue for additional inquiry.

In sum, the current study sheds light on how we manage to maintain objects' representations in a dynamic world with all kinds of distractors surrounding us. It is almost inevitable that we get drawn away from our task-relevant target in such a distracting environment from time to time. The current study provides some novel insights about how these distractions could potentially alter our representations of object features. Here, we showed that the behavioral effect of distractors is more than RT slowing, accuracy decrements, and saccades to the distractor. We found that participants are susceptible to two types of feature-binding errors during capture. Critically, when strongly captured by distractors, people can make dramatic errors, without even being aware of it. Even when successfully resisting capture, people still tend to exhibit subtle feature errors. Thus, capture not only induces a spatial shift of attention, it also alters feature perception in striking ways.

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