Unseeing the White Bear: Negative Search Criteria Guide Visual Attention Through Top-Down Suppression

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Abstract

In three spatial cueing experiments, we investigated whether a negative search criterion (i.e., a task-relevant feature that negatively defines the target) can guide visual attention in a top-down manner. Our participants searched for a target defined by a negative feature (e.g., red if the target was a nonred horizontal bar). Before the target, a peripheral singleton cue was shown at the target position (valid condition) or a nontarget position (invalid condition). We found slower reaction times in valid than invalid trials only with singleton cues matching the negative feature. Importantly, we ruled out that participants searched for target-associated features instead of suppressing the negative feature (Experiment 1). Furthermore, we demonstrated that suppression of cues with a negative feature was stronger than mere ignorance of singleton cues with a task-irrelevant feature. Finally, cue-target intervals of 60 ms and 150 ms elicited the same suppression effects for cues matching the negative feature. These findings suggest that the usage of a negative search criterion elicited feature-selective proactive suppression (Experiments 2 and 3). Thus, our results provide first evidence of top-down attentional suppression dependent on current task goals as a strategy operating in parallel to the goal-directed search for target-defining features (Experiment 2).

Keywords: visual attention, inhibition, top-down, contingent capture of visual attention, suppression

Word count: 12,233

Public Significance Statement:

Previous research indicated that even if features should be ignored, the to-be-ignored features nevertheless capture attention. However, we showed that if participants searched for a target defined by a negative feature (i.e., the target was a nonred horizontal bar), the negative feature (here: the color red) was actively suppressed during attentional guidance. Our results extend the knowledge of attentional guidance by showing selective suppression of task-relevant features that negatively define the target.

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Any goal-directed behavior leads to selecting task-relevant stimuli while ignoring irrelevant ones (Geng, 2014). Thus, ignoring task-irrelevant stimuli is a necessary by-product of attending to goal-relevant stimuli (cf. Desimone & Duncan, 1995). However, task-irrelevant stimuli might also be actively suppressed during visual search (Cepeda et al., 1998; Gaspelin et al., 2015, 2017; Gaspelin & Luck, 2018; Ruff & Driver, 2006). Whereas ignoring refers to not attending a task-irrelevant stimulus, actively suppressing implies down-regulating sensitivity below a default baseline (Chelazzi et al., 2019). So far, studies have identified three primary candidates for sources of suppression.

First, suppression of known distractor features can emerge from statistical learning based on location (Wang & Theeuwes, 2018a, 2018b) or feature regularities (Stilwell et al., 2019). Second, distractor feature interference is reduced over time, suggesting that suppression of to-be-ignored features emerges with practice (Vatterott & Vecera, 2012). Third, irrelevant stimuli might be voluntarily suppressed depending on an observer's intention to ignore them (Arita et al., 2012). However, evidence for such voluntary (or controlled) top-down suppression is yet limited (de Vries et al., 2019) or could be alternatively explained. For example, studies showed that participants re-code foreknowledge about a distractor feature into (more accessible) positive target features or locations (Beck & Hollingworth, 2015; Becker et al., 2015; but see Carlisle & Nitka, 2019). To understand this, suppose participants are informed that a distractor is always red, and the target is always blue, grey, or yellow. In that case, participants could neglect the distractor information and search for the target by its possible colors. As a result, the to-be-ignored feature becomes unnecessary and, thus, would no longer influence visual attention. A second alternative explanation for the voluntary suppression of distractor features offers the search-and-destroy hypothesis (Moher & Egeth, 2012).

According to this hypothesis, task-irrelevant distractors initially capture attention before their suppression (cf. Cunningham & Egeth, 2016; Tsal & Makovski, 2006). Such initial unwanted allocation of attention towards to-be-ignored stimuli has been described as the attentional white bear effect (Tsal & Makovski, 2006). This term refers to the well-known paradox that attempting to ignore an unwanted thought (e.g., a white bear) paradoxically prompts its mental representation (Wegner et al., 1987). Similarly, Tsal and Makovski (2006) found that initially, attention was automatically allocated towards an expected but to-be-ignored location. Subsequent studies further substantiated the search-and-destroy hypothesis with to-be-ignored but entirely task-irrelevant salient distractors (cf. Beck et al., 2018; Moher & Egeth, 2012). Therefore, evidence for voluntary suppression before target onset can, for example, only be found with relatively long intervals between to-be-suppressed distractor and target (Tanda & Kawahara, 2019).

To sum up, evidence is convincing that implicit processes such as habituation, statistical learning, or experience with distractor features evoke suppression of task-irrelevant stimuli, even if salient. However, whether an observer’s intention to ignore a distractor feature can trigger active suppression is less clear. Therefore, we addressed this open question in the current study.

In three spatial cueing experiments, we investigated top-down suppression with a not-to-be-selected feature that cannot be re-coded into a positive, target-defining feature. To note, if participants are only told what not to look for, but re-coding is not an option, they cannot directly search for the target by other known features. Therefore, the not-to-be-selected feature becomes necessary to identify the target – that is, it is task-relevant and should, thus, influence attentional guidance (cf. Wolfe, 2021). In response to instructions about task-relevant features, usually, participants set up attentional control settings that lead to involuntary capture of visual attention by features matching the instructions (cf. Folk et al., 1992). However, task-relevant features that negatively define the target (i.e., negative search criteria) might impact attentional guidance differently. For example, suppose you are shopping for new shoes. You might be undecided about the color but determined not to buy white ones as they quickly get dirty. In this situation, besides the known category (shoes), the target is negatively defined (non-white). Using this known nontarget feature would be helpful to find appropriate shoes, as no additional positive target information is available. Nevertheless, an attentional control setting to search for white shoes would not be beneficial. It would lead to the capture of attention by the not-to-be-selected color. In contrast, a negative search criterion or an attentional control setting to suppress or guide attention away from the negative feature would serve the purpose. To find out if this is possible, in the current study, we investigated the influence of negative search criteria on the guidance of visual attention. Thereby, we aim to provide new insights into how knowing what not to look for contributes to attentional control.

In our study, a negative search criterion is necessary to successfully identify the target. Thus, it comprises task-relevant information on what the target will not look like. For example, in Experiment 1, participants were told to search for the horizontal bar that was not red, and two horizontal bars were presented in each target display. One of the bars had the pre-defined negative color (e.g., red). The other bar had an alternative color from a set of three (e.g., green, grey, and yellow) that unforeseeably changed from trial to trial. Of course, participants could have learned the target-defining colors across trials. Therefore, each of the three possible target colors was shown in each target display, alternately defining the target or one of the two remaining distractors. Hence, it would not have been expedient to search for the target by its color. Thereby, we ensured that the negative search criterion was task-relevant and not translatable into to-be-searched-for features. Moreover, using such an experimental task, we paved the way for examining top-down guidance of visual attention by features that negatively define the target.

Experiment 1

First, we investigated how colors influence attentional allocation if they negatively define the target and are necessary to identify the target. We will use the term negative search criterion for a task-relevant feature that negatively defines the target. Moreover, features that match the negative search criterion will be referred to as negative features.

In all experiments, we measured attentional allocation with peripheral singleton cues that preceded the search display and were not predictive of the target position. With four possible target positions, our cue preceded the target at the same (valid condition, 25% of all trials) or a different position (invalid condition, 75% of all trials). Based on this spatial cue-target relation, we calculated the validity effect – a standard measure for quantifying attentional allocation – by subtracting mean reaction times in valid from invalid trials (cf. Büsel et al., 2020).

According to the contingent-capture hypothesis (Folk & Remington, 1998; Folk et al., 1992), attentional capture directly depends on a feature's task relevance (i.e., its match to a search criterion). Usually, salient stimuli that pop out in at least one feature dimension (i.e., singletons; e.g., a green stimulus among several red stimuli) elicit a strong attend-to-me signal irrespective of task goals (Sawaki & Luck, 2010; cf. Theeuwes, 1992). However, it has been shown that a feature's task relevance also determines whether physically salient stimuli capture or not capture attention (Folk et al., 1992; Schoeberl et al., 2019).

For example, suppose you are searching for a red target. In that case, a red target-preceding singleton cue will automatically capture attention depending on its fit to an attentional control setting for red. Consequently, a (matching) red cue produces a positive validity effect due to faster reaction times if the target appears at a cued (valid trial) than uncued position (invalid trial). In contrast, task-irrelevant singletons (e.g., green singleton cues when searching for red targets) are usually successfully ignored in this situation (Folk & Remington, 1998; Goller et al., 2016). Thus, such nonmatching cues typically produce no significant validity effects. However, singleton cues might also produce inverse validity effects if they are suppressed (Lamy et al., 2004). It has been shown that visual processing is diminished at a suppressed distractor's location Chelazzi et al. (2019). Thus, suppose a negative search criterion elicits suppression dependent on an attentional control setting that already applies before the target display's onset. In that case, reaction times would be slower in valid than invalid trials, resulting in an inverse validity effect.

In Experiment 1, we used three distinct singleton cues to examine attentional control settings for negative search criteria. First, we used cues with features that matched the negative search criterion (negative cues). For example, negative cues were red if participants searched for a nonred target. Second, we used cues with a task-irrelevant feature (nonmatching cues) to distinguish the effects of ignoring and top-down suppression. Notably, task-irrelevant cues might also lead to an inverse validity effect (Carmel & Lamy, 2014; Schoeberl et al., 2018). However, inverse validity effects should be more pronounced for negative than nonmatching cues if top-down suppression applies (cf. Chelazzi et al., 2019). Third, we used cues with one of the three possible target colors (possible-target-color cues) to control once more for the negative search criterion's task relevance. For example, our participants searched for a negatively defined target (i.e., a nonred horizontal bar) with one of three possible target colors (e.g., blue, yellow, or grey) changing from trial to trial. In this case, in Experiment 1, possible-target-color cues were always blue. In other words, possible-target-color cues had one of the three colors a target could have. Suppose participants actively searched for the target by its three possible colors rather than relying on the negative search criterion (here, e.g., the target's being not red). In that case, such possible-target-color cues would correspond to matching cues. Therefore, they should produce standard top-down-contingent capture – that is, positive validity effects (cf. Folk & Remington, 1998; Irons et al., 2012; Kerzel & Witzel, 2019). It might also be that such positive validity effects are only evident near the experiment's end. Then, chances were theoretically the highest that participants had finally learned the possible target colors and how to search for them effectively. Therefore, we also conducted an exploratory block analysis which is shown in the Appendix to shed further light on how top-down attentional guidance by negative versus positive search criteria evolved throughout the experiment.

Method

Participants

For Experiments 1-3, we conducted a generalized extreme Studentized deviate (ESD) test (Rosner, 1983) for mean individual error rates to detect one or more outliers. Participants were excluded if the generalized ESD test's result was significant (α = .5). All participants received course credits for completing the task, were naïve to the purpose of the experiment, and were treated in compliance with the Declaration of Helsinki's ethical standards. Participants had normal or corrected to normal visual acuity, no red-green deficiency, and gave written informed consent before the experiment.

According to G*Power (Faul et al., 2007), a sample size of 20 was required to detect an effect size of Cohen's *d* = 0.9 for a two-sided one-sample *t* test with a significance level of α = .05 and statistical power of 95%. To our knowledge, no previous studies investigated the influence of negative search criteria on visual attention using peripheral cues. Therefore, we used half of the mean effect size reported in a meta-analysis on contingent capture studies (Büsel et al., 2020) where the influence of (positive) search criteria on attentional guidance is investigated in a similar design as in the current study. We only used half of the mean effect size, as previous studies have shown that negative features guide attention less effectively than positive ones (cf. Arita et al., 2012; Rajsic et al., 2020). Additionally, we used an independently chosen minimum effect size of interest (here: 20 ms) to estimate the achieved statistical power for each experiment (cf. O'Keefe, 2007). To reach a high precision, we used simulations to account for several factors (e.g., the actual trial number for each experimental condition per participant and the experiment's reaction time distribution) that influence the statistical power (Arnold et al., 2011) but are only available after data collection. Noteworthy, we used the term "achieved power" to differentiate between the flawed approach of post hoc power calculations based on the obtained effect size and our simulation approach based on an independently chosen effect size. More details about our simulation approach can be found in the Appendix.

In Experiment 1, we tested three negative color conditions as we were interested in whether colors differ in their susceptibility to top-down suppression. Thus, for each negative color condition, we tested 20 participants at least, resulting in a sample size of 60. However, we did not send away participants who had already registered if the sample size per negative color condition was smaller than 25.

After excluding two participants due to a high error rate (outlier 1 = 61% errors, $R_1 = 3.79$, $p = .004$, outlier 2 = 55% errors, $R_2 = 3.59$, $p = .010$), sixty-three participants were analyzed (42 females; $Mdn_{\text{Age}} = 21$ years, range 18–39 years). Within experimental conditions, the average intraclass correlation 1 (ICC1) was .06, and the intraclass correlation 2 (ICC2) was .88. Across all experimental conditions, the ICC1 was .06, and the ICC2 was .98. A value of .80 for the ICC2 is recommended (cf. Brysbaert, 2019).

Apparatus and Stimuli

The experiment was conducted in a dimly lit room. Participants used a chin rest to maintain a stable viewing distance at 57 cm and a hearing protection against possible background noise. Stimuli were generated and controlled with PsychoPy3 (Peirce et al., 2019) and displayed on an LCD monitor, with a resolution of 1,920 x 1,080 pixels (54.4 x 30.3 cm) and a refresh rate of 100 Hz. Stimuli displays consisted of four stimuli presented at the corners of an imaginary rectangle centered on the screen. All stimuli were presented with a horizontal and vertical offset of 4° visual angle from the screen center and were displayed against a dark grey background (CIELAB color space: $L^* = 35$, $a^* = 0$, $b^* = 0$).

Each trial started with a fixation display, followed by the cueing display consisting of four disks (2° diameter). Each disk was surrounded by a white ($L^* = 140$, $a^* = 0$, $b^* = 0$) ring (3.5° diameter). One of the disks was the singleton cue which had a different color than the three grey ($L^* = 70$, $a^* = 0$, $b^* = 0$) nonsingleton disks. We used three cue conditions (negative vs. nonmatch vs. possible-target-color), and all cues were singletons. The negative cue had the negative color. The possible-target-color cue had one of three possible target colors (but only one color per participant). The nonmatching cue's color was task-irrelevant and, thus, never occurred in the target display. The singleton cue colors were red ($L^* = 70$, $a^* = 99$, $b^* = 90$), green ($L^* = 70$, $a^* = -70$, $b^* = 67$), and blue ($L^* = 70$, $a^* = 25$, $b^* = -110$). However, their function depended on the definition of the negative color. For example, if participants searched for the nonred horizontal bar, the negative cue was red, the nonmatching cue was green, and the possible-target-color cue was blue. The cue appeared at each of the four positions equally often. Also, cue positions varied pseudo-randomly between trials, independently of target positions. Therefore, cue and target positions were the same in 25% of all trials (valid trials) and different in 75% of all trials (invalid trials).

An additional display was presented between cueing and target display, consisting of four white disks (3.5° diameter), one per each of the four positions. This display was implemented to prevent perceptual facilitation or color-merging of stimuli between cueing and target display. Throughout the current study, we will refer to this display as a masking display.

The target display consisted of two vertical and two horizontal bars (each 0.5° wide and 1.5° long). One of the horizontal bars had the negative color. This bar was never the target. We used three negative colors (red, green, or blue) that were counter-balanced across participants. In the red and blue negative color conditions, per each target display, the bars were red, yellow (L* = 70, a* = 0, b* = 73), blue, and grey. In the green negative color condition, in each target display, the bars were green, red, grey, and yellow. Each bar had a white contour (0.03°). The colors and orientations appeared equally often at each of the four possible target positions. The target color and position changed pseudo-randomly from trial to trial. Each bar was surrounded by a white ring with a gap at one of four possible positions (up, down, left, right). Each gap position appeared only once per target display and was pseudo-randomized so that each one appeared almost equally often at each stimulus position. However, each of the four gap positions appeared equally often at the target.

Procedure

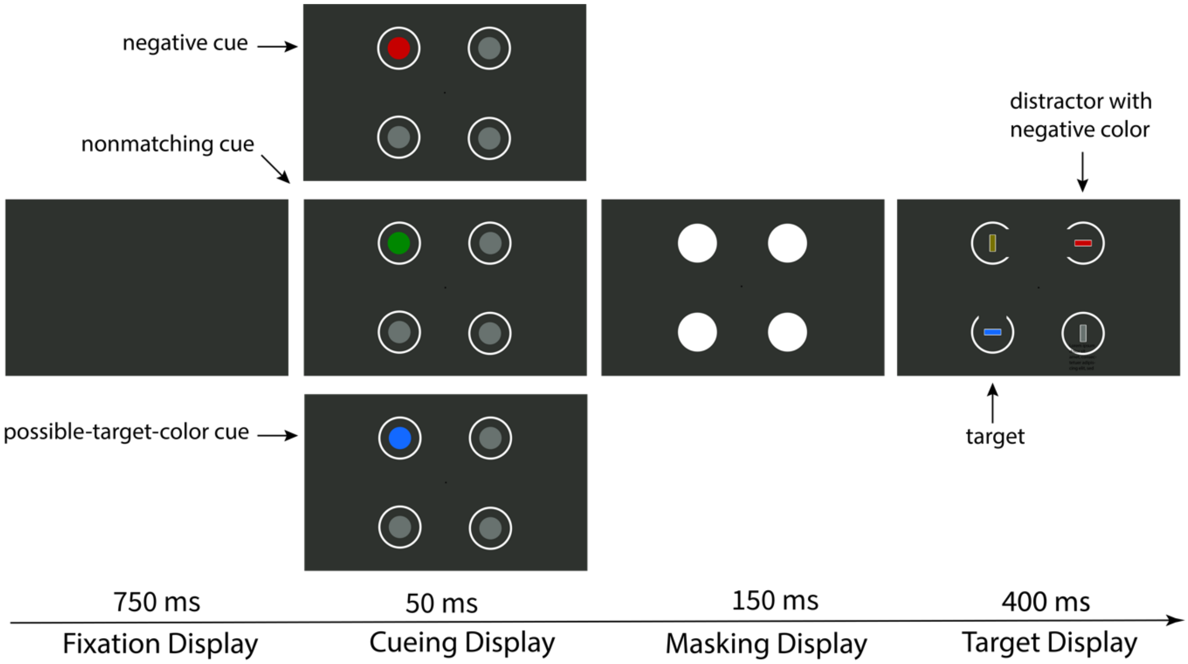
We instructed our participants to search for a nonred horizontal bar and report the gap position in the ring surrounding the target. The gap position was reported with the arrow keys on a standard computer keyboard (e.g., press arrow left when the ring's gap is left).

Each trial started with a central fixation dot that remained visible on the screen until the trial ended. Then the cueing display was presented for 50 ms, followed by the masking display (150 ms). Next, the target display was shown, consisting of four bars in different colors. The bars were presented for 200 ms, while the surrounding rings were presented for 400 ms to ease recognizing the gap position (i.e., the response criterion). Then a response display was shown until participants pressed an arrow key or until timeout (1.5 s). Participants received written feedback displayed on the screen for each correct ("Richtig!" [Wrong!]) and wrong ("Falsch!" [Wrong!]) response. In addition, if they did not respond before the timeout, the words "Zu langsam, bitte schneller reagieren" [Too slow, please react faster.] were presented. The procedure for Experiment 1 is shown in Figure 1.

Participants started with practice trials. After a minimum of 25 practice trials, data acquisition started once participants performed 80% correct or better. We used three different between-participants negative color conditions (red, green, and blue). The red and green negative color condition comprised 864 trials with three self-paced breaks after every 216 trials. The blue negative color condition consisted of 1,440 trials for a more reliable

Figure 1

Illustration of an Invalid Trial in Experiment 1



Note. The stimuli are drawn to scale, but the display is cropped. Depicted cueing displays correspond to the three cue conditions (from top to bottom: negative, nonmatching, possible-target-color cue). In the target display, one horizontal bar had the negative color. The target was horizontal, too. However, its color varied unforeseeably from trial to trial (here, the target color changed between blue, yellow, and grey). Participants had to report the gap position in the white ring surrounding the target.

measurement (cf. Brysbaert & Stevens, 2018) with five self-paced breaks after every 240 trials.

Data Analysis

We used R (Version 4.0.5; R Core Team, 2020) and the R-packages *broom* (Version 0.7.6.9001; Robinson et al., 2020), *data.table* (Version 1.14.0; Dowle & Srinivasan, 2020), *emmeans* (Version 1.6.0; Lenth, 2020), *ggplot2* (Version 3.3.3; Wickham, 2016), and *lme4* (Version 1.1.27; Bates et al., 2015) for data analysis.

We calculated effect sizes from one-sample *t* tests as the group mean divided by the standard deviation. In addition, effect sizes were corrected using Hedges's correction factor (Hedges, 1981) as recommended by Cumming (2012) for small samples. Reaction times and validity effects were analyzed with linear mixed-effects models, which have more statistical power than analyses of variance (ANOVAs) if the design is unbalanced[1] (cf. Brown, 2021; Kliegl et al., 2010). We evaluated the best fitting models based on the result of hierarchical model comparisons using Likelihood Ratio Tests. Thereby, we tested which effects had to be included into our models to describe our data best (Meteyard & Davies, 2020).

In Experiment 1, we used two independent within-subject variables: cue condition (negative vs. nonmatch vs. possible-target-color) and validity (valid vs. invalid). Our main dependent variables were reaction times and error rates. Additionally, we calculated a validity effect as our main parameter of attentional allocation.

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[1] The designs in the current study are all unbalanced due to the smaller number of valid compared to invalid trials (25% vs. 75%, respectively).

Results

In all experiments, we excluded reaction times below 150 ms and over 1.5 s (fast guesses and timeouts). In Experiment 1, we excluded 3.26% trials and analyzed only reaction times on correct trials (19.92% wrong trials excluded).

Reaction Times

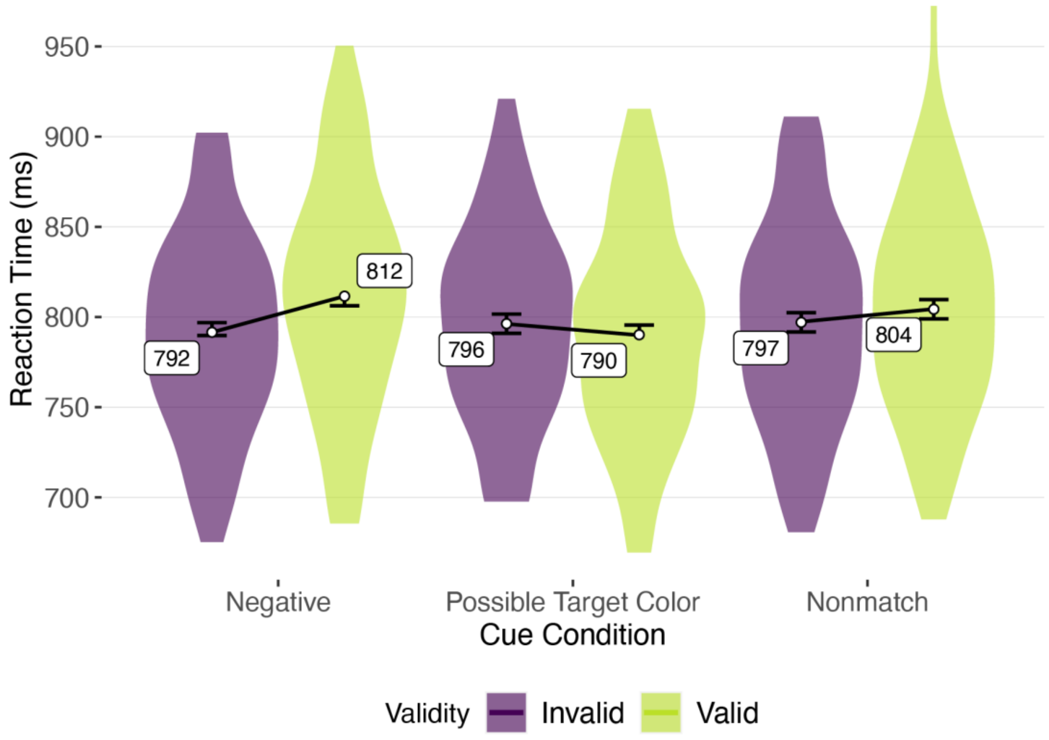
Reaction times were analyzed using a linear mixed-effects model. We included cue condition and validity as fixed factors and random by-participant intercepts as a random factor. Hierarchical model comparisons showed that a model including an interaction between cue condition (negative vs. nonmatch vs. possible-target-color) and validity (valid vs. invalid) fitted the data significantly better than a model with only a main effect of cue condition, $\chi^2(2) = 24.55$, $p < .001$. This interaction was driven by a different validity effect (i.e., difference between valid and invalid trials) between cue conditions (see Validity Effect Analysis for a detailed post hoc analysis of this interaction). Adding a main effect of negative color condition did not significantly improve the model fit, $\chi^2(2) = 2.83$, $p = .243$. Therefore, we analyzed data collapsed across all negative color conditions (but see Appendix for plotted mean reaction times for each negative color condition). The mean reaction times of correct trials for each experimental condition and more details about significant differences between conditions of Experiment 1 are shown in Figure 2.

Validity Effects

We calculated a validity effect for each participant and each cue condition separately. Validity effects were analyzed with a linear mixed-effects model. Hierarchical model

Figure 2

Mean Reaction Times of Correct Trials for Each Experimental Condition of Experiment 1



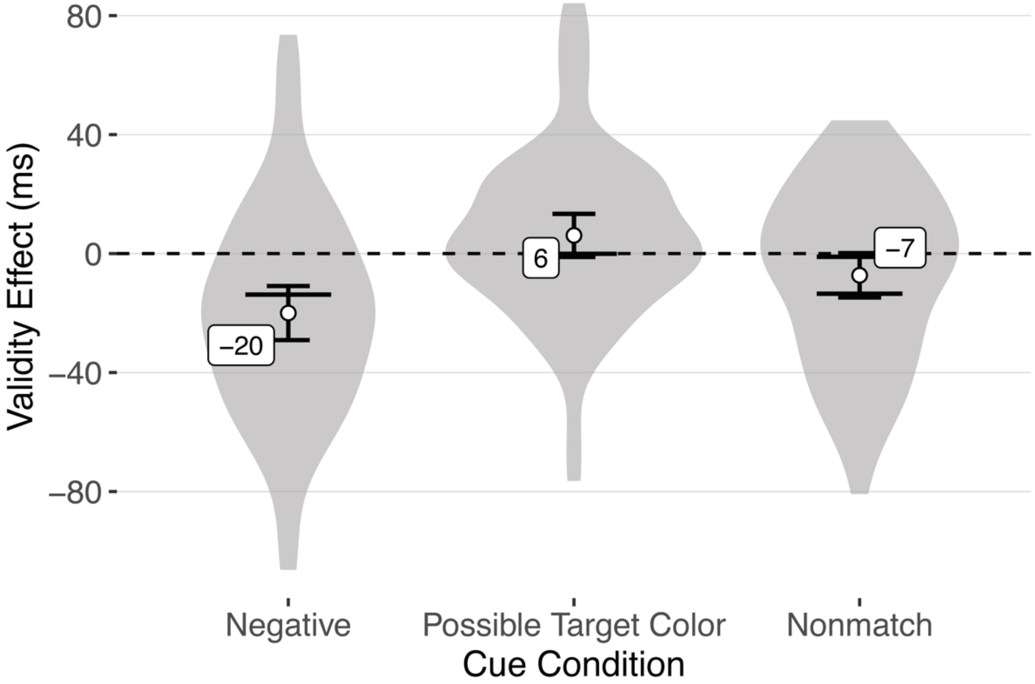
Note. The violin plots represent the distributions of the individual mean reaction times. The error bars represent 95% CIs for the mean comparisons of all conditions, adjusted using Tukey's honestly significant difference (HSD; cf. Salkind, 2010). There is only one error bar for the largest and smallest value, as they cannot be compared with a more extreme mean. The difference between conditions is significant if the error bars do not overlap.

comparisons showed that a model including cue condition as a fixed factor and a random by-participant intercept described the data significantly better than a model without a main effect of cue condition, $\chi^2(2) = 23.14$, $p < .001$. We found a significant main effect of cue condition consisting of a significant inverse validity effect for negative cues, while nonmatching and possible-target-color cues produced no significant validity effects. Again, we analyzed data collapsed across all negative color conditions, as there was no significant effect of negative color condition on the validity effects (but see Appendix for plotted validity effects for each negative color condition). For post hoc analyses, we used two-sided one-sample *t* tests to investigate whether the validity effects differed significantly from zero. Moreover, we conducted two-sided one-sample *t* tests to test if validity effect differences between cue conditions are significantly different from zero. For all analyses, we used a significance level of $\alpha = .05$ and corrected *p* values for multiple comparisons using the procedure of Benjamini and Yekutieli (2001).

A Shapiro-Wilk test for normality showed that the validity effect and the validity effect differences were normally distributed in all cue conditions (all *p* values > .112). We found a statistically significant inverse validity effect for negative cues, $M = -20$ ms, 95% CI [−29, −11], $SD = 36$ ms, $t(62) = -4.40$, $p < .001$, $d_{unb} = -0.55$ [−0.82, −0.29]. Based on our simulations, the estimated achieved statistical power to find a validity effect of −20 ms for negative cues as significant ($\alpha = .05$) was 98%. In contrast, we found no significant validity effect for nonmatching cues, $M = -7$ ms, 95% CI [−15, 0], $SD = 30$ ms, $t(62) = -1.95$, $p = .152$, $d_{unb} = -0.24$ [−0.5, 0.01] or possible-target-color cues, $M = 6$ ms, 95% CI [−1, 13], $SD = 29$ ms, $t(62) = 1.69$, $p = .177$, $d_{unb} = 0.21$ [−0.04, 0.46]. Compared to valid and invalid trials with nonmatching cues that had neutral attentional priority, respectively, stronger inverse validity effects for negative cues were driven by slower reaction times in valid trials, M = 14 ms, 95% CI [6, 23], SD = 33 ms, t(62) = 3.46, p = .003, $d_{unb} = 0.43$ [0.18, 0.69], instead of faster reaction times in invalid trials, M = −5 ms, 95% CI [−11, 0], SD = 21 ms, t(62) = −2.12, p = .057, $d_{unb} = -0.26$ [−0.52, −0.01].

Figure 3

Mean Validity Effects for Each Cue Condition of Experiment 1



Note. The violin plots represent the distributions of the individual mean validity effects. The short error bars represent the 95% CIs for the one-sample *t* test against zero (grey dashed line). The long error bars represent 95% CIs for the comparisons between conditions, adjusted using Tukey's HSD. The largest and smallest values have only one error bar, as they cannot be compared with a more extreme mean. The difference between conditions is significant if their error bars do not overlap.

Furthermore, we found statistically significant validity effect differences between possible-target-color cues and negative cues, Δ 26 ms, 95% CI [15, 37], *SD* = 44 ms, $t(62) = 4.73$, $p < .001$, $d_{unb} = 0.59$ [0.33, 0.86] and between nonmatching and negative cues, Δ 13 ms, 95% CI [2, 23], *SD* = 42 ms, $t(62) = 2.40$, $p = .036$, $d_{unb} = 0.30$ [0.05, 0.55]. The validity effect difference between possible-target-color and nonmatching cues was also statistically significant, Δ

13 ms, 95% CI [4, 23], *SD* = 38 ms, *t*(62) = 2.78, *p* = .020, d_{unb} = 0.35 [0.09, 0.6]. Figure 3 shows the mean validity effects for each cue condition of Experiment 1 with error bars representing 95% CIs. The validity effect difference between cue conditions is significant if the error bars do not overlap.[2]

Error Rates

Error rates were analyzed using a generalized linear mixed-effects model with a binomial link function, and we included cue condition, validity, and negative color condition as fixed factors and random by-participant intercepts into our hierarchical model comparisons. We found that a model including a main effect of cue condition described the data significantly better than a model without this main effect, $\chi^2(2) = 12.42$, *p* = .002. This main effect was driven by significantly lower error rates in trials with negative cues compared to possible-target-color cues, *M* = −1.26%, 95% CI [−1.97, −0.56], *SD* = 0.03%, *t*(62) = −3.60, *p* = .003, d_{unb} = −0.45 [−0.71, −0.19] and nonmatching cues, *M* = −0.90%, 95% CI [−1.57, −0.24], *SD* = 0.03%, *t*(62) = −2.73, *p* = .023, d_{unb} = −0.34 [−0.6, −0.09]. We found no significant error rate difference between trials with possible-target-color cues and nonmatching cues. Adding an additional main effect of validity or negative color condition

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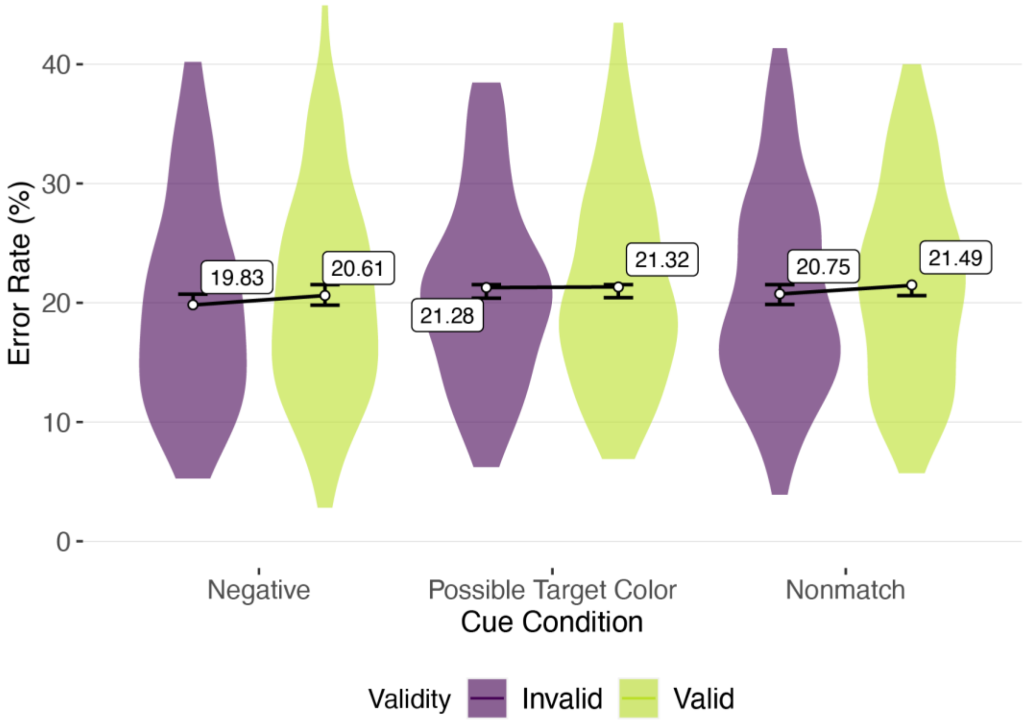
[2] Generally, CIs can be misleading when used for comparisons. However, the CIs we plotted are based on the comparison arrows from the R package *emmeans*. These CIs indicate a significant difference adjusted for multiple comparisons (if applicable).

Figure 4

Mean Error Rates of Experiment 1



Note. The violin plots show the distributions of the individual mean error rates. The error bars represent the 95% CIs for all mean comparisons, adjusted using Tukey's HSD. There is only one error bar for the largest and smallest value, as they cannot be compared with a more extreme mean. The difference between conditions is significant if the error bars do not overlap.

did not further improve the model fit (all *p* values >= .114). For Experiment 1, the mean error rates for each experimental condition are shown in Figure 4.

Discussion

In Experiment 1, we found inverse validity effects for singleton cues with a negative color and no evidence for attentional capture or suppression by cues with a possible target color and nonmatching cues (no significant validity effects). Additionally, validity effects were significantly different between negative and nonmatching cues. These findings indicate that negative cues were top-down suppressed dependent on the negative search criterion. This interpretation was also supported by slower reaction times in valid trials with negative cues than invalid trials with nonmatching cues that had neutral attentional priority indicated by a nonsignificant validity effect. In contrast, faster reaction times in invalid trials with negative than nonmatching cues could have indicated that negative cues were not suppressed, but the remaining possible target positions were facilitated. Furthermore, our results underscore the difference between passive ignoring task-irrelevant features and top-down suppression of task-relevant negative features (cf. Chelazzi et al., 2019). Moreover, validity effects were significantly different between nonmatching and possible-target-color cues. However, since neither the possible-target-color cue nor the nonmatching cue captured attention or was suppressed, it is hard to interpret this difference in the context of attentional guidance.

After Experiment 1, two questions were still open. First, it was suggested that suppression might result from a two-stage search-and-destroy process consisting of initial capture of attention followed by active suppression (Moher & Egeth, 2012). Thus, our 200 ms cue-target interval might have been long enough to cover attentional capture by negative cues before their suppression. In contrast, however, it has been argued that top-down attentional control might prevent even initial salience-driven capture of attention (Sawaki & Luck, 2010, 2011). Therefore, a negative feature may evoke suppression even at the earliest visual processing stages. Thus, in Experiment 2, we aimed to replicate our results with cue-target intervals of 150 ms and 60 ms to make it more likely to detect early attentional capture by negative features before their suppression.

Second, in Experiment 1, we selectively tested for top-down attentional guidance by the negative search criterion. However, our targets were also consistently defined by a positive target feature (here, orientation). Therefore, the search process was presumably guided by a combination of features, one positive criterion for the (capture by) orientation and one negative criterion for the (suppression of) color simultaneously. Alternatively, the need to suppress one feature (here, the negative color) might also affect the ability of participants to simultaneously search for other target features (here, the horizontal orientation). Thus, in Experiment 2, besides cues with the negative feature, we additionally used cues with the positive target feature. Thereby, we aimed to examine whether a combination of negative and positive features can simultaneously guide visual attention in opposite ways (suppression vs. capture).

For example, suppose attentional control settings for the positive and for the negative feature can be simultaneously maintained and applied. In that case, we should observe positive validity effects (i.e., top-down contingent capture) for cues with the positive target feature (cf. Folk et al., 1992; for a review, see Büsel et al., 2020) and again inverse validity effects for cues with the negative feature. Alternatively, using a negative search criterion might prevent the simultaneous search for other known target features. In that case, cues with a positive target feature would produce neutral validity effects.

Experiment 2

Method

Participants

Twenty-one participants took part in this experiment in return for course credits, but we excluded one participant due to a high error rate (33% errors, $R_1 = 3.79$, $p = .004$). Therefore, we analyzed data of 20 participants (15 females; $Mdn_{\text{Age}} = 21$ years, range 18–28 years). In Experiment 2, 64 (*SD* = 5) valid trials in each cue condition remained on average. Within experimental conditions, the average ICC1 was .09, and the ICC2 was .90. Across experimental conditions, the ICC1 was .06, and the ICC2 was . 99.

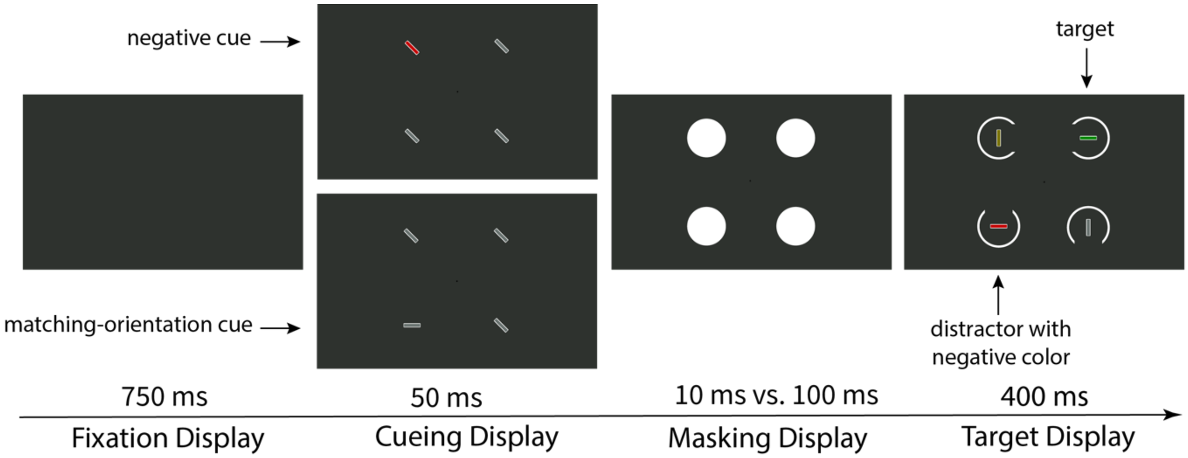
Stimuli and Procedure

In Experiment 2, we used the same stimuli as in Experiment 1, with four exceptions. First, the cueing display consisted of four oriented bars with white contours. One bar was the singleton cue, and three were homogeneous nonsingletons. Second, we used only two cue conditions (negative vs. matching-orientation). The negative (color-)singleton cue was red and had the same orientation as the nonsingletons in the cueing display (right-tilted or left-tilted). In half of all trials, the grey cue nonsingletons were right-tilted, and in the other half, they were left-tilted. Their orientation changed randomly from trial to trial. The target-matching orientation (here, expected to be top-down matching) singleton cue was grey (an irrelevant color) and horizontal, which was the target orientation. Third, due to relatively substantial error rates in Experiment 1, we decreased all bars' width (0.3°) to make it easier to perceive their orientation. Lastly, we used cue-target interval (long vs. short) as an additional independent within-subject variable in addition to cue condition (negative vs. matching-orientation) and validity (valid vs. invalid). Cue-target-intervals were manipulated blockwise (60 ms vs. 150 ms) by presenting the masking display for 10 ms or 100 ms, leaving the cue presentation time constant (50 ms). Each cue-target interval block consisted of 576 trials, and the block order was counterbalanced across participants.

Participants started with practice trials, and data acquisition started once their accuracy level reached 80% or above. Each participant completed 1,152 trials with five self-paced breaks in between. The procedure of Experiment 2 is shown in Figure 5.

Figure 5

Illustration of an Invalid Trial in Experiment 2 with a Negative and Matching Cue



Note. The stimuli are drawn to scale, but the display is cropped. In the target display, the distractor with the negative color was always red and horizontal. The target (a nonred horizontal bar) was also always horizontal but changed its color unpredictably from trial to trial. Participants had to report the gap position in the white ring surrounding the target.

Results

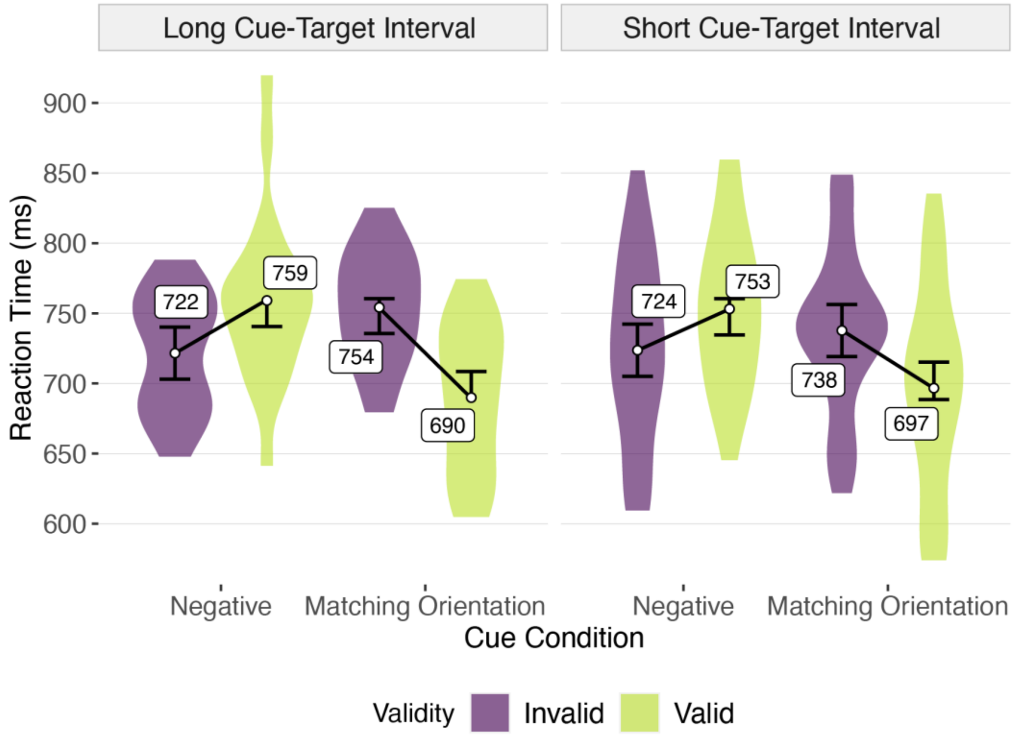
We removed trials with timeouts and too fast responses (1.47%) as well as wrong trials (9.12%) from further data analysis.

Reaction Times

Reaction times were analyzed using a linear mixed-effects model, and we included the fixed factors cue condition, validity, and cue-target interval as well as random by-participant intercepts into our hierarchical model comparisons. We found that a model including an interaction between cue condition and validity described our data significantly better than a model including only main effects of these fixed factors, $\chi^2(2) = 8.58$, $p = .014$. This interaction was driven by faster reaction times in valid than invalid trials for matching-orientation cues. In contrast, reaction times were slower in valid than invalid trials for negative cues (for post hoc tests of this interaction see Validity Effects analysis below). Adding a main effect of cue-target interval did not further improve the model fit, $\chi^2(1) = 3.52$, $p = .061$, indicating that cue-target interval did not significantly influence the reaction times. For Experiment 2, the mean reaction times of correct trials for each experimental condition and more details about significant differences between conditions are shown in Figure 6.

Figure 6

Mean Reaction Times of Correct Trials for Each Experimental Condition of Experiment 2



Note. The violin plots show the distributions of the individual mean reaction times. The error bars represent 95% CIs for the mean comparisons of all experimental conditions, adjusted using Tukey's HSD. The largest and smallest values have only one error bar, as they cannot be compared with a more extreme mean. The difference between conditions is significant if their error bars do not overlap.

Validity Effects

We analyzed validity effects using a linear mixed-effects model and included cue condition and cue-target interval as fixed factors as well as random by-participant intercepts into our hierarchical model comparisons. We found that a model including a significant main effect of cue condition fitted the data significantly better than a model without this main effect, $\chi^2(1) = 58.36$, $p < .001$. Adding a main effect of cue-target interval to this model did not further improve the model fit, $\chi^2(1) = 0.68$, $p = .411$. Although we found no significant validity effect difference between cue-target intervals (short vs. long), we analyzed the validity effect for each cue condition (negative vs. matching orientation) and each cue-target interval separately. Shapiro Wilk tests for normality showed that the validity effect differences from zero and the validity effect difference between cue types and cue-target intervals were normally distributed, except for negative cues in the long cue-target interval ($W = .88$, $p = .021$).

We used two-sided one-sample *t* tests to investigate whether validity effects of different cue conditions in both cue-target intervals were different from zero. As the validity effect for negative cues with long cue-target interval was not normally distributed, we used a Wilcoxon signed-rank test. However, the result of the Wilcoxon signed-rank test ($Z = 31$, $p = .004$) did not differ from the *t* test result. Therefore, for consistency, we also used a two-sided one-sample *t* test for negative cues with long cue-target intervals.

We found a significant inverse validity effect for negative cues with a long cue-target interval, $M = -38$ ms, 95% CI [−63, −12], $SD = 54$ ms, $t(19) = -3.13$, $p = .011$, $d_{unb} = -0.67$ [−1.18, −0.2] and with a short cue-target interval, $M = -29$ ms, 95% CI [−49, −10], $SD = 41$ ms, $t(19) = -3.19$, $p = .011$, $d_{unb} = -0.69$ [−1.2, −0.21]. According to our simulations, the statistical power was 0.73% to find a validity effect of −20 ms for negative cues in one cue-target interval condition as significant ($\alpha = .05$). Nevertheless, the estimated achieved power to find a validity effect of −25 ms was 89%. Additionally, we found a significant positive validity effect for matching-orientation cues with a long cue-target interval, $M = 64$ ms, 95% CI [49, 79], *SD* = 32 ms, $t(19) = 9.01$, $p < .001$, $d_{unb} = 1.93$ [1.23, 2.78] and with a short cue-target interval, *M* = 41 ms, 95% CI [24, 58], *SD* = 37 ms, $t(19) = 4.96$, $p < .001$, $d_{unb} = 1.06$ [0.54, 1.66].

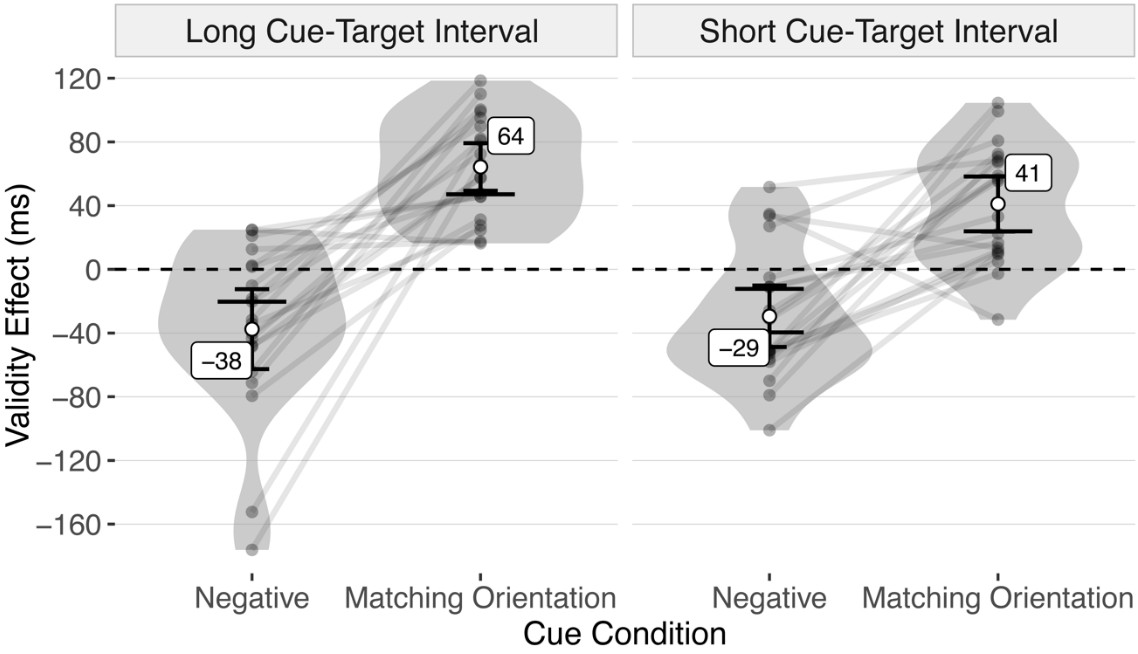
We found no statistically significant validity effect difference for negative cues between cue-target intervals, Δ 8 ms, 95% CI [−17, 33], *SD* = 53 ms, $t(19) = 0.68$, $p = 1$, $d_{unb} = 0.15$ [−0.29, 0.59]. For matching-orientation cues, the validity effect difference between cue-target intervals was also not significant, Δ −23 ms, 95% CI [−43, −4], *SD* = 42 ms, $t(19) = -2.49$, $p = .062$, $d_{unb} = -0.53$ [−1.02, −0.08]. The validity effect difference between matching-orientation cues and negative cues was significant with a long cue-target interval, Δ −102 ms, 95% CI [−134, −70], *SD* = 69 ms, $t(19) = -6.60$, $p < .001$, $d_{unb} = -1.42$ [−2.11, −0.83] and with a short cue-target interval, Δ −71 ms, 95% CI [−98, −43], *SD* = 59 ms, $t(19) = -5.37$, $p < .001$, $d_{unb} = -1.15$ [−1.77, −0.61]. Figure 7 shows the validity effects for each cue condition and each cue-target interval for Experiment 2, with error bars representing 95% CIs.

Re-Analysis of Validity Effects

Additionally, we further tested whether a search-and-destroy strategy could have produced inverse validity effects for negative cues (cf. Moher & Egeth, 2012). Suppose the negative color was always automatically selected before being suppressed. In that case, reaction times should be shorter if a negative cue preceded the distractor with the negative color at the same position. Then, the selection process could be virtually omitted, and reaction times could be faster. Therefore, we analyzed the validity effects again but excluded invalid trials with the negative color distractor and cue being presented at the same position. Evidently, we still found substantial inverse validity effects for negative cues with a short

Figure 7

Mean Validity Effects for Each Cue Condition and Each Cue-Target Interval of Experiment 2

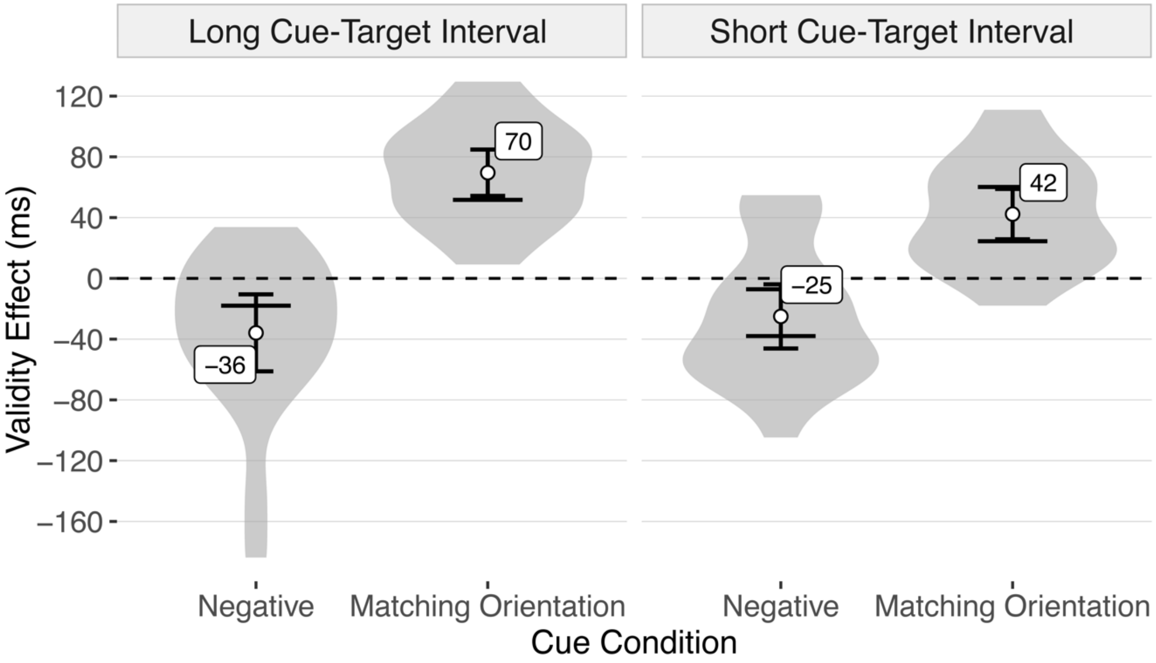


Note. The semitransparent points represent the individual mean validity effects, and the violin plots represent their distributions. Lines connect the values of each participant in the different experimental conditions. The short error bars represent the 95% CIs for the one-sample *t* test against zero (grey dashed line). The long error bars represent 95% CIs for the comparisons between conditions, adjusted using Tukey's HSD. The largest and smallest values have only one error bar, as they cannot be compared with a more extreme mean. The difference between conditions is significant if their error bars do not overlap.

cue-target interval, *M* = −25 ms, 95% CI [−46, −4], *SD* = 45 ms, *t*(19) = −2.48, *p* = .047, d_{unb} = −0.53 [−1.02, −0.08] and with a long cue-target interval, *M* = −36 ms, 95% CI [−61, −10], *SD* = 54 ms, *t*(19) = −2.96, *p* = .022, d_{unb} = −0.64 [−1.14, −0.17]. Figure 8 shows the validity effects for each cue condition and each cue-target interval of Experiment 2, excluding invalid trials in which negative color distractors and cues appeared at the same position.

Figure 8

Re-Analysis of Mean Validity Effects for Each Cue Condition and Each Cue-Target Interval of Experiment 2



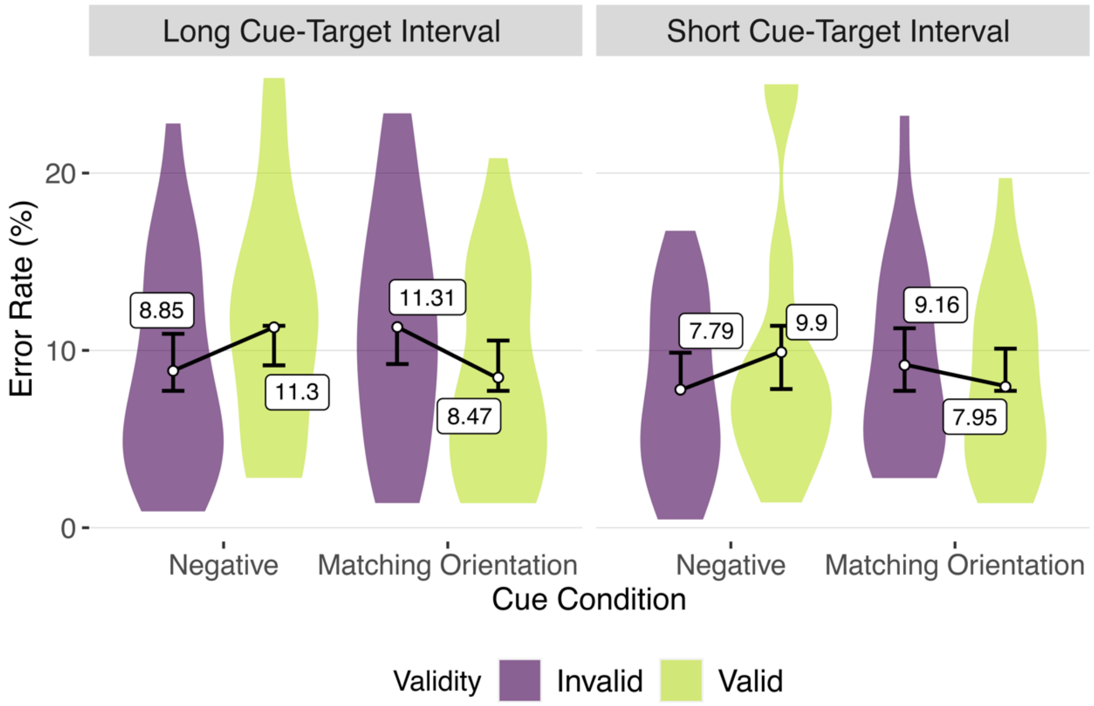
Note. We excluded trials in which the negative color distractor was presented at the same position as the preceding cue. The violin plots represent the distributions of the individual mean validity effects. The short error bars represent the 95% CIs for the one-sample *t* test against zero (grey dashed line). The long error bars represent 95% CIs for the comparisons between conditions, adjusted using Tukey's HSD. The largest and smallest values have only one error bar, as they cannot be compared with a more extreme mean. The difference between conditions is significant if their error bars do not overlap.

Error Rates

Error rates were again analyzed with a generalized linear mixed-effects model with a binomial link function. We included cue condition, validity, and cue-target interval as fixed factors and random by-participant intercepts into our hierarchical model comparisons. We found that a model including an interaction between cue condition and validity as well as a main effect of cue-target interval described our data significantly better than a model without a main effect of cue-target interval, $\chi^2(1) = 14.22$, $p < .001$. The model fit was yet not improved by adding additional interactions between the fixed factors (all *p* values >= .39). The interaction consisted of significantly higher error rates in valid compared to invalid trials with negative cues, $M = 2.10\%$, 95% CI [0.46, 3.74], $SD = 0.04\%$, $t(19) = 2.68$, $p = .031$, $d_{unb} = 0.58$ [0.12, 1.07]. In contrast, for matching-orientation cues, error rates were significantly lower in valid than invalid trials, $M = -2.18\%$, 95% CI [−3.31, −1.05], $SD = 0.02\%$, $t(19) = -4.04$, $p = .006$, $d_{unb} = -0.87$ [−1.42, −0.37]. The significant model-based main effect of cue-target interval consisted of overall lower error rates in the short cue-target interval compared to the long cue-target interval. However, a paired two-sided *t* test showed that the error rate difference was not significant between cue-target intervals, $M = -1.44\%$, 95% CI [−4.47, 1.59], $SD = 0.06\%$, $t(19) = -0.99$, $p = .334$, $d_{unb} = -0.21$ [−0.66, 0.22]. The mean error rates for each experimental condition of Experiment 2 are shown in Figure 9.

Figure 9

Mean Error Rates of Experiment 2



Note. The violin plots show the distributions of individual mean error rates. The error bars represent the 95% CIs for all mean comparisons, adjusted using Tukey's HSD. There is only one error bar for the largest and smallest value, as they cannot be compared with a more extreme mean. The difference between conditions is significant if the error bars do not overlap.

Discussion

The results of Experiment 2 showed that inverse validity effects for negative cues were independent of cue-target interval, suggesting that suppression occurred swiftly without preceding attentional capture. Furthermore, from our analysis, we excluded invalid trials in which the distractor with the negative color was presented at the same position as the cue. This was done to further test for a search-and-destroy strategy as an explanation for the negative cue's inverse validity effect. For example, suppose the negative cue captured attention before being swiftly discarded (reactive suppression). In that case, this process should be faster when the distractor with the negative color appeared at the cued (already attended) position. Dropping these trials from the critical analyses showed an inverse validity effect of negative cues meaning that these particular conditions were not responsible for the inverse validity effect.

Notably, a search-and-destroy strategy could also be uncovered in trials with short cue-target intervals when the time for suppression following initial attentional capture was drastically limited (cf. Moher & Egeth, 2012; Theeuwes et al., 2000). However, cue-target interval did not significantly modulate our results, arguing against a strategy of attending followed by suppression (Moher & Egeth, 2012), but, in turn, for proactive suppression dependent on the negative search criterion.

Additionally, besides inverse validity effects for negative cues, we found a significant positive validity effect for matching-orientation cues. This pattern of results was consistently observed for most participants suggesting that, based on our instructions, each participant used both an attentional control setting to guide attention towards stimuli with the target-matching orientation and suppress stimuli with the negative color. Noteworthy, our results may be limited to attentional control settings for positive and negative search criteria separated by dimension, here color versus orientation (Liesefeld et al., 2019; cf. Liesefeld & Müller, 2019). Future research may address whether participants can also up- and-down-regulate attentional control settings for features within the same dimension.

So far, our evidence for selective inverse validity effects for negative cues was limited to the dimension of color. Therefore, we were interested in whether negative search criteria can guide visual attention irrespective of feature dimension. There are multiple well-studied guiding features of visual attention (cf. Wolfe & Horowitz, 2004; Wolfe & Utochkin, 2019). Nevertheless, evidence suggests they might be differently effective in top-down attentional control, with color usually producing the most pronounced effects (Hulleman, 2020). Therefore, in Experiment 3, we used orientation as a negative feature. Thereby, we aimed to see whether inverse validity effects indicating top-down suppression also apply to other guiding features of visual attention.

Experiment 3

Method

Participants

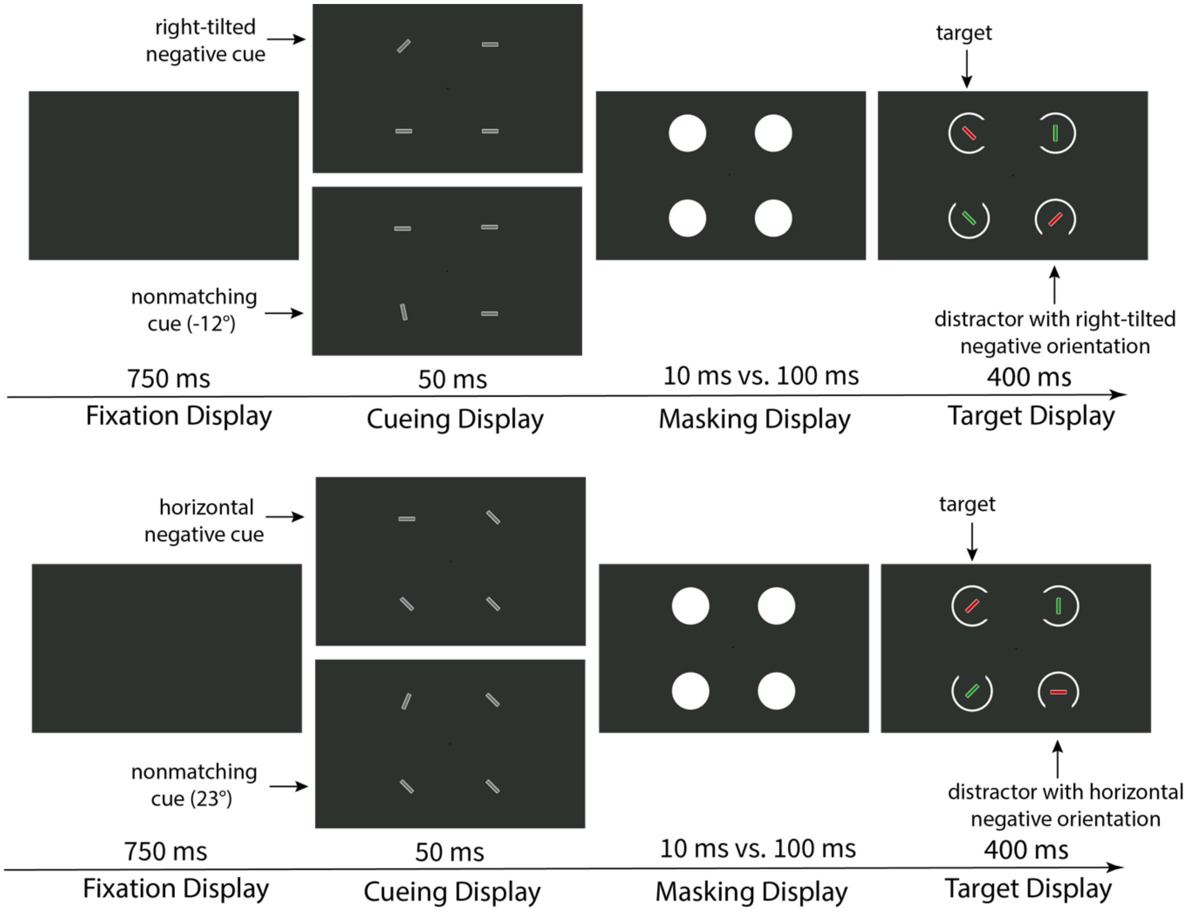
Twenty-two participants took part in this experiment in return for course credits. After excluding two participants due to a high error rate (Outlier 1 = 35% errors, $R_1 = 2.62$, $p = .093$, Outlier 2 = 31% errors, $R_2 = 2.82$, $p = .033$), 20 participants (13 females; $Mdn_{\text{Age}} = 20$ years, range 18–31 years) were analyzed. In Experiment 3, 131 (*SD* = 10) valid trials across cue conditions remained on average. Within experimental conditions, the average ICC1 was .17, and the ICC2 was .98. Across experimental conditions, the ICC1 was .17, and the ICC2 was 1.00.

Apparatus, Stimuli, and Procedure

In Experiment 3, we used cue condition (negative vs. nonmatch), validity (valid vs. invalid), and cue-target interval (long vs. short) as independent within-subject variables. Except for three adjustments, Experiment 3 was identical to Experiment 2. First, we adapted the cueing display. All stimuli in the cueing display were grey bars with a white contour. We used two cue conditions (negative vs. nonmatch) and two negative orientations (right-tilted vs. horizontal; only one per participant, counterbalanced across participants). The negative cue had the negative orientation assigned at the beginning of the experiment. For example, for half of our participants, the negative orientation was horizontal. For the other half, the negative orientation was right-tilted. Negative cues were horizontal or right-tilted, respectively. The nonmatching cue's orientation was different from any orientation used in the target display. If the negative orientation was right-tilted, the negative cue was right-tilted, too, and the nonmatching cue was rotated by −12°. If the negative orientation was horizontal, the nonmatching cue was 23° rotated, and the cue distractors were left-tilted. In both cases, all nonsingletons in the cueing displays were horizontal. Second, we used two target color conditions (red vs. green) that were counterbalanced across participants. In both target color conditions, the target display consisted of two red and two green bars. The target and the negative orientation distractor consistently had the same color (e.g., red),

Figure 10

Illustration of a Valid Trial with Negative and Nonmatching Cues in Experiment 3



Note. The stimuli are drawn to scale, but the display is cropped. In both depicted designs, the target is red and tilted. Participants were told to report the gap position of the white ring surrounding the target.

while the other two bars had the remaining color (e.g., green). If the negative orientation distractor was horizontal, two right-tilted bars and one vertical bar were presented in the target display. If the negative orientation distractor was right-tilted, two of the remaining three bars were left-tilted, and one was vertical. Lastly, we presented all stimuli in the target display for 400 ms to facilitate perception of the different orientations. Participants searched for a color-defined target (red vs. green; counterbalanced across participants) that was either not right-tilted or not horizontal (also balanced across participants). For example, we instructed them to search for the nonhorizontal red bar. The target changed its orientation from trial to trial and had the same color as the negative orientation distractor. For example, if the target was red and not horizontal, it could be left-tilted or vertical. Thus, the target could neither be found by its color nor by a single orientation. As in Experiments 1 and 2, participants were told to report the gap position in the white ring surrounding the target by pressing the corresponding arrow key.

Before data acquisition started, participants practiced until they accomplished at least 80% accuracy. Each participant completed 1,152 trials with five self-paced breaks in between. The procedure of Experiment 3 is shown in Figure 10.

Results

Too fast reaction times and timeouts (0.98%) as well as wrong trials (7.35%) were removed from further data analysis.

Reaction Times

Reaction times were analyzed using a linear mixed-effects model and we included cue condition, validity, cue-target interval, and negative orientation[3] as fixed factors and random by-participant intercepts into our hierarchical model comparisons. A model including an interaction between cue condition and validity fitted our data significantly better than a model with only main effects of these fixed factors, $\chi^2(1) = 7.77$, $p = .005$. Adding a main effect of negative orientation to this interaction model further improved the model fit, $\chi^2(1) = 5.68$, $p = .017$, as well as adding an additional main effect of cue-target interval, $\chi^2(1) = 22.79$, $p < .001$. Thus, the best fitting model consisted of a significant interaction between cue condition and validity as well as main effects of negative orientation and cue-target interval. The significant interaction was driven by different validity effects between cue conditions (see Validity Effects analysis). The main effect of cue-target interval was due to faster reaction times in the short cue-target interval compared to the long cue-target interval. However, a paired two-sided *t* test showed this model-based reaction time difference between cue-target intervals was not significant, *M* = −12 ms, 95% CI [−76, 52], *t*(19) = −0.39,

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[3] Evidence suggests that within the color dimension, attentional control settings for distinct feature values (e.g., red and blue) are similarly effective (e.g., Ansorge & Becker, 2014; Irons et al., 2012). In contrast, studies have shown that for orientations, search performance can vary substantially depending on the searched-for orientation on the one hand (Appelle, 1972; Kong et al., 2017) and singleton-nonsingleton differences on the other hand (Treisman & Gormican, 1988).

Figure 11

Mean Reaction Times of Correct Trials for Each Experimental Condition of Experiment 3

Note. The violin plots represent the distributions of the individual mean reaction times. The error bars represent 95% CIs for the mean comparisons of all experimental conditions, adjusted using Tukey's HSD. There is only one error bar for the largest and smallest value, as they cannot be compared with a more extreme mean. The difference between conditions is significant if their error bars do not overlap.

p = .700, $d_{unb} = -0.08$ [−0.52, 0.35]. Additionally, an unpaired two-sided t test showed that the main effect of negative orientation was driven by significantly slower reaction times when the negative orientation was right-tilted compared to horizontal, *M* = 78 ms, 95% CI [13, 144], *t*(17.88) = 2.51, *p* = .022, d_{unb} = 1.05 [0.13, 1.94]. The mean reaction times of correct trials for each experimental condition of Experiment 3 are shown in Figure 11.

Validity Effects

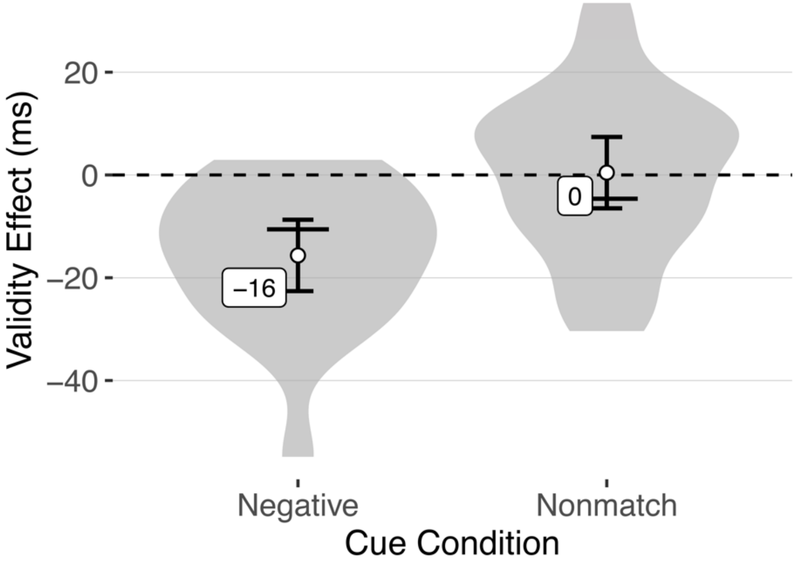
Validity effects were analyzed with a linear mixed-effects model and we included cue condition, negative orientation and cue-target interval as fixed factors and random by-participant intercepts into our hierarchical model comparisons. A model including a main effect of cue condition (negative vs. nonmatch) described the data significantly better than a model without this main effect, $\chi^2(1)$ = 10.19, *p* = .001. However, the model fit was not further improved by adding a second main effect of cue-target interval (long vs. short) or negative orientation (horizontal vs. right-tilted), all *p* values >= .213.

Shapiro Wilk tests for normality showed that the validity effects for negative cues (*W* = .93, *p* = .173) and nonmatching cues were normally distributed (*W* = .97, *p* = .793). Additionally, the validity effect difference between negative and nonmatching cues was normally distributed, too (*W* = .98, *p* = .956).

In this experiment, the estimated achieved statistical power to find a validity effect of −20 ms as significant (α = .05) was 0.97%. We found a significant inverse validity effect for negative cues, *M* = −16 ms, 95% CI [−22, −9], *SD* = 14 ms, *t*(19) = −4.91, *p* < .001, d_{unb} = −1.05[−1.65, −0.53]. In contrast, we found no significant validity effect for nonmatching cues, *M* = 0 ms, 95% CI [−7, 8], *SD* = 16 ms, *t*(19) = 0.12, *p* = 1, d_{unb} = 0.03 [−0.41, 0.47]. Furthermore, we found a significant validity effect difference between negative cues and

Figure 12

Mean Validity Effects for Each Cue Condition of Experiment 3



Note. The violin plots represent the distributions of the individual mean validity effects. The short error bars represent the 95% CIs for the one-sample *t* test against zero (grey dashed line). The long error bars represent 95% CIs for the comparisons between conditions, adjusted using Tukey's HSD. The largest and smallest values have only one error bar, as they cannot be compared with a more extreme mean. The difference between conditions is significant if their error bars do not overlap.

nonmatching cues, Δ −16 ms, 95% CI [−27, −6], *SD* = 23 ms, *t*(19) = −3.19, *p* = .005, d_{unb} = −0.68 [−1.2, −0.21]. Figure 12 shows the validity effect for each cue condition of Experiment 3 with error bars representing 95% CIs.

Error Rates

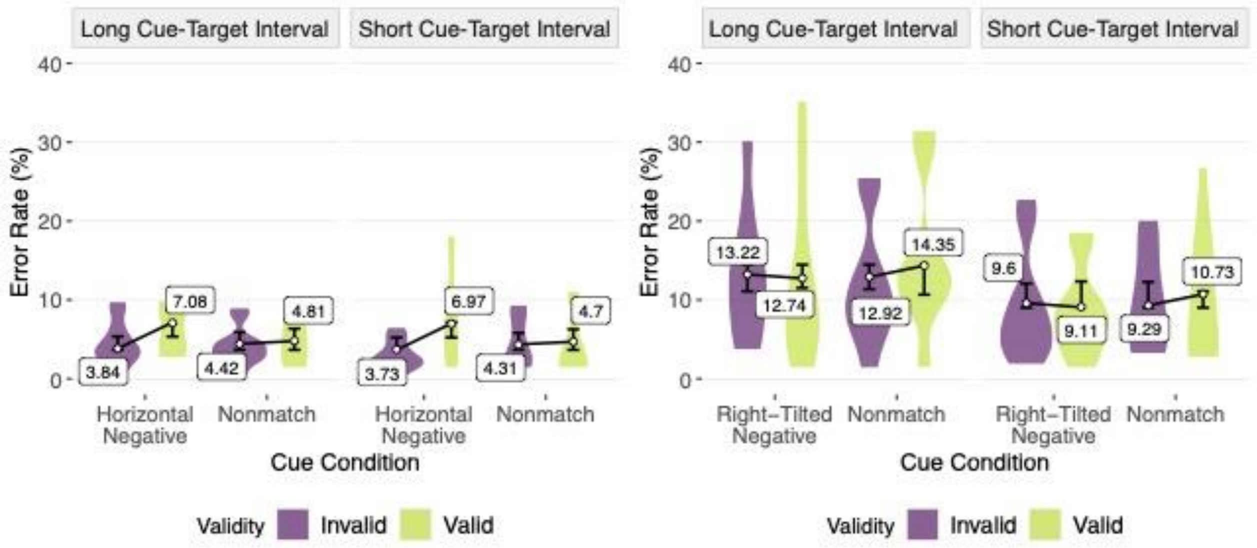
Error rates were analyzed using a generalized linear mixed-effects model with a binomial link function. We included cue condition, validity, negative orientation and cue-target interval as fixed factors, and random by-participant intercepts into our hierarchical model comparisons. We found that a model including a main effect of negative orientation described our data significantly better than the null model, $\chi^2(1) = 11.06$, $p = .001$. Adding a main effect of cue-target interval further improved the model fit, $\chi^2(1) = 28.89$, $p < .001$. An unpaired two-sided *t* test showed that error rates were significantly lower if the negative orientation was right-tilted compared to when it was horizontal, *M* = −6.98%, 95% CI [−12, −1.96], $t(19) = -3.13$, $p = .012$, $d_{unb} = -1.47$ [−2.42, −0.48]. Although participants' performance was worse if the cue-target interval was long compared to when it was short, a paired two-sided *t* test showed that this error rate difference was not significant, *M* = -1.83%, 95% CI [−4.72, 1.07], *SD* = 0.06%, $t(19) = -1.32$, $p = .203$, $d_{unb} = -0.28$ [−0.74, 0.16]. The model fit was no further improved by adding additional effects or fixed factors (all *p* values >= .05). The mean error rates for each experimental condition of Experiment 3 are shown in Figure 13.

Discussion

In Experiment 3, we replicated our main findings of Experiments 1 and 2 but with orientation as a negative feature. Again, we found significant inverse validity effects for negative cues while task-irrelevant, nonmatching orientation cues were ignored. Also, the cue-target interval did not modulate these effects. Thus, these findings indicate that negative orientation cues were also swiftly suppressed depending on an attentional control setting induced by the negative search criterion.

Figure 13

Mean Error Rates of Experiment 3



Note. The violin plots show the distributions of the individual mean error rates. The error bars represent the 95% CIs for all mean comparisons, adjusted using Tukey’s HSD. There is only one error bar for the largest and smallest value, as they cannot be compared with a more extreme mean. The difference between conditions is significant if the error bars do not overlap.

In Experiment 3, between participants, we used two different negative orientations because we were interested in whether orientations differ in their ability to allow top-down suppression. For example, research suggests that implementing attentional control settings for orientations is more difficult centered around 45° than cardinal (90° or 0°) orientations (Kong et al., 2017). In line with this observation, we found overall faster responses for negative horizontal than right-tilted orientations. Additionally, error rates were significantly higher with targets defined as not right-tilted. This result indicates that it might be easier to suppress horizontal than right-tilted orientations, similar to evidence for searching different orientations (Appelle, 1972). Nevertheless, in contrast, the inverse validity effects of the differently oriented negative cues were similar. Finally, Experiment 3 supports the conclusion that negative search criteria guide visual attention irrespective of feature dimension through top-down suppression.

General Discussion

In three experiments, we found that cues matching a negative search criterion elicited inverse validity effects. These results provide novel evidence for top-down guided suppression of visual attention. Features that negatively define a target and are necessary to solve a search task are incorporated as guiding features in attentional control settings, leading to selective suppression of these features. In contrast, cues with task-irrelevant features (e.g., possible-target-color cues and nonmatching cues in Experiment 1 and nonmatching cues in Experiment 3) produced no significant validity effects. Importantly, the inverse validity effects elicited by cues matching a negative search criterion were significantly lower (i.e., more inverted) than the (nonsignificant) validity effects elicited by nonmatching cues. Additionally, the validity effects did not vary as a function of the cue-target interval. They were similar with a cue-target interval of 200, 150, and 60 ms. This finding argues against a search-and-destroy process, but for proactive suppression, which is task-dependent and arguably a process similar to other forms of proactive control of the capture of attention that are the same for different cue-target intervals (Folk et al., 1992; Remington et al., 2001).

Possible alternative processes accounting for inverse validity effects

Object-updating costs cannot explain inverse validity effects of negative cues

Noteworthy, inverse validity effects have been observed before in standard contingent-capture studies (e.g., Belopolsky & Theeuwes, 2010; Folk & Remington, 2008; Goller et al., 2020; Schoeberl et al., 2019). Sometimes, such inverse validity effects were attributed to same-location costs, mainly understood as the consequence of updating stored information about the target in visual working memory (Carmel & Lamy, 2014). However, suppose the present inverse validity effects of negative cues reflected such object-updating costs. In that case, they should have occurred for nonmatching cues that differed from targets as well. However, our nonmatching cues in Experiments 1 and 3 (and possible-target-color cues in Experiment 1) produced no significant inverse validity effects and, thus, their validity effects were significantly higher than the inverse validity effects elicited by the negative cues. Moreover, short cue exposure durations such as 50 ms usually prevent same-location costs (Carmel & Lamy, 2015), rendering this alternative explanation of our results unlikely in the first place.

The role of experience and habituation in task-dependent suppression

Theoretically, implicit processes (e.g., statistical learning, experience with the negative feature, or habituation) could have produced inverse validity effects for negative cues. However, as we discuss in the following, they are unlikely to explain our results.

First, it has been shown that participants can learn to suppress consistent task-irrelevant distractor features over time (Chang & Egeth, 2019; Stilwell et al., 2019; Stilwell &

Vecera, 2019b, 2020). Moreover, such experience-driven suppression of distractors might evolve within only 24 trials (Vatterott & Vecera, 2012), which equals the minimum number of practice trials in our study. Thus, for example, as we started data acquisition only after the practice trials were completed, inverse validity effects could potentially reflect learned suppression. However, to date, evidence for experience-based suppression is limited to irrelevant distractors (for a review, see Moorselaar & Slagter, 2020), suggesting that participants can learn to suppress features unnecessary for a current task. In contrast, our negative search criterion was a task-relevant feature crucial for accomplishing the task. To be precise, even at the experiment's beginning, when participants had no experience with the negative feature, they had to rely on the negative search criterion to find the target. Moreover, suppression of negative features unlikely resulted from habituation, a process independent of an observer's intention that serves to ignore known irrelevant sensory input (Chelazzi et al., 2019; Rankin et al., 2009; Thompson, 2009).

To sum up, implicit processes could have contributed to inverse validity effects of negative cues, albeit not in the sense that they triggered feature-selective suppression per se. However, it might take some trials to implement an attentional control setting to suppress a negative feature (Vecera et al., 2014). For example, some practice might be necessary until participants can effectively use the negative search criterion, which is possibly less intuitive to implement than a positive search criterion. We addressed this possibility with exploratory block analyses for validity effects of each experiment. Thereby, we aimed to investigate whether proactive suppression of a negative feature was present already at the beginning of an experiment or built up over time. Overall, these exploratory analyses showed that inverse validity effects for cues with the negative feature were present throughout the experiment and were not significantly modulated by experience. However, we want to point out that we did not design the experiment for investigating the time course of validity effects. Therefore, the statistical power to find significant effects at the level of single blocks was too low to draw reliable conclusions. Nevertheless, Figures 16, 17, and 18 in the Appendix show the plotted blocked validity effects for each experiment to give a visual impression of the time course of validity effects.

Examining the role of practice for implementing attentional control settings for negative search criteria in detail is, thus, left to future studies. Additionally, it would be interesting to see whether multiple negative search criteria can flexibly guide visual attention, similar to positive ones (Lien et al., 2010). The experimental design used in the current study provides a starting point for future research on this topic.

Possible influence of low spatial cue-target regularities on suppression of negative cues

Additionally, participants could have picked up upon the low spatial cue-target relation (only 25% of all trials were valid), therefore, suppressing the cued position. However, this type of position suppression cannot explain the stronger inverse validity effects for negative cues. To note the position contingencies were identical for each cue type. Thus, attentional suppression based on spatial cue-target position relations should have occurred with all cue types. However, in Experiment 2, cues with the target-matching orientation produced standard contingent-capture effects (Folk & Remington, 1998; Folk et al., 1992), while no significant validity effect was elicited by nonmatching cues (Experiments 1 and 3).

At the same time, negative cues still elicited inverse validity effects. Thus, our results do not support a general influence of cue-target position regularities on suppression.

Proactive versus reactive suppression of features matching a negative search criterion

While attentional control processes can be classified as proactive or reactive (Braver, 2012), this dichotomy is also applied to evidence on suppression (Chelazzi et al., 2019; Moorselaar & Slagter, 2020). On the one hand, reactive suppression supports goal-directed behavior through swiftly rejecting an irrelevant distractor after its onset and initial attentional capture (Moorselaar & Slagter, 2020). On the other hand, proactive suppression operates in anticipation of a to-be-ignored distractor's onset (Chelazzi et al., 2019; Noonan et al., 2018). In the current study, three aspects support the notion that negative features were proactively suppressed contingent on a corresponding negative search criterion.

First, our participants searched for a target consistently defined by a negative search criterion. Notably, consistent distractor features usually evoke (tonic) proactive suppression, whereas frequently changing distractor features are mainly reactively suppressed (Noonan et al., 2018). Second, our tasks required participants to maintain the task-relevant negative feature throughout the experiment, thus, promoting proactive attentional control (Braver, 2012). Third, we would have most likely uncovered a search-and-destroy strategy in the short cue-target interval conditions of Experiments 2 and 3 (Moher & Egeth, 2012). Nevertheless, we did not find evidence supporting that participants initially attended the negative feature. Moreover, Ansorge and Heumann (2003) and Ansorge and Horstmann (2007) showed that even with cue-target intervals of 0 ms, attentional allocation is proactively determined by top-down control settings (see also Burnham, 2020; Chen & Mordkoff, 2007; for evidence from very short cue-target intervals). Based on these observations with positive features, participants might have proactively applied suppression dependent on the usage of a negative search criterion. However, future research may address this issue with, for example, electrophysiological measures that provide a higher temporal resolution and tentatively supported the idea of proactive suppression (cf. Hopf et al., 2000). Moreover, it has been shown that anticipated task-relevant distractor features cannot be proactively suppressed if they randomly change from trial to trial (de Vries et al., 2019). For example, de Vries et al. (2019) also used cues with a task-relevant negative color that informed participants about which color the upcoming target would not have. However, their study's results supported the notion that to-be-suppressed features initially attract visual attention automatically before being discarded. Possibly, it takes some trials to establish an attentional control setting to suppress a specific feature that subsequently guides visual attention proactively. Otherwise, a to-be-suppressed feature might invite a search-and-destroy strategy even if it is not optimal for accomplishing the current task goal. Therefore, it would be interesting to compare top-down suppression between consistent versus frequently changing negative search criteria.

How do negative search criteria influence the attentional selection process?

Current research suggests that observers' task goals, among other sources of selection biases, modulate the attentional signals on a spatial priority map that guides visual attention (cf. Awh et al., 2012; Wolfe, 2021). For example, visual attention may be guided towards high-priority spatial locations where task-relevant features are represented. In contrast, negative search criteria may bias attentional allocation top-down through selectively de-prioritizing matching features. As a result of top-down de-prioritization, visual processing might be impaired at the location of a feature matching the negative search criterion (cf. Chelazzi et al., 2019). In addition, following this logic, target detection should be delayed if a cue with the negative feature precedes the target at the same de-prioritized position, resulting in slower reaction times. In contrast, reaction times should be faster when the target is presented at an unsuppressed position with neutral priority (spatially invalid negatively cued trials). Therefore, the inverse validity effects elicited by negative cues could arise due to the de-prioritization of the negative search criterion's position (cf. Hickey et al., 2009).

Notably, attentional control settings induced by a negative search criterion might bias visual attention to be directed away from these features or locations showing these features. Yet, negative search criteria might not bias the attentional selection process in an additional (positive) way towards another particular feature or position. This assumption is based on the overall observation that in our Experiments 1 and 3, reaction times were slower in valid trials with negative than nonmatching cues. At the same time, reaction times did not substantially differ between invalid trials (neutral-priority positions) with negative and nonmatching cues. Suppose negative search criteria biased attention away from matching features and simultaneously guided attention towards other unsuppressed features or locations. In that case, we might have observed faster reaction times in invalid trials with negative than nonmatching cues, which was not found. Therefore, our results indicate that negative features or positions with negative features were selectively suppressed. At the same time, visual processing of other features at other stimulus positions was seemingly not facilitated in turn. In other words, task-dependent suppression of a specific feature or such a feature's location does not appear to provoke faster than baseline selection of another feature or position with neutral priority.

Furthermore, our results suggest that participants could not control the suppression of negative cues. This assumption is based on slower reaction times in valid than invalid trials with negative cues. Notably, why would participants suppress an uninformative cue's position if they could do differently? Moreover, why would they do so if the cued position could be the target position, and suppression would be detrimental to the current task goal? Based on these considerations, negative search criteria seem to elicit involuntary suppression of locations, where the negative features are presented (cf. Folk et al., 1992).

Finally, it is also possible that not all our validity effects occurred directly in response to the cues. Similar to older interpretations of validity effects as reflecting processes in the target displays (cf. Shiu & Pashler, 1994), researchers recently suggested that some validity effects could also reflect processes following the target's onset, during target search, and dependent on the difficulty of target search (Yaron & Lamy, 2021). Thus, in line with the priority-accumulation framework by Yaron and Lamy (2021), the spatial de-prioritization induced by our negative features might not solely reflect cue-elicited suppression. Instead, our suppression effects could have partially emerged in the target display.

Relation to bottom-up capture by salient singletons

In all experiments, we used singleton cues that were theoretically eliciting attentional capture by their salience alone. However, we did not observe stimulus-driven capture for any cue type. (Note that in Experiment 2, the feature-match between cue and target rather than the cue's salience determined attentional capture by matching-orientation cues). Moreover, our negative singleton cues produced inverse validity effects. However, recent research suggests that top-down processes can only override a singleton's attentional capture with relatively low salience (Wang & Theeuwes, 2020), which might apply to our cues. For example, Wang and Theeuwes (2020) showed that task-irrelevant singletons could be suppressed in search arrays of four stimuli. On the contrary, increasing the set size to six led to salience-driven attentional capture by singleton-distractors. Although this might explain why we did not find a significant validity effect for nonmatching (task-irrelevant) cues, the significantly more negative (inverse) validity effects elicited by the equally low salient negative cues cannot be explained with bottom-up processes but indicates a top-down influence on attentional guidance.

Conclusion

Research has shown that suppression comprises multiple distinct processes that ultimately support goal-directed behavior. However, in visual search, previous studies were mainly concerned with examining how task-irrelevant distractors can be suppressed. In this study, we investigated whether task-relevant negative search criteria can guide visual attention in a top-down manner. Based on our results, we conclude that features necessary to accomplish a task can be selectively suppressed depending on the observer's search goal.

To summarize, our study extends the understanding of visual attentional guidance as exclusively facilitating visual processing to feature-selective suppression contingent on search goals.

References

Anderson, G. M., Heinke, D., & Humphreys, G. W. (2010). Featural guidance in conjunction search: The contrast between orientation and color. *Journal of Experimental Psychology: Human Perception and Performance*, *36*(5), 1108–1127. https://doi.org/10.1037/a0017179

Ansorge, U., & Becker, S. I. (2014). Contingent capture in cueing: The role of color search templates and cue-target color relations. *Psychological Research*, *78*(2), 209–221. https://doi.org/10.1007/s00426-013-0497-5

Ansorge, U., & Heumann, M. (2003). Top-down contingencies in peripheral cuing: The roles of color and location. Journal of Experimental Psychology: Human Perception and Performance, 29(5), 937–948. https://doi.org/10.1037/0096-1523.29.5.937

Ansorge, U., & Horstmann, G. (2007). Preemptive control of attentional capture by colour: Evidence from trial-by-trial analyses and orderings of onsets of capture effects in reaction time distributions. *Quarterly Journal of Experimental Psychology, 60*(7), 952-975. https://doi.org/10.1080/17470210600822795

Appelle, S. (1972). Perception and discrimination as a function of stimulus orientation: The "oblique effect" in man and animals. *Psychological Bulletin*, *78*(4), 266–278. https://doi.org/10.1037/h0033117

Arita, J. T., Carlisle, N. B., & Woodman, G. F. (2012). Templates for rejection: Configuring attention to ignore task-irrelevant features. *Journal of Experimental Psychology: Human Perception and Performance*, *38*(3), 580–584. https://doi.org/10.1037/a0027885

Arnold, B. F., Hogan, D. R., Colford, J. M., & Hubbard, A. E. (2011). Simulation methods to estimate design power: An overview for applied research. *BMC Medical Research Methodology*, *11*(1), Article 94. https://doi.org/10.1186/1471-2288-11-94

Awh, E., Belopolsky, A. V., & Theeuwes, J. (2012). Top-down versus bottom-up attentional control: A failed theoretical dichotomy. *Trends in Cognitive Sciences*, *16*(8), 437–443. https://doi.org/10.1016/j.tics.2012.06.010

Bates, D., Mächler, M., Bolker, B., & Walker, S. (2015). Fitting linear mixed-effects models using lme4. *Journal of Statistical Software*, *67*(1), 1–48. https://doi.org/10.18637/jss.v067.i01

Beck, V. M., & Hollingworth, A. (2015). Evidence for negative feature guidance in visual search is explained by spatial recoding. *Journal of Experimental Psychology: Human Perception and Performance*, *41*(5), 1190–1196. https://doi.org/10.1037/xhp0000109

Beck, V. M., Luck, S. J., & Hollingworth, A. (2018). Whatever you do, don't look at the . . .: Evaluating guidance by an exclusionary attentional template. *Journal of Experimental Psychology: Human Perception and Performance*, *44*(4), 645–662. https://doi.org/10.1037/xhp0000485

Becker, M. W., Hemsteger, S., & Peltier, C. (2015). No templates for rejection: A failure to configure attention to ignore task-irrelevant features. *Visual Cognition*, *23*(9-10), 1150–1167. https://doi.org/10.1080/13506285.2016.1149532

Belopolsky, A. V., & Theeuwes, J. (2010). No capture outside the attentional window. *Vision Research*, *50*(23), 2543–2550. https://doi.org/10.1016/j.visres.2010.08.023

Benjamini, Y., & Yekutieli, D. (2001). The control of the false discovery rate in multiple testing under dependency. *The Annals of Statistics*, 29(4), 1165-1188. https://doi.org/10.1214/aos/1013699998

Braver, T. S. (2012). The variable nature of cognitive control: A dual mechanisms framework. *Trends in Cognitive Sciences*, *16*(2), 106–113. https://doi.org/10.1016/j.tics.2011.12.010

Brown, V. A. (2021). An introduction to linear mixed-effects modeling in R. *Advances in Methods and Practices in Psychological Science*, *4*(1), 1-19. https://doi.org/10.1177/2515245920960351

Brysbaert, M. (2019). How many participants do we have to include in properly powered experiments? A tutorial of power analysis with reference tables. *Journal of Cognition*, 2(1), Article 16. https://doi.org/10.5334/joc.72

Brysbaert, M., & Stevens, M. (2018). Power analysis and effect size in mixed effects models: A tutorial. *Journal of Cognition*, *1*(1), Article 9. https://doi.org/10.5334/joc.10

Burnham, B. R. (2020). Evidence for early top-down modulation of attention to salient visual cues through probe detection. *Attention, Perception, & Psychophysics*, *82*(3), 1003–1023. https://doi.org/10.3758/s13414-019-01850-0

Büsel, C., Voracek, M., & Ansorge, U. (2020). A meta-analysis of contingent-capture effects. *Psychological Research*, *84*(3), 784–809. https://doi.org/10.1007/s00426-018-1087-3

Carlisle, N. B., & Nitka, A. W. (2019). Location-based explanations do not account for active attentional suppression. *Visual Cognition*, *27*(3-4), 305–316. https://doi.org/10.1080/13506285.2018.1553222

Carmel, T., & Lamy, D. (2014). The same-location cost is unrelated to attentional settings: An object-updating account. *Journal of Experimental Psychology: Human Perception and Performance*, *40*(4), 1465–1478. https://doi.org/10.1037/a0036383

Carmel, T., & Lamy, D. (2015). Towards a resolution of the attentional-capture debate. *Journal of Experimental Psychology: Human Perception and Performance*, *41*(6), 1772–1782. https://doi.org/10.1037/xhp0000118

Cepeda, N. J., Cave, K. R., Bichot, N. P., & Kim, M. S. (1998). Spatial selection via feature-driven inhibition of distractor locations. *Perception & Psychophysics, 60*, 727–746. https://doi.org/10.3758/BF03206059

Chang, S., & Egeth, H. E. (2019). Enhancement and suppression flexibly guide attention. *Psychological Science*, *30*(12), 1724–1732. https://doi.org/10.1177/0956797619878813

Chelazzi, L., Marini, F., Pascucci, D., & Turatto, M. (2019). Getting rid of visual distractors: The why, when, how, and where. *Current Opinion in Psychology*, *29*, 135–147. https://doi.org/10.1016/j.copsyc.2019.02.004

Chen, P., & Mordkoff, J. T. (2007). Contingent capture at a very short SOA: Evidence against rapid disengagement. *Visual Cognition*, *15*(6), 637–646. https://doi.org/10.1080/13506280701317968

Cumming, G. (2012). *Understanding the new statistics: Effect sizes, confidence intervals, and meta-analysis*. Routledge, Taylor & Francis Group.

Cunningham, C. A., & Egeth, H. E. (2016). Taming the white bear: Initial costs and eventual benefits of distractor inhibition. *Psychological Science*, *27*(4), 476–485. https://doi.org/10.1177/0956797615626564

de Vries, I. E. J., Savran, E., van Driel, J., & Olivers, C. N. L. (2019). Oscillatory mechanisms of preparing for visual distraction. *Journal of Cognitive Neuroscience*, *31*(12), 1873–1894. https://doi.org/10.1162/jocn_a_01460

Desimone, R., & Duncan, J. (1995). Neural mechanisms of selective visual attention. *Annual Review of Neuroscience*, *18*(1), 193–222. https://doi.org/10.1146/annurev.ne.18.030195.001205

Dowle, M., & Srinivasan, A. (2020). *Data.table: Extension of ‘data.frame‘*. https://CRAN.R-project.org/package=data.table

Faul, F., Erdfelder, E., Lang, A.-G., & Buchner, A. (2007). G*Power 3: A flexible statistical power analysis program for the social, behavioral, and biomedical sciences. *Behavior Research Methods*, *39*(2), 175–191. https://doi.org/10.3758/BF03193146

Folk, C. L., & Remington, R. (1998). Selectivity in distraction by irrelevant featural singletons: Evidence for two forms of attentional capture. *Journal of Experimental Psychology: Human Perception and Performance*, *24*(3), 847–858. https://doi.org/10.1037/0096-1523.24.3.847

Folk, C. L., & Remington, R. W. (2008). Bottom-up priming of top-down attentional control settings. *Visual Cognition*, *16*(2-3), 215–231. https://doi.org/10.1080/13506280701458804

Folk, C. L., Remington, R. W., & Johnston, J. C. (1992). Involuntary covert orienting is contingent on attentional control settings. *Journal of Experimental Psychology: Human Perception and Performance*, *18*(4), 1030–1044.

Gaspelin, N., Leonard, C. J., & Luck, S. J. (2015). Direct evidence for active suppression of salient-but-irrelevant sensory inputs. *Psychological Science*, *26*(11), 1740–1750. https://doi.org/10.1177/0956797615597913

Gaspelin, N., Leonard, C. J., & Luck, S. J. (2017). Suppression of overt attentional capture by salient-but-irrelevant color singletons. *Attention, Perception, & Psychophysics*, *79*(1), 45–62. https://doi.org/10.3758/s13414-016-1209-1

Gaspelin, N., & Luck, S. J. (2018). The role of inhibition in avoiding distraction by salient stimuli. *Trends in Cognitive Sciences*, *22*(1), 79–92. https://doi.org/10.1016/j.tics.2017.11.001

Geng, J. J. (2014). Attentional mechanisms of distractor suppression. *Current Directions in Psychological Science*, *23*(2), 147–153. https://doi.org/10.1177/0963721414525780

Goller, F., Ditye, T., & Ansorge, U. (2016). The contribution of color to attention capture effects during search for onset targets. *Attention, Perception, & Psychophysics*, *78*(3), 789–807. https://doi.org/10.3758/s13414-015-1053-8

Goller, F., Schoeberl, T., & Ansorge, U. (2020). Testing the top-down contingent capture of attention for abrupt-onset cues: Evidence from cue-elicited N2pc. *Psychophysiology*, *57*(11), Article e13655. https://doi.org/10.1111/psyp.13655

Hedges, L. V. (1981). Distribution theory for Glass's estimator of effect size and related estimators. *Journal of Educational Statistics,* 6(2), 107-128. https://doi.org/10.3102/10769986006002107

Hickey, C., Di Lollo, V., & McDonald, J. J. (2009). Electrophysiological indices of target and distractor processing in visual search. *Journal of Cognitive Neuroscience, 21*(4), 760-775. https://doi.org/10.1162/jocn.2009.21039

Hopf, J.-M., Luck, S. J., Girelli, M., Hagner, T., Mangun, G. R., Scheich, H., & Heinze, H. J. (2000). Neural sources of focused attention in visual search. *Cerebral Cortex*, *10*(12), 1233–1241. https://doi.org/10.1093/cercor/10.12.1233

Hulleman, J. (2020). Quantitative and qualitative differences in the top-down guiding attributes of visual search. *Journal of Experimental Psychology: Human Perception and Performance*, *46*(9), 942–964. https://doi.org/10.1037/xhp0000764

Irons, J. L., Folk, C. L., & Remington, R. W. (2012). All set! Evidence of simultaneous attentional control settings for multiple target colors. *Journal of Experimental Psychology: Human Perception and Performance*, *38*(3), 758–775. https://doi.org/10.1037/a0026578

Kerzel, D., & Witzel, C. (2019). The allocation of resources in visual working memory and multiple attentional templates. *Journal of Experimental Psychology: Human Perception and Performance*, *45*(5), 645–658. https://doi.org/10.1037/xhp0000637

Kliegl, R., Wei, P., Dambacher, M., Yan, M., & Zhou, X. (2010). Experimental effects and individual differences in linear mixed models: Estimating the relationship between spatial, object, and attraction effects in visual attention. *Frontiers in Psychology*, *1*, Article 238. https://doi.org/10.3389/fpsyg.2010.00238

Kong, G., Alais, D., & Van der Burg, E. (2017). Orientation categories used in guidance of attention in visual search can differ in strength. *Attention, Perception, & Psychophysics*, *79*(8), 2246–2256. https://doi.org/10.3758/s13414-017-1387-5

Lamy, D., Leber, A., & Egeth, H. E. (2004). Effects of task relevance and stimulus-driven salience in feature-search mode. *Journal of Experimental Psychology: Human Perception and Performance*, *30*(6), 1019–1031. https://doi.org/10.1037/0096-1523.30.6.1019

Lenth, R. (2020). *Emmeans: Estimated marginal means, aka least-squares means*. https://CRAN.R-project.org/package=emmeans

Lien, M.-C., Ruthruff, E., & Johnston, J. C. (2010). Attentional capture with rapidly changing attentional control settings. *Journal of Experimental Psychology: Human Perception and Performance*, *36*(1), 1–16. https://doi.org/10.1037/a0015875

Liesefeld, H. R., Liesefeld, A. M., & Müller, H. J. (2019). Distractor-interference reduction is dimensionally constrained. *Visual Cognition*, *27*(3–4), 1–13. https://doi.org/10.1080/13506285.2018.1561568

Liesefeld, H. R., & Müller, H. J. (2019). Distractor handling via dimension weighting. *Current Opinion in Psychology*, *29*, 160–167. https://doi.org/10.1016/j.copsyc.2019.03.003

Meteyard, L., & Davies, R. A. I. (2020). Best practice guidance for linear mixed-effects models in psychological science. *Journal of Memory and Language*, *112*, Article 104092. https://doi.org/10.1016/j.jml.2020.104092

Moher, J., & Egeth, H. E. (2012). The ignoring paradox: Cueing distractor features leads first to selection, then to inhibition of to-be-ignored items. *Attention, Perception, & Psychophysics*, *74*(8), 1590–1605. https://doi.org/10.3758/s13414-012-0358-0

Moorselaar, D., & Slagter, H. A. (2020). Inhibition in selective attention. *Annals of the New York Academy of Sciences*, *1464*(1), 204–221. https://doi.org/10.1111/nyas.14304

Noonan, M. P., Crittenden, B. M., Jensen, O., & Stokes, M. G. (2018). Selective inhibition of distracting input. *Behavioural Brain Research*, *355*, 36–47. https://doi.org/10.1016/j.bbr.2017.10.010

O'Keefe, D. J. (2007). Brief report: Post hoc power, observed power, a priori power, retrospective power, prospective power, achieved power: Sorting out appropriate uses of statistical power analyses. *Communication Methods and Measures*, *1*(4), 291–299. https://doi.org/10.1080/19312450701641375

Peirce, J., Gray, J. R., Simpson, S., MacAskill, M., Höchenberger, R., Sogo, H., Kastman, E., & Lindeløv, J. K. (2019). PsychoPy2: Experiments in behavior made easy. *Behavior Research Methods*, *51*(1), 195–203. https://doi.org/10.3758/s13428-018-01193-y

R Core Team. (2020). *R: A language and environment for statistical computing*. R Foundation for Statistical Computing. https://www.R-project.org/

Rajsic, J., Carlisle, N. B., & Woodman, G. F. (2020). What not to look for: Electrophysiological evidence that searchers prefer positive templates. *Neuropsychologia*, *140*, Article 107376. https://doi.org/10.1016/j.neuropsychologia.2020.107376

Rankin, C. H., Abrams, T., Barry, R. J., Bhatnagar, S., Clayton, D. F., Colombo, J., Coppola, G., Geyer, M. A., Glanzman, D. L., Marsland, S., McSweeney, F. K., Wilson, D. A., Wu, C.-F., & Thompson, R. F. (2009). Habituation revisited: An updated and revised description of the behavioral characteristics of habituation. *Neurobiology of Learning and Memory*, *92*(2), 135–138. https://doi.org/10.1016/j.nlm.2008.09.012

Remington, R. W., Folk, C. L., & McLean, J. P. (2001). Contingent attentional capture or delayed allocation of attention?. *Perception & Psychophysics*, 63(2), 298-307. https://doi.org/10.3758/BF03194470

Robinson, D., Hayes, A., & Couch, S. (2020). *Broom: Convert statistical objects into tidy tibbles*. https://CRAN.R-project.org/package=broom

Rosner, B. (1983). Percentage points for a generalized ESD many-outlier procedure. *Technometrics*, 25(2), 165–172. https://doi.org/10.1080/00401706.1983.10487848

Ruff, C. C., & Driver, J. (2006). Attentional preparation fora lateralized visual distractor: Behavioral and fMRI evidence. *Journal of Cognitive Neuroscience, 18*, 522–538. https://doi.org/10.1162/jocn.2006.18.4.522

Salkind, N. (2010). Tukey's Honestly Significant Difference (HSD). In *Encyclopedia of Research Design*. SAGE Publications, Inc. https://doi.org/10.4135/9781412961288.n478

Sawaki, R., & Luck, S. J. (2010). Capture versus suppression of attention by salient singletons: Electrophysiological evidence for an automatic attend-to-me signal. *Attention, Perception, & Psychophysics*, *72*(6), 1455–1470. https://doi.org/10.3758/APP.72.6.1455

Sawaki, R., & Luck, S. J. (2011). Active suppression of distractors that match the contents of visual working memory. *Visual Cognition*, *19*(7), 956–972. https://doi.org/10.1080/13506285.2011.603709

Schoeberl, T., Ditye, T., & Ansorge, U. (2018). Same-location costs in peripheral cueing: The role of cue awareness and feature changes. *Journal of Experimental Psychology:*

Human Perception and Performance, *44*(3), 433–451. https://doi.org/10.1037/xhp0000470

Schoeberl, T., Goller, F., & Ansorge, U. (2019). Testing a priming account of the contingent-capture effect. *Attention, Perception, & Psychophysics*, *81*, 1262–1282. https://doi.org/10.3758/s13414-019-01672-0

Shiu, L., & Pashler, H. (1994). Negligible effect of spatial precuing on identification of single digits. *Journal of Experimental Psychology: Human Perception and Performance*, *20*(5), 1037–1054. https://doi.org/10.1037/0096-1523.20.5.1037

Stilwell, B. T., Bahle, B., & Vecera, S. P. (2019). Feature-based statistical regularities of distractors modulate attentional capture. *Journal of Experimental Psychology: Human Perception and Performance*, *45*(3), 419–433. https://doi.org/10.1037/xhp0000613

Stilwell, B. T., & Vecera, S. P. (2019a). Learned and cued distractor rejection for multiple features in visual search. *Attention, Perception, & Psychophysics*, *81*(2), 359–376. https://doi.org/10.3758/s13414-018-1622-8

Stilwell, B. T., & Vecera, S. P. (2019b). Cued distractor rejection disrupts learned distractor rejection. *Visual Cognition*, *27*(3–4), 1–16. https://doi.org/10.1080/13506285.2018.1564808

Stilwell, B. T., & Vecera, S. P. (2020). Learned distractor rejection in the face of strong target guidance. *Journal of Experimental Psychology: Human Perception and Performance*, *46*(9), 926–941. https://doi.org/10.1037/xhp0000757

Tanda, T., & Kawahara, J. I. (2019). Association between cue lead time and template-for-rejection effect. *Attention, Perception, & Psychophysics*, *81*(6), 1880–1889. https://doi.org/10.3758/s13414-019-01761-0

Theeuwes, J. (1992). Perceptual selectivity for color and form. *Perception & Psychophysics*, *51*(6), 599–606. https://doi.org/10.3758/BF03211656

Theeuwes, J., Atchley, P., & Kramer, A. F. (2000). On the time course of top-down and bottom-up control of visual attention. In *Control of cognitive processes: Attention and performance XVIII* (pp. 105–125). MIT Press.

Thompson, R. F. (2009). Habituation: A history. *Neurobiology of Learning and Memory*, *92*(2), 127–134. https://doi.org/10.1016/j.nlm.2008.07.011

Treisman, A., & Gormican, S. (1988). Feature analysis in early vision: Evidence from search asymmetries. *Psychological Review*, *95*(1), 15–48. https://doi.org/10.1037/0033-295X.95.1.15

Tsal, Y., & Makovski, T. (2006). The attentional white bear phenomenon: The mandatory allocation of attention to expected distractor locations. *Journal of Experimental Psychology: Human Perception and Performance*, *32*(2), 351–363. https://doi.org/10.1037/0096-1523.32.2.351

Vatterott, D. B., & Vecera, S. P. (2012). Experience-dependent attentional tuning of distractor rejection. *Psychonomic Bulletin & Review*, *19*(5), 871–878. https://doi.org/10.3758/s13423-012-0280-4

Vecera, S. P., Cosman, J. D., Vatterott, D. B., & Roper, Z. J. J. (2014). The control of visual attention. Toward a unified account. In B. H. Ross (Ed.), *Psychology of Learning and Motivation: Vol. 60* (pp. 303–347). Elsevier. https://doi.org/10.1016/B978-0-12-800090-8.00008-1

Wang, B., & Theeuwes, J. (2018a). How to inhibit a distractor location? Statistical learning versus active, top-down suppression. *Attention, Perception, & Psychophysics*, *80*(4), 860–870. https://doi.org/10.3758/s13414-018-1493-z

Wang, B., & Theeuwes, J. (2018b). Statistical regularities modulate attentional capture. *Journal of Experimental Psychology: Human Perception and Performance*, *44*, 13–17. https://doi.org/10.1037/xhp0000472

Wang, B., & Theeuwes, J. (2020). Salience determines attentional orienting in visual selection. *Journal of Experimental Psychology: Human Perception and Performance*, *46*(10), 1051–1057. https://doi.org/10.1037/xhp0000796

Wegner, D. M., Schneider, D. J., Carter, S. R., & White, T. L. (1987). Paradoxical effects of thought suppression. *Journal of Personality and Social Psychology*, *53*(1), 5–13. https://doi.org/10.1037/0022-3514.53.1.5

Wickham, H. (2016). *ggplot2: Elegant graphics for data analysis*. Springer-Verlag New York. https://ggplot2.tidyverse.org

Wolfe, J. M. (2021). Guided Search 6.0: An updated model of visual search. *Psychonomic Bulletin & Review*, *28*, 1060–1092. https://doi.org/10.3758/s13423-020-01859-9

Wolfe, J. M., & Horowitz, T. S. (2004). What Attributes Guide the Deployment of Visual Attention and How Do They Do It? *Nature Reviews Neuroscience*, *5*(6), 495–501. https://doi.org/10.1038/nrn1411

Wolfe, J. M., & Utochkin, I. S. (2019). What is a preattentive feature? *Current Opinion in Psychology*, *29*, 19–26. https://doi.org/10.1016/j.copsyc.2018.11.005

Yaron, I., & Lamy, D. (2021). Spatial cueing effects are not what we thought: On the timing of attentional deployment. *Journal of Experimental Psychology: Human Perception and Performance*, *47*(7), 946–962. https://doi.org/10.1037/xhp0000918

Appendix

Simulation Approach to Estimate the Achieved Statistical Power

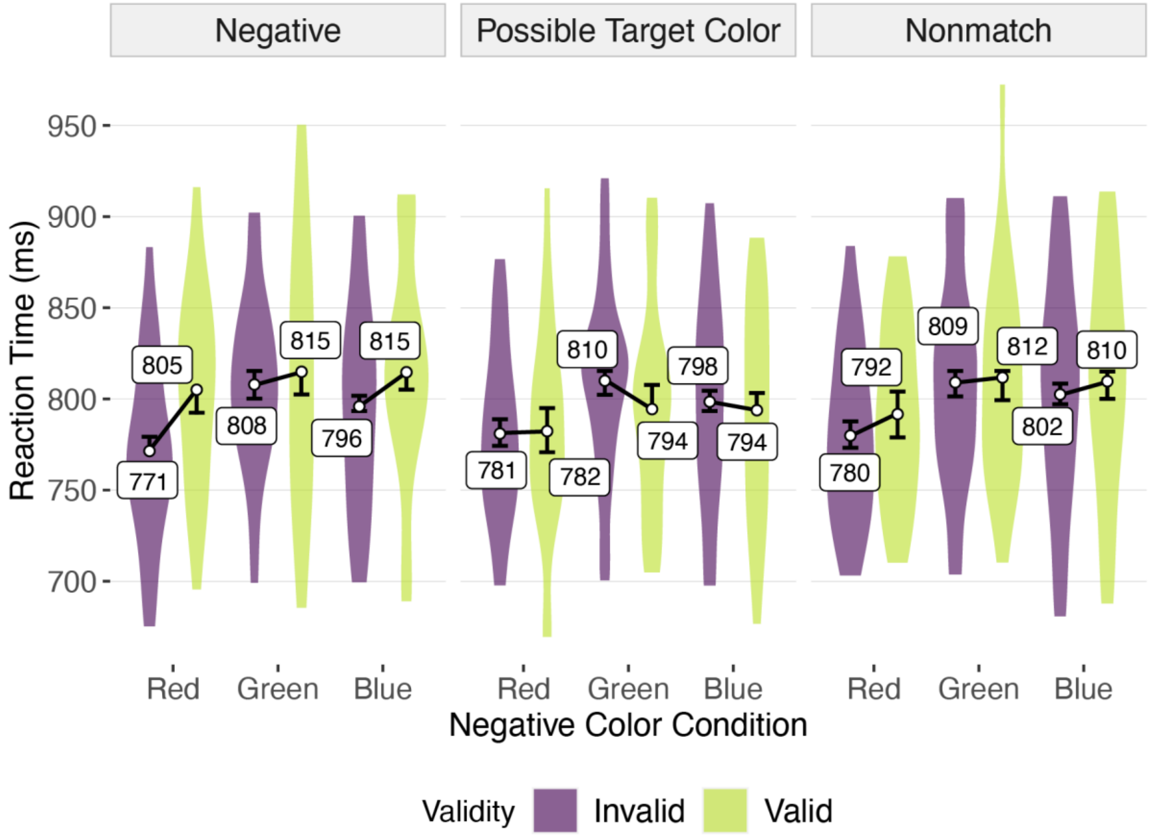
We conducted simulations to estimate the achieved statistical power of our experiments. Thereby, we aimed to see whether our experiments had sufficient statistical power to find a validity effect of −20 ms as significant and, thus, whether our results were reliable. (We decided for a validity effect of −20 ms as the minimum effect size of interest.) First, we normalized each participant's reaction times in each experimental condition. Due to this normalization of reaction times, individual and between-condition reaction time differences were removed without changing the actual reaction time distribution. Second, we made the normalized reaction time values more realistic by adding the general mean reaction time to the normalized reaction times. Third, we randomly drew values from these reaction times with replacement to simulate the reaction times. Fourth, we implemented the validity effect by adding 20 ms to the drawn reaction times in the experimental condition with valid targets and negative cues. Notably, we also simulated our data's variance by adding a random number drawn from a normal distribution to each participant's mean parameter of the distribution. Additionally, we implemented a variance between the experimental conditions within each participant by adding a random number drawn from a normal distribution. Thereby, our simulated data resembled our actual data regarding measurement precision and the standard deviation of the validity effect. Also, the number of simulated trials per participant and experimental condition matched those of our actual experiments to account for the exclusion of fast guesses, timeouts, and wrong answers. After simulating the data, we calculated a validity effect for each experiment's respective cue conditions. Based on the resulting data, we conducted a two-sided one-sample *t* test to test whether the validity effect differed significantly from zero. The statistical power was the relative frequency of tests in which we found the simulated effect (an inverse validity effect of 20 ms) as significant in 1,000 simulations. This statistical power provides an estimation of the achieved power in the actual experiment.

Mean Reaction Times and Validity Effect for Each Negative Color Condition of Experiment 1

The mean reaction times of correct trials for each experimental condition and each negative color condition of Experiment 1 are shown in Figure 14. Figure 15 shows the mean validity effects for each negative color condition and cue condition of Experiment 1.

Figure 14

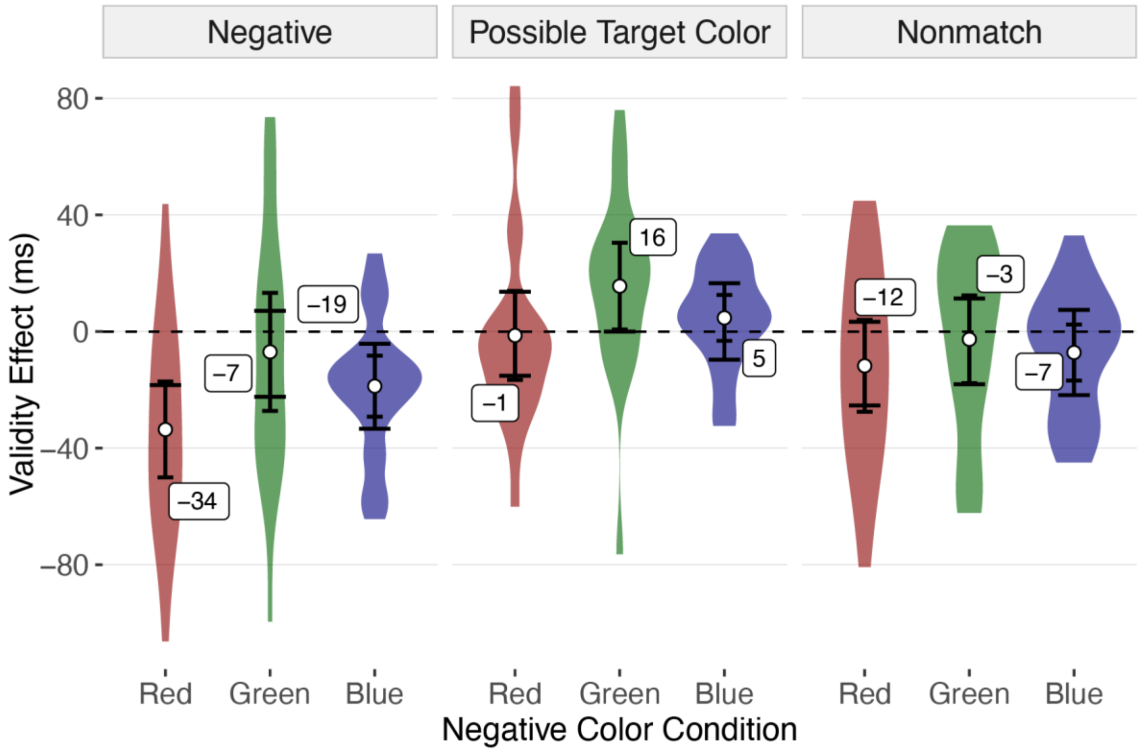
Mean Reaction Times of Correct Trials for Each Experimental Condition and Each Negative Color Condition of Experiment 1



Note. The violin plots show the distribution of the individual mean reaction times. The error bars represent 95% CIs for the mean comparisons within each negative color condition, adjusted using Tukey's HSD. There is only one error bar for the largest and smallest value, as they cannot be compared with a more extreme mean. The difference between conditions is significant if their error bars do not overlap.

Figure 15

Mean Validity Effects for Each Negative Color Condition and Cue Condition of Experiment 1



Note. The violin plots represent the distribution of the individual mean validity effects. The short error bars represent the 95% CIs for the one-sample *t* test against zero (grey dashed line). The validity effect difference between cue types is significant if the long error bars do not overlap. There is only one long error bar for the largest and smallest value, as they cannot be compared with a more extreme mean.

Time Course of Validity Effects and Mean Accuracy

We aimed to provide further insight into how attentional control settings for negative features are maintained and applied over time. For example, several studies suggested that active suppression of colors requires learning or practice (Cunningham & Egeth, 2016; Stilwell et al., 2019; Stilwell & Vecera, 2019a, 2019b; Vatterott & Vecera, 2012). Consequently, we were interested in how the overall mean accuracy and validity effects of each cue condition evolved during the experiment. Therefore, we divided the trials into blocks of equal size (216 trials per block in Experiment 1, 144 trials per block in Experiments 2 and 3) and then calculated the validity effect for each cue condition and block. The accuracy was calculated per participant and trial as the relative frequency of correct answers in the previous 30 trials. Therefore, the accuracy was calculated only starting with the 31st trial. Then we calculated the mean accuracy per trial across participants. Notably, we did not conduct further statistical analyses on the blocked data due to the limited number of observations in each experimental condition per block. Nevertheless, we were interested in apparent trends of validity effects indicative of practice effects on attentional control settings for negative features or participants adopting a different search strategy over time (e.g., searching for the target by its possible target colors).

In Experiment 1, inverse validity effects for negative cues were equally evident throughout the experiment. In contrast, possible target-color and nonmatching cues produced overall neutral validity effects during the whole experiment. These exploratory results did not indicate that suppression depended on extended practice with the negative color or that participants switched to search for the target by its colors. Therefore, we found at least no counter-evidence against the assumption that suppression depended directly on the negative search criterion used to find the target. For Experiment 1, the mean validity effects per block and the continuous general mean accuracy are shown in Figure 16.

Figure 16

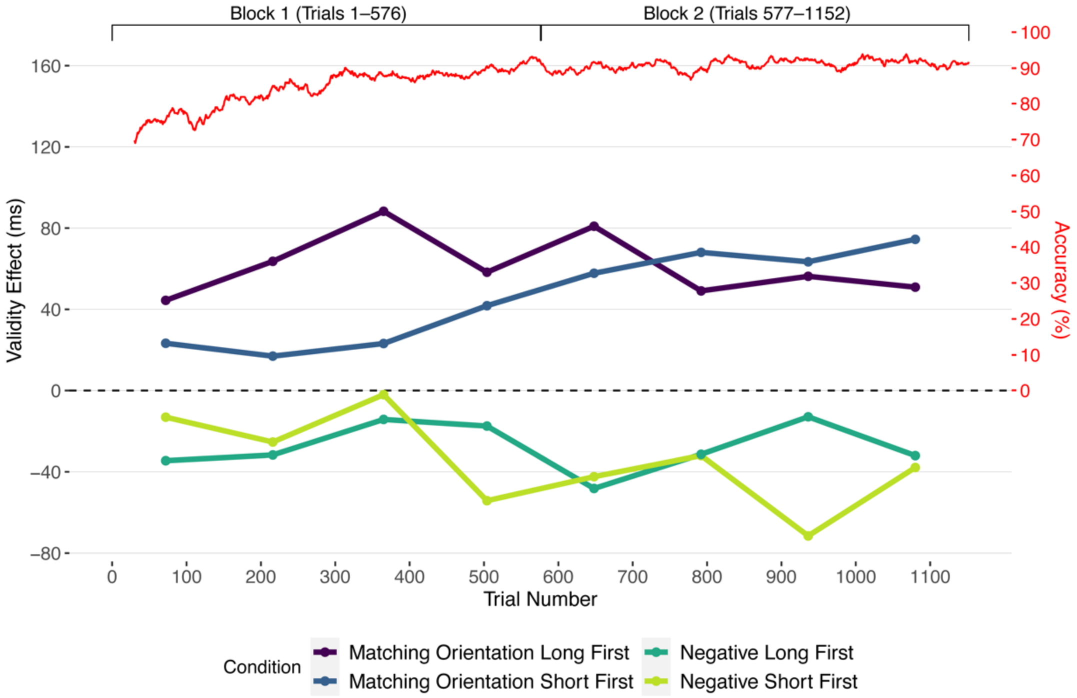
Time Course of the General Mean Accuracy and Validity Effect in Each Cue Condition of Experiment 1

Note. The right y-axis shows the mean accuracy (red line) throughout the experiment, excluding the first 30 trials. For each cue condition, colored lines and points show the mean validity effects of one block with 216 trials. Validity effects were calculated for each of eight blocks in the blue negative color condition (1,440 trials) and each of six blocks in the red and green negative color condition (864 trials).

Figure 17 shows the continuous general mean accuracy and the mean validity effects per cue condition in both cue-target interval conditions of Experiment 2 for blocks á 144 trials. Consistent with the primary analysis, analyzing the validity effects over time showed that negative cues were suppressed while matching-orientation cues captured attention

Figure 17

Time Course of the Mean Accuracy and Validity Effects in Each Cue Condition per Cue-Target Interval of Experiment 2

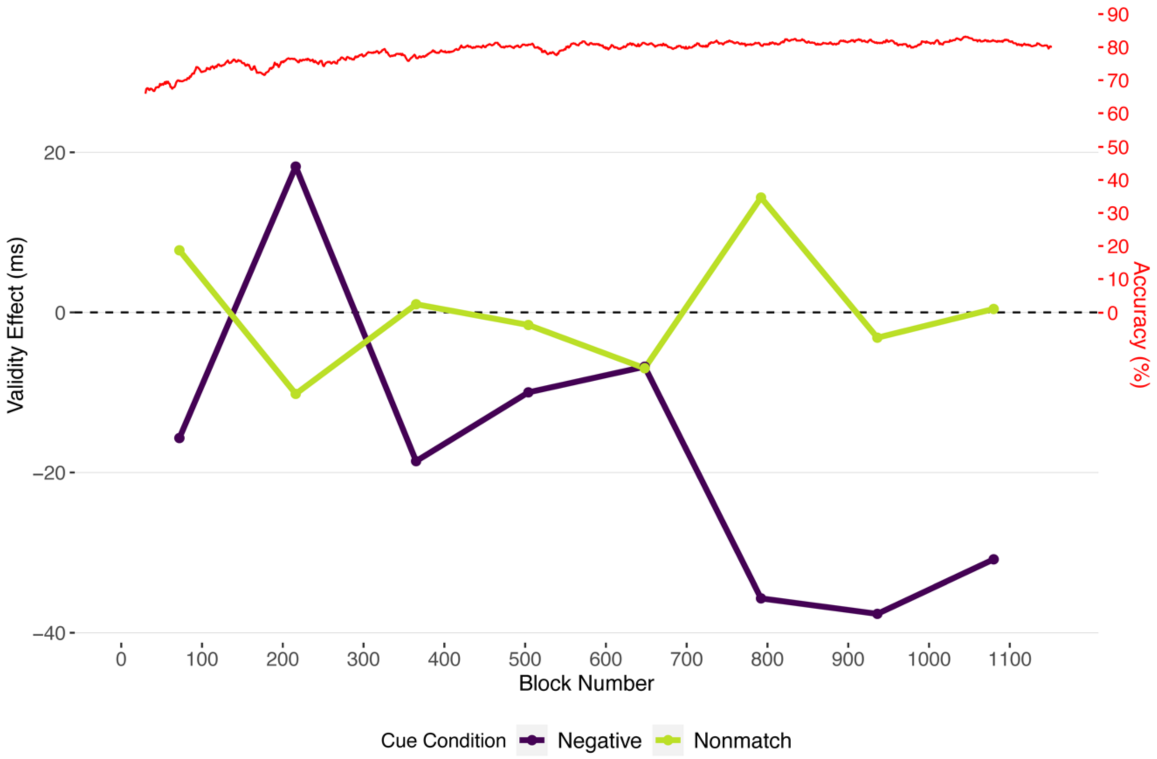


Note. Condition (below x-axis) refers to the respective cue and cue-target interval conditions. The right y-axis shows the mean accuracy (red line) throughout the experiment, excluding the first 30 trials. For each cue condition in each cue-target interval condition, colored lines and points show the mean validity effects of one block á 144 trials.

throughout the experiment. For Experiment 3, Figure 18 shows the continuous general mean accuracy and the validity effects of each block per cue condition.

Figure 18

Time Course of the Mean Accuracy and Validity Effects for Each Block and Cue Condition of Experiment 3



Note. The right y-axis shows the mean accuracy (red line) throughout the experiment, excluding the first 30 trials. For each cue condition, colored lines and points show the mean validity effects of one block, including 144 trials.

Overall, these exploratory block analyses show that inverse validity effects for negative cues were present even at the beginning of the experiment. These observations suggest that attentional control settings to suppress the negative feature were instantiated through our instructions and did not depend on experience with the negative search criterion. However, in contrast to Experiments 1 and 2, the block analysis of Experiment 3 could indicate that inverse validity effects for negative orientation cues depended more on experience with the negative orientation compared to color. This assumption is based on somewhat inconsistent validity effects in the first blocks but more pronounced inverse validity effects in later blocks. Although this finding must be interpreted with caution due to the small number of observations per block, it could reflect differences between color and orientation as attentional guiding features. For example, it has been suggested that participants might only use orientation as a guiding feature if color is not available as a sufficient target feature (Anderson et al., 2010; Hulleman, 2020). Possibly, participants only proactively suppress an orientation if color cannot be used to find the target. As our target in Experiment 3 was conjunctively defined by a negative orientation and a (positive) color, participants might have tried to focus on the target's color instead of using the negative orientation to find the target. Only over time, participants might have realized that the negative orientation was task-relevant and, thus, engaged in proactively suppressing the negative orientation. However, future research is needed to test possible dimensional differences between color and orientation in top-down proactive suppression.