


ORIGINAL ARTICLE

Combined influences of strategy and selection history on attentional control

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Abstract

Visual attention is guided by top-down mechanisms and pre-stimulus task preparation, but also by selection history (i.e., the bias to prioritize previously attended items). Here we examine how these influences combine. Two groups of participants completed two intermingled tasks. One task involved categorization of a unique target; one group categorized the target based on color, and the other based on shape. The other task involved searching for a target defined by unique shape while ignoring a distractor defined by unique color. Our expectation was that the search task would be difficult for the color-categorization group because their categorization task required attentional resolution of color, but the search task required that they ignore color. In some experimental blocks, trials from the two tasks appeared predictably, giving the color-categorization group an opportunity to strategically prepare by switching between color-prioritizing and shape-prioritizing attentional templates. We looked to pre-stimulus oscillatory activity as a direct index of this preparation, and to reaction times and post-stimulus ERPs for markers of resultant change in attentional deployment. Results showed that preparation in the color-categorization group optimized attentional templates, such that these participants became less sensitive to the color distractor in the search task. But preparation was not sufficient to entirely negate the influence of selection history, and participants in the color-categorization group continued to show a propensity to attend to the color distractor. These results indicate that preparatory effort can be scaled to the anticipated attentional requirements, but attention is nevertheless considerably biased by selection history.

KEYWORDS

attention capture, early Pd, ERPs, N2pc, pre-stimulus alpha-band, selection history

Hossein Abbasi and Hanna Kadel shared first authorship.

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1 | INTRODUCTION

Our daily life consists of many circumstances where we must switch between cognitive tasks and adapt our behavior to new situations. To accomplish this, visual selective attention can be tuned to current task settings so that task-relevant stimuli are prioritized and task-irrelevant stimuli are ignored (Maunsell & Treue, 2006; Olivers et al., 2011). This attentional set affects neural processing from early in the visual hierarchy (Battistoni et al., 2017; Moore & Zirnsak, 2017) and prioritizes relevant stimuli while preventing or overcoming selection of distractors (see e.g., Ansorge et al., 2011; Kiss et al., 2013; Sawaki & Luck, 2013; Wykowska & Schubö, 2011). It relies on mnemonic representations of target and distractor templates and facilitates both target processing and the suppression of stimuli known to be task-irrelevant (see e.g., Arita et al., 2012; Feldmann-Wüstefeld & Schubö, 2016; Reeder et al., 2017; Vatterott & Vecera, 2012).

Proactive attentional set can be indexed in its impact on task completion, but it can also be directly assessed in brain activity prior to stimulus onset. For example, the power and phase of pre-stimulus alpha-band EEG oscillations predict subsequent detection rate and discrimination performance (Busch et al., 2009; Chaumon & Busch, 2014; van Dijk et al., 2008; Hanslmayr et al., 2007). The preparatory establishment of attentional control seems to be reflected in a systematic decrease of posterior alpha power (Capotosto et al., 2016; Clayton et al., 2018; Mathewson et al., 2014), in line with the idea that alpha desynchronization reflects a release from inhibition (Klimesch, 2012) and thus induces a state of perceptual readiness (Hanslmayr et al., 2011; Mathewson et al., 2012; Sawaki et al., 2015). Although some studies have challenged the direct relation between post-stimulus alpha-band power and attentional selection (Antonov et al., 2020; Gundlach et al., 2020; Zhigalov & Jensen, 2020), a recent study has provided convincing results supporting the notion that pre-stimulus alpha-band power directly impacts post-stimulus attentional selection (van Zoest et al., 2021). According to their findings, van Zoest et al. (2021) suggested that increased power of pre-stimulus alpha-band reflects an advanced suppression mechanism which results in less attentional capture and less need for distractor suppression after stimulus onset.

Alpha oscillations are also associated with cognitive flexibility in task switching paradigms. In paradigms requiring shifts in attentional strategy, cues identifying a task shift elicit a reduction of frontal alpha power, and this has been linked to the need to adjust attentional control settings in switch trials (e.g., Foxe et al., 2014; Gladwin & de Jong, 2005; Poljac & Yeung, 2014; Proskovec et al., 2019). This “task-set reconfiguration” requires effort (Mayr & Keele, 2000; Monsell, 2003; Monsell & Mizon, 2006), but has a direct benefit: when participants are given sufficient

time between cue and task onset, the cue reduces task-switching costs (Monsell & Mizon, 2006).

Human observers are therefore equipped with a dynamic top-down control system that directs attention according to current task goals. However, other influences on attention can interfere with this optimization. In particular, attentional selection is strongly shaped by prior experience (Awh et al., 2012; Failing & Theeuwes, 2018; Ferrante et al., 2018). Aside from effects of prior reward (e.g., Anderson et al., 2011; Feldmann-Wüstefeld et al., 2016; Hickey et al., 2010), attention is biased toward stimuli that have been predictive, even when this predictive power has explicitly ended (Feldmann-Wüstefeld et al., 2015; Kadel et al., 2017; Le Pelley et al., 2011; O'Brien & Raymond, 2012). In Feldmann-Wüstefeld et al. (2015), for example, selection history was manipulated by having two groups of participants complete different categorization tasks with the same stimuli. One group categorized the shape of stimuli, the other the color, and both subsequently completed the same visual search task. In the search task, participants showed a pronounced attentional bias toward a task-irrelevant distractor defined in the feature dimension that had been predictive in the categorization task. Subsequent research has shown that this sustains even when participants are explicitly told that the tasks are unrelated and when the tasks are completed on different days. The lingering bias disappears only after several hundred visual search trials have been completed (Kadel et al., 2017).

Selective attention is thus sensitive to proactive top-down control on one hand and selection history on the other. How are these mechanisms related? How do we reconcile situations in which selection history is in conflict with top-down control settings? Can top-down control compensate for effects of selection history?

The mere possibility for top-down control seems to do little in negating the effect of selection history. We have recently found that the opportunity for trial-wise top-down preparation (enabled by pretrial cueing) will not override selection history effects (Kadel et al., 2017, Exp. 1 and 2). However, little is known about the mechanisms underlying proactive top-down preparation in situations with a selection history bias. The purpose of the current study is therefore to directly index the preparation of attentional control settings and determine if this preparation, when present, can compensate for individual selection history. We tracked proactive control in pre-stimulus alpha power (Schneider et al., 2021; van Zoest et al., 2021) and we looked at the post-stimulus ERP in switch trials to identify the effect of this preparation and the effect of selection history on stimulus processing. In the ERP, the early distractor positivity (early Pd; Hickey et al., 2009; Sawaki & Luck, 2010; Weaver et al., 2017; van Zoest et al., 2021) was employed to track rapid, stimulus-triggered suppression

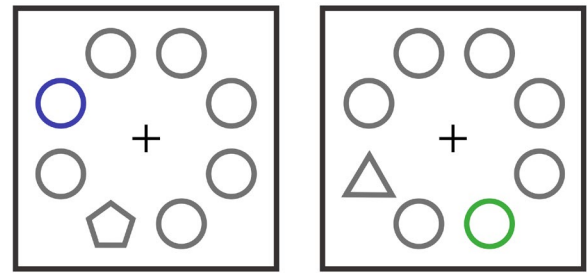
of irrelevant stimuli. The subsequent N2pc (Eimer, 1996; Luck & Hillyard, 1994a, 1994b) was used to index changes in the attentional resolution of attended stimuli. Both components emerge as voltage differences across visual cortex ipsilateral and contralateral to eliciting stimuli.

We manipulated selection history by having participants complete two intermingled types of trial. In one trial type, they categorized stimuli that varied in color and shape (Figure 1a). Half of the participants (color-categorization group) were required to categorize the uniquely-colored stimulus (blue vs. green), while the other half (shape-categorization group) were required to categorize the uniquely-shaped stimulus (triangles vs. pentagons). In the other type of trial, all participants completed a visual search task that required them to attentionally select a uniquely shaped target and ignore a uniquely colored distractor (Figure 1b). For the color-categorization group, the predictive dimension in the categorization task was task-irrelevant and potentially distracting in the search task. For the shape-categorization group, in contrast, the predictive dimension in the categorization task was also relevant in the visual search task.

To provide the opportunity for proactive attentional control, the categorization and search tasks were performed within the same experiment, but the sequence of trial types changed between blocks (Figure 2a). In random-sequence blocks, the tasks were intermingled unpredictably so that no task-specific proactive preparation was possible. In fixed-sequence blocks, the tasks alternated in a fixed, predictable pattern. Our expectation was that participants would proactively reconfigure their attentional control settings in fixed-sequence blocks, where such preparation was possible, and that this would be reflected in preparatory oscillations in the alpha frequency band and in effects on behavior, Pd, and N2pc.

Most importantly, we were interested in whether proactive attentional control in fixed-sequence blocks would differ between the color- and shape-categorization groups. Participants in the shape-categorization group could rely on a similar attentional set for both the categorization and search tasks, because in both cases the target stimulus was defined in the same featural dimension. In contrast, participants in the color-categorization group attended to color targets in categorization trials, but shape targets in search trials, and therefore had to substantially reconfigure attentional control when the task switched. Our expectation was that correlates of reconfiguration would therefore emerge prominently when participants in the color-categorization group completed switch trials in fixed-sequence blocks. If participants are able to properly reconfigure in this circumstance, we expected this to benefit their attentional control in fixed-sequence blocks. As a result, in the search task, the color-categorization group

(a) Categorization task



(b) Search task

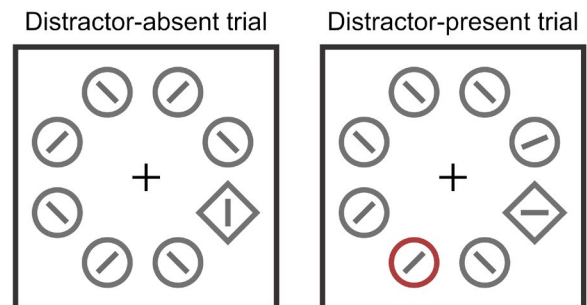


FIGURE 1 (a) Exemplar displays in the categorization task. Participants in the color-categorization group had to press one button for a green and another button for a blue circle. Participants in the shape-categorization group had to press one button for a pentagon and another button for a triangle. Participants were naïve to their group assignment when the experiment started and had to learn on a trial-and-error basis by receiving immediate auditory feedback in incorrect trials. (b) Exemplar displays in the search task. Both groups searched for the diamond-shaped target and reported the orientation (horizontal vs. vertical) of the embedded line. In 60% of the trials, an additional color distractor was presented (right panel) which had to be ignored

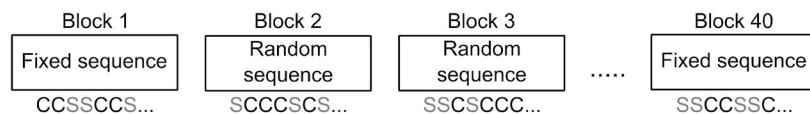
should demonstrate less attentional capture in fixed-sequence blocks relative to random-sequence blocks.

2 | METHOD

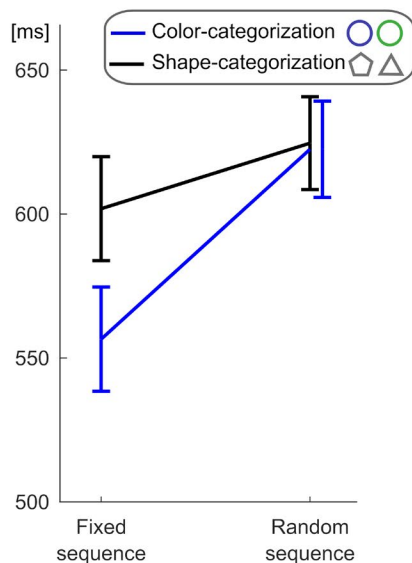
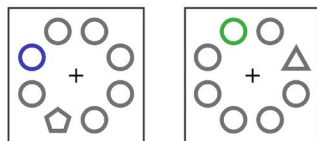
2.1 | Participants

Forty volunteers (9 male) participated in the experiment for course credit or monetary payment (8€/h). Written consent for participation was obtained before the experimental session. All but two participants were right-handed and all had normal or corrected-to-normal vision. Eight participants had to be excluded from analysis due to excessive eye movement artefacts in EEG data (over 25% of the trials; see below for details). Of the remaining 32 participants (6 male), 16 were assigned to the color-categorization group (mean age \pm SD: 23.5 \pm 2.5 years) and 16 to the shape-categorization group (mean age \pm SD: 23.3 \pm 2.5 years).

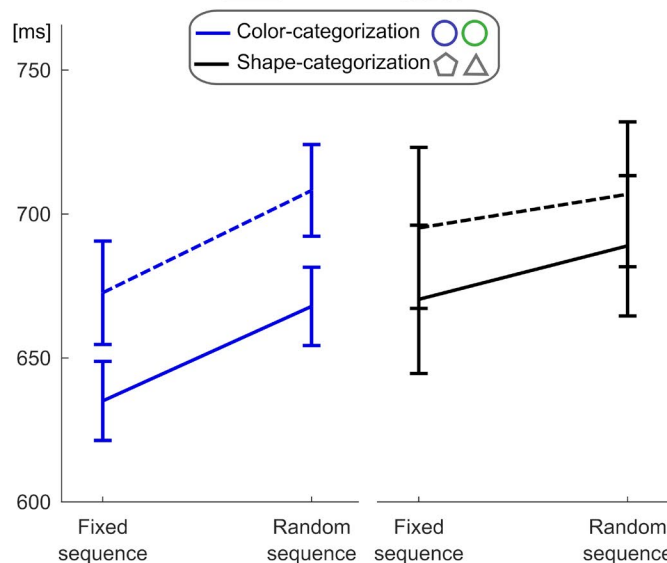
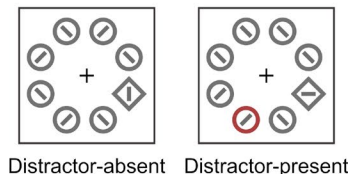
(a) Task sequence



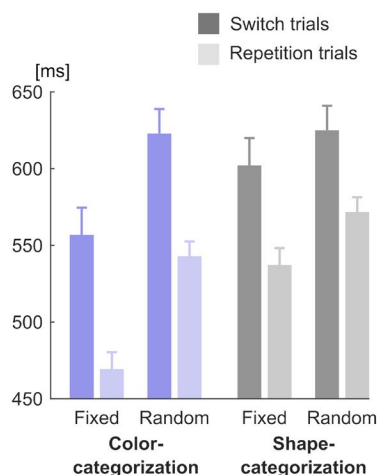
(b) Categorization task RTs: switch trials



(c) Search task RTs: switch trials



(d) Categorization task RTs



(e) Search task RTs

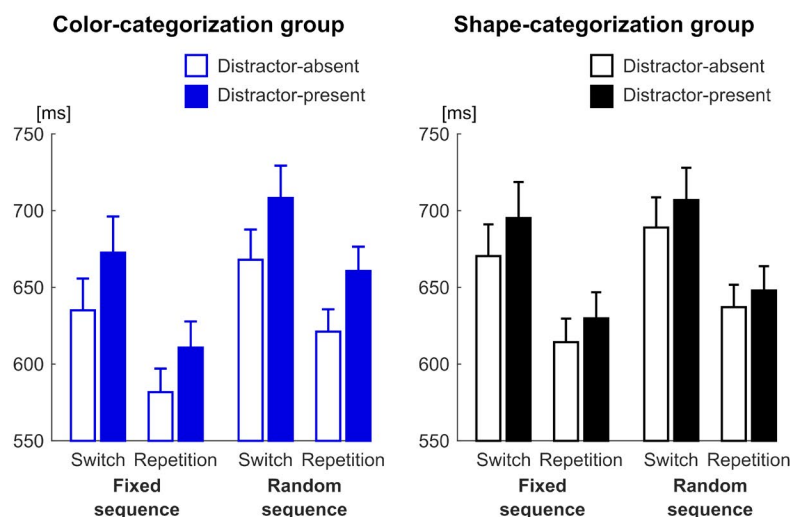


FIGURE 2 Legend on next page

2.2 | Stimulus and apparatus

Participants were seated in a comfortable chair in a dimly lit, electrically shielded and sound attenuated room and responded via a customizable keypad (Ergodex DX1) held

on their lap. Two response buttons on the left half of the pad were used in the categorization task and two separate buttons on the right half of the pad were used in the search task. Participants used the thumb and ring finger of their left hand to respond during the categorization task and

FIGURE 2 (a) Schematic depiction of the two task sequences used in the experiment. Each rectangle represents one experimental block and each of the small letters below the rectangles represents one trial. Letters “C” represent categorization trials, and letters “S” represent search trials. Participants completed 20 blocks in each task sequence. In fixed-sequence blocks, categorization trials and the search task trials alternated in fixed sequences of two trials per task. In random-sequence blocks, trials of both tasks alternated in random order. Panels B and C are included for clarity with the focus on the switch trials and they are redundant to the complete presentation of the data depicted in panels D and E. (b) Mean response times in switch trials in the categorization task for the color-categorization (blue) and the shape-categorization group (black), separated for fixed and random task sequences. Error bars represent standard errors of the mean. (c) Mean response times in switch trials in the search task for the color-categorization (blue) and the shape-categorization group (black), separated for fixed and random task sequences. Solid lines show RTs for distractor-absent trials, dashed lines represent RTs for trials with an additional color distractor. Error bars represent standard errors of the mean. (d) Mean response times in the categorization task for the color-categorization (blue) and the shape-categorization group (gray), separated for fixed-sequence (left bars in each panel) and random-sequence blocks (right bars in each panel). Bars with darker colors show RTs for switch trials, bars with lighter colors show RTs for repetition trials. Error bars represent standard errors of the mean. (e) Mean response times in the search task in the color-categorization group (blue) and the shape-categorization group (black) in fixed-sequence (left panel) and random-sequence blocks (right panel). Filled bars show RTs for trials with an additional color distractor, unfilled bars show RTs for distractor-absent trials. Error bars represent standard errors of the mean

the index and middle finger of their right hand to respond during the search task. Task presentation was controlled via E-Prime 2.0 (Psychology Software Tools, Inc.) on a standard PC under Windows XP. Stimuli were presented on a 22" LCD-TN screen (Samsung Syncmaster 2233) at a viewing distance of 100 cm. For auditory feedback, two stereo speakers were positioned behind the screen, each on one side (Logitech Z120 2.0).

In both tasks, the display consisted of eight objects of 2.3° visual angle placed equidistant from the screen center in a circular search array on a dark gray background (CIELAB coordinates with reference white point of D65: $L^* = 25.32$, $a^* = 0$, and $b^* = 0$; distance screen center to stimulus center: 6.3°; horizontal eccentricity: 5.7°). The display was not color-calibrated, but we measured and matched the luminance of the stimuli (~27–30 candela). In the categorization task, the display contained six neutral distractor stimuli (gray circles, $L^* = 46.44$, $a^* = 0$, and $b^* = 0$) and two unique objects (see Figure 1a). One unique object had a distinct color, either green ($L^* = 61.62$, $a^* = -56.72$, and $b^* = 51.06$) or blue ($L^* = 28.59$, $a^* = 40.83$, and $b^* = -65.28$). The other unique object had a distinct shape, either a triangle or a pentagon. This type of stimulus, which differs from its surroundings in a single featural dimension, is known as a singleton. The color and shape singletons were presented at any of eight equidistant locations with exactly one neutral distractor between them. All singleton combinations (blue/triangle, blue/pentagon, green/triangle, green/pentagon) were presented equally often in all possible locations.

In the search task, the target was a diamond-shaped singleton with a horizontal or vertical line inside (see Figure 1b). Neutral distractor stimuli were gray circles ($L^* = 46.44$, $a^* = 0$, and $b^* = 0$) that contained a gray oblique line tilted 45° to the left or right. In 40% of the search trials, the target was presented with seven neutral distractors (distractor-absent trials, Figure 1b). In the

remaining 60% of trials, a color singleton in red ($L^* = 39.56$, $a^* = 49.69$, and $b^* = 29.59$, circular shape) with an embedded oblique line appeared with one neutral distractor separating it from the target (distractor-present trials, Figure 1b). Target and distractor appeared with equal likelihood in each of the eight stimulus positions and equally often in the same side of the visual field (distractor-present, same side) as on opposite sides (distractor-present, opposite sides). Each trial began with a centrally presented gray fixation cross (0.6° visual angle) 500 ms before the stimulus display, which remained on the screen throughout the trial.

It is common in the literature to isolate target and distractor processing in visual search by selectively presenting targets and distractors on the vertical meridian of the display (e.g., Hickey et al., 2009). When the target is presented on the vertical midline, this supports discrete identification of lateralized distractor processing in the ERP within a condition. However, there is an associated cost: if target and distractor positions are randomized in a dense search array, target-vertical trials occur rarely and ERPs are based on relatively few trials. With this in mind, we have not adopted this design in the current study, instead identifying variance in target and distractor processing through comparison of results across physically identical conditions. Within-condition ERPs are therefore based on many trials without the need for a long, exhausting experiment.

2.3 | Procedure

2.3.1 | General trial procedure

Categorization and search trials started with a fixation cross for 500 ms that was followed by the stimulus display for 200 ms. A blank screen with a central fixation cross was subsequently displayed for up to 1800 ms, indicating that participants should respond while maintaining

fixation. A correct response within that time interval triggered the beginning of the inter-trial-interval (1000 ms). An erroneous or missing response led to acoustic feedback in form of a low buzzing tone.

2.3.2 | Feedback-guided learning phase

Participants started the experiment by completing a block of 64 categorization learning trials. Participants were informed that in each trial one stimulus would be different in color and another would be different in shape. They were asked to respond by pressing either the upper or lower response button with their left hand and told that errors were followed by a buzzing tone. They were not told which stimulus was assigned to which button press, or that only one dimension was response predictive. Instead, they had to use the acoustic feedback to find out which dimension was response relevant and how the two possible stimuli within that dimension were mapped to the response keys (see Kadel et al., 2017, for details). Participants in the color-categorization group learned to respond to color singletons and ignore shape singletons, pressing one key for a blue singleton and another for a green singleton. Participants in the shape-categorization group learned to respond to shape singletons and ignore color singletons, pressing one key for a triangle and another for a pentagon. The assignment of response buttons was varied across participants and response accuracy and speed were emphasized equally. In the first 32 trials of the learning phase, stimulus presentation was prolonged to 500 ms to facilitate learning. Participants proceeded to the next block when accuracy was >75%, otherwise they had to repeat the block. On average, participants performed 2.23 blocks of the learning categorization task ($SD = 1.39$) before shifting to the mixed practice phase.

2.3.3 | Mixed practice phase

This block was performed after the initial learning and combined 32 categorization learning task trials (as described above) with 32 search task trials in a random order. In search task trials, all participants responded to the orientation of the line embedded in the diamond shape target by pressing either the left or right response-board button with their right hand. Stimulus-response mapping was counter-balanced over participants within each of the color- and shape-categorization groups. In this phase of the experiment, stimuli were presented for 1000 ms in search trials in order to facilitate learning. As in the learning phase of the experiment, participants proceeded to the next block of trials when accuracy was >75%.

2.3.4 | Main experiment

The main experimental session was performed the next day and EEG was recorded throughout. Participants were informed that the task was to be performed in two types of experimental blocks. In random-sequence blocks, categorization and search trials were intermingled in a random, unpredictable order (with the limitation that no more than four trials of one task could follow each other). In fixed-sequence blocks, trials of the categorization and search task alternated in a fixed and predictable sequence of exactly two trials per task. The task trial sequence (fixed or random) was identified on the screen before the block started.

In total, participants completed 40 blocks of 64 trials each, 20 in each task sequence, 2560 trials in total, and 1280 trials in each of the categorization and search tasks. In the search task, 512 of the 1280 trials were distractor-absent trials, where in the remaining trials the distractor was presented either on the same side as the target (384 trials) or on the opposite side (384 trials). Immediate auditory feedback was given after incorrect responses. After errors, participants took a forced break of at least 8 s, and they were given performance feedback (RT and accuracy) after each block. Participants were prompted to take longer breaks of several minutes on two occasions.

2.4 | EEG recording

EEG was recorded from 64 Ag-AgCl active electrodes (actiCAP by Brain Products GmbH, Munich, Germany). Electrodes were placed according to the international 10–10 system. Vertical EOG (vEOG) was recorded from Fp1 and an electrode placed below the left eye, and horizontal EOG (hEOG) was recorded from electrode positions F9 and F10. Impedances were kept below 5 k Ω . All electrodes were referenced to FCz during recording and re-referenced offline to the average of all electrodes. The signal was recorded with a BrainAmp amplifier (Brain Products, Munich, Germany) at a sampling rate of 1000 Hz and high pass filtered at 0.016 Hz and a low pass filtered at 250 Hz (–3 dB cutoff, Butterworth filter, 30 dB/oct roll-off).

2.5 | Data analysis

2.5.1 | Behavioral data

The first trial of each block was rejected from analysis, as were trials with incorrect responses and trials with outlier RT (>2 SD from mean RT calculated separately for each participant and separately for each block and each task). This

led to exclusion of 9.30% of trials in the shape-categorization group and 9.22% in the color-categorization group.

2.5.2 | EEG data

Brain Vision Analyzer (Brain Products, Munich, Germany), the Fieldtrip toolbox (Oostenveld et al., 2011) and custom scripts for Matlab R2019a (Mathworks, <http://www.mathworks.com>) were used for off-line EEG data processing.

Event-related potentials

EEG was segmented into 700-ms epochs time-locked to the display onset, including a 200-ms pre-stimulus baseline. Vertical EOG (vEOG) was calculated as the difference between Fp1 and the electrode placed below the left eye, and horizontal EOG (hEOG) was calculated as the difference between electrodes F9 and F10. The four channels were filtered using a low-pass filter of 35 Hz. Trials with eyeblink (vEOG > $\pm 80 \mu\text{V}$), or horizontal eye movements (hEOG > $\pm 35 \mu\text{V}$ step criterion) within the first 350 ms after stimulus onset were excluded from analysis. Channels with activity > $\pm 80 \mu\text{V}$ in the first 350 ms after stimulus onset in a trial were also excluded. The first trial of each block was rejected from analysis, as were trials with incorrect responses. Participants with less than 75% artifact-free trials were excluded from further analysis (8 participants). The remaining 32 participants had 88.1% artifact-free trials on average. In total, 12.0% of trials had to be excluded in the shape-categorization, and 11.8% in the color-categorization group.

To quantify the early Pd and N2pc in both categorization and search tasks, mean contralateral and ipsilateral activity in the ERP was calculated for electrodes PO7/PO8 and cross-conditional effect peaks were identified. A 40 ms window was centered on this peak latency and amplitude measures reflect the mean across this interval.

For the categorization task, the N2pc peak emerged at 224 ms. For the search task, Pd and N2pc measurements were separated across the conditions identified in Figure 4. In distractor-absent trials, the N2pc peaked at 246 ms (Figure 4a). When the target and distractor were in the same visual hemifield the early Pd peaked at 127 ms and the N2pc peaked at 236 ms (Figure 4b). When the target and distractor were in opposite visual hemifields, the positive-polarity early Pd expresses as a negative-polarity peak, because the ERP is locked to the location of the target stimulus (such that a positivity contralateral to the distractor emerges as a negativity contralateral to the target). In this condition, the early Pd peaked at 142 ms and the N2pc peaked at 294 ms (Figure 4c).

In addition to mean amplitude, onset latency of the N2pc component was analyzed in search task trials (distractor absent, distractor-present same side, distractor-present opposite sides) using a jackknife-based approach (Kiesel et al., 2008; Miller et al., 1998; Smulders, 2010). Conditional onset was defined as the point where 50% of maximum N2pc amplitude was reached (Kiesel et al., 2008). Relevant statistics are corrected for the jackknife procedure and this is identified with the subscript “c”.

Time-frequency analysis

Oscillatory activity was analyzed over a 3000 ms epoch beginning 2000 ms before display onset. Trials excluded from ERP analyses were also excluded from time-frequency analysis. Before performing time-frequency analysis, data were downsampled to 500 Hz. The spectral analysis of the zero-padded time series was performed using a Fast-Fourier transformation. Zero-padding was done using the “nextpow2” function which returns the smallest power-of-two larger than the length of the time series. The power spectrum of the EEG was computed within a 500 ms Hanning window which moved in steps of 30 ms, so that every bin represented data from 250 ms before and after the nominal latency. This analysis was performed for frequencies 2 to 32 Hz with a resolution of 1 Hz. Trials were sorted according to the factors task sequence (fixed vs. random sequence), and task repetition (task switch vs. task repetition), resulting in four conditions per participant. Power values of each frequency at each time point and electrode were averaged separately for each condition.

Because task-set reconfiguration was not required in repetition trials, our expectation was that differences in task-set reconfiguration should emerge as a difference in pre-stimulus alpha power between switch and repetition trials, but only for fixed-sequence blocks. In random-sequence blocks, there was no opportunity for participants to know when task repetitions would occur, and accordingly no opportunity for preparation.

To compute the difference in preparatory alpha between switch and repetition trials in fixed and random-sequence blocks, we contrasted power values in each time and frequency bin using $[(\text{switch} - \text{repetition}) / (\text{switch} + \text{repetition})] \times 100$ individually for each posterior channel (O1/2, PO7/8, PO3/4, P7/8, P5/6, P3/4, P1/2, Oz, POz and Pz). Next, power values were averaged over channels, separately for participants in each group. Finally, the power values of switch and repetition trials were forwarded to a statistical analysis based on a cluster-based permutation test with 5000 permutations. A cluster-defining threshold of $\alpha < .01$ was employed (corresponding to a critical t -value of 2.95; Maris & Oostenveld, 2007).

We used cluster-based permutation tests for the data in the frequency range of 6 to 32 Hz and in the time range

of 800-ms pre-stimulus interval. Focusing the analysis on this range of data involved 27 frequency bins and 28 time bins in the analysis. Analysis was based on the average power spectrum of 17 posterior channels and compared the power spectrum of switch and repetition trials separately for fixed and random trial sequences. According to this, in each type of trial sequence and in each group, the labels of switch and repetition trials were permuted. In this analysis, a significant cluster indicated that the corresponding frequency power differed significantly between switch and repetition trials. To subsequently test whether this switch-vs-repetition effect differed in color- vs shape-categorization groups, the normalized power differences between switch and repetition were compared between the groups. In this analysis, the labels of color-categorization and shape-categorization were permuted. This analysis employed a cluster-based permutation test with 5000 permutations. A cluster-defining threshold of $\alpha < .05$ was employed (corresponding to a critical t -value of 2.04).

3 | RESULTS

A core motivating hypothesis for the study was that preparation would differ between shape- and color-categorization groups in task switch trials. Accordingly, we constrained the analysis of the ERP to switch trials. To provide a comprehensive description of participants' performance, RT analysis was conducted for all data.

3.1 | Categorization task

3.1.1 | Behavioral results

(See Figure 2b,d) RT and accuracy were analyzed in a 3-way ANOVA with a between-subject factor for categorization group (color-categorization group vs. shape-categorization group) and within-subject factors for task sequence (fixed vs. random sequence) and task repetition (task switch vs. task repetition). All reports in the results section identify mean plus/minus standard error of the mean ($M \pm SEM$).

A main effect of task sequence emerged, with faster responses in fixed-sequence blocks ($M = 541 \pm 10$ ms, $M = 590 \pm 9$ ms), $F(1,30) = 176.71$, $p < .001$, $\eta_p^2 = 0.85$. An additional main effect of task repetition was detected, with faster responses when the task repeated ($M = 530 \pm 7$ ms, $M = 601 \pm 12$ ms), $F(1,30) = 153.02$, $p < .001$, $\eta_p^2 = 0.84$. Task repetition interacted with task sequence: the benefit of task repetition was greater in fixed-sequence blocks (fixed-sequence:

$\Delta M_{(\text{switch-rep})} = 76 \pm 6$ ms, random-sequence: $\Delta M_{(\text{switch-rep})} = 67 \pm 7$ ms), $F(1,30) = 7.32$, $p = .01$, $\eta_p^2 = 0.20$.

In line with the idea that participants in the color-categorization group would most benefit from the opportunity to prepare, task sequence interacted with categorization group: participants in the color-categorization group benefited from fixed task sequence more than did participants in the shape-categorization group (color-categorization group: $\Delta M_{(\text{rand-fix})} = 70 \pm 6$ ms, shape-categorization group: $\Delta M_{(\text{rand-fix})} = 29 \pm 4$ ms), $F(1,30) = 30.84$, $p < .001$, $\eta_p^2 = 0.51$). Similarly, task repetition interacted with categorization group: participants in the color-categorization group benefited from task repetition more than did participants in the shape-categorization group (color-categorization group: $\Delta M_{(\text{switch-rep})} = 84 \pm 10$ ms, shape-categorization group: $\Delta M_{(\text{switch-rep})} = 59 \pm 6$ ms), $F(1,30) = 4.55$, $p = .04$, $\eta_p^2 = 0.13$. Although participants in the color-categorization group responded nominally faster than participants in the shape-categorization group ($M = 548 \pm 13$ ms, $M = 584 \pm 13$ ms), this effect failed to reach significance, $F(1,30) = 3.58$, $p = .07$, $\eta_p^2 = 0.11$. No other effects emerged (all $ps > .1$).

The only reliable effect on accuracy was a main effect of task repetition ($M_{\text{repetition}} = 98.4 \pm 0.2\%$ vs. $M_{\text{switch}} = 96.3 \pm 0.5\%$), $F(1,30) = 40.18$, $p < .001$, $\eta_p^2 = 0.57$.

3.1.2 | ERP results

(See Figure 3) Focusing on the switch trials, the N2pc was analyzed in a 2-way ANOVA with between-subject factor for categorization group and within-subject factor for task sequence. Figure 3 further separates the data as a function of the location of the non-predictive singleton, but statistical analysis was collapsed across this factor. As evident in Figure 3, color singletons create an early positive-polarity effect in the lateral ERP. This early lateral positivity emerges contralateral to the location of the color singleton for both color-categorization and shape-categorization groups without differing between these groups. This appears to reflect the "positivity posterior contralateral" component (PPC), which is thought to reflect stimulus salience and does not vary as a function of whether an eliciting stimulus is a target or distractor (Corriveau et al., 2012). Consistent with the idea that preparation would improve attentional resolution of the target, analysis of the N2pc identified a main effect of task sequence, with the N2pc larger in fixed-sequence blocks ($M = -0.96 \pm 0.21 \mu V$, $M = -0.73 \pm 0.21 \mu V$), $F(1,30) = 5.73$, $p = .02$, $\eta_p^2 = 0.16$. No other effects emerged (all $ps > .1$).

3.2 | Search task

3.2.1 | Behavioral results

(See Figure 2c,e) RT and accuracy were analyzed in a 4-way ANOVA with a between-subject factor for categorization group (color-categorization group vs. shape-categorization group) and within-subject factors for distractor-presence (distractor present vs. absent), task sequence (fixed vs. random sequence), and task repetition (task switch vs. task repetition).

In analysis of RT, a main effect of distractor-presence emerged, with slower responses when the distractor was present ($M = 640 \pm 12$ ms, $M = 667 \pm 13$ ms), $F(1,30) = 84.09$, $p < .001$, $\eta_p^2 = 0.74$. An additional main effect of task sequence emerged, with faster responses in fixed-sequence blocks ($M = 639 \pm 13$ ms, $M = 667 \pm 12$ ms), $F(1,30) = 44.31$, $p < .001$, $\eta_p^2 = 0.60$. The main effect of task repetition was also significant, with faster responses in task repetition trials ($M = 625 \pm 11$ ms, $M = 681 \pm 15$ ms), $F(1,30) = 68.37$, $p < .001$, $\eta_p^2 = 0.70$.

Categorization group interacted with distractor-presence: the distractor cost was larger in the color-categorization group ($\Delta M = 37 \pm 5$ ms, $\Delta M = 17 \pm$

3 ms), $F(1,30) = 10.82$, $p = .003$, $\eta_p^2 = 0.27$. The history of selecting color during the categorization task appears to have increased sensitivity to color during the search task.

Categorization group also interacted with task sequence: the propensity toward faster responses in fixed-sequence blocks was accentuated in the color-categorization group (color-categorization group: $\Delta M_{(\text{rand-fix})} = 39 \pm 7$ ms, shape-categorization group: $\Delta M_{(\text{rand-fix})} = 18 \pm 5$ ms), $F(1,30) = 6.29$, $p = .02$, $\eta_p^2 = 0.17$. This suggests increased preparation in this group, who had to switch task sets between trial types. Note that even though the color-categorization group responded numerically faster than the shape-categorization group in the fixed-sequence blocks ($M_{\text{color-categorization}} = 625 \pm 19$ ms, $M_{\text{shape-categorization}} = 652 \pm 19$ ms, $t(30) = 1.04$, $p = .30$), the distractor cost remained marginally larger ($\Delta M_{\text{color-categorization}} = 33 \pm 5$ ms, $\Delta M_{\text{shape-categorization}} = 20 \pm 4$ ms, $t(30) = 2.05$, $p = .05$).

Task sequence interacted with task repetition: the benefit of task repetition was greater in fixed-sequence blocks than in random-sequence blocks ($\Delta M_{(\text{switch-rep})} = 59 \pm 7$ ms, $\Delta M_{(\text{switch-rep})} = 51 \pm 6$ ms), $F(1,30) = 6.57$, $p = .02$,

Difference waves in the categorization task locked to the predictive singleton: switch trials

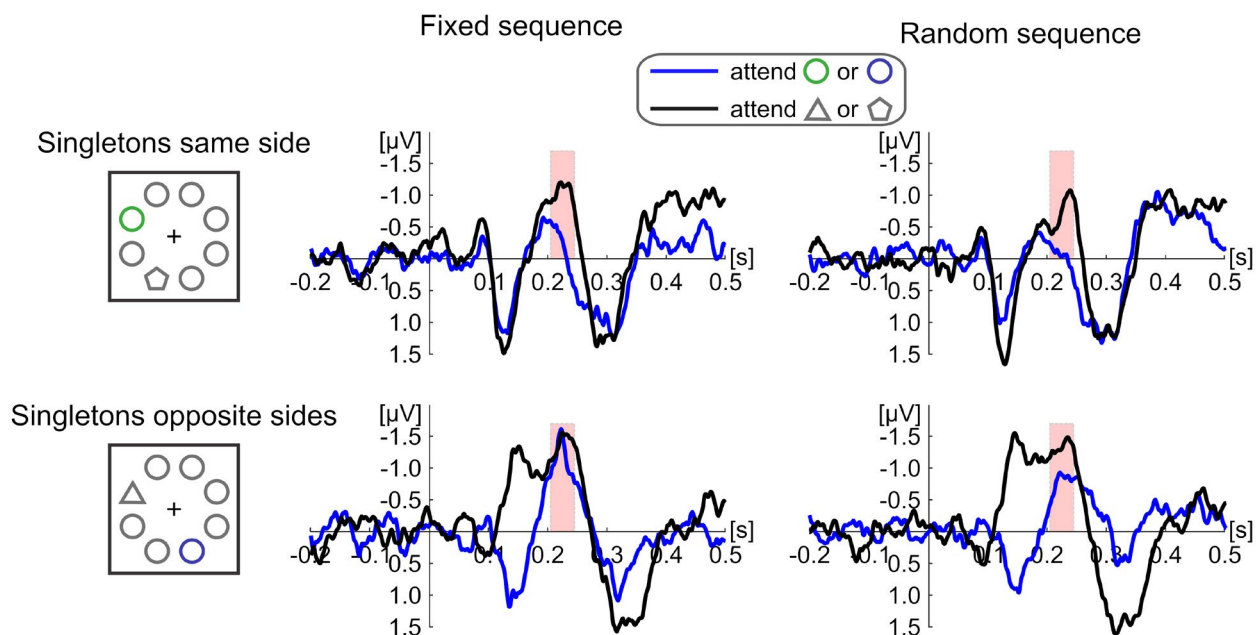


FIGURE 3 Grand-average of difference waves recorded at parieto-occipital electrodes PO7 and PO8, elicited by predictive singletons in switch trials in the categorization task, locked to the location of the color singleton in the color-categorization group (blue lines) or locked to the location of the shape singleton in the shape-categorization group (black lines). The upper panels represent the waveforms when singletons appear on the same side and the lower panels represent the waveforms when singletons appear on the opposite sides for fixed (left panels) and random-sequence blocks (right panels). For illustration purposes, EEG waveforms were filtered using a low-pass Butterworth filter with high cutoff frequency of 35 Hz (12 dB/oct)

$\eta_p^2 = 0.18$. Task repetition also interacted with distractor cost: the distractor cost was smaller when the task was repeated ($\Delta M = 24 \pm 4$ ms, $\Delta M = 30 \pm 3$ ms), $F(1,30) = 8.40$, $p = .007$, $\eta_p^2 = 0.22$.

A marginal three-way interaction between distractor-presence, task sequence, and categorization group emerged: participants showed a numerically smaller distractor cost in fixed-sequence blocks, but only in the color-categorization group (color-categorization group: $\Delta M_{\text{fixed}} = 33 \pm 5$ ms, $\Delta M_{\text{random}} = 40 \pm 6$ ms; shape-categorization group: $\Delta M_{\text{fixed}} = 20 \pm 4$ ms, $\Delta M_{\text{random}} = 14 \pm 3$ ms), $F(1,30) = 3.89$, $p = .058$, $\eta_p^2 = 0.11$.

No other effects on RT emerged ($ps > .1$) and the only reliable effect on accuracy was an improvement in repetition trials ($M = 96.6 \pm 0.4\%$, $M = 95.7 \pm 0.6\%$), $F(1,30) = 5.21$, $p = .03$, $\eta_p^2 = 0.15$.

3.2.2 | ERP results. Distractor-absent trials (Figure 4a)

Target-elicited N2pc

Focusing on the switch trials, the N2pc was analyzed with a 2-way ANOVA with a between-subjects factor for categorization group and within-subject factor for task sequence. This identified a trend toward an interaction of categorization group and task sequence, with the effect of task sequence more pronounced in the color-categorization group ($M_{\text{fixed}} = -1.16 \pm 0.30$ μV , $M_{\text{random}} = -0.78 \pm 0.28$ μV) than in the shape-categorization group ($M_{\text{fixed}} = -1.47 \pm 0.30$ μV , $M_{\text{random}} = -1.58 \pm 0.28$ μV), $F(1,30) = 3.27$, $p = .08$, $\eta_p^2 = 0.10$. No other effects emerged ($ps > .1$). N2pc onset did not reliably vary in any analysis ($ps > .1$).

3.2.3 | ERP results. Distractor-present trials: target and distractor in same hemifield (Figure 4b)

Distractor-elicited early Pd

We focused on switch trials in analysis of the early Pd. A 2-way ANOVA with a between-subject factor for categorization group and a within-subject factor for task sequence identified a main effect of categorization group: early Pd was larger in the shape-categorization group ($M = 0.98 \pm 0.14$ μV , $M = 0.57 \pm 0.14$ μV), $F(1,30) = 4.36$, $p = .045$, $\eta_p^2 = 0.13$. A main effect of task sequence also emerged, with the Pd larger in fixed-sequence blocks ($M = 0.99 \pm 0.14$ μV , $M = 0.57 \pm 0.12$ μV), $F(1,30) = 5.25$, $p = .03$, $\eta_p^2 = 0.15$, as well as a trend toward an interaction of categorization group and task sequence, with the effect of

task sequence more pronounced in the shape-categorization group ($M_{\text{fixed}} = 1.36 \pm 0.20$ μV , $M_{\text{random}} = 0.60 \pm 0.18$ μV) than in the color-categorization group ($M_{\text{fixed}} = 0.61 \pm 0.20$ μV , $M_{\text{random}} = 0.53 \pm 0.18$ μV), $F(1,30) = 3.36$, $p = .08$, $\eta_p^2 = 0.10$. Separate comparisons between the early Pd in fixed and in random-sequence blocks for each group showed that the marginal interaction of categorization group and task sequence was driven by the shape-categorization group ($t(15) = 3.58$, $p = .003$) rather than the color-categorization group ($t(15) = 0.28$, $p = .78$).

Target-elicited N2pc

Focusing on the switch trials, the N2pc was analyzed with a 2-way ANOVA with a between-subject factor for categorization group and within-subject factor for task sequence. This identified a significant interaction of categorization group with task sequence, with the effect of task sequence more pronounced in the color-categorization group ($M_{\text{fixed}} = -1.18 \pm 0.32$ μV , $M_{\text{random}} = -.69 \pm 0.30$ μV) than in the shape-categorization group ($M_{\text{fixed}} = -1.19 \pm 0.32$ μV , $M_{\text{random}} = -1.48 \pm 0.30$ μV), $F(1,30) = 5.77$, $p = .02$, $\eta_p^2 = 0.16$. No other effects emerged ($ps > .1$) and there was no effect on N2pc onset latency ($ps > .1$).

3.2.4 | ERP results. Distractor-present trials: target and distractor in opposite hemifield (Figure 4c)

Distractor-elicited early Pd

As noted above, the Pd in this condition expresses as a negativity contralateral to the target (and thus a positivity contralateral to the distractor). Focusing on the switch trials, a 2-way ANOVA with a between-subject factor for categorization group and a within-subject factor for task sequence identified a significant interaction of categorization group with task sequence, with the effect of task sequence more pronounced in the shape-categorization ($M_{\text{fixed}} = -1.31 \pm 0.22$ μV , $M_{\text{random}} = -0.80 \pm 0.18$ μV) than in the color-categorization group ($M_{\text{fixed}} = -0.54 \pm 0.22$ μV , $M_{\text{random}} = -0.78 \pm 0.18$ μV), $F(1,30) = 6.39$, $p = .02$, $\eta_p^2 = 0.18$. This significant interaction was further analyzed by comparing the early Pd in fixed and random-sequence blocks for each group using two dependent sample t tests. This analysis showed that the amplitude of the early Pd significantly differed between fixed and random-sequence blocks, but only for the shape-categorization group (shape-categorization: $t(15) = 2.35$, $p = .03$; color-categorization: $t(15) = 1.20$, $p = .25$). There were no other significant effects on the early Pd (all $ps > .1$). Further analysis of the Pd—collapsed across the results illustrated in Figure 4b,c—is described below.

Difference waves in the search task: switch trials

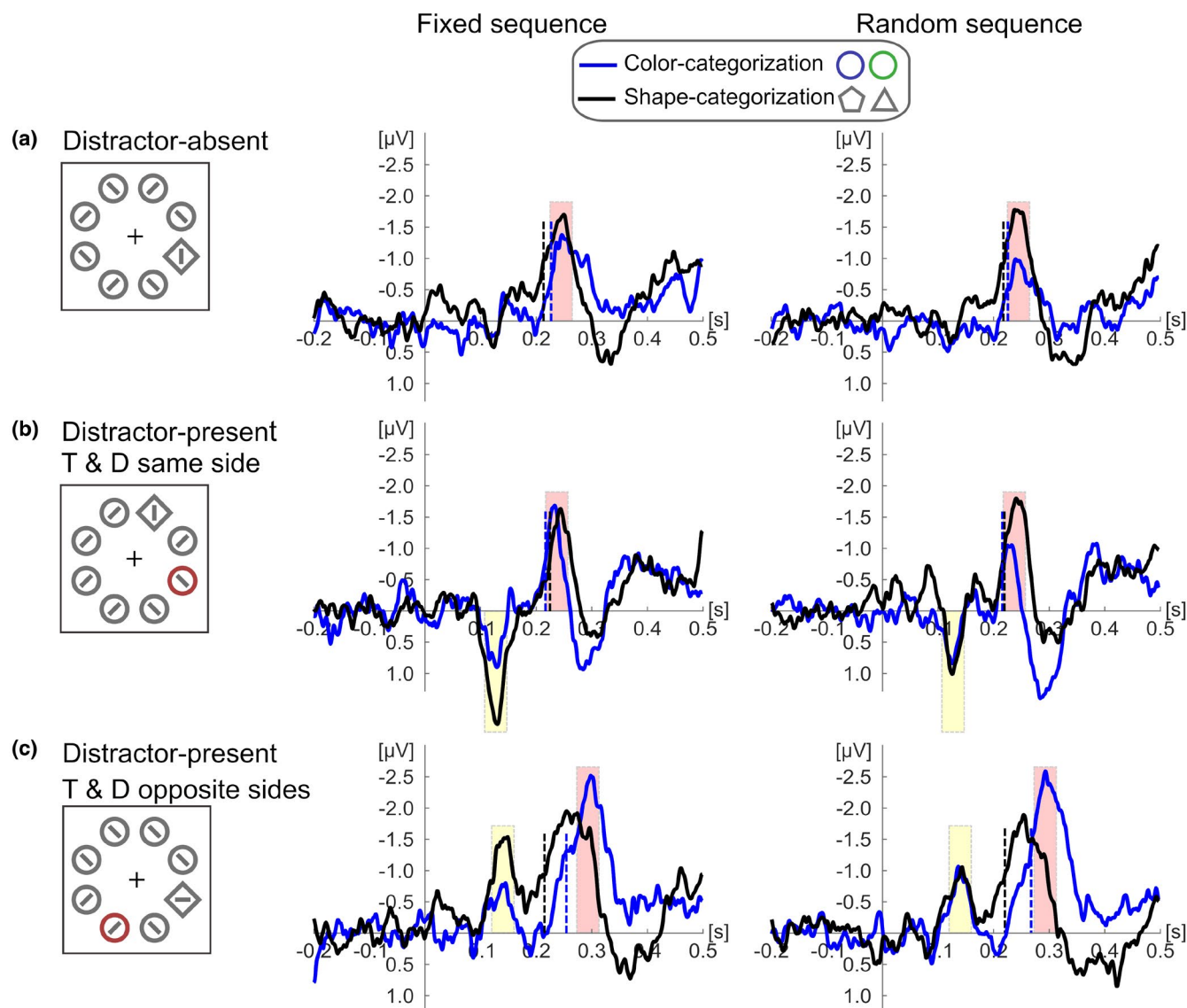


FIGURE 4 ERP difference waves computed from contra- minus ipsilateral waveforms recorded at parieto-occipital electrodes PO7 and PO8 in switch trials in the search task: (a) ERPs in distractor-absent trials, (b) ERPs in trials with target and distractor presented on the same side of the visual field and (c) ERPs in trials with target and distractor presented on opposite sides of the visual field. ERPs are visualized separately for fixed (left panels) and random-sequence blocks (right panels). Blue lines represent difference waves of the color-categorization group; black lines represent difference waves of the shape-categorization group. The epochs marked in yellow represent the early Pd component and the epochs marked in red represent the N2pc component. Vertical dotted lines represent the time point at which 50% of the maximum amplitude was reached. For illustration purposes, time series were filtered using a low-pass Butterworth filter with high cutoff frequency of 35 Hz (12 dB/oct)

Target-elicited N2pc

Focusing on switch trials, a 2-way ANOVA with a between-subject factor for categorization group and within-subject factor for task sequence identified a trend to an effect of categorization group: the N2pc amplitude was numerically larger in the color-categorization group ($M = -2.20 \pm 0.36 \mu\text{V}$) than in the shape-categorization group ($M = -1.23 \pm 0.36 \mu\text{V}$), though this did not reach significance, $F(1,30) =$

3.72 , $p = .06$, $\eta_p^2 = 0.11$. No other effects emerged (all $ps > .1$). The N2pc emerged earlier in the shape-categorization group ($M_{\text{shape-categorization}} = 218 \pm 0.8 \text{ ms}$, $M_{\text{color-categorization}} = 261 \pm 0.8 \text{ ms}$). When jackknife latency measures were submitted to a 2-way ANOVA with a between-subject factor for categorization group and within-subject factor for task sequence, a main effect of categorization group emerged, $F_c(1,30) = 7.25$, $p = .01$, $\eta_p^2 = 0.98$, all other $ps > .1$.

3.2.5 | ERP results. Early Pd collapsed across “Target and distractor in same hemifield” (Figure 4b) and “Target and distractor in opposite hemifield” (Figure 4c) conditions

To gain statistical power, we additionally analyzed the early Pd elicited in switch trials across the “target and distractor in same hemifield” and “target and distractor in opposite hemifield” conditions. Because the early Pd expressed as a positivity when target and distractor were in one hemifield, but as a negativity when these stimuli were located contralateral to one another, this analysis was based on rectified polarity as measured at its cross-conditional peak.

A 2-way ANOVA with a between-subject factor for categorization group and within-subject factor for task sequence identified a main effect of categorization group, with the Pd larger in the shape-categorization group ($M = 1.02 \pm 0.13 \mu\text{V}$, $M = 0.62 \pm 0.13 \mu\text{V}$), $F(1,30) = 4.53$, $p = .04$, $\eta_p^2 = 0.13$, and a main effect of task sequence ($M_{\text{fixed}} = 0.96 \pm 0.12 \mu\text{V}$, $M_{\text{random}} = 0.68 \pm 0.10 \mu\text{V}$), $F(1,30) = 5.31$, $p = .03$, $\eta_p^2 = 0.15$.

Importantly, categorization group interacted with task sequence: the difference between fixed and random-sequence blocks was larger for participants in the shape-categorization group (shape-categorization group: $M_{\text{fixed}} = 1.33 \pm 0.17 \mu\text{V}$ vs. $M_{\text{random}} = 0.70 \pm 0.14 \mu\text{V}$, color-categorization group: $M_{\text{fixed}} = 0.58 \pm 0.17 \mu\text{V}$ vs. $M_{\text{random}} = 0.66 \pm 0.14 \mu\text{V}$), $F(1,30) = 8.79$, $p = .006$, $\eta_p^2 = 0.23$. The stimulus-triggered suppression indexed in the early Pd was thus larger in the shape-categorization group, when the fixed task sequence gave the opportunity for quick stimulus-triggered suppression when the stimulus appeared. Finally, separate comparisons between the early Pd in fixed and in random-sequence blocks for each group showed that the interaction of categorization group and task sequence was solely driven by the shape-categorization group ($t(15) = 4.59$, $p < .001$), and not by the color-categorization group ($t(15) = 0.40$, $p = .69$).

3.2.6 | Time-frequency results (Figure 5)

To index pre-stimulus preparation we contrasted oscillatory power in switch trials with oscillatory power in repetition trials. This was separately achieved for fixed and random-sequence blocks for each of the color-categorization (Figure 5a) and shape-categorization groups (Figure 5b).

In fixed-sequence blocks, participants in the color-categorization group showed less power in posterior alpha (8–14 Hz) in the –470–800 interval in switch compared

to repetition trials ($p < .01$; mean power spectrum in the significantly different bins: $M_{\text{switch}} = 9.65 \pm 2.52 \mu\text{V}^2$, $M_{\text{repetition}} = 10.72 \pm 2.70 \mu\text{V}^2$; Figure 5a, upper panels). No corresponding effect emerged in random-sequence blocks (Figure 5a, lower panels).

This pattern did not emerge with the same strength in the shape-categorization group (Figure 5b). In fixed-sequence blocks, participants in the shape-categorization group showed less power in posterior alpha (12–14 Hz) in the –530–800 interval in switch compared to repetition trials ($p < .01$; mean power spectrum in the significantly different bins: $M_{\text{switch}} = 7.25 \pm 3.01 \mu\text{V}^2$, $M_{\text{repetition}} = 7.86 \pm 3.20 \mu\text{V}^2$; Figure 5b, upper panels). No corresponding effect emerged in random-sequence blocks (Figure 5b, lower panels). To contrast the groups, we compared the normalized switch-vs-repetition effect using cluster-based permutation tests (Figure 5c). When comparing pre-stimulus power between switch and repetition trials in the categorization task, no significant difference in the range of alpha-band was observed.

4 | DISCUSSION

This study investigated the relation of two potentially conflicting influences on attentional selection, namely proactive top-down control and selection history. The primary motivating question was whether participants would adjust proactive attentional control to compensate for an attention bias resulting from individual selection history. The study was designed to identify the specific mechanisms that might support this kind of control.

Participants performed a combination of two intermingled visual tasks, a categorization task and a search task. In the categorization task, they were presented with stimuli arrays containing a shape singleton and a color singleton (Figure 1a). Half of the participants—the shape-categorization group—reported the shape of the shape singleton, whereas the other half—the color-categorization group—reported the color of the color singleton. In the search task, all participants searched for a shape singleton in an array that sometimes contained a task-irrelevant color singleton (Theeuwes, 1991).

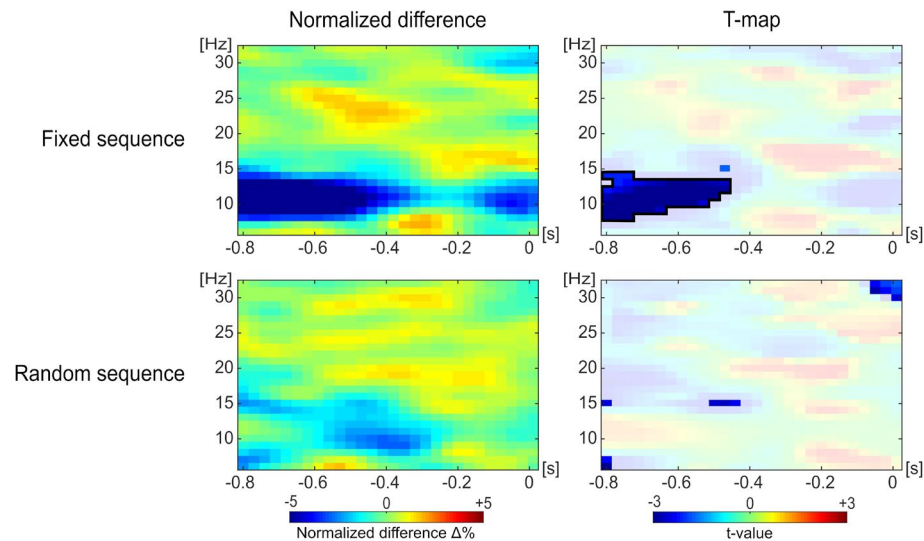
Preparing for a new task after having performed a different task requires an updating process known as *task-set reconfiguration* (e.g., Karayanidis et al., 2010; Longman et al., 2013; Meiran et al., 2008). Although both groups in our experiment had to reconfigure their task set (e.g., shift from categorization to search, respond with different effectors), switching between tasks was more complex for the color-categorization group. These participants had to search for color singletons in the categorization task and

ignore shape singletons, but search for shape singletons in the search task and ignore color singletons. Participants in the shape-categorization group had it easier: they always searched for shape singletons and ignored color singletons.

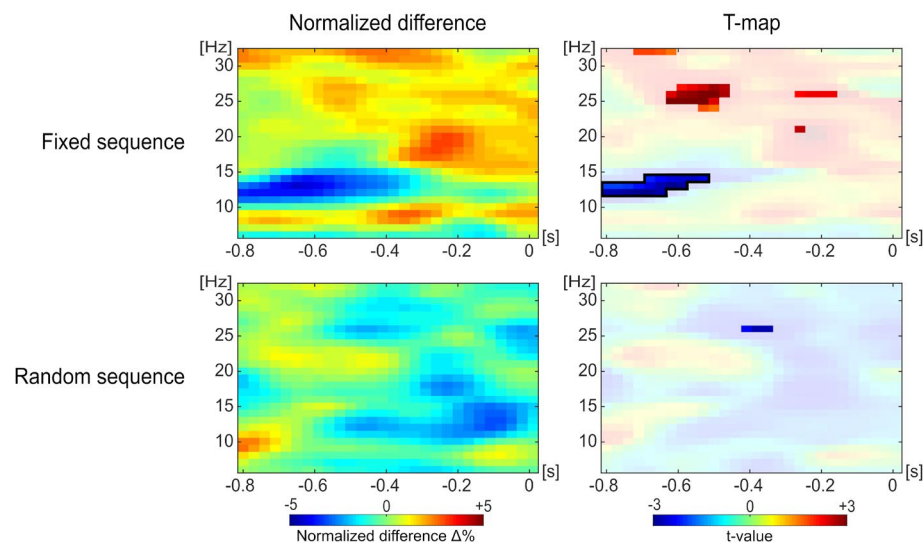
Based on prior work, we expected that participants in the color-categorization group would show a strong attentional bias toward the color singleton in the search task, reflecting the influence of selection history and the cost of having to switch attentional templates

Differential pre-stimulus oscillation between switch and repetition trials in the search task

(a) Color-categorization group (●○)



(b) Shape-categorization group (△◇)



(c) Color- vs. shape-categorization group: fixed sequence

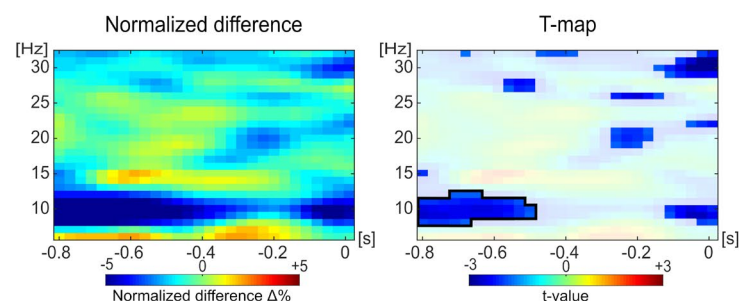


FIGURE 5 (a and b) Differential pre-stimulus oscillation between switch and repetition trials in the color-categorization (a) and the shape-categorization group (b) in fixed (upper panels) and random-sequence blocks (lower panels). Left graphs show normalized differences in pre-search power between switch and repetition trials at posterior channels (pool of O1/2, PO7/8, PO3/4, P7/8, P5/6, P3/4, P1/2, Oz, POz and Pz). Normalized differences were calculated as $[(\text{switch} - \text{repetition}) / (\text{switch} + \text{repetition})] \times 100$ for each time (28 bins) and frequency (27 bins) point for each channel. Right panels show *t*-values, calculated by cluster-based permutation tests. For illustration purposes, bins in the T-maps with $p > .01$ were plotted with less opacity. (c) Comparison of normalized differences in pre-search power between switch and repetition trials in the color-categorization group with that in the shape-categorization group in fixed-sequence blocks. The left graph represents between-group differences of the averaged power over 17 posterior channels. The right panel shows *t*-values calculated by cluster-based permutation tests using independent *t* test. For illustration purposes, bins in the T-maps with $p > .05$ were plotted with less opacity

(Feldmann-Wüstefeld et al., 2015; Kadel et al., 2017). The question was whether participants would be able to establish control over this residual attentional bias and how this control would be mechanistically implemented. To give participants the opportunity to establish control, in some experimental blocks the categorization and search tasks alternated in fixed sequence, so that participants were afforded the opportunity to prepare (Figure 2a). We expected to find that the color-categorization group would use this opportunity more than would the shape-categorization group because their task required greater control.

As expected, results showed that the color-categorization group was more sensitive to the distractor during search. Importantly, the color-categorization group also showed behavioral and electrophysiological evidence of greater preparation. In behavior, this expressed as a RT benefit in fixed-sequence blocks that was stronger for the color-categorization group (Figure 2b,c). In particular, distractor costs in fixed-sequence blocks nominally reduced in the color-categorization group (though this did not reach statistical significance; Figure 2c). In electrophysiology, enhanced preparation was apparent in posterior alpha oscillations. When fixed task sequence allowed them to prepare, both color-categorization and shape-categorization groups showed a reduction of pre-stimulus oscillatory power in the alpha band that was stronger before task-switch trials (Figure 5a,b). However, this effect was substantially larger in the color-categorization group, consistent with the idea that these participants prepared more before the task switch than did the shape-categorization group (Figure 5c).

Preparation thus appears indexed in pre-stimulus posterior alpha and had an impact on post-stimulus behavior. To gain insight on the specific selective mechanisms through which preparation facilitated behavior, we looked to the early Pd and N2pc components of the post-stimulus ERP. The early Pd is known to index rapid, stimulus-triggered distractor suppression (Gaspar & McDonald, 2014; Sawaki & Luck, 2013; Weaver et al., 2017; van Zoest et al., 2021), whereas the N2pc tracks attentional resolution of target features (Luck & Hillyard, 1994a).

4.1 | Preparation in fixed task sequence reduces the need for post-stimulus suppression

Strikingly, enhanced preparation in the color-categorization group was associated not with an increase in early Pd, but with its reduction. That is, the shape-categorization group showed a larger distractor-elicited early Pd in task-switch trials within fixed-sequence blocks than was observed for the color-categorization group (Figure 4b,c). Our interpretation of this pattern is that the preparation tracked in posterior alpha did not facilitate post-stimulus distractor suppression. Rather, this preparation led to a reduction in need for such suppression (cf. van Moorselaar & Slagter, 2020; van Zoest et al., 2021). That is, pre-stimulus suppression led to a situation where the color singleton, when it appeared, had less salience, and therefore required less stimulus-triggered suppression. This could reflect the silencing of feature channels in visual cortex.

It is important to note that an alternative interpretation of this data pattern is available. The early Pd in fixed-sequence blocks may not be reduced in the color-categorization group, but rather increased in the shape-categorization group. This could indicate that the shape-categorization group did not prepare prior to task switches to the same degree as the color-categorization group. As a result, they relied more heavily on stimulus-triggered distractor suppression in order to limit the disruptive influence of the color singleton, resulting in a prominent Pd in fixed-sequence switch trials (Figure 4b,c). Why might participants in the shape-categorization group use post-stimulus suppression when there was the opportunity for pre-stimulus suppression? One possibility is that stimulus-triggered, reactive distractor suppression is less effortful than pre-stimulus maintenance of attentional set. If participants in the shape-categorization group were to employ pre-stimulus attentional set, they would have had to switch sets very commonly in our task—at least once every two trials. The shape-categorization group may have not engaged in this effortful task-switching, instead relying on reactive control (Braver, 2012), and thus the stimulus-triggered suppression reflected in early Pd. Critically, both

interpretations offered here share the notion that pre-stimulus preparation in the color-categorization group resulted in a decrease in need for stimulus-triggered distractor suppression, relative to the shape-categorization group.

The current results add to a growing body of work showing that goal-oriented top-down control mechanisms are especially efficient in guiding attention when they can be instantiated and fine-tuned to current task requirements *before* stimulus onset (Amit et al., 2019; Burra & Kerzel, 2013; Nessler et al., 2012). When participants were faced with a challenging task, they employed such pre-stimulus preparation in an attempt to best optimize their performance.

For example, Liu et al. (2016) found that the N2pc in a perceptually difficult discrimination task was larger when that task was presented predictably and in isolation than when it was intermixed with other difficulty levels of the same task. Similarly, Burra and Kerzel (2013) showed that blockwise predictability of the exact target feature not only increased the target-elicited N2pc during search, but also reduced the distractive potential of a simultaneously presented additional singleton distractor. They argued that observers had used the predictable task blocks to adjust feature selection in an anticipatory, top-down manner. The present study supports and extends this interpretation with neural evidence for predictability-specific task preparation. This is not trivial, as participants in our study were neither instructed nor required to prepare proactively for the upcoming task, and results from the shape-categorization group show that participants could adopt reactive control processes to support task completion (Braver, 2012).

4.2 | Proactive control in predictable versus unpredictable task switching

Our results show a reduction of posterior alpha power that seems to track the establishment of task preparation and the need for changes in attentional set. Several previous studies have reported alpha modulations in paradigms in which observers switched their attention between different visual or sensory tasks. For example, Gladwin and de Jong (2005) found that pre-stimulus posterior alpha decreased in power when participants were cued to switch between auditory and visual tasks, and Foxe et al. (2014) found similar results when the switch was voluntary. Poljac and Yeung (2014) found the same alpha decrease when voluntary task switches were made between unimodal visual tasks. Cooper et al. (2016) have recently investigated the nature of alpha reduction elicited by cues indicating the need for task switching across variety of paradigms

(oddball, go/nogo and task switching). Results suggest that reductions in alpha power may reflect a working memory/rule updating process. Although our study did not use a cue to indicate task switch or repetition, working memory processes and rule updating might have played a role here, as participants had to memorize the trial sequence to prepare for the upcoming trial in fixed-sequence blocks.

Interestingly, pre-stimulus alpha-band power in the categorization task did not differ between switch and repetition trials in fixed-sequence blocks in either of the color-categorization or shape-categorization groups. This further suggests that the pre-stimulus alpha-band modulation observed in fixed-sequence blocks in the search task is probably specific to the setting-up of proactive color suppression, rather than establishment of any general template supporting task completion.

4.3 | The functional significance of early positive-polarity laterality: PPC versus early Pd

What we have referred to as the early Pd in consideration of results from the search task is very similar in latency and polarity to the PPC we identify in the categorization task. That is, in results from both the categorization and search tasks, the ERP shows a strong positive deflection contralateral to the color singleton (Figures 3 and 4), but we label this positive component “PPC” in interpreting the categorization results, but “early Pd” in interpreting the search results. In using these labels, we are attempting to define distinct nomenclature that reflects differences in function. The PPC has been convincingly linked to processing of raw stimulus salience (Corriveau et al., 2012; Pomerleau et al., 2014). Consistent with this, the PPC observed in the categorization task consistently emerges contralateral to the color singleton in all conditions; it is sensitive to the raw physical salience of the color singleton, but not to changes in task context. In contrast, the early Pd has been linked to distractor suppression (Weaver et al., 2017; van Zoest et al., 2021). In line with this idea, the early Pd observed in the search task varies as task context changes the need for selective processing and distractor handling (though physical stimulation remains identical). The PPC and early Pd are therefore distinct in their functional significance. Importantly, it seems likely to us that the positive-polarity effect observed in the search task is composed, in part, of a PPC elicited by the raw physical salience of the color distractor. However, because the PPC is defined by its insensitivity to task context, the fact that the early positivity is sensitive to experimental manipulations (when physical stimulation remains identical) identifies the additional emergence of early Pd.

5 | CONCLUSION

The current results demonstrate that participants will proactively tune their attentional control settings to an upcoming task, and that this will reduce the attentional bias created by prior task set and selection history. However, such proactive control is not necessarily sufficient to compensate for these biases. In these results, participants showed a propensity to be strongly distracted by previous task-relevant objects even in spite of neural and behavioral evidence of their preparation for the appearance of these stimuli. Strategic attentional control thus plays a role in defining attentional prioritization, but does not necessarily have the power to negate the influence of residual attentional biases created by earlier experience.

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AUTHOR CONTRIBUTIONS

Hossein Abbasi: Formal analysis; Methodology; Software; Visualization; Writing—original draft. **Hanna Kadel:** Conceptualization; Data curation; Formal analysis; Methodology; Writing—original draft. **Clayton Hickey:** Methodology; Validation; Writing—review & editing. **Anna Schubö:** Conceptualization; Funding acquisition; Methodology; Resources; Supervision; Writing—review & editing.

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