Abbreviated title: Learned distractor inhibition

Neural mechanisms underlying distractor inhibition on the basis of feature and/or spatial expectations.

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Abstract

A rapidly growing body of research indicates that inhibition of distracting information may not be under flexible, top-down control, but instead heavily relies on expectations derived from past experience about the likelihood of events or statistical learning. Yet, how expectations about distracting information influence distractor inhibition at the neural level remains unclear. To determine how learned expectations about distractor features and/or location modulate distractor processing, we measured EEG while participants performed two variants of the additional singleton paradigm. Critically, in these different variants target and distractor features either randomly swapped across trials, favoring stimulus-driven selection (singleton detection mode), or were fixed, allowing for goal-driven selection (feature search mode) and the development of distractor feature-based expectations. Moreover, participants performed these tasks both with and without a high probability distractor location. Our results show that both distractor feature- and location learning contributed to distractor inhibition, as indicated by corresponding reductions in distractor costs during visual search and an earlier distractor-evoked Pd ERP. Large individual differences further suggest a functional dissociation between early and late Pd components, with the former reflecting early sensory suppression related to intertrial priming and the latter reflecting suppression sensitive to statistical learning over a longer time scale. Spatial expectations did not increase anticipatory alpha-band activity over visual regions representing the expected distractor location, suggesting that statistical learning may rely on activity-silent mechanisms, such as synaptic plasticity. Together, our findings provide further support to the idea that distractor suppression strongly relies on expectations derived from past experience and reveal the neural mechanisms underlying spatial and non-spatial distractor learning.

1. Introduction

Our visual environment is filled with distractions, ranging from billboards alongside the road to the blinking light on your smart phone demanding your attention. An ongoing debate in the attention literature centers around the question whether such visual distractors automatically capture attention in a stimulus-driven fashion (Theeuwes, 2010), or alternatively, only capture attention in a goal-driven manner, when they match the current attentional set (e.g.,)(Folk, Remington, & Johnston, 1992). These competing theories are often studied with variants of the additional singleton paradigm. In this paradigm, observers search for an item with a unique shape (e.g., a circle; target) among non-target shapes, one of which can have a unique feature (e.g., a diamond with a unique color; singleton distractor). Despite their opposing viewpoints, both theories continue to receive empirical support, which can be explained by a subtle, yet important difference in experimental design. Whereas singleton distractors tend to slow down reaction times when target (and non-target) features are not known in advance and can only be identified reactively, such distractor costs are reduced or even disappear when target and non-target features are fixed and target features can therefore be used as an attentional set (Bacon & Egeth, 1994). This shows that the propensity of a salient distractor to capture attention in a given context varies depending on whether the observer is searching for target singletons (called singleton detection mode) or specifically searching for targets with a known feature (called feature search mode).

Event-related potential (ERP) studies support the notion that in feature search mode, attentional capture by salient distractors can be prevented. That is, in mixed-feature variants of the additional singleton paradigm in which target and non-target features randomly swap across trials and search hence relies on singleton detection mode, salient distractors typically elicit an N2pc (Burra & Kerzel, 2013), an ERP index of attentional selection (Luck & Hillyard, 1994b), especially after feature swaps (Hickey, Olivers, Meeter, & Theeuwes, 2011)(but see)(McDonald, Green, Jannati, & Di Lollo,

2013). By contrast, using the same display configurations, but keeping target and non-target shapes fixed across trials, instead of an N2pc salient distractors elicit a Pd, an ERP index linked to inhibition (Gaspelin & Luck, 2018b; Sawaki & Luck, 2010), indicating that salient distractors were effectively filtered out before they could capture attention (Burra & Kerzel, 2013; Jannati, Gaspar, & McDonald, 2013).

Although there are many situations in which salient distractors inevitably capture attention, there is a growing consensus that even in singleton detection mode, salient distractors can nevertheless be suppressed before they capture attention. Critically, however, this appears specific to conditions that allow observers to learn, often implicitly, from statistical regularities across search displays (Chelazzi, Marini, Pascucci, & Turatto, 2019; van Moorselaar & Slagter, 2020). For example, a recent study by Wang and Theeuwes (2018) demonstrated that in a mixed-feature variant of the additional singleton paradigm, salient singleton distractors were more efficiently ignored at locations with a high distractor probability, even though almost all participants were unaware of the embedded statistical regularity (see also)(Ferrante et al., 2018; Goschy, Bakos, Müller, & Zehetleitner, 2014; Leber, Gwinn, Hong, & O'Toole, 2016). These findings add to a rapidly growing body of research that shows that distractor inhibition may not be under voluntary, top-down control, but greatly relies on expectations derived from past experience about the likelihood of events or statistical learning (Noonan, Crittenden, Jensen, & Stokes, 2018; Theeuwes, 2019; van Moorselaar & Slagter, 2020).

While in recent years the Pd and N2pc have been extensively studied under conditions that either favor a singleton detection or a feature search mode, it is less clear how distractor processing is modulated at the neural level by expectations derived from past experience, i.e., when statistical regularities can guide attentional selection. To shed light on this, Wang, van Driel, Ort, and Theeuwes (2019) introduced a high probability distractor location in a mixed-features additional singleton task and showed that at high probability distractor locations, singleton distractors elicited a Pd, whereas without this spatial bias, they elicited an N2pc (measured in an independent set of participants). Critically, not only distractors but also targets elicited a Pd at the high probability distractor location,

which was accompanied by longer search times, suggesting that learning-dependent spatial suppression was set up in advance in a feature blind manner. Consistent with this, alpha-band activity, a marker of top-down neural inhibition (Jensen & Mazaheri, 2010), tuned to the high probability distractor location already increased before search display onset. While such anticipatory and generic spatial suppression may be the relatively most optimal strategy under conditions that enforce singleton detection, it is obviously more advantageous from an ecological perspective to selectively suppress only distractors using feature-based selection. In this respect, it is notable that two recent EEG studies did not observe any changes in anticipatory alpha-band activity as a function of distractor location learning when target and distractor features did not swap across trial (Noonan et al., 2016; van Moorselaar & Slagter, 2019). This suggests that the level at which learning takes place in the visual system can be flexibly fine-tuned as a function of whether the location and/or non-spatial features of an upcoming distractor can be predicted in advance. Indeed, recent behavioral studies have shown that impaired target processing at high probability distractor locations disappears when distractor and target colors are fixed instead of variable across trials (Sauter, Liesefeld, Zehetleitner, & Müller, 2018; Zhang, Allenmark, Liesefeld, Shi, & Muller, 2019). Here, we therefore set out to examine the neural mechanisms underlying distractor inhibition as a function of whether it's likely location and/or specific features (i.e., color and shape) could be predicted in advance.

For this purpose, we measured EEG while observers performed, in separate sessions, fixed-feature and mixed-feature variants of the additional singleton paradigm (Theeuwes, 1992). In the fixed-feature version, all features were fixed throughout an experimental block and participants could apply a feature search mode. By contrast, in the mixed-feature version, target and non-target shapes and colors randomly swapped so that participants could not predict target or distractor features on each subsequent search and had to rely on singleton detection mode (see Figure 1). Of importance, distractor-featured based learning was thus possible only in the fixed-feature task variant. Critically, in both variants, halfway through the experiment, and unbeknownst to the participant, we introduced a high probability distractor location. This allowed us to examine how (implicit) expectations about

distractor features and/or location modulate distractor processing and interference. Without any spatial regularities we expected distractors to elicit a Pd in feature-search mode, but an N2pc, possibly followed by a subsequent Pd signaling reactive distractor inhibition, in singleton detection mode (van Moorselaar & Slagter, 2019). By contrast, with a spatial distractor bias we expected a distractor Pd irrespective of search mode, and no distractor-evoked N2pc. Moreover, following Wang et al. (2019), we expected a feature-blind Pd (i.e., a Pd elicited by both targets and distractors) at high probability distractor locations only in singleton detection mode. Whether the distractor Pd in feature search mode was also sensitive to spatial statistical learning was an open question. Finally, we expected distractor location learning to induce increased anticipatory alpha power contralateral to the high probability distractor location in singleton-detection mode, indicative of generic spatial suppression, but not in feature search mode, when expectations about distractor features could also be formed.

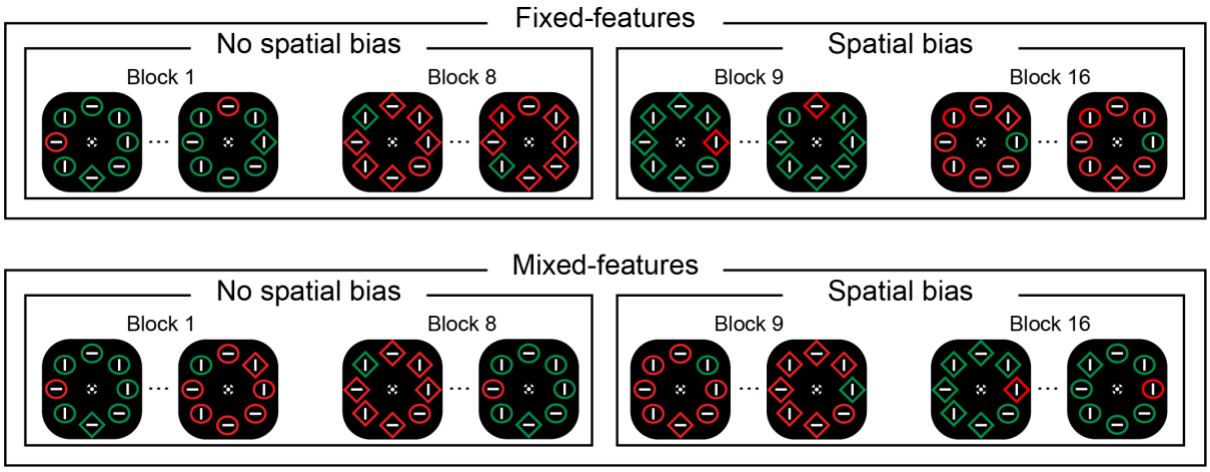

Figure 1 | Experimental paradigm. In each trial participants had to indicate the orientation (vertical or horizontal) of the line inside the unique shape (the target), a diamond among circles or vice versa. In fixed-feature conditions (top row) the display configuration was fixed within an experimental block, whereas in mixed-feature conditions (bottom row) target and non-target features randomly varied across trials. On a subset of trials, the search display also contained a singleton distractor color. Critically, in no spatial bias blocks (i.e., first half of experiment) this distractor appeared equally often at all search locations, whereas in spatial bias blocks it appeared with a higher probability on one specific location (i.e., high probability distractor location).

2. *Methods*

Experiment and analyses were based on the OSF preregistration at Open Science Framework (https://osf.io/n35xa/).

A planned number of 24 participants (Mean age = 23 years, range 18 – 37; 4 men) participated in the experiment after replacement of 2 participants because EEG preprocessing (for details see below) resulted in exclusion of >30% of trials. Participants were seated in a sound-attenuated and dimly lit laboratory at a viewing distance of ~80 cm.

The paradigm was modeled after the Wang et al. (2019) study. Each trial started with a randomly jittered blank display (0-ms – 350-ms) followed by a 1200-ms fixation display. This display contained a shape that looks like a combination of bulls eye and cross hair, which has been shown to improve stable fixation (Thaler, Schütz, Goodale, & Gegenfurtner, 2013) and that remained visible throughout the trial. Subsequently, a search display appeared with eight shapes in a circular configuration around fixation (radius 4.3^{o}), which remained visible until response. Each display contained one circle (radius 1.05^{o}) and seven diamonds (2.7^{o} x 2.7^{o}), or vice versa, each with a red or green outline on a black background and a horizontal or vertical white line segment (1.6^{o}) in their center. Participants were instructed to keep their eyes at fixation and covertly search for the unique shape in the display and indicate the orientation of the line segment in this target shape via a button press (i.e., 'z' or '/' button) as quickly as possible while keeping the number of errors to a minimum. Whereas on 40% of trials all stimuli in the search display had the same color, in the other trials the outline of one of the distractor shapes had a different color than the other stimuli in the display. Participants were instructed to ignore this singleton distractor. Targets and singleton distractors were only presented along the vertical and horizontal axis. Critically, in the first half of the experiment, targets and distractors appeared equally often at these four locations (no spatial bias blocks). In the second half of the experiment, the singleton distractor appeared with 66.7% probability at one of the horizontal locations (counterbalanced across participants), while targets nevertheless continued to appear equally often on all locations (spatial bias blocks).

Crucially, in separate experimental sessions (separated by 5-7 days) participants performed the task in the mixed- or the fixed-feature condition. In the mixed-feature condition, targets were equally likely to be a circle among diamonds or a diamond among circles and the singleton distractor

colors were also equally likely to be red or green. By contrast, in the fixed-feature condition, a new display configuration was introduced at the start of each block, but target and distractor features (i.e., shape and color) remained fixed throughout a block of trials (features counterbalanced across blocks).

Participants completed 16 blocks of 60 trials per session, each preceded by a sequence of training blocks (60 trials; no spatial bias) until they felt comfortable with the task. At the start of each block participants received written instructions about the dynamics of the upcoming set of trials (e.g., 'In the upcoming block the target and distractor will have random shapes and colors'). After each block participants received feedback on their performance (i.e., mean reaction time (RT) and accuracy) and were encouraged to take a break. At the end of the second session, a display with only circles, each with a unique number (i.e., 1-8) corresponding to one of the search locations was shown. Participants were asked to indicate (and if necessary, guess) which location they believed had contained the singleton distractor most frequently throughout the experiment.

Behavioral analysis. All data were preprocessed in a Python environment (Python Software Foundation, https://www.python.org/). As preregistered, behavioral analyses were limited to reaction time (RT) data of correct trials only. RTs were filtered in a two-step trimming procedure: trials with reaction times (RTs) shorter than 200 ms were excluded, after which data were trimmed on the basis of a cutoff value of 2.5 SD from the mean per participant. Remaining RTs were analyzed with repeated measures ANOVAs, where reported *p*-values are Greenhouse-Geiser corrected in case of sphericity violations, followed by planned comparisons with paired t-tests using JASP software *(JASP-TEAM, 2018).*

EEG recording and preprocessing. EEG data were recorded at a sampling rate of 512 Hz using a 64-electrode cap with electrodes placed according to the 10-20 system (Biosemi ActiveTwo system; biosemi.com) and from two earlobes (used as offline reference). Vertical and horizontal EOG (VEOG/HEOG) were recorded via external electrodes placed ~2 cm above and below the eye, and ~1 cm lateral to the external canthi, respectively. EEG from the separate sessions were preprocessed independently (as specified below) after which the two data sets were concatenated.

As preregistered, EEG data were re-referenced off-line to the average of the left and the right earlobe, and subsequently high-pass filtered using a zero-phase 'firwin' filter at 0.1 Hz to remove slow drifts. Continuous EEG was then epoched from -1500 – 1100-ms relative to search display onset (to avoid filter artefacts during preprocessing and time-frequency analysis), with trial rejection procedures and independent component analysis (ICA) being limited to smaller time windows (i.e., -1000 – 600-ms). The resulting epochs were baseline normalized using the whole epoch as a baseline. Prior to trial rejection, malfunctioning electrodes (*M* = 1, range = 0 - 6) were temporarily removed on the basis of visual inspection. EMG contaminated epochs were then identified using an adapted version of an automatic trial-rejection procedure as implemented in the Fieldtrip toolbox (Oostenveld, Fries, Maris, & Schoffelen, 2011). To specifically capture muscle activity we used a 110-140 Hz band-pass filter, and allowed for variable z-score cut-offs per subjects based on within-subject variance of z-scores (de Vries, van Driel, & Olivers, 2017) resulting in an average removal of 9.2% (range 2.3% - 22.4%) of trials thus identified as containing artifacts. Next, ICA as implemented in MNE (method = 'picard') was performed on the continuous EEG to identify and remove eye-blink components from the epoched data. Finally, malfunctioning electrodes were interpolated using spherical splines (Perrin, Pernier, Bertrand, & Echallier, 1989) before the data of the separate sessions was combined.

Throughout the EEG recording, eye movements were monitored using an Eyelink 1000 (SR Research), sampled at 500 Hz, and a head mount. Gaze data were analyzed online, so that every time the participant broke fixation, auditory feedback was provided, signaling to the participant to keep their gaze at fixation. In some cases, this auditory feedback was turned off, but only once fixation was relatively stable, as it was considered distracting by a subset of participants when it did occur. The Eyelink data were also analyzed offline. As in our previous work (van Moorselaar & Slagter, 2019), to control for drifts in the eye-tracker, epochs without a saccade (Nyström & Holmqvist, 2010) in the 300 ms pre-display interval were shifted towards fixation. Each epoch was then summarized by a single value indicating the largest deviation in visual degrees from fixation measured in a segment of data (> 40 ms). The results of the EEG analyses presented next are limited to trials with a fixation deviation

<= 1° or in case of missing Eyelink data, trials with sudden sharp jumps in the HEOG as detected via a step algorithm with a window length of 200-ms, a step size of 10 ms, and with a threshold of $20\mu V$, which led to the exclusion of 7.7% of the cleaned data (range = 0.7% - 21.8%). All EEG preprocessing parameters per subject are summarized at OSF, alongside the raw data files.

Time-frequency analysis. We adopted the same analysis approach as reported in Wang et al. (2019). Using Morlet wavelet convolution, EEG time series were decomposed into their time-frequency representation for frequencies ranging from 1 to 40 Hz in 25 logarithmically spaced steps. To create complex Morlet wavelets, for each frequency a sine wave ($e^{i2\pi ft}$, where i is the complex operator, f is frequency, and t is time) was multiplied by a Gaussian ($e^{-t^2/2s^2}$, where s is the width of the Gaussian). To keep a good trade-off between temporal and frequency precision, the Gaussian width s varied (i.e., $s = \delta/(2\pi f)$, where δ represents the number of wavelet cycles, in 25 logarithmically spaced steps between 3 and 12). Frequency-domain convolution was then applied by multiplying the Fast Fourier Transform (FFT) of the EEG data and Morlet wavelets. The resulting signal was converted back to the time domain using the inverse FFT. Time-specific frequency power was defined as the squared magnitude of the complex signal resulting from the convolution.

Condition-averaged lateralized alpha-power (contra- vs. ipsilateral to high probability distractor location) in the pre-stimulus period (i.e., -1000 – 0-ms.) was evaluated via Z-transformed time-frequency power. Z-values were computed by a statistical transformation of real observed lateralized power for each contra- and ipsilateral channel pair with respect to the mean and standard deviation of a "lateralized" power distribution under the null hypothesis of no difference between a contra- an ipsilateral channel pair. This distribution was obtained with a permutation procedure (*N* = 1000), where we swapped electrode pairs for a random subset of trials. This procedure yields a metric that shows interpretable dynamics over time and frequency and has the benefit of not having to select a pre-stimulus interval, the same interval that we are interested in, for baseline normalization.

Event-related potential (ERP) analysis. We next examined effects of feature- and location-expectations on distractor and target processing using ERPs, which were computed for a prespecified

time window from -100 to 600-ms separately per condition of interest. First, epochs were 30 Hz low-pass filtered and baseline corrected using a -100 to 0 ms pre-stimulus baseline period. To enable isolation of lateralized distractor- and target-specific ERP components, ERP analyses focused on trials in which the stimulus of interest (distractor or target) was presented to the left or right of fixation, while the other stimulus was presented on the vertical meridian. Waveforms evoked by the various search displays were collapsed across left and right visual hemifield and left and right electrodes to produce separate waveforms for contralateral and ipsilateral scalp regions. Lateralized difference waveforms were then computed by subtracting the ipsilateral waveform from the corresponding contralateral waveform.

Following Wang et al. (2019), we focused the analysis of distractor- and target-elicited Pd and/or N2pc ERP waveforms on electrodes PO7/8. The Pd epoch was determined as ± 25-ms from the most positive peak between 100 and 400-ms in the condition-averaged distractor-tuned waveform, whereas the N2pc was determined as ± 25-ms from the most negative peak between 200 and 400-ms in the condition-averaged target-tuned waveform. This data driven approach resulted in a Pd window (110 – 160ms) within the early range of the Pd. Note, however, that in many studies, as was also the case in the Wang et al. (2019) an early Pd is followed by a second positive peak within the N2pc time range. As visual inspection of distractor waveforms confirmed that this late Pd was also present in the current data, we also determined a time-window for this component as ± 25-ms from the most positive peak between 200 and 400-ms in the condition-averaged distractor-tuned waveform.

Analysis software. Preprocessing and subsequent analyses were performed using custom-written analysis scripts, which were largely based on functionalities implemented within MNE (Gramfort et al., 2014). These scripts can be downloaded at https://github.com/dvanmoorselaar/DvM.

3. *Results*

Search times. Exclusion of incorrect responses (6.5%) and data trimming (3.1%) resulted in an overall loss of 9.6% of the behavioral data. We first analyzed distractor costs as a function of search condition (Figure 2A/B). A repeated measures ANOVA with the within subject factors Condition (mixed-features, fixed features) and Distractor (present, absent) using only data from no spatial bias blocks showed faster RTs in fixed- than in mixed-feature conditions (main effect Condition: F (1, 23) = 31.5, $p < 0.001$) and reliable distractor interference (main effect Distractor: F (1, 23) = 119.6, $p < 0.001$). Importantly, a Condition by Distractor interaction (F (1, 23) = 20.6, $p < 0.001$) showed that attentional capture by the distractor was larger in the absence of feature foreknowledge, in the mixed-feature condition (862 vs. 937 ms; t (23) = 7.4, $p < 0.001$) compared to when features were entirely predictable, in the fixed-feature condition (675 vs. 694 ms; t (23) = 5.6, $p < 0.001$). Notably, and counter to previous findings (Bacon & Egeth, 1994), while distractor interference was reduced, it was still far from complete in feature search mode. Conceivably, this may have been the case because in each block observers were introduced to a new display configuration and target and distracter features, which while fixed within a given block, hence varied from block-to-block. Indeed, an exploratory analysis (Figure 2B) in which trials per experimental block were grouped in bins of 10 trials, yielded a close to significant three-way interaction (F (5, 115) = 2.0, $p = 0.086$), which was driven by reliable distractor costs across all bins in mixed-feature condition (all t's > 4.0, all p's < 0.001), but only in the first two bins in fixed-feature condition (all t's > 2.7, all p's < 0.0013) and not in bins 3 – 5 (all t's < 2.0, all p's > 0.057). This finding is in line with the notion that distractor inhibition critically relies on statistical learning and that to resist distractor interference in feature search mode, a specific target template needs to be accompanied by learning-dependent tuning to distractor features (Vatterott & Vecera, 2012).

To subsequently analyze how distractor interference was modulated by distractor location learning, we entered RTs into a repeated measures ANOVA with the within subjects' factors Block Type (no spatial bias, spatial bias), Condition (mixed-features, fixed-features) and Distractor Location (high probability distractor location, low probability distractor location). For this purpose, within no

spatial bias blocks, distractor locations were artificially coded as 'high' and 'low' probable locations as the spatial bias was only introduced in the second half of the experiment. Overall RTs were faster in spatial bias blocks (main effect of Block Type: F (1, 23) = 62.7, $p < 0.001$) and in the fixed-feature condition (main effect of Condition: F (1, 23) = 38.6, $p < 0.001$). Crucially, as visualized in Figure 2C, and reflected in a Block Type by Distractor Location interaction (F (1, 23) = 14.2, $p < 0.001$), distractors were more efficiently ignored at high probability distractor locations in spatial bias blocks, both in mixed- (t (23) = 2.1, $p = 0.047$) and fixed-feature conditions (t (23) = 2.3, $p = 0.028$), yet no such benefit was observed in no spatial bias blocks (all $t's < 1.0$, all $p's > 0.33$). Importantly, distractors continued to produce reliable attentional capture effects (i.e., relative to no distractor trials) at both the low and high probability locations in mixed-feature blocks with a spatial bias (all t's > 6.5, all p's < 0.001). However, in fixed-feature blocks, capture only remained reliable at low probability locations (t (1,23) = 3.3, $p < 0.01$), but no longer at high probability distractor locations (t (1,23) = 2, $p = 0.055$). Together these findings suggest that both feature- and location-based distractor learning reduced distractor interference, and may interact in distractor inhibition.

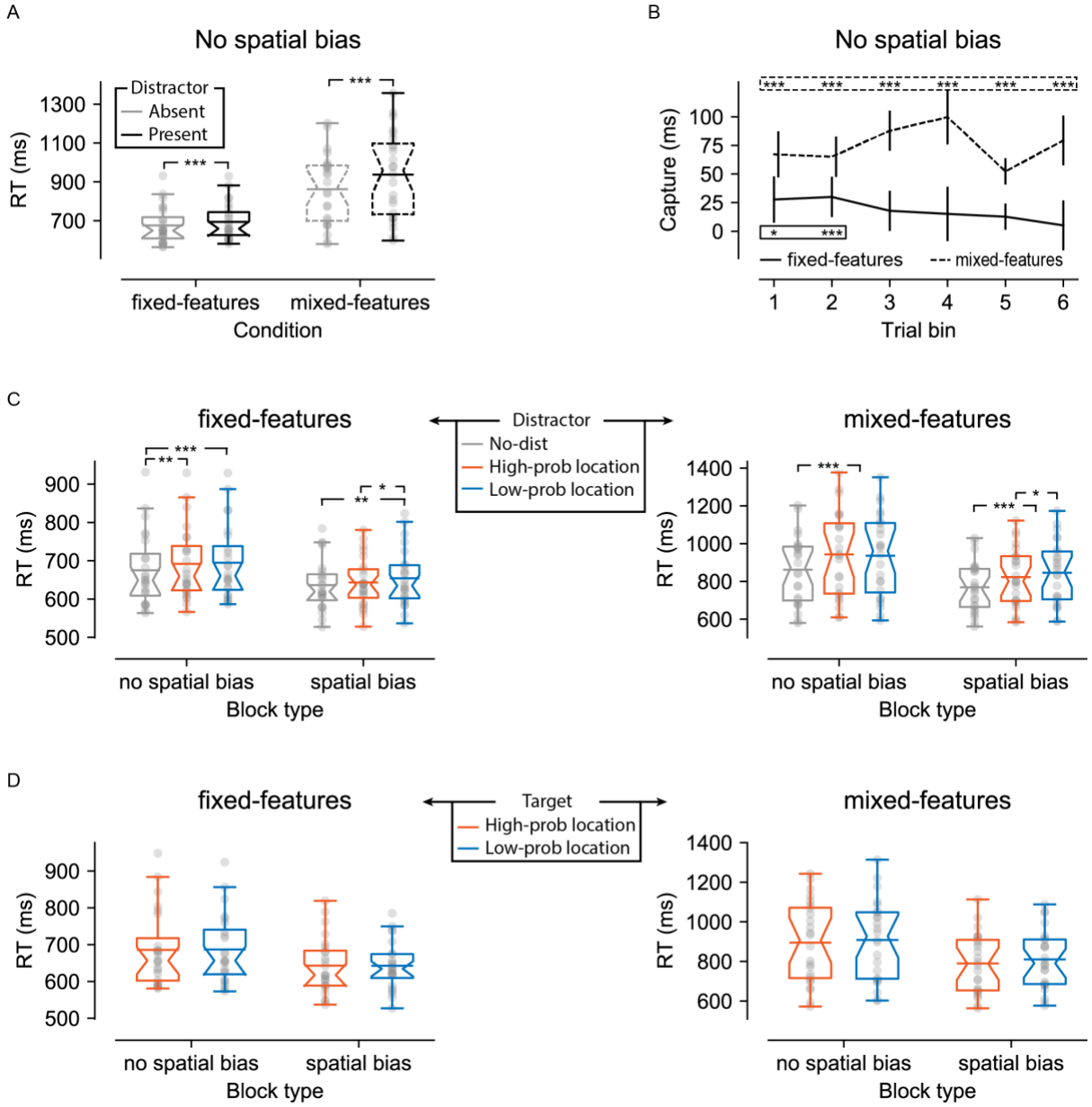

Figure 2 | Behavioral findings visualized by notched boxplots with solid horizontal lines corresponding to the mean. (**A**) Reaction times in no spatial bias blocks shown separately for distractor absent and distractor present trials in the fixed-features and mixed-features conditions. (**B**) Binned distractor interference (distractor present – distractor absent RT) per conditions. Each trial bin corresponds to 10 trials (bin 1: trial 1 – trial 10, bin 2: trial 11 – trial 20, etc). Error bars represent condition-specific, within-subject 95% confidence intervals (Morey, 2008) (**C**) Reaction times as a function of distractor location in no spatial bias and spatial bias blocks for fixed-features (left) and mixed feature (right) conditions. Note that in no spatial bias blocks, distractor locations were artificially coded as high and low probable distractor locations (**D**) Reaction times as a function of target location in no spatial bias and spatial bias blocks for fixed-features (left) and mixed feature (right) conditions. Data is based on distractor absent trials only.

Arguably, a significant proportion of the observed RT benefits in the preceding analysis are explained by short-lasting, intertrial location priming (Maljkovic & Nakayama, 1994). However, previous studies have shown that distractor probability effects cannot solely be explained in terms of

intertrial location priming (e.g.,)(Failing, Feldmann-Wustefeld, Wang, Christian, & Theeuwes, 2019; Ferrante et al., 2018). To examine whether the observed RT benefits remained reliable after controlling for intertrial priming, we repeated the same analysis but now excluding trials in which the distractor location repeated. Although numerically, the pattern remained the same, the Block Type by Distractor Location interaction was no longer significant (F (1, 23) = 1.8, p = 0.19). Also, there no longer was a reliable difference between high and low probability locations, neither in fixed-features (t (23) = 1.0, p = 0.31) nor in mixed-feature conditions (t (23) = 0.9, p = 0.39). This suggests that in our study the observed spatial probability effects largely reflected intertrial location priming rather than spatially specific suppression as a function of distractor location learning.

To further examine the influence of distractor location regularities on spatial suppression, we repeated the preceding analyses, but now tuned to target locations and only including distractor absent trials (Figure 2D). Counter to previous findings (e.g.,)(Failing et al., 2019; Wang et al., 2019), there was no evidence that target processing was impaired at high probability distractor locations across conditions (Block Type by Distractor Location interaction: F (1, 23) = 0.048, p = 0.83), not even when the analysis was limited to the mixed-feature condition (t = 0.8, p = 0.44), where we a priori did expect impaired target processing.

Finally, we examined if participants could correctly identify the high probability distractor location. Eight out of 24 participants correctly identified the high probability distractor location (chance level = 12.5% or 3 participants) suggesting that the spatial bias was noted by at least a subset of participants. However, the average deviation from the high probability location was 2.1 and thus not above chance (chance level = 2). After excluding the eight participants that indicated the correct location, the results from the distractor and target location tuned ANOVA's did not change (i.e., same effects were reliable).

3.1 Interim discussion and exploratory analyses

Consistent with previous studies (e.g.,)(Bacon & Egeth, 1994; Theeuwes, 1992), in mixed-feature blocks the colored distractor singleton reliably captured attention, while in fixed-feature blocks this capture was reduced, but nevertheless reliable. It should be noted though that in fixed-feature blocks, distractor interference was only evident at the start of each block when observers were introduced to a new stimulus configuration, and it disappeared once they were accustomed to the new context, in line with the idea that statistical learning plays a critical role in distractor inhibition (van Moorselaar & Slagter, 2020). Also replicating previous findings, introducing a spatial bias greatly reduced distractor interference at high probability distractor locations. Yet, our findings unexpectedly differ from previous findings in two important aspects. First, distractor suppression was not accompanied by impaired target processing at high probability locations (Wang & Theeuwes, 2018). Second, whereas previous studies have shown that spatial distractor suppression cannot solely be explained in terms of intertrial location priming (Failing et al., 2019; Ferrante et al., 2018), here distractor suppression at high probability locations did appear to be largely driven by lingering biases from the preceding trial. These two discrepancies are especially relevant as we aimed to investigate whether neural mechanisms underlying learning from spatial regularities differ under conditions that either favor stimulus- or goal-driven selection.

One notable difference with previous studies (Wang & Theeuwes, 2018; Wang et al., 2019) is that in the currently study, the high probability location was not introduced immediately, but only halfway through the experiment. It has been shown that different strategies may be applied to the search task depending on the specifics of the individual paradigms (Zhang et al., 2019). Although speculative, in the current study, observers may generally have been less prone to learn more subtle probabilities once they already had developed a strategy specifically tuned to conditions without such probabilities. If distractor rejection is efficient in the absence of spatial regularities, there is also less need for spatial distractor learning, simply because distractors are already efficiently ignored. Indeed, an explorative correlational analysis between distractor interference in the first half of the experiment

(i.e., distractor present vs. absent) and statistical learning (distractor at high vs. low probability location) yielded a robust positive correlation both in mixed- ($r_s = 0.43$, p = 0.038) and fixed-feature blocks ($r_s = 0.45$, p = 0.026). That is, participants who exhibited high distractor interference when its location could not be predicted in advance in the first half of the experiment, generally showed increased statistical learning in the second half of the experiment. This may suggest that whereas spatial statistical learning occurs more or less automatic when regularities are immediately introduced, as in previous studies (e.g.,)(Wang & Theeuwes, 2018; Wang et al., 2019), it becomes increasingly sensitive to individual differences in initial task strategy when the spatial regularity is introduced at a later stage. To investigate these potential individual differences further we divided the participants in two groups ('learners' and 'non-learners') based on whether or not target processing was impaired at high probability distractor locations. As a priori, we expected this impaired target processing to be specific to mixed-feature conditions, we only used this condition to label individual participants as 'learners' and 'non-learners' on the basis of whether the target impairment score (i.e., target at high probability distractor location vs. target at low probability distractor location) was larger or equal to/smaller than zero, respectively. The logic here is that if this division is not simply taking two halves of a normal distribution around zero, but is truly diagnostic of individual differences, then spatial suppression should not only also go above and beyond intertrial priming in 'learners', but one would also expect neural markers of suppression to differ between groups (e.g., a Pd to targets at high probability distractor location in spatial bias blocks in the mixed-features condition in the learners, but not in the non-learners).

Intriguingly, the two groups, which were thus selected on the basis of a target impairment score in spatial bias blocks (i.e., second half of experiment), already differed in no spatial bias blocks (i.e., first half of experiment) with 'learners' exhibiting larger distractor costs than 'non-learners' (Distractor by group interaction: F (1, 22) = 5.1, p = 0.034), while being marginally slower overall (main effect Group: F (1, 22) = 4.0, p = 0.059). More importantly, a Distractor Location by Group interaction showed that 'learners' suppressed distractors more efficiently than 'non-learners' in the spatial bias

blocks (F (1, 22) = 5.7, p = 0.026), and the same interaction remained reliable after exclusion of trials in which the distractor location repeated (F (1, 22) = 5.6, p = 0.027). Moreover, after controlling for intertrial priming, a repeated measures ANOVA using only the 'learners' data yielded a main effect of Distractor Location (F (1, 11) = 8.6, p = 0.014) demonstrating that in 'learners', distractor suppression could not be explained by intertrial priming alone. Finally, although 'learners' were selected on the basis of the target impairment score in the mixed-feature condition, they also exhibited impaired target processing at high probability distractor location in the fixed-feature condition, although this effect was marginally significant (t (11) = 2.00, p = 0.07). Together, these findings suggest that our group division was not an arbitrary split, but rather separated participants that were sensitive to the introduced statistical regularity over longer time scales from those where suppression did not go above and beyond intertrial priming. Therefore, in addition to the preregistered whole group ERP and time-frequency analyses, we also separate between 'learners' and 'non-learners' in these analyses.

3.2 ERPs.

We next examined effects of distractor feature and location expectations on the lateralized Pd and N2pc ERP components. Visual inspection of Figure 3 shows that in the no spatial bias blocks, a positive difference, corresponding to the Pd, emerged to lateral distractors with midline targets. Notably, while this positivity consisted of an early and a late component in the fixed-feature condition, in the mixed-feature condition, in which participants could not predict what the distractor would look like in advance, only a late Pd can be observed. By contrast, in the spatial bias blocks, at the high probability distractor location, the distractor Pd was virtually identical in mixed- and fixed-feature conditions.

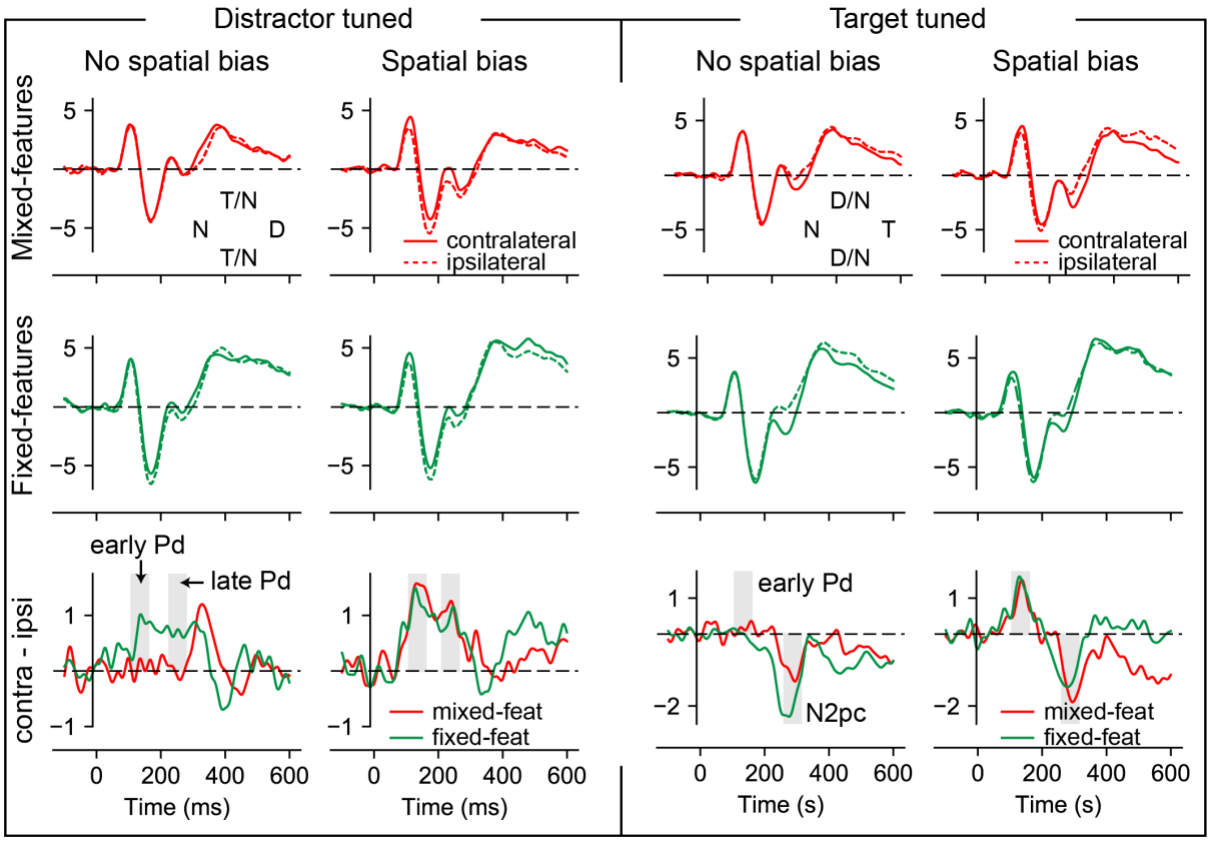

Figure 3 | Electrophysiological results from search trials with lateral distractors (distractor tuned ERPs; columns 1 and 2) and with lateral targets (target tuned ERPS; columns 3 and 4), separately for no spatial bias (columns 1 and 3) and spatial bias blocks (columns 2 and 4). Rows 1 and 2 show the contra- and ipsilateral waveforms for the mixed- and fixed-features conditions, respectively. Row 3 shows the difference between contra- and ipsilateral waveforms for the mixed- and fixed-features conditions. Microvolts are plotted on the y-axes. Inserts shows the schematic target (T), distractor (D) and non-target N) positions. Grey transparent rectangles show the mean averaging windows for early and late Pd and N2pc analyses.

Differences in contra- vs. ipsilateral voltage elicited by lateralized distractors at "high" probability distractor locations at electrodes PO7/8 within the early Pd interval (110 – 160-ms; for window selection, see methods section) were analyzed with a Condition (mixed features, fixed features) by Block Type (no spatial bias, spatial bias) by Hemifield (contralateral, ipsilateral) repeated measures ANOVA. A significant three-way interaction (F (1, 23) = 7.9, p = 0.01) confirmed that the early Pd was reliably larger in fixed- than mixed-feature conditions, but only in no spatial bias blocks (t (23) = 2.9, p = 0.009). The early Pd did not differ between mixed- and fixed-feature conditions at high probability distractor locations in spatial bias blocks (t = 0.8, p = 0.43). The late Pd (217 – 267-ms) mimicking the early Pd results, was also reliably larger in fixed- than mixed-feature conditions, but again only in no spatial bias blocks (t (23) = 2.3, p = 0.031) and not in spatial bias blocks (t = 0.3, p =

0.8), yielding a marginally significant three-way interaction (F (1, 23) = 3.7, p = 0.07). Although this result is in line with the idea that an early suppressive mechanism can only develop in mixed-feature conditions as a function of spatial learning, a clear delayed positivity, albeit outside the late Pd window (see Figure 3 bottom row), could nevertheless be observed in the mixed-feature condition in no spatial bias blocks. This may indicate that distractor inhibition is delayed when inhibition can only be implemented reactively, i.e., post-stimulus, as was the case in the mixed-feature condition no spatial bias blocks in which distractor features and location varied unpredictably from trial to trial. Indeed, an exploratory jack-knife procedure (Miller, Patterson, & Ulrich, 1998) demonstrated that as a function of spatial statistical learning the onset of the late Pd shifted back in time (Δ = 107 ms , t = 2.8).

The presence of a Pd in fixed-feature conditions irrespective of the spatial bias suggests that the observed reduction in distractor interference during feature search mode cannot solely be explained by a more precise target template, but may also reflect feature-based experience-dependent distractor inhibition. In line with this, behaviorally, in fixed feature conditions, distractor interference gradually decreased over the course of a block when observers increasingly gained experience with the distracting information. One would hence expect that in no spatial bias blocks, the Pd also emerged gradually. To test this prediction, following the behavioral analysis where distractor interference was only reliable in the first 20 trials, in an explorative analysis we analyzed the positive area under the curve in a 100 – 400-ms window using only non-spatial bias blocks with a repeated measures ANOVA with the within subjects' factors Condition (mixed-features, fixed-features) and Trial Bin (1 – 20, 21 – 60). Here, we focused on area under the curve rather than mean amplitude as this method is less sensitive to potential latency differences between subjects' as a function of learning. A reliable interaction (F (1, 23) = 5.5, p = 0.028) demonstrated that in fixed-feature blocks the Pd area was indeed larger in the final 40 trials of the block then in the first 20 trials (t (23) = 2.4, p = 0.027), whereas no such difference was observed in mixed-feature conditions (t = 1.3, p = 0.21) (Figure 4). Intriguingly, while the same feature-based learning effect was absent in spatial bias

blocks (F = 1.2, p = 0.29), in fixed-feature conditions the Pd area was larger in spatial bias blocks than in non-spatial blocks, not only for the final 40 (t (23) = 2.5, p = 0.019), but already for the first 20 trials in a block (t (23) = 3.4, p = 0.003). Together these findings suggest that the inhibitory mechanism reflected by the Pd was dependent on both feature-based and location-based information in the fixed feature conditions, whereas in mixed-feature conditions, distractor suppression was purely spatially informed.

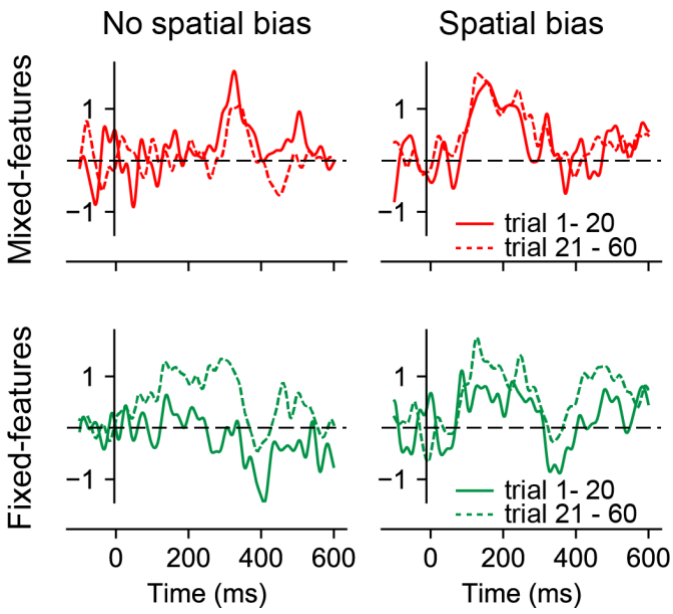

Figure 4 | In fixed features conditions the Pd only emerged 20 trials into each no spatial bias block, suggestive of feature-based learning. Results from exploratory analysis: difference between contra- and ipsilateral waveforms across conditions separately for first 20 (solid lines) and last 40 trials (dashed lines) within a block. Microvolts are plotted on the y-axes.

We next examined effects feature and spatial expectations on target processing. Lateralized ERPs evoked by lateral targets with midline (or absent) distractors are shown in Figure 3. As can be seen, targets evoked a clear N2pc in all conditions. In no spatial bias blocks, this N2pc was larger in amplitude in fixed-feature than in mixed-feature conditions. As expected, after introduction of the spatial bias, targets at high probability distractor locations first appeared to elicit an early Pd, both in the fixed-features and mixed-features condition. Yet, counter to Wang et al. (2019), targets appeared to evoke only an early Pd, which was immediately followed by an N2pc rather than a late Pd.

Voltages elicited by lateralized targets within the N2pc interval (260 – 310-ms; for window selection see method section) were analyzed as above. While the N2pc was reliable across all

conditions (main effect Hemifield: F (1, 23) = 8.3, p = 0.008), there was no evidence that it differed between conditions or was reduced in amplitude at high probability distractor locations, as neither Condition nor Block Type interacted with Hemifield (all F's < 1.5, all p's > 0.23). An analysis of the early Pd interval (110 – 160-ms) did not yield a Block Type by Hemifield interaction (F (1,23) = 1.6, p = 0.69), nor did planned-pairwise comparisons identify hemispheric differences in any of the conditions (all t's < 1.4, all p's > 0.17). This suggests that at a group level, although clearly visible in the group-average lateralized waveforms (Figure 3), the early Pd at high probability distractor locations was not reliably evoked by targets across subjects (but see below).

One potential explanation for the finding that the target-evoked Pd at high probability distractor locations was not reliable, is that it is selectively elicited by a subset of participants. Note that our exploratory behavioral analysis showed that some participants demonstrated spatial statistical learning and impaired target processing, while other participants only exhibited intertrial priming. Therefore, in an exploratory analysis, we included Group ('learners', 'non-learners') as a between subjects' factor to explore whether the target-evoked Pd was selectively elicited by the learners. Surprisingly, however, a Group by Block Type interaction (F (1, 22) = 5.2, p = 0.032) showed that 'non-learners' rather than 'learners' were driving the target Pd effect (see Figure 5), strongly suggesting that the early Pd at the high probability distractor location discussed above thus largely reflects intertrial priming, as some studies have also suggested (Gokce, Geyer, Finke, Müller, & Töllner, 2014), instead of spatial statistical learning. Consistent with this, in spatial bias blocks the early Pd in response to distractors was virtually absent in 'learners', but especially pronounced in 'non-learners' (Group by Block type interaction: F (1, 22) = 4.3, p = 0.05). Intriguingly, the opposite pattern was observed for the late Pd, which appeared largely driven by learners, although this effect was not statistically significant (F (1,22) = 0.8, p = 0.37). This apparent dissociation may suggest that early and late distractor Pd's observed at the group level in spatial bias blocks did not reflect two sequential processes, but instead individual differences in early and late suppression mechanisms. Moreover, the current results may suggest that the early Pd is especially sensitive to intertrial priming.

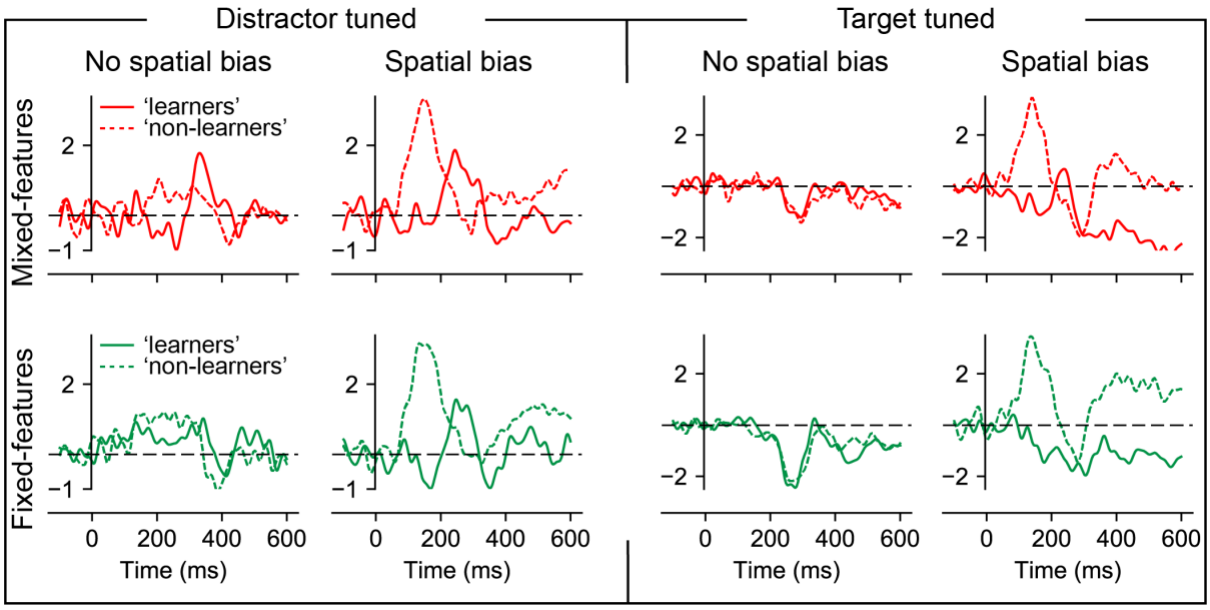

Figure 5 | Individual differences in spatial statistical learning were associated with individual differences in the early and late Pd. Results from exploratory analysis: difference between contra- and ipsilateral waveforms across conditions separately for 'learners' and 'non-learners'. Microvolts are plotted on the y-axes.

3.3 *Time-frequency analysis*.

To investigate whether the introduction of the high probability distractor location lead to anticipatory spatial inhibition, we focused our analysis on pre-stimulus alpha-band oscillatory activity (7.5 – 12 Hz; Figure 6A/B). Counter to Wang et al. (2019), after introduction of the spatial bias, no reliable increase in pre-stimulus alpha-band power was observed at contralateral compared to ipsilateral electrodes relative to the high probability distractor location in the mixed-feature condition, nor in the fixed-feature condition. That is, cluster-based permutation tests across time and alpha frequencies between spatial and non-spatial blocks separately for the fixed-features and mixed-features conditions did not yield any reliable differences, neither did the same tests across time on averaged alpha power. Also, a Condition (mixed-features, fixed-features) by Block Type (no spatial bias, spatial bias) repeated measures ANOVA on averaged alpha power within the anticipatory window did not show reliable effects (-1000 – 0ms) (all F's < 2.0, all p's > 0.17).

It is possible that the development of generic suppression by alpha-band activity is dependent on spatial statistical learning. In an exploratory analysis we therefore next investigated whether lateralized alpha power modulations were specific to participants who exhibited slower search times

when the target was presented at the high probability distractor location (i.e., the learners). As visualized in Figure 6B, however, here again there was no evidence that lateralized alpha power was increased in spatial bias blocks relative to no spatial bias blocks, neither in 'learners' nor in 'non-learners' (all Group interactions: all F's < 1.0, all p's > 0.33). Together, and in line with findings from two other EEG studies (Noonan et al., 2016; van Moorselaar & Slagter, 2019), our findings thus argue against the idea that activity of brain regions representing the high probability distractor location can be suppressed in advance, at least as indexed by modulations of alpha-band activity.

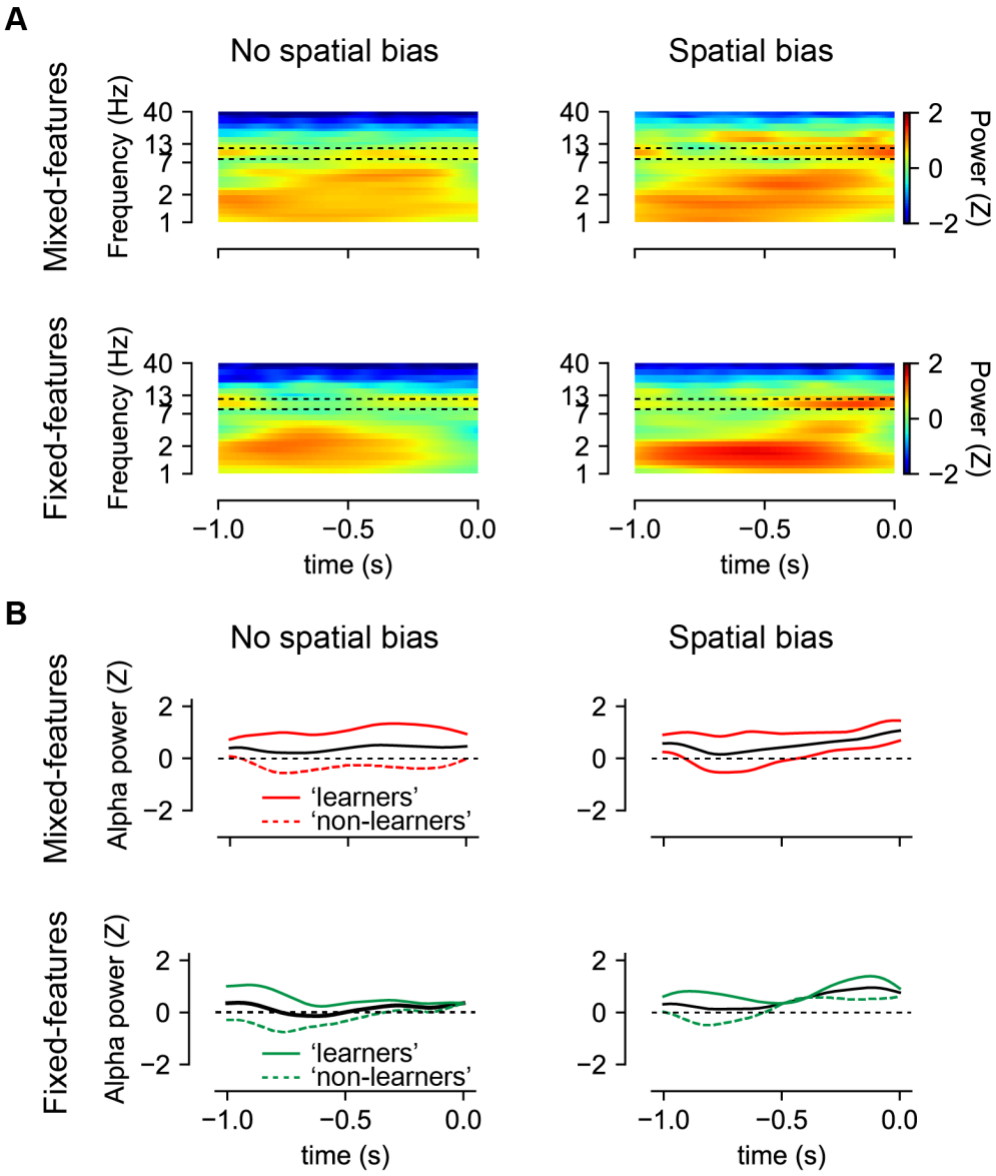

Figure 6 | Distractor location learning was not associated with any changes in pre-stimulus alpha-band activity contralateral to the likely distractor location. Shown is posterior lateralized Z scored power. (**A**) Time-frequency representation of contralateral minus ipsilateral (relative to the high probability distractor location) power averaged over electrodes O1/2, PO3/4 and PO7/8. Dotted black outlines show the frequency bands of interest (7.5 – 12 Hz) (**B**) Time series of contralateral minus ipsilateral averaged alpha power (7.5 – 12 Hz) averaged over electrodes O1/2, PO3/4 and PO7/8. Solid black lines show the group mean, whereas colored lines show the effect separately for participants labeled as 'learners' and 'non-learners'.

4. General discussion

The aim of the present study was to gain more insight into the neural mechanisms underlying distractor inhibition as a function of whether it's specific features and/or likely location could be predicted in advance or not. To this end, observers searched for a unique shape among homogeneous

non-target shapes, either in conditions where target and non-target shapes randomly swapped or were fixed across a sequence of trials, favoring singleton detection mode or feature search mode, respectively. They performed these search tasks both when the distractor location was not, and when it was predictable in advance. We found that the ability to suppress distracting information was dependent on both distractor feature and location learning, although large individual differences were observed in the extent to which individuals exhibited spatial statistical learning. In no-spatial bias blocks, distractor interference was greatly reduced and associated with an earlier Pd when distractor and target features were fixed (i.e., in feature search mode) compared to when they varied across trials (i.e., in singleton detection mode). These findings suggest that distractors could be inhibited faster and more efficiently when distractor features were predictable in advance. Exploratory analyses showed that these effects were dependent on feature-based learning, as only after 20 trials into each fixed-features block, distractor costs disappeared, an effect that was accompanied by the emergence of a distractor-evoked Pd.

Distractor inhibition was in addition affected by distractor location learning, as in both fixed-features and mixed-features conditions, after introduction of the spatial bias, distractor interference was reduced at high-probability distractor locations. This finding indicates that distractor location learning can not only facilitate attentional selection during stimulus-driven selection, but also during goal-driven selection. This is further supported by the observation that the distractor-evoked Pd no longer differed between conditions. However, we also found that at the group level, intertrial priming rather than spatial statistical learning could account for the observed decrease in distractor interference in spatial bias blocks. Exploratory analyses showed that while some participants, those in which target processing was not slowed down at the high probability distractor location, indeed did not exhibit spatial statistical learning ('non-learners'), other participants, in which target processing was impaired at the high probability distractor location, did exhibit spatial statistical learning ('learners'). That is, in 'learners' the observed reduction in distractor interference in spatial bias blocks could not solely be explained by intertrial priming. Interestingly, post-hoc analyses of the ERP data

showed that 'non-learners' only exhibited the early Pd, while, although not reaching statistical significance, 'learners' only exhibited the typical late Pd. Albeit speculative, these findings may suggest that the early Pd selectively reflects changes in sensory processing related to intertrial priming, while the late Pd may more selectively reflect distractor inhibition and be more sensitive to distractor-specific spatial statistical learning. Finally, no location learning-related changes in anticipatory alpha-band activity were observed, suggesting that distractor location learning did not result in generic proactive spatial suppression, in line with two previous studies (Noonan et al., 2016; van Moorselaar & Slagter, 2019), but in contrast to another recent study (Wang et al., 2019). Together, the current findings corroborate the idea that distractor suppression strongly depends on learning based on previous experiences with distracting information (Noonan et al., 2018; van Moorselaar & Slagter, 2020) and reveal the neural mechanisms underlying learned inhibition. In the below, we discuss these findings in more detail in light of the existing literature.

Although distractor interference was reduced in feature-search mode, as in Vatterott and Vecera (2012), it was not eliminated until sufficient experience rejecting a specific distractor accumulated. This not only argues against the idea that a precise target representation is sufficient to prevent distractor interference (Bacon & Egeth, 1994), but also highlights that attentional selection is dependent on learning about distractor properties (Stilwell, Bahle, & Vecera, 2019). As in the current study target and distractor features were fixed throughout an entire block of trials, it remains however, unclear to what extent the observed elimination of distractor costs reflects learning-dependent feature-based suppression, or alternatively intertrial priming (Lamy, Carmel, Egeth, & Leber, 2006). Within the spatial domain, it has been shown that the benefit of distractor predictability cannot solely be accounted for in terms of intertrial priming (e.g.,)(Ferrante et al., 2018; Zhang et al., 2019), although it should be noted that the standard control still allows for influences from more distant trials in the past (Maljkovic & Nakayama, 1994). By contrast and surprisingly, we found that the benefit of distractor location predictability was no longer robust after elimination of all trials in which the distractor location repeated, suggesting that intertrial priming may account for the effects

observed. We also did not observe impaired target processing at the high probability distractor location, as other studies have also shown (e.g.,)(Wang & Theeuwes, 2018). Counter to these studies, here, the spatial regularity was not introduced immediately, but only halfway into the experiment. This raises the possibility that the initial spatially neutral blocks may have induced a particular task strategy in many participants that was insensitive to the subsequently introduced distractor location regularity. Indeed, we found that the same set of participants that were distracted most by the singleton distractor in the first half of the experiment, were also the most sensitive to subsequent spatial distractor regularities. In these participants, in spatial bias blocks irrespective of the search mode, distractor suppression did not only go above and beyond intertrial priming, but was also accompanied by impaired target processing. While the current results thus argue against the idea that generic spatial suppression inevitably arises in singleton detection mode when distractor location learning is possible (Wang & Theeuwes, 2018), future research is necessary to establish the exact prerequisites for such generic suppression and the influence of preceding task contexts on current distractor learning.

Mirroring our behavioral findings that distractor suppression was dependent on feature-based and space-based learning, the distractor Pd only emerged once feature and/or spatial expectations were formed. Extending previous studies (Burra & Kerzel, 2013; Gaspelin & Luck, 2018a), in feature-search mode, a Pd was evoked by distractors irrespective of spatial regularities. Yet, this neural inhibitory mechanism was feature learning dependent, as in no spatial bias blocks the Pd was absent in the beginning of the block when distractors still captured attention, and only emerged once distractor interference gradually decreased. Moreover, at high probability distractor locations, the Pd was also larger in amplitude after feature-based learning, demonstrating that spatial and feature expectations can interactively shape distractor suppression. There is some disagreement on the presence of distractor Pd in singleton detection mode, with some studies reporting an N2pc confirming attentional capture by the singleton distractors (Burra & Kerzel, 2013; Hickey, McDonald, & Theeuwes, 2006), whereas other studies observed a Pd albeit selectively on fast RT trials (McDonald

et al., 2013). Here, at least on a group level, we observed neither an N2pc or a Pd in no-spatial bias blocks in the mixed-features condition, although a delayed contralateral positivity outside our window of interest was observed, suggestive of a delayed late Pd. However, replicating the Wang et al. (2019) study, a robust distractor Pd emerged at the high probability distractor location in the mixed-features conditions, confirming that in singleton detection mode, distractor inhibition can also be guided by distractor location regularities.

In many studies reporting a distractor Pd, the Pd can be separated into an early and a late component (e.g.,)(Wang et al., 2019; Weaver, van Zoest, & Hickey, 2017). Similarly, the distractor Pd observed here clearly contained two separate peaks, suggestive of two sequential inhibitory processes. Whereas initial reports linked the early Pd (also referred to as PPC or lateralized P1) to lateral asymmetries in stimulus processing (Luck & Hillyard, 1994a) or saliency driven selection (Jannati et al., 2013), later studies suggest that the early Pd contributes to active suppression (Gokce et al., 2014), possibly via intertrial priming (Gokce et al., 2014). This has led to the idea that the early Pd reflects negative weights on a saliency map (Feldmann-Wüstefeld & Vogel, 2019). Our finding that the early Pd was specific to conditions that allowed for distractor learning, either at the feature or the spatial level, are directly in line with such an interpretation. Critically, however, our exploratory findings also demonstrate that while the early Pd may signal some pre-attentive suppression, by itself the early Pd is insufficient to filter out new sensory input. This is illustrated by the fact that an early target Pd was only observed in subjects that did not show impaired target processing at high probability distractor locations ('non-learners'). By contrast, in the Wang et al. (2019) study, in which target processing was impaired at high probability distractor locations, the early target Pd was followed by a late target Pd. This discrepancy strongly suggests that the late Pd reflects an additional inhibitory process that ultimately determines whether automatic attentional capture by salient distractors can be prevented (Gaspelin & Luck, 2018b). It is notable in this respect that 'non-learners' who did not exhibit impaired target processing and whose performance improvements in spatial blocks could be accounted for by inter-trial priming, only showed an early distractor Pd, while

‘learners’, who did exhibit impaired target processing and spatial statistical learning above and beyond intertrial priming, only exhibited hints of the late Pd. This further suggests a functional dissociation between the early and late Pd. Albeit speculative, given the post-hoc nature of these latter findings and the low statistical power, the early Pd may hence reflect sensory suppression related to intertrial priming in retinotopically organized visual regions (given that the eyes were at fixation at all times), while the late Pd may reflect suppression related to spatial statistical learning at a higher level in the processing hierarchy, where information is integrated over a longer time scale, at the spatiotopic level. Future research is necessary to more conclusively determine the functional significance of the early and late Pd, and to more systematically examine individual differences in statistical learning.

While it is typically assumed that pre-attentive suppression as indexed by the (early) Pd relies upon proactive inhibition, to date very few studies have also examined anticipatory markers of suppression. Of the few studies that did, despite the prevailing view that alpha oscillations implement active top-down inhibition (Jensen & Mazaheri, 2010), only a single study observed an increase in anticipatory alpha-band activity contralateral to the likely distractor location that was followed by a subsequent Pd to any stimulus presented at that location (Wang et al., 2019). By contrast, two other studies observed expectation-based distractor suppression as indexed via (early) Pd modulations in the absence of any distractor location-related anticipatory alpha lateralization (Noonan et al., 2016; van Moorselaar & Slagter, 2019). A notable difference that might explain this discrepancy in findings is that in these latter two studies, distractor (and target) features were fixed, whereas in the former study they varied from trial to trial, rendering it possible that generic space-based proactive suppression only develops when distractors cannot be predicted at the feature level. Yet, in the current study, even in singleton detection mode, where learning by design could only occur at the spatial level, we also failed to observe any modulation of pre-stimulus alpha activity as a function of distractor location predictability. The current null finding, together with previous null findings (Noonan et al., 2016; van Moorselaar & Slagter, 2019) may suggest that distractor learning exerts it’s effects via an activity silent mechanism, such as plastic changes in synaptic weights. Nevertheless, it

remains also possible that here we did not observe changes in alpha-band activity in singleton detection mode in spatial bias blocks as in Wang et al. (2019), because we did not introduce the spatial regularity immediately. This may have made a subset of participants less sensitive to spatial statistical learning. Nevertheless, even the participants that were most sensitive to spatial statistical learning did not show any modulation of anticipatory alpha activity. It should lastly be noted that despite the widely held view that alpha-band activity reflects active, top-down inhibition, empirical evidence for this notion is limited (Foster & Awh, 2018).

To conclude, here we find that the ability to inhibit distracting information is strongly dependent on both feature-based and space-based distractor learning, as indicated by corresponding reductions in distractor costs during visual search and in the amplitude and latency of the distractor-evoked Pd ERP component. Furthermore, exploratory analyses revealed individual differences in sensitivity to distractor location regularities that may suggest a functional dissociation between the early and late Pd: while the early Pd may reflect early sensory suppression related to intertrial priming, the late Pd may reflect later spatiotopic suppression related to statistical learning over a longer time scale. Finally, our findings suggest that current distractor learning may be influenced by the preceding task context.

References

Bacon, W. F., & Egeth, H. E. (1994). Overriding stimulus-driven attentional capture. *Perception & psychophysics*, *55*(5), 485-496.

Burra, N., & Kerzel, D. (2013). Attentional capture during visual search is attenuated by target predictability: evidence from the N2pc, Pd, and topographic segmentation. *Psychophysiology*, *50*(5), 422-430.

Chelazzi, L., Marini, F., Pascucci, D., & Turatto, M. (2019). Getting rid of visual distractors: The why, when, how and where. *Current opinion in psychology*.

de Vries, I. E., van Driel, J., & Olivers, C. N. (2017). Posterior alpha EEG dynamics dissociate current from future goals in working memory guided visual search. *Journal of Neuroscience*, 2945-2916.

Failing, M., Feldmann-Wustefeld, T., Wang, B., Christian, O., & Theeuwes, J. (2019). Statistical regularities induce spatial as well as feature-specific suppression. *Journal of Experimental Psychology: Human Perception and Performance*.

Feldmann-Wüstefeld, T., & Vogel, E. K. (2019). Neural evidence for the contribution of active suppression during working memory filtering. *Cerebral Cortex, 29*(2), 529-543.

Ferrante, O., Patacca, A., Di Caro, V., Della Libera, C., Santandrea, E., & Chelazzi, L. (2018). Altering spatial priority maps via statistical learning of target selection and distractor filtering. *Cortex, 102*, 67-95.

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.

Foster, J. J., & Awh, E. (2018). The role of alpha oscillations in spatial attention: Limited evidence for a suppression account. *Current opinion in psychology*.

Gaspelin, N., & Luck, S. J. (2018a). Combined Electrophysiological and Behavioral Evidence for the Suppression of Salient Distractors. *Journal of cognitive neuroscience*, 1-16.

Gaspelin, N., & Luck, S. J. (2018b). The role of inhibition in avoiding distraction by salient stimuli. *Trends in cognitive sciences, 22*(1), 79-92.

Gokce, A., Geyer, T., Finke, K., Müller, H. J., & Töllner, T. (2014). What pops out in positional priming of pop-out: insights from event-related EEG lateralizations. *Frontiers in psychology, 5*, 688.

Goschy, H., Bakos, S., Müller, H. J., & Zehetleitner, M. (2014). Probability cueing of distractor locations: both intertrial facilitation and statistical learning mediate interference reduction. *Frontiers in psychology, 5*, 1195.

Gramfort, A., Luessi, M., Larson, E., Engemann, D. A., Strohmeier, D., Brodbeck, C., . . . Hämäläinen, M. S. (2014). MNE software for processing MEG and EEG data. *Neuroimage, 86*, 446-460.

Hickey, C., McDonald, J. J., & Theeuwes, J. (2006). Electrophysiological evidence of the capture of visual attention. *Journal of cognitive neuroscience, 18*(4), 604-613.

Hickey, C., Olivers, C., Meeter, M., & Theeuwes, J. (2011). Feature priming and the capture of visual attention: Linking two ambiguity resolution hypotheses. *Brain research, 1370*, 175-184.

Jannati, A., Gaspar, J. M., & McDonald, J. J. (2013). Tracking target and distractor processing in fixed-feature visual search: evidence from human electrophysiology. *Journal of Experimental Psychology: Human Perception and Performance, 39*(6), 1713.

JASP-TEAM. (2018). JASP (Version 0.8.2) [Computer software].

Jensen, O., & Mazaheri, A. (2010). Shaping functional architecture by oscillatory alpha activity: gating by inhibition. *Frontiers in human neuroscience, 4*, 186.

Lamy, D., Carmel, T., Egeth, H. E., & Leber, A. B. (2006). Effects of search mode and intertrial priming on singleton search. *Perception & psychophysics, 68*(6), 919-932.

Leber, A. B., Gwinn, R. E., Hong, Y., & O'Toole, R. J. (2016). Implicitly learned suppression of irrelevant spatial locations. *Psychonomic Bulletin & Review, 23*(6), 1873-1881.

Luck, S. J., & Hillyard, S. A. (1994a). Electrophysiological correlates of feature analysis during visual search. *Psychophysiology, 31*(3), 291-308.

Luck, S. J., & Hillyard, S. A. (1994b). Spatial filtering during visual search: evidence from human electrophysiology. *Journal of Experimental Psychology: Human Perception and Performance, 20*(5), 1000.

Maljkovic, V., & Nakayama, K. (1994). Priming of pop-out: I. Role of features. *Memory & cognition, 22*(6), 657-672.
McDonald, J. J., Green, J. J., Jannati, A., & Di Lollo, V. (2013). On the electrophysiological evidence for the capture of visual attention. *Journal of Experimental Psychology: Human Perception and Performance, 39*(3), 849.
Miller, J., Patterson, T., & Ulrich, R. (1998). Jackknife-based method for measuring LRP onset latency differences. *Psychophysiology, 35*(1), 99-115.
Morey, R. D. (2008). Confidence intervals from normalized data: A correction to Cousineau (2005). *reason, 4*(2), 61-64.
Noonan, M. P., Adamian, N., Pike, A., Printzlau, F., Crittenden, B. M., & Stokes, M. G. (2016). Distinct mechanisms for distractor suppression and target facilitation. *Journal of Neuroscience, 36*(6), 1797-1807.
Noonan, M. P., Crittenden, B. M., Jensen, O., & Stokes, M. G. (2018). Selective inhibition of distracting input. *Behavioural brain research, 355*, 36-47.
Nyström, M., & Holmqvist, K. (2010). An adaptive algorithm for fixation, saccade, and glissade detection in eyetracking data. *Behavior research methods, 42*(1), 188-204.
Oostenveld, R., Fries, P., Maris, E., & Schoffelen, J.-M. (2011). FieldTrip: open source software for advanced analysis of MEG, EEG, and invasive electrophysiological data. *Computational intelligence and neuroscience, 2011*, 1.
Perrin, F., Pernier, J., Bertrand, O., & Echallier, J. (1989). Spherical splines for scalp potential and current density mapping. *Electroencephalography and clinical neurophysiology, 72*(2), 184-187.
Sauter, M., Liesefeld, H. R., Zehetleitner, M., & Müller, H. J. (2018). Region-based shielding of visual search from salient distractors: Target detection is impaired with same-but not different-dimension distractors. *Attention, Perception, & Psychophysics, 80*(3), 622-642.
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.
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.
Thaler, L., Schütz, A. C., Goodale, M. A., & Gegenfurtner, K. R. (2013). What is the best fixation target? The effect of target shape on stability of fixational eye movements. *Vision research, 76*, 31-42.
Theeuwes, J. (1992). Perceptual selectivity for color and form. *Perception & psychophysics, 51*(6), 599-606.
Theeuwes, J. (2010). Top–down and bottom–up control of visual selection. *Acta Psychologica, 135*(2), 77-99.
Theeuwes, J. (2019). Goal-driven, stimulus-driven, and history-driven selection. *Current opinion in psychology, 29*, 97-101.
van Moorselaar, D., & Slagter, H. A. (2019). Learning What Is Irrelevant or Relevant: Expectations Facilitate Distractor Inhibition and Target Facilitation through Distinct Neural Mechanisms. *Journal of Neuroscience, 39*(35), 6953-6967. doi:https://doi.org/10.1523/JNEUROSCI.0593-19.2019
van Moorselaar, D., & Slagter, H. A. (2020). Inhibition in selective attention. *Annals of the New York Academy of Sciences*.
Vatterott, D. B., & Vecera, S. P. (2012). Experience-dependent attentional tuning of distractor rejection. *Psychonomic Bulletin & Review, 19*(5), 871-878.

Wang, B., & Theeuwes, J. (2018). Statistical regularities modulate attentional capture. *Journal of Experimental Psychology: Human Perception and Performance*, *44*(1), 13.

Wang, B., van Driel, J., Ort, E., & Theeuwes, J. (2019). Anticipatory distractor suppression elicited by statistical regularities in visual search. *Journal of cognitive neuroscience*, 1-14.

Weaver, M. D., van Zoest, W., & Hickey, C. (2017). A temporal dependency account of attentional inhibition in oculomotor control. *Neuroimage*, *147*, 880-894.

Zhang, B., Allenmark, F., Liesefeld, H. R., Shi, Z., & Muller, H. (2019). Probability cueing of singleton-distractor locations in visual search: priority-map-or dimension-based inhibition? *Journal of Experimental Psychology: Human Perception and Performance*.