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Learning to Suppress Salient Distractors in the Target Dimension: Region-Based Inhibition Is Persistent and Transfers to Distractors in a Nontarget Dimension

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It was shown previously that observers can learn to exploit an uneven spatial distribution of singleton distractors to better shield visual search from distractors in the frequent versus the rare region (i.e., distractor location probability cueing; Sauter, Liesefeld, Zehetleitner, & Müller, 2018). However, with distractors defined in the same dimension as the search target, this comes at the cost of impaired detection of targets in the frequent region. In 3 experiments, the present study investigated the learning and unlearning of distractor location probability cueing and the carry-over of cueing effects from same- to different-dimension distractors. All experiments involved a visual search for an orientation-defined singleton *target* in the presence of either a more salient color-defined (different-dimension) or orientation-defined (same-dimension) distractor singleton, and all were divided into a learning session and a subsequent test session. The present study showed that with same-dimension (but not with different-dimension) distractors, the acquired cueing effect persists over a 24-h break between the training and test session and takes several hundred trials to be unlearned when the distribution is changed to even (50%/50%) in the test session. Furthermore, the target location effect as well as (somewhat less marked) the cueing effect carries over from learning with same-dimension distractors to test with different-dimension distractors. These carry-over effects are in line with the assumption that the learned distractor suppression effects are implemented at different levels in the hierarchical architecture of search guidance: the saliency map with same-dimension distractors versus a dimension-based level below the saliency map with different-dimension distractors.

Keywords: statistical learning, attentional capture, distractor location probability cueing, distractor suppression, dimension-weighting account

In visual search for singleton pop-out targets, observers are able to learn, over time, statistical regularities in the locations of highly salient but task-irrelevant singletons (henceforth referred to as "distractors") that compete with the search target for attentional selection. This learning effect is expressed in reduced interference, that is, relatively faster RTs, when the distractor occurs at one, statistically frequent compared with other, rare distractor locations (Ferrante et al., 2018; Leber, Gwinn, Hong, & O'Toole, 2016; Wang & Theeuwes, 2018) or even when it occurs at one of multiple locations within a frequent compared with a rare distractor region of the search display (Goschy, Bakos, Müller, & Zehetleitner, 2014; Sauter et al., 2018). Goschy et al. (2014) termed this "distractor location probability cueing," in analogy to Geng and Behrmann (2005) who introduced the label "target location probability cueing" to refer to the statistical learning of likely target locations in visual search.

Typically in these so-called "additional-singleton" tasks, the attributes singling out the distractor from the background items (henceforth referred to as "nontargets") are quite distinct from those defining the target. In the majority of studies since Theeuwes' (1992) pioneering work, the target was defined by an aspect of form (e.g., shape, orientation), whereas the distractor was defined by color, that is, in a different visual dimension to the target. This applies, for instance, to most of the electrophysiological studies of attentional capture (e.g., Burra & Kerzel, 2013; Hickey, McDonald, & Theeuwes, 2006; Jannati, Gaspar, & McDonald, 2013; Kiss, Grubert, Petersen, & Eimer, 2012; Wykowska & Schubö, 2011). In Goschy et al. (2014), the 34 nontarget items were all vertical gray bars. The target was the only bar having a 12° tilt to the left or the right from the vertical (i.e., it was orientation-defined), while the distractor was the only red (vertical) bar (i.e., it was color-defined and, thus, relative to the target-defining dimension, a "different-dimension distractor"). This can be compared

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with Wang and Theeuwes (2018) and Ferrante et al. (2018), who examined search for a shape singleton target in the presence of a color-defined, that is, different-dimension, distractor that was highly likely to appear at one specific location. In Goschy et al. (2014), by contrast, color-defined distractors were more likely to appear in a whole display region (encompassing multiple possible locations). More recently, Sauter et al. (2018) extended Goschy et al.'s (2014) paradigm to distractors defined in the same visual dimension as the target by replacing the color-defined (red vertical) distractor by an orientation-defined (a gray horizontal) distractor. Given that the orientation difference of the distractor to the nontargets (horizontal vs. vertical) was larger than that of the target (12° tilt vs. vertical), the distractor was more salient than the target (with the latter still affording "pop-out," i.e., set-size-independent search; see Liesefeld, Moran, Usher, Müller, & Zehetleitner, 2016), while being of comparable saliency to the color distractor in Goschy et al. (2014). Although Sauter et al. (2018) found such "same-dimension distractors" to cause massive interference (over four times the interference caused by different-dimension distractors), participants learned to reduce the interference generated by distractors in the frequent region, compared with distractors in the rare region. In addition to this distractor location (probability cueing) effect, there was also a cost in terms of the speed of target processing: RTs were slower to targets in the frequent region compared with targets in the rare region (target location effect). Crucially, this was the case even on trials on which no distractor was actually present in the display (target location effect on distractor-absent trials: 56 participants, $BF_{10} = 51$). This effect pattern did not exist with different-dimension distractors (128 participants, $BF_{10} = 0.27$; providing evidence for the absence of a target location effect), for which there was just a reduction of interference for distractors in the frequent as compared with the rare region (distractor location effect). Sauter et al. (2018) took this differential effect pattern—a distractor location effect coupled with a target location effect with same-dimension distractors versus a distractor location effect without a target location effect with different-dimension distractors—to conclude that interference reduction relies on fundamentally different mechanisms with same- as compared with different-dimension distractors.

In principle, the interference reduction within the frequent (as compared with the rare) distractor area might be based on stronger suppression on any of three levels: inhibition of distractor-defining features (feature-based suppression), down-modulation of feature-contrast signals in the distractor-defining dimension (dimension-based suppression), or inhibition of "dimension- and feature-less" saliency signals on the search-guiding attentional priority, or "overall-saliency," map (global-saliency suppression). The fact that, with same-dimension distractors, Sauter et al. (2018) found the reduction of distractor interference to be accompanied by impaired target processing rules out feature-based suppression as a general account of the findings: if the distractor-defining feature could be selectively inhibited, it should not have mattered whether the distractor was defined in a different or the same dimension as the target. Likewise, the fact that, with different-dimension distractors, distractor, interference was reduced without affecting target processing. rules out overall-saliency map inhibition as a general account of the findings: if the overall-saliency map is inhibited, target processing should be impaired not only with same- but also with different-dimension distractors. By contrast, dimension-based suppression (e.g., Müller, Geyer, Zehetleitner, & Krummenacher, 2009; Zehetleitner, Goschy, & Müller, 2012) could account for the findings. The notion of dimension-based suppression derives from the "dimension-weighting account" (DWA) of Müller and colleagues (e.g., Found & Müller, 1996; Müller, Heller, & Ziegler, 1995; Müller, Reimann, & Krummenacher, 2003; for a recent review, see Liesefeld, Liesefeld, Pollmann, & Müller, in press). On this account, local feature contrast signals (coding, e.g., the orientation difference of a horizontal bar to the vertical bars in its surround) are transferred in a dimensionally weighted fashion to the (supradimensional) overall-saliency map, which sums the dimensionally weighted signals to determine overall-saliency. Accordingly, down-modulating the weight of the distractor-defining dimension would not only down-modulate the distractor (feature contrast) signal in this dimension (reducing interference) but also the target signal if the target is defined within the same dimension (slowing target selection). By contrast, if the target feature is defined within a different dimension, target processing is unaffected by the down-modulation of the distractor-defining dimension. This could explain the pattern of results observed by Sauter et al. (2018): suppressing the distractor dimension, and more so in the frequent as compared with the rare distractor region, led to impaired processing of an orientation-defined target when the distractor was also orientation-defined (same dimension: target location effect), but not when it was color-defined (different dimension: no target location effect).

While for different-dimension distractors, it appears clear that the suppression is essentially dimension-based (including a spatial modulation of dimension-based suppression), the situation is more complicated with same-dimension distractors: suppression of the orientation dimension when the target, too, is defined within this dimension conflicts with the goal of detecting a target in this dimension. To deal with this, observers may instead resort to a global space-based inhibition strategy, suppressing any saliency signals in the frequent distractor area at the overall-saliency map level (thus giving rise to a distractor location effect). This, too, would yield impaired target processing in this area (i.e., a target location effect) while avoiding a direct goal conflict; for instance, global space-based inhibition (overall-saliency map level) may be more readily combinable with template-based top-down enhancement of the target-defining feature (feature-based level) compared with inhibition at the dimensional level.

More important, while the results of Sauter et al. (2018) provided strong indication that spatial suppression of different-dimension distractors occurs at the dimensional level, they are inconclusive with regard to whether spatial suppression of same-dimension distractors occurs at the dimensional or the overall-saliency map level. The present study was designed to address this issue, by examining the learning and unlearning of distractor location probability cueing and the carry-over of cueing (including both the distractor and target location) effects from same- to different-dimension distractors.

Rationale and Overview of the Present Study

The study followed a two-stage logic. In the first instance, it was designed to test the hypothesis that distractor location probability learning is ultimately better consolidated with same-dimension distractors as compared with different-dimension distractors. Müller et al. (2009) considered the shielding of search from distraction as a skill, that is a set of learned, executive routines to either avoid attentional capture or effectively deal with its consequences. Now assume that same-dimension distractors give rise to greater system-internal conflict than different-dimension distractors (evidenced by the fact that they cause massive interference, even after extended practice; see, e.g., Liesefeld, Liesefeld, Töllner, & Müller, 2017, and Sauter et al., 2018); thus, engaging a greater degree of "controlled processing" (Schneider & Shiffrin, 1977) to find and consolidate ways, or control routines, to minimize their interference. In the present paradigm, we predicted this would lead to deeper spatial learning for same-dimension distractors, as their statistical distribution might provide the only effective approach for reducing their interference, at least to some extent, namely: space-based suppression. Different-dimension distractors, by contrast, produce little conflict in the first place (Sauter et al., 2018), as they can be very effectively dealt with by a readily available routine: dimension-based suppression. Accordingly, distributional cues are less important with different-dimension distractors and lead to relatively shallow spatial learning. Therefore, finding better consolidation of distractor location probability learning with same- as compared with different-dimension distractors would provide converging evidence for the qualitative difference in dealing with the two types of distractors that is assumed by the DWA.

One way to probe the depth of learning (in our case: statistical learning) is to assess how strong and persistent an acquired behavioral disposition, or attentional bias, is after the original "incentive" in the task structure that gave rise to this learning (e.g., a statistical bias in some task-critical event) is removed (Jiang, Swallow, Rosenbaum, & Herzig, 2013; Leber & Egeth, 2006a, 2006b; Zellin, Conci, von Mühlenen, & Müller, 2013; Zellin, von Mühlenen, Müller, & Conci, 2014). In a comparable study to the present one, Ferrante et al. (2018), for example, observed that the learned attentional enhancement of a frequent target location (in search for a shape-defined singleton target) did persist during an "extinction" epoch which was administered immediately after the learning epoch and in which the target appeared equally likely at each display location. By contrast, suppression of a location at which a (color-defined) distractor singleton appeared frequently during learning was no longer significant in the extinction epoch (in which the distractor appeared equally frequently at each display location)—indicating that, at least with the different-dimension distractor used by Ferrante et al. (2018), a spatial bias in distractor suppression is unlearnt rapidly.

Adopting this logic, Experiment 1 was designed to probe the strength of learnt spatial suppression by examining for carry-over effects of distractor location probability learning from one day (Day 1: learning phase) to the next (Day 2, some 24 h later: test phase), separately for a group of same-dimension distractor participants and one of different-dimension distractor participants. Of note, our main focus was to examine whether a transfer of spatial suppression across sessions could be established when the original incentive to spatially suppress is strong enough (as with a highly disruptive, same-dimension distractor); the different-dimension-distractor group was merely included to replicate Ferrante et al. (2018) in our region-cueing paradigm.

Participants were presented with an uneven distribution of distractors (90% of distractors in the frequent area, 10% in the rare area) only during the learning phase (Day 1). In the test phase (Day 2), the distribution was equal (50% in frequent area, 50% in rare area), so as not to provide an incentive for relearning (and, instead, to permit unlearning to be examined). We expected a carry-over effect from Day 1 to Day 2 for same-dimension learners (but not for different-dimension learners; see Ferrante et al., 2018), as well as a gradual unlearning of the uneven distribution on Day 2. The results were in line with this prediction: there was a significant carry-over effect (crucially including carry-over of the target location effect) only with same-dimension distractors, but not with different-dimension distractors. Experiment 2 went on to examine whether the failure to find a significant carry-over effect with different-dimension distractors was because of the length of the interval between the learning and the test phase, that is: would a carry-over effect be discernible when the interval is reduced (from 24 h plus) to 5 min? The answer was negative, indicating that unlearning occurred rather rapidly, within the first few blocks of encountering an even distribution of different-dimension distractors. For the sake of comparison, Experiment 2 also included a same-dimension distractor condition, which essentially produced the same effect pattern as in Experiment 1.

Given these differential (un-)learning effects, Experiment 3 was designed to examine whether whatever strategy is acquired in the learning phase (on Day 1) to deal with same-dimension distractors would be carried over and applied, in the test phase (on Day 2), to search displays that exclusively contain different-dimension distractors (i.e., the type of distractor was switched from Day 1 to Day 2, in addition to the change from an uneven to an even distractor distribution). Recall, that only same-dimension distractors produce a target location effect: impaired processing of targets appearing in the frequent versus the rare distractor area. If this effect carries over from same-dimension distractor learning (on Day 1) to the test with different-dimension distractors (on Day 2), this would have implications for the locus of the target location effect in the search architecture. The answer is: there was indeed a carry-over effect (including carry-over of the target location effect), indicative of spatial distractor suppression operating at a different level with same- versus different-dimension distractors: overall-saliency map versus a dimension-based level below the saliency map.

Experiment 1

Experiment 1 was designed to test whether distractor location probability cueing carries over from one day (training) to the next (test), even if the test condition provides no (longer an) incentive to apply more distractor suppression to one as compared with the other half of the search display. For the reasons set out above, we hypothesized that there would be such a carry-over effect—in terms of reduced distractor interference for the previously frequent versus the previously rare display region (in the test session), coupled with a persistent target location effect—with same-dimension distractors.

Method

Participants. There were 48 (28 female, 20 male) right-handed observers, all students at LMU Munich, with a median age of 28 (range = 18–38) years, who participated in Experiment 1. Note that, as concerns the first eight blocks from the learning session, these participants' data were part of the larger sample analyzed in the context of Sauter et al.'s (2018) study. To clarify: We originally tested all 48 participants for the purpose of this experiment and later included parts of their data in the Sauter et al. (2018) study. The other participants from Sauter et al. (2018) were not tested over two sessions as detailed below and, therefore, could not be included in the present article. The rationale of recruiting 24 participants per distractor condition was based on the original study of Goschy et al. (2014), who demonstrated a convincing distractor location probability cueing effect for the "weaker," different-dimension distractor condition with 24 observers. Distractor interference and, hence, the cueing modulation is weaker in this condition than in the same-dimension distractor condition compared in Sauter et al. (2018). All observers reported normal or corrected-to-normal vision (including normal color vision) and gave prior informed consent (in writing). They received 8 € per hour or course credits in compensation. Note that one participant had to be excluded from the analysis of the same-dimension condition because of a loss of data. The study received ethics approval by the ethics committee of the Faculty of Psychology and Pedagogy of the LMU within the Grant MU-774.

Set-up. The experiment was conducted in a sound-reduced, moderately lit test chamber. The search displays were presented on a 1024 × 768 px screen, at a refresh rate of 60Hz. Stimuli were generated with OpenSesame 3.1 (Mathôt, Schreij, & Theeuwes, 2012) using a Psychopy backend (Peirce, 2007). Observers issued their responses using a QWERTZ keyboard, by pressing the "y" or the "m" key with their left- or right-hand index finger, respectively. The stimulus displays were identical to those used in the study of Sauter et al. (2018), which, in terms of the present design, consisted of only an initial learning phase (without a subsequent test or unlearning phase). The screen background was black. The search displays (illustrated in Figure 1) consisted of gray (RGB: 127, 127, 127; CIE [Yxy]: 13.6, 0.28, 0.32) vertical nontarget bars (0.25° of visual angle wide, 1.35° high), with their geometric centers equidistantly arranged on three (imaginary) concentric circles with radii of 2°, 4°, and 6°, comprising 6, 12, and 18 bars, respectively. A further gray bar occupied the position in the center of the three circles. In every bar, there was a gap 0.25° in size, which was randomly located 0.25° from the top or the bottom of the bar. The singleton target (present on every trial) differed from the nontargets by its unique orientation: it was (randomly) tilted 12° to either the left or the right.

A singleton distractor was present in 50% of the trials. For one group of 23 participants, one of the (gray vertical) nontargets was rotated from vertical to 90° (i.e., a horizontal bar; distractor defined in the same dimension as the target). This orientation contrast modulation ensured that the target was less salient (12° vs. vertical) than the distractor (horizontal vs. vertical; see Liesefeld et al., 2016, 2017). For the other group of 24 participants, one of the nontargets was changed from gray to red (distractor defined in a different dimension, namely color, to the orientation-defined target). Note that pilot testing, with different participants, had revealed the two distractors to be of comparable saliency: they produced comparable RTs when presented as the sole, to-be-detected singleton item in the display (see Zehetleitner, Koch, Goschy, & Müller, 2013, for a probabilistic model of distractor interference based on this procedure for estimating distractor saliency). Targets and distractors were presented exclusively at positions on the intermediate circle, to ensure consistent feature contrast to the nontargets in their surround (e.g., Liesefeld et al., 2016, 2017; Nothdurft, 1993; Rangelov, Müller, & Zehetleitner, 2013, 2017).

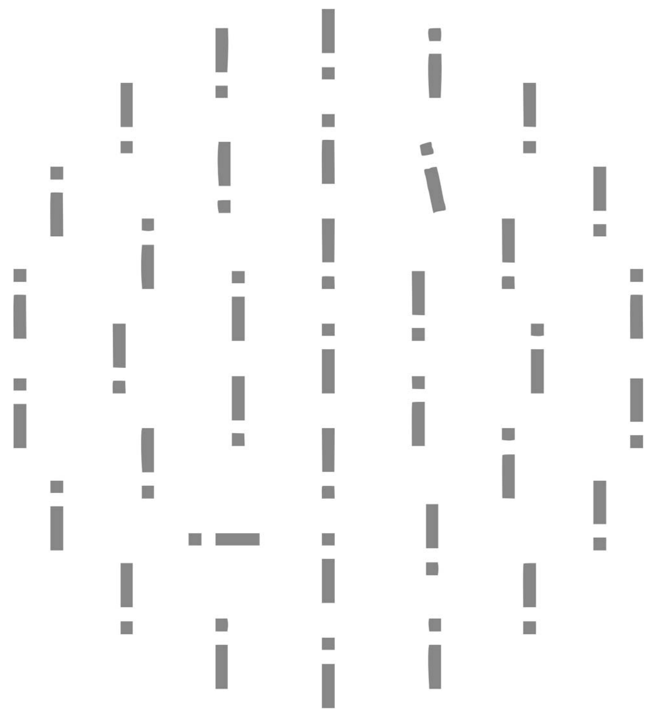

Figure 1. Example of a stimulus display. The search target is the 12°-tilted bar at the 1 o'clock position, and the (same-dimension) distractor is the 90°-tilted bar at the 7 o'clock position.

Design. The type of the singleton distractor (same vs. different dimension) was introduced as a between-subjects factor. The distractor distribution in the learning session was also manipulated between subjects. The distractor frequency differed between the top half of the display (ranging from the 10 o'clock to the 2 o'clock position on the intermediate circle) and the bottom half (ranging from the 4 o'clock to the 8 o'clock position; see Figure 1). For half of the participants within each group, the top semicircle was the frequent and the bottom semicircle the rare distractor area, and vice versa for the other half (see below). Neither the distractor nor the target could appear at the 3 o'clock and 9 o'clock positions, as these positions could not be unambiguously assigned to the top or bottom area of the search display.

The learning session consisted of a total of 1,440 trials, separated into 12 blocks. A distractor was present in half the trials and absent in the other half. If a distractor was present, it appeared in the frequent area 90% of the time and in the rare area 10% of the time. The target appeared equally often in both areas, with an equal probability for all 10 possible positions, but it never occurred at the same position as the distractor. The test session also consisted of 12 blocks with a total of 1,440 trials. More important, in the test session, targets and distractors occurred equally likely in the (previously, i.e., in the learning session) frequent and the (previously) rare display region. The order of the trials within each block was completely randomized.

Procedure. The experimental procedure was identical similar to Experiment 1 of Sauter et al. (2018). Observers were instructed, in writing and orally, that their task was to discern whether the target bar was interrupted (by a gap) at the top or the bottom. If it was interrupted at the bottom, they were told to press the "y" key; if it was interrupted at the top, they had to press the "m" key. They were informed that on some trials, there would be a horizontal (same-dimension group) or, respectively, a red (different-dimension group) distractor bar which they should simply ignore as it would be irrelevant to the task. They were not informed that the distractor was more likely to appear in one particular region (in the top or bottom half of the display).

Each trial started with a white fixation cross in the middle of the screen for a random duration between 700 and 1,100 ms. Then the search display appeared and stayed on until the observer gave a response indicating the gap position in the target bar. If the response was incorrect, the word "Fehler" (German for "Error") appeared in the center of the screen for 500 ms. Thereafter, the next trial started without a delay. After each block of trials, observers received RT and accuracy feedback and could resume the experiment at their discretion. Each participant performed both the learning and the test session, with a separation of about 24 h between the two sessions.

After completing each of the sessions, participants filled in a brief questionnaire, which was intended to gauge whether they had any explicit knowledge of the singleton distractors' spatial (frequency) distribution. As in Goschy et al. (2014; see also Sauter et al., 2018), participants were asked "Did the horizontal [red] distractor appear equally often in all or more often in one specific display half?", with the forced-choice response alternatives being "equal," "top half," "bottom half," "right half," and "left half." For the present study, we limited the formal "explicitness" analysis to the learning session, in particular, to examine whether the initial development of the probability cueing effect did depend on explicit awareness of the distractor distribution.

Analysis. For the analyses presented below, we opted for Cohen's d to assess effect sizes. Apart from classical frequentist measures, to address issues raised by the "replication crisis" (e.g., cf. Open Science Collaboration, 2015), we further report 95% highest posterior density (HDP) intervals (essentially a Bayesian equivalent to confidence intervals [CIs]), calculated using the "coda" package (Plummer, Best, Cowles, & Vines, 2006) for R (R Core Team, 2014); and we report JZS BF_{10} Bayes factors (Rouder, Speckman, Sun, Morey, & Iverson, 2009) with standard priors (i.e., with a scaling factor of 0.707), calculated using the BayesFactor package (Morey, Rouder, & Jamil, 2014) for R, for hypothesis-guided t tests.

Results

To examine for carry-over of probability learning effects from Day 1 to Day 2, and specifically differential carry-over effects between the same- and different-dimension distractor groups, we assessed (a) the (successful) establishment of the probability-cueing effect for both same- and different-dimension distractors in the learning phase, (b) the "peak" probability cueing effect in the last block of the learning phase, and (c) whether or not there was still an area bias (i.e., probability-cueing effect) during early blocks of the second session (despite the fact that the distractor distribution was now equal between the previously frequent and rare areas).

The results are illustrated in Figure 2 for the two sessions (panel A, learning session; panel B, test session); each panel presents the median correct RTs as a function of the distractor condition (in frequent area vs. in rare area vs. absent) and distractor type (same-dimension vs. different-dimension).

Before more hypothesis-driven analysis (using t tests; see below), we examined the RT data by means of repeated-measures analysis of variances (ANOVAs) with the factors distractor condition (frequent vs. rare vs. absent), target position (frequent distractor region vs. rare distractor region), and session (training vs. test), separately for same- and different-dimension distractors. For same-dimension distractors, the ANOVA revealed all main effects to be significant: distractor condition ($F(2, 44) = 116.34$, $p < .001$, $\eta_p^2 = .84$), indicative of significant distractor interference, and differential interference dependent on the region in which the distractor occurred; target position ($F(1, 22) = 5.69$, $p = .026$, $\eta_p^2 = 0.21$), because of slower RTs to targets in the frequent as compared with the rare distractor region; and session ($F(1, 22) = 51.24$, $p < .001$, $\eta_p^2 = 0.7$), reflecting faster responding in Session 2 than in Session 1. Furthermore, the following interactions were significant: distractor Condition × Target position ($F(2, 44) = 10.24$, $p < .001$, $\eta_p^2 = 0.32$); distractor Condition × Session ($F(2, 44) = 81.79$, $p < .001$, $\eta_p^2 = 0.7$), with reduced distractor interference (and equivalent interference between the two distractor regions) in Session 2 than in Session 1; target Position × Session ($F(1, 22) = 42.91$, $p < .001$, $\eta_p^2 = 0.66$), reflecting a target position effect in Session 1, but not (i.e., no longer) in Session 2; and (the three-way interaction) distractor Condition × Target Position × Session ($F(2, 44) = 8.87$, $p = .001$, $\eta_p^2 = 0.29$).

For different-dimension distractors, there were also significant main effects of distractor condition ($F(2, 46) = 73.18$, $p < .001$, $\eta_p^2 = 0.76$) and session ($F(1, 23) = 14.14$, $p = .001$, $\eta_p^2 = 0.38$), the distractor Condition × Session was significant ($F(2, 46) = 18.11$, $p < .001$, $\eta_p^2 = 0.44$) as well as the interaction distractor Condition × Target position ($F(2, 46) = 8.42$, $p = .001$, $\eta_p^2 = 0.27$). Crucially, however, there were no other reliable effects involving target position (main effect: $F(1, 23) = 0$, $p = .947$, $\eta_p^2 = 0$; interaction target Position × Session: $F(1, 23) = 0.18$, $p = .672$, $\eta_p^2 = 0.01$; three-way interaction distractor Condition × Target Position × Session: $F(2, 46) = 0.94$, $p = .4$, $\eta_p^2 = 0.04$).

Effects in the learning session: Establishing the probability-cueing effect. To ascertain that distractors caused interference and a probability-cueing effect was successfully established, we first examined for this effect pattern for the learning session (in which there was a 90/10 distribution). Also, we examined for the presence (same-dimension condition) versus absence (different-dimension condition) of a target position effect.

Same-dimension distractors. Same-dimension distractors caused considerable interference: RTs were 92 ms slower when a distractor was present (averaged across trials with distractors in the frequent and rare regions) versus absent (717 vs. 625 ms; $t(22) = 10.6$, $p < .001$, $d_z = 2.21$, 95% HPD [71 ms, 108 ms], $BF_{10} = 50 \times 10^6$. In addition, there was a large probability-cueing effect: RTs were 90 ms faster when a distractor was presented in the frequent area compared with the rare area (707 vs. 797 ms; $t(22) = -10.83$, $p < .001$, $d_z = 2.26$, 95% HPD [−107 ms, −72 ms], $BF_{10} = 7.379 \times 10^7$). In line with this, distractor interference (relative to the distractor-absent baseline) was reduced for distractors in the frequent area (81 ms; $t(22) = 10.18$,

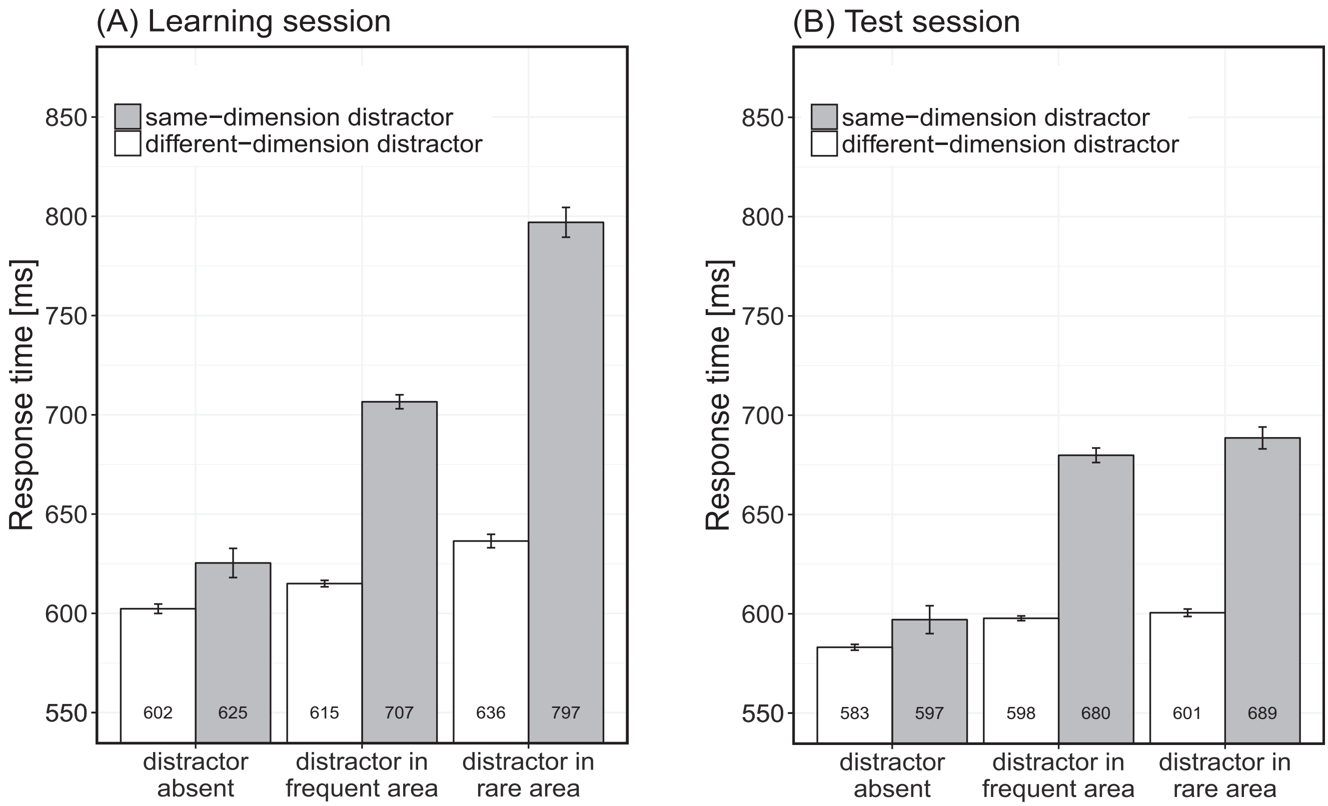

Figure 2. RTs as a function of the distractor condition (in frequent area vs. in rare area vs. absent) and distractor type (same-dimension in gray vs. different-dimension in white) for both the learning session (A) and the test session (B) of Experiment 1.

$p < .001$, $d_z = 2.12$, 95% HPD [64 ms, 96 ms], $BF_{10} = 1.25 \times 10^7$) compared with distractors in the rare area (171 ms; $t(22) = 13.02$, $p < .001$, $d_z = 2.71$, 95% HPD [140 ms, 198 ms], $BF_{10} = 1.012 \times 10^9$). Additionally, there was a significant target location effect: targets were responded to slower in the frequent distractor region compared with the rare region (687 vs. 646 ms; $t(22) = 3.39$, $p = .001$, $d_z = 0.71$, 95% HPD [13 ms, 61 ms], $BF_{10} = 30$).[1]

The same pattern was evident in the last block of the training session—which, arguably, provides the most appropriate reference condition for examining for a carry-over effect to the test session (see below). RTs were 189 ms faster when a distractor was present in the frequent compared with the rare area (664 vs. 853 ms; $t(22) = -3.46$, $p = .001$, $d_z = 0.72$, 95% HPD [−289 ms, −65 ms], $BF_{10} = 35$), and distractor interference was greatly reduced (though still significant) for distractors in the frequent rare area (55 ms; $t(22) = 6$, $p < .001$, $d_z = 1.25$, 95% HPD [35 ms, 72 ms], $BF_{10} = 4224$) compared with distractors in the rare area (244 ms; $t(22) = 4.2$, $p < .001$, $d_z = 0.88$, 95% HPD [112 ms, 337 ms], $BF_{10} = 86$). Moreover, targets were responded to slower in the frequent distractor region compared with the rare region (656 vs. 618 ms; $t(22) = 3.43$, $p = .001$, $d_z = 0.72$, 95% HPD [12 ms, 56 ms], $BF_{10} = 33$).

Different-dimension distractors. Different-dimensions distractors, too, caused general interference: RTs were slightly, but significantly, slower overall on distractor-present compared with distractor-absent trials (617 vs. 602 ms; $t(23) = 6.67$, $p < .001$, $d_z = 1.36$, 95% HPD [9 ms, 19 ms], $BF_{10} = 42{,}240$). Further, different-dimension distractors too led to location probability learning: RTs were faster when a distractor appeared in the frequent as compared with the rare area (615 vs. 636 ms; $t(23) = -4.94$, $p < .001$, $d_z = 1.01$, 95% HPD [−30 ms, −12 ms], $BF_{10} = 930$—though, again, this effect (of

[1] Note that the target-location effect reported here is the "raw" effect, uncorrected for positional intertrial and target-to-distractor distance effects (see Supplement in Sauter et al., 2018, for details). More important, Sauter et al. (2018) showed that, in the same-dimension condition, the target location effect survives the various corrections that may be considered necessary for estimating the "pure" effect. Part of the reason for this is that there is not only carry-over, into the current trial, of inhibition of the distractor location on the previous trial, but also carry over of facilitation for the previous target location. That is, while processing is slowed for a current target at the previous distractor location, a current distractor at this (inhibited) location causes reduced interference. Conversely, processing of a currant target at the previous target location is expedited, while a distractor at this location causes increased interference. The net result is that positive and negative positional intertrial effects cancel each other out. Applying all these corrections to the present, limited data set is not feasible as this would involve the loss of too many data points for the condition with a distractor appearing in the rare region. For the present purposes, it is sufficient to note that there is a significant (raw) target location effect in the same-dimension distractor condition, but no evidence of such an effect in the different-dimension distractor condition—reproducing, in this subsample, the pattern that Sauter et al. (2018) established for the complete data set. Also note that any carry-over of distractor location (probability cueing) and target location effects from the learning to the test session cannot be attributed to differential intertrial dynamics between distractors in the (previously) frequent versus the rare region, because in the distractor distribution was equal in the test session (see Jiang et al., 2013).

21 ms) was much smaller than that with same-dimension distractors (90 ms). Accordingly, the net distractor interference (with reference to the distractor-absent baseline) was reduced for distractors in the frequent area (13 ms; $t(23) = 6.21$, $p < .001$, $d_z = 1.27$, 95% HPD [8 ms, 16 ms], $BF_{10} = 7802$) compared with distractors in the rare area (34 ms; $t(23) = 6.64$, $p < .001$, $d_z = 1.36$, 95% HPD [21 ms, 43 ms], $BF_{10} = 19{,}880$). Additionally, in contrast to the same-dimension condition, there was no target location effect; rather, with different-dimension distractors, targets were responded to equally fast in the frequent and the rare distractor region (612 vs. 610 ms; $t(23) = 0.23$, $p = .409$, $d_z = 0.05$, 95% HPD [0 ms, 16 ms], $BF_{10} = 0.2583$).

A similar pattern was also evident by the end (in the last block) of the training session. RTs were 32 ms faster when a distractor was present in the frequent area compared with the rare area (596 vs. 630 ms; $t(23) = -3.22$, $p = .002$, $d_z = 0.66$, 95% HPD [−52 ms, −10 ms], $BF_{10} = 22$). And while distractor interference (relative to the distractor-absent baseline) had been effectively abolished for distractors in the frequent area (4 ms; $t(23) = 0.63$, $p = .534$, $d_z = 0.13$, 95% HPD [−9 ms, 15 ms], $BF_{10} = 0.26$), interference remained significant for distractors in the rare area (38 ms; $t(23) = 2.96$, $p = .007$, $d_z = 0.6$, 95% HPD [11 ms, 60 ms], $BF_{10} = 7$). There was also no target location effect: RTs were equally fast to targets in the frequent and rare distractor areas (596 vs. 593 ms; $t(23) = 0.44$, $p = .333$, $d_z = 0.09$, 95% HPD [0 ms, 15 ms], $BF_{10} = 0.31$).

Cross-distractor comparisons. Comparing the magnitude of the probability cueing and target location effects between the same- and different-dimension distractor conditions revealed both effects to be significantly larger for same-dimension than for different-dimension distractors (distractor probability cueing effect: 90 vs. 21 ms, $t(33.2) = 7.33$, $p < .001$, $d = 2.17$, 95% HPD [46 ms, 65 ms], $BF_{10} = 6517000$; target location effect: 41 vs. 2 ms, $t(38.06) = 2.71$, $p = .005$, $d = 0.8$, 95% HPD [35 ms, 7 ms], $BF_{10} = 11$).

Thus, we established that both types of distractors generated the crucial, expected probability-cueing effect in the learning session, with a larger effect for same- compared with different-dimension distractors. Additionally, distractor location probability cueing was associated with a marked target location effect in the same-dimension distractor condition, but the absence of such an effect in the different-dimension condition.

Explicitness of learning. Next, we evaluated whether participants were able to correctly indicate the spatial distribution of the distractor at the end of the learning session. Across the two distractor conditions, 19% of the participants answered the distribution question correctly (e.g., they indicated the "top" half as the frequent region when the top was, in fact, the frequent region). Thus, overall, explicit knowledge appeared at chance level (recall that the distribution response involved a forced choice among five alternatives), while it was somewhat higher with different-dimension distractors (33% correct, though still chance level: $\chi^2(1) = 0.95$, $p = .330$), and lower with same-dimension distractors (4%, i.e., only one participant responded correctly).

For the different-dimension distractor group, a further comparison examining whether having indicated the distribution correctly (vs. incorrectly) influenced the probability cueing effect in the learning session failed to reveal a significant difference: cueing effects of 17 versus 24 ms (independent-samples two-tailed) $t(20.98) = -0.9$, $p = .381$, $d = 0.33$, 95% HPD [11 ms, 30 ms], BF10 = 0.50. Thus, there is no evidence for a modulation of the distractor location effect by explicit awareness of distractor distribution.

Distractor interference in the test session: Is there carry-over of probability cueing from the learning to the test session? Recall that the probability distribution in the test session was changed (from uneven, 90/10, in the learning session) to even (50/50) for the two distractor regions. Thus, given that the previously frequent and the previously rare area were now equally likely to contain a distractor, there would no longer be a benefit in suppressing one half of the display more than the other. Also, there cannot be any renewed learning of the previous, uneven distribution, which might instead be unlearned based on the sampling of the now even distribution. Thus, given the likelihood of unlearning (brought about by the changed, even distribution), we examined for carry-over by comparing performance between the last block of trials in the learning session, which can be taken to reflect maximum learning (see results above), with the first block in the test session (performed at least 24 h after the last block of the training session!), which involves minimum unlearning. See Figure 3 for a depiction of the RT data (the last block of the learning session and the first block of the test session). We had hypothesized that such a carry-over effect would be manifest with same-dimension distractors.

Same-dimension distractors. In the first block of the test session, a probability-cueing effect was still evident: RTs were still faster, by 29 ms, when a distractor was presented in the (previously)

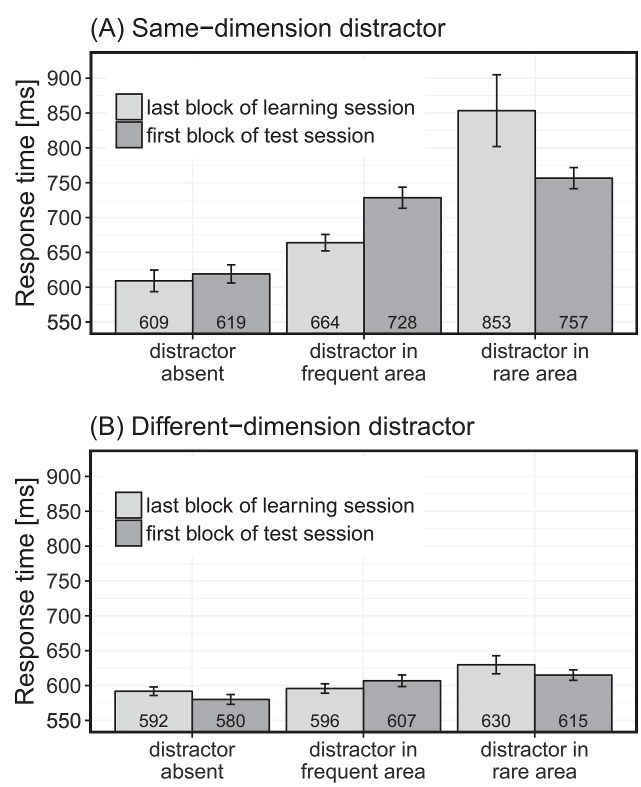

Figure 3. RTs as a function of the distractor condition (absent vs. frequent area vs. rare area) for the last block of the learning session (light gray) and the first block of the test session (dark gray) for same-dimension (top panel) and different-dimension distractors (bottom panel).

frequent area compared with the (previously) rare area (728 vs. 757 ms; $t(22) = -2.63$, $p = .008$, $d_z = 0.55$, 95% HPD [−46 ms, −6 ms], $BF_{10} = 6.761$). This goes along with the net distractor interference effect (with reference to the distractor-absent baseline) being still smaller for distractors in the frequent area (109 ms; $t(22) = 8.45$, $p < .001$, $d_z = 1.76$, 95% HPD [79 ms, 131 ms], $BF_{10} = 5.723 \times 10^5$) compared with distractors in the rare area (138 ms; $t(22) = 10.45$, $p < .001$, $d_z = 2.18$, 95% HPD [108 ms, 165 ms], $BF_{10} = 1.978 \times 10^7$). There was also a numerical, though nonsignificant target-location effect (676 vs. 665 ms; $t(22) = 0.86$, $p = .200$, $d_z = 0.18$, 95% HPD [0 ms, 31 ms], $BF_{10} = 0.4803$).

Different-dimension distractors. The probability-cueing effect was no longer significant in the first block of the test session, that is, there was no longer an RT advantage for distractors appearing in the (previously) frequent versus the (previously) rare area (607 vs. 615 ms; $t(23) = -1.2$, $p = .12$, $d_z = 0.25$, 95% HPD [−19 ms, 0 ms], $BF_{10} = 0.71$). This also means that the (significant) net distractor interference effects were comparable between distractors in the frequent area (27 ms; $t(23) = 4.53$, $p < .001$, $d_z = 0.92$, 95% HPD [14 ms, 38 ms], $BF_{10} = 187$) and distractors in the rare area (35 ms; $t(23) = 5.2$, $p < .001$, $d_z = 1.06$, 95% HPD [20 ms, 47 ms], $BF_{10} = 833$). Also, there was no target location effect ($M = -7.239$ ms; $t(23) = -0.75$, $p = .771$, $d_z = 0.15$, 95% HPD [4.271e-05 ms, 14.78 ms], BF10 = 0.1328).

Cross-distractor comparisons. Direct comparisons of the magnitudes of the carry-over effects between the same- and different-dimension distractors conditions revealed a marginal difference for the distractor probability cueing effect (same- vs. different-dimension distractors: 28 vs. 8 ms, $t(37.28) = 1.58$, $p = .061$, $d = 0.47$, 95% HPD [6 ms, 31 ms], $BF_{10} = 1.486$), while there was only a numerical difference for the target location effect (11 vs. −7 ms, $t(41.07) = 1.14$, $p = .131$, $d = 0.33$, 95% HPD [−14 ms, 18 ms], $BF_{10} = 0.8341$). Thus, there is some evidence even from the cross-group comparisons for the existence of differential carry-over effects between the same- and different-dimension conditions, even though the present study was not designed (i.e., it was underpowered) to resolve such relatively subtle differences in independent-samples tests.

Explicitness test. After the test session, 64% of the participants indicated the correct (equal) distribution (same- vs. different-dimension distractor groups: 61 vs. 67%). This may not be too surprising, given that participants had been alerted to the relevance of the distractor distribution by having to answer the explicitness question at the end of the learning session. Also note that even in the learning session, the majority of participants had given an (incorrect) equal—in a noncommittal choice—response (54%), so that it is hard to tell whether to what extent the correct equal response in the test session reflects true awareness of the 50/50 distribution.

Distractor location probability cueing: Learning and unlearning. Figure 4 depicts the development of distractor probability cueing over time in the training (learning) and the test sessions (unlearning/relearning); that is, the probability-cueing effect (RT difference with distractors in rare minus frequent area) is depicted as a function of experimental "epoch," where an epoch summarizes the effect across two consecutive trial blocks, to smooth a more noisy, block-wise developmental pattern. As can be seen, learning occurs quite rapidly—essentially within the first epoch—with both same- and different-dimension distractors. Distractor position (frequent, rare region) × Epoch ANOVA failed to reveal the interaction to be

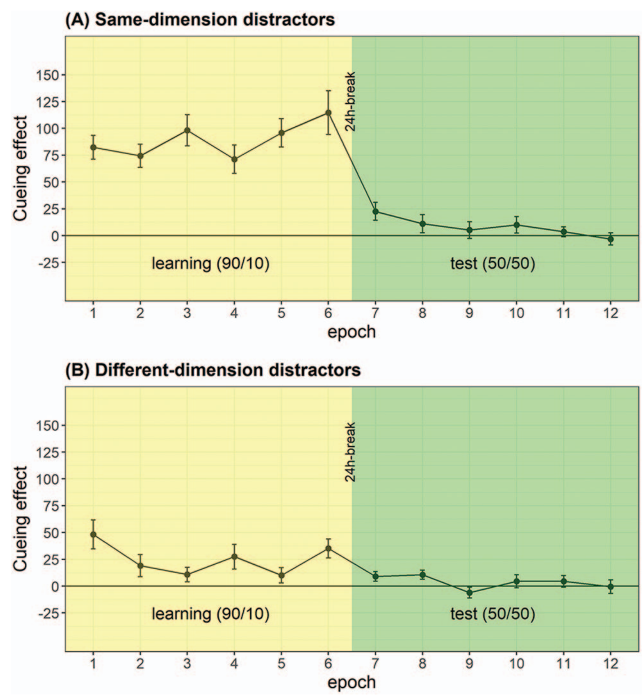

Figure 4. Development of the probability cueing effect over the learning session (yellow; uneven, 90/10, distractor distribution) and test session (green; even, 50/50, distractor distribution) for same- (A) and different dimension (B) distractors. Error bars indicate within-subject *SEM* (Morey, 2008). See the online article for the color version of this figure.

significant, both with same-dimension distractors, $F(5, 105) = 1.77$, $p = .125$, $\eta_p^2 = 0.08$, and with different-dimension distractors $F(5, 115) = 2.02$, $p = .081$, $\eta_p^2 = 0.08$. Concerning unlearning, residual effects of the uneven distribution (during learning) appears to reduce gradually, over the course of four to five epochs (960 to 1,200 trials) with the even distribution, with same-dimension distractors. With different-dimension distractors, by contrast, unlearning of the old, uneven distribution appears to happen relatively quickly: within one epoch (240 trials) the most (recall that there was no significant carry-over effect into the first block of the test session, suggesting that adaptation to the new, even distribution occurs within 120 trials).

Discussion

Taken together, Experiment 1 reproduced, within subsamples of the original two data sets, the findings of Sauter et al. (2018; obtained with samples of 128 and 56 participants in the same- and different-dimension conditions, respectively), confirming differential distractor location probability-cueing effects between same- and different dimension distractors. With both types of distractors, though, the learning of the spatial distractor distribution occurred rather rapidly, within the first few hundred (if not tens) of trials, yielding only minor, if any, increases in the cueing effect beyond the first epoch. This finding of rapid spatial learning is in line with other studies, such as Ferrante et al. (2018; see also Jiang et al., 2013), that used much sparser displays and specific locations (e.g., four-item displays with a single likely distractor location) rather than probability cueing of larger display regions.

Our main goal, however, was to test how persistent these learning effects would be when distractors in the second (test) session are equally likely to appear in the previously frequent and the previously rare display region (i.e., after the removal of the biased distractor distribution) and whether this would differ between the two types of distractors. In agreement with Ferrante et al. (2018)—who used a shape-defined target singleton and a color-defined distractor singleton—Experiment 1 revealed near-instant "extinction" of the learned distractor location cueing effect with different-dimension distractors (orientation-defined target, color-defined distractor), consistent with Ferrante et al. (2018).

For same-dimension distractors, by contrast, the probability-cueing effect and, associated with it, the target location effect were still evident (significant distractor location effect, numerical target location effect) in the second session (i.e., 24 h plus after initial learning), indicating relatively robust long-term learning of the likely distractor locations. These effects were, however, significantly reduced relative to the last block of the training session, likely because of the time elapsed as well as (potentially rapid) "unlearning" of the old distractor distribution. Nevertheless, residual effects of the induced probability-cueing effect remained for (at least) one epoch of some 400 trials, indicating that some training is needed to successfully adapt to (i.e., relearn) the new distribution for same-dimension distractors.

The carry-over effect for same-dimension distractors is in line with our hypothesis: same-dimension distractors motivate considerable recruitment of cognitive control to mitigate the massive interference they cause (Liesefeld et al., 2017), resulting in robust spatial learning that even transfers to a session, conducted some 24 h later, without a spatial bias in the distractor distribution. That is, the learned (spatial) suppression routines tend to be retrieved (invoked by aspects of the search displays) even if the learned distractor distribution does not apply any longer, and unlearning takes several 100 (400+) trials to adapt to the even distribution. Different-dimension distractors, by contrast, are easier to deal with, as an effective and essentially nonspatial routine—namely, dimension-based suppression—is readily available. Note that, according to the DWA, dimensional weighting works in a spatially parallel manner across the whole display (e.g., Krummenacher, Müller, Zehetleitner, & Geyer, 2009), though it may also be spatially tuned to particular display regions, for instance, selectively, down-weighting regions in which distracting stimuli are likely to occur (Goschy et al., 2014; Sauter et al., 2018). Accordingly, with different-dimension distractors, the acquired spatial modulation of this routine is rather shallow and effectively instantaneously adapted to the changed distribution.

Besides yielding insight into the stability of distractor location probability learning, the carry-over effect allows probability learning to be disentangled from potentially confounding intertrial (sequence) effects: Given that, in the learning session, the distractor occurred more often in one particular display area, the likelihood of a target or distractor occurring at a location that was occupied by a distractor on the previous trial was also increased for the frequent as compared with the rare area. Accordingly (part of) the location effects (for targets and distractors) in the learning session may be attributable to short-lived inhibition of the distractor location that influences only the next trial(s), rather than to longer-term learning. Sauter et al. (2018; see their Supplement for details) showed that such intertrial effects cannot account for the full location effects, because the effects survived control analyses that excluded problematic intertrial sequences. This conclusion is reinforced by the present finding of location effects in the test session: as the distractor distribution was even, any location effects can only be explained by previously acquired long-term biases (see Jiang et al., 2013, for the same argument in relation to target location probability cueing).

Experiment 2

In Experiment 1, carry-over of probability cueing from the learning and to the test session, conducted after a gap of at least 24 h, was observed only with same-dimension distractors in both sessions, but not with different-dimension distractors. The latter result leaves it open whether, with different-dimension distractors, forgetting of the initially learned, unequal distractor distribution occurred more or less immediately or whether it took a longer delay (of up to 24-plus hours) for between initial learning and test for forgetting to manifest. Experiment 1 was designed to examine this by running the learning and test phases consecutively on one and the same day, with only a 5-min break in between. The question, thus, was whether, with the immediate change (from the uneven distribution during learning) to the even distribution during test, there would be discernible carry-over of the initially learned distribution for some time (i.e., experimental blocks or epochs) before the cueing effect is effectively abolished by the acquisition of the new distribution, and for how many epochs such a carry-over effect could be demonstrated. Accordingly, Experiment 2 focused on the different-dimension (distractor) condition. However, to establish any differential unlearning or relearning relative to the same-dimension condition (for which Experiment 1 had shown long-lasting and robust effects of the initial distribution, even though this was no longer reinforced by the distractor location probabilities in the test session), we also included a same-dimension condition in Experiment 2.

Method

The design of Experiment 2 was essentially the same as that of Experiment 1, with two exceptions. First, and most importantly, the break between the learning and test phases was only 5 min. Second, to make the experiment doable within one extended experimental session, we reduced the number of blocks per session (from 12 in Experiment 1) to 4 in Experiment 2. This appeared to be justified given that learning of the uneven distractor distribution was very swift in the different-dimension condition, occurring with the maximum cueing effect achieved within two trial blocks (first epoch; see also Ferrante et al., 2018; Jiang et al., 2013). We further removed the equal answer alternative from the explicitness question to force a more committal choice decision (see Sauter et al., 2018, for a discussion).

Participants. There were 47 (25 female, 22 male) right-handed observers, all recruited from the LMU Munich subject pool, with a median age of 26 (range = 18–39) years, who participated in Experiment 2 (24 participants with same-dimension distractors; 23 participants with different-dimension distractors). All of them reported normal or corrected-to-normal vision (including normal color vision) and gave prior informed consent. They received 8 € per hour or course credits in compensation.

Results

All analyses were analogous to those of Experiment 1. The results are illustrated in Figure 5 for the two sessions (panel A, learning session; panel B, test session); each panel presents the median correct RTs as a function of the distractor condition (in frequent area vs. in rare area vs. absent) and distractor type (same-dimension vs. different-dimension).

As can be seen from Figure 5, the results for *learning* sessions (with uneven distractor distribution) perfectly replicated those of Experiment 1: Same-dimension distractors caused more interference overall than different-dimension distractors (relative to the respective baseline: 39 vs. 134 ms). Also, while there was a (learnt) distractor location probability cueing effect in both distractor conditions, this effect was much more pronounced, by a factor of 5, with same-dimension relative to different-dimension distractors (same-dimension, distractor in frequent vs. rare area: 708 vs. 808 ms, $t(23) = -6.65$, $p < .001$, $d_z = 1.36$, 95% HPD [−128 ms, −65 ms], $BF_{10} = 40{,}300$; different-dimension: 643 vs. 665 ms, $t(22) = -1.98$, $p = .03$, $d_z = 0.41$, 95% HPD [−39 ms, −1 ms], $BF_{10} = 2.20$). Note, that the net interference effect for conditions with distractors in the frequent area (relative to the baseline conditions) were reliable both for the same-dimension (84-ms interference; 84 ms; $t(23) = 9.54$, $p < .001$, $d_z = 1.95$, 95% HPD [65 ms, 102 ms], $BF_{10} = 6.254 \times 10^6$) and for the different-dimension condition (28-ms interference; $t(22) = 5.74$, $p < .001$, $d_z = 1.2$, 95% HPD [16 ms, 37 ms], $BF_{10} = 2410$). Finally, there was a differential target position effect between the two distractor conditions: for same-dimension distractors, responses were slower to targets that appeared in the frequent distractor area compared with targets in the rare area (70-ms difference: 704 vs. 634 ms, $t(23) = 3.8$, $p < .001$, $d_z = 0.78$, 95% HPD [26 ms, 100 ms], $BF_{10} = 76$), whereas there was no such effect with different-dimension distractors (−1 ms difference: 629 vs. 630 ms, $t(22) = -0.07$, $p = .526$, $d_z = 0.01$, 95% HPD [0 ms, 23 ms], $BF_{10} = 0.208$).

For the *test sessions* (with even distractor distributions), the results also turned out very similar to Experiment 1. Differential interference from distractors in the (previously) frequent versus the rare region was still evident for the same-dimension distractor condition (676 vs. 707 ms, $t(23) = -2.50$, $p = .010$, $d_z = 0.51$, 95% HPD [−51 ms, −5 ms], $BF_{10} = 5.39$), but being completely abolished for the different-dimension distractor condition (623 vs. 624 ms, $t(22) = -0.4$, $p = .347$, $d_z = 0.08$, 95% HPD [−8 ms, −0 ms], $BF_{10} = 0.304$). In other words, there was carry-over of the learnt distractor distribution from the learning to the test session in the same-dimension condition (despite the fact that both regions were equally likely to contain a distractor in the test session), but no carry-over in the different-dimension condition. Also, there remained a robust target location effect (with slower RTs to targets in the previously frequent vs. the rare distractor

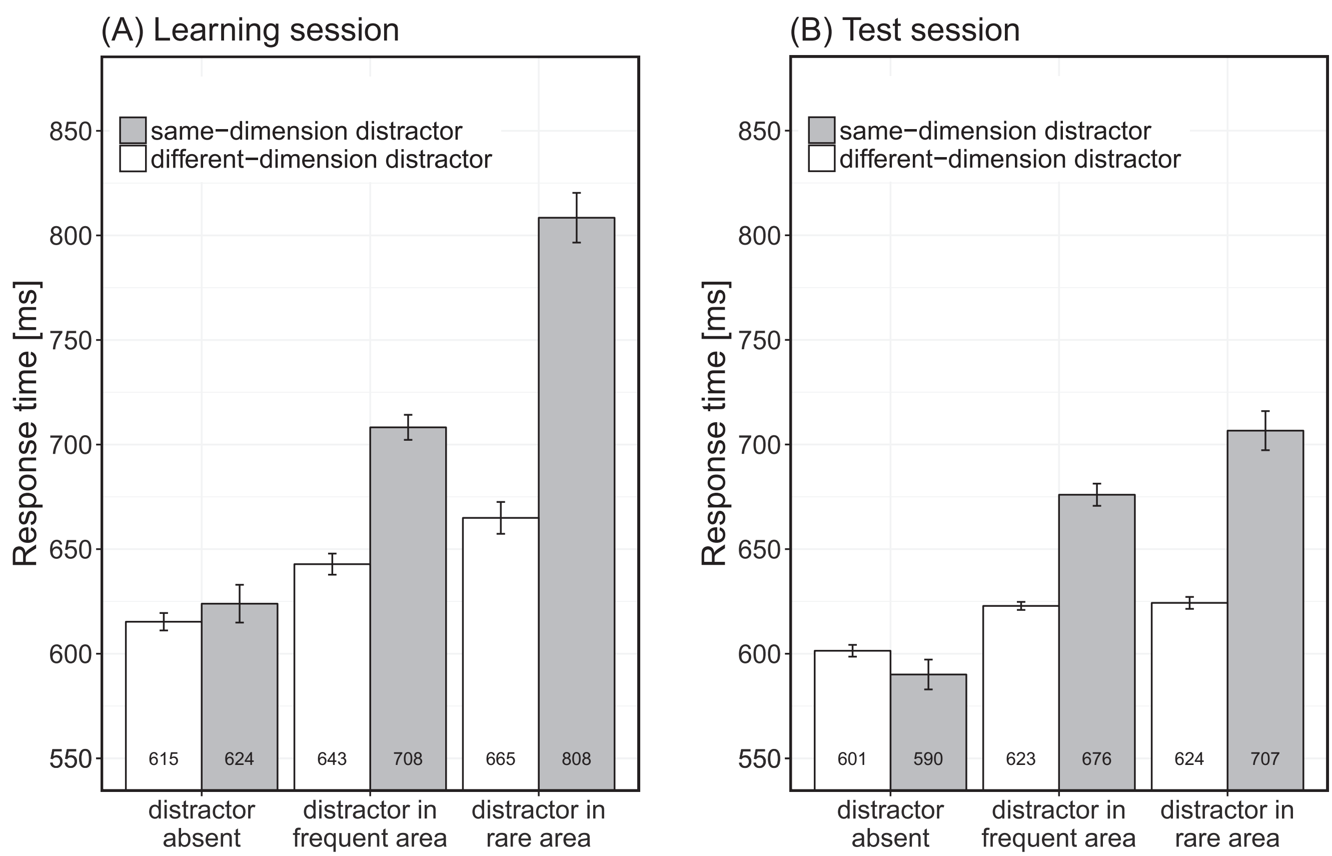

Figure 5. RTs as a function of the distractor condition (in frequent area vs. in rare area vs. absent) and distractor type (same-dimension in gray vs. different-dimension in white) for both the learning session (A) and the test session (B) of Experiment 2.

area) in the same-dimension: 36-ms difference (653 vs. 617 ms, $t(23) = 2.26$, $p = .017$, $d_z = 0.46$, 95% HPD [4 ms, 62 ms], $BF_{10} = 3.47$), which compares with a 70-ms difference in the learning session. In the different-dimension condition, by contrast there was no such effect (-13 ms difference, 606 vs. 619 ms, $t(22) = -1.21$, $p = .88$, $d_z = 0.25$, 95% HPD [0 ms, 16 ms], $BF_{10} = 0.11$); recall that there was also no target location effect in the learning session (-1 ms difference).

Direct comparisons of the magnitudes of the carry-over effects between the same- and different-dimension distractors conditions revealed a significant difference both for the distractor probability cueing effect (same- vs. different-dimension distractors: 31 vs. 1 ms, $t(26.98) = 2.29$, $p = .015$, $d = 0.65$, 95% HPD [3 ms, 29 ms], $BF_{10} = 4.15$), and for the target location effect (36 vs. -13 ms, $t(40.85) = 2.54$, $p = .007$, $d = 0.74$, 95% HPD [-8 ms, 31 ms], $BF_{10} = 6.91$).

This differential pattern indicates that not only the distractor location effect was carried over from the learning to the test session in the same-dimension condition, but also, coupled with this, the target position effect. (As there was no target position effect in the learning session of the different-dimension condition, no such effect could be carried over to the test session.)

Looking at the carry-over effects in an epoch-wise manner (see Figure 7; see also Figure 6 for a depiction of the carry-over effects between the last block of the learning session and the first block of the test session), it appears that there was relatively little unlearning of the initially acquired distractor distribution over time (i.e., experience with the even distribution) in the test session with the same-dimension condition: The carry-over effects were 33 and 19 ms in the first and the second epoch of the test session, respectively (first epoch: 690 vs. 723 ms; $t(23) = -2.66$, $p = .007$, $d_z = 0.54$, 95% HPD [-53 ms, -7 ms], $BF_{10} = 7.315$; second epoch, 670 vs. 690 ms; $t(23) = -1.48$, $p = .076$, $d_z = 0.3$, 95% HPD [-39 ms, -0 ms], $BF_{10} = 1.023$).

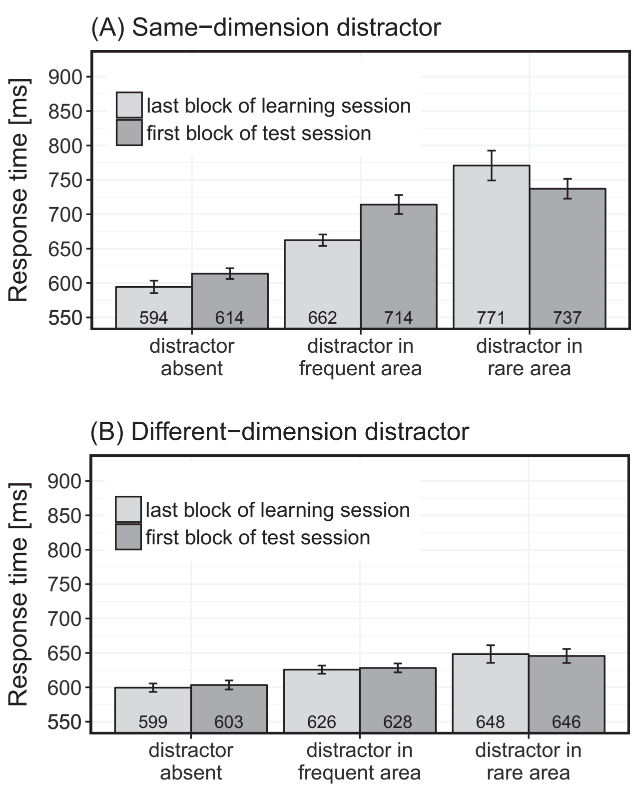

Figure 6. RTs as a function of the distractor condition (absent vs. frequent area vs. rare area) for the last block of the learning session (light gray) and the first block of the test session (dark gray) for same-dimension (top panel) and different-dimension distractors (bottom panel).

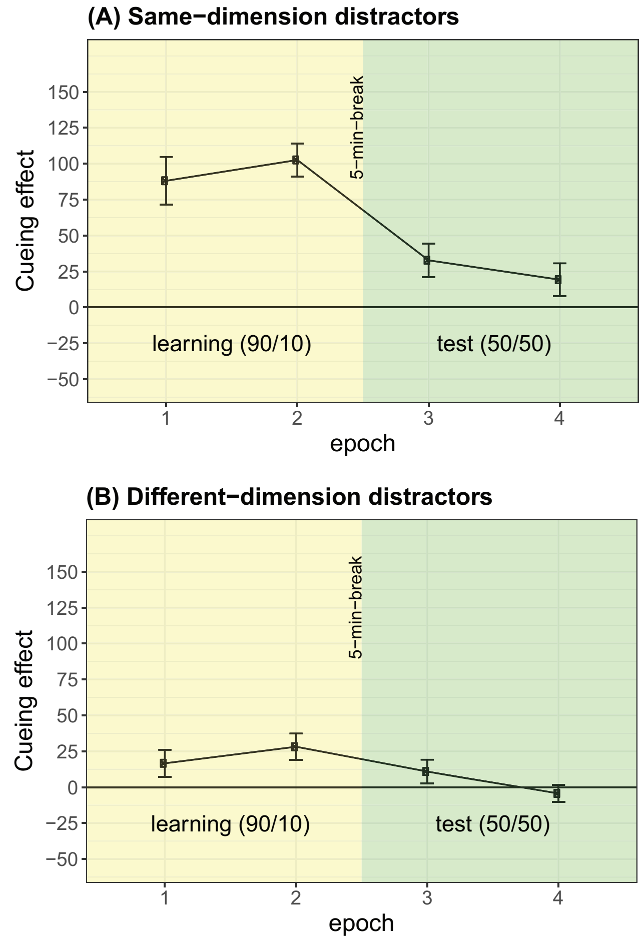

Figure 7. Development of the probability cueing effect over the learning session (yellow; 90/10 distribution) and test session (green; 50/50 distribution) for same- (A) and different dimension (B) distractors. Error bars indicate within-subject *SEM* (Morey, 2008). See the online article for the color version of this figure.

In the different-dimension condition, there was a numerical, but nonsignificant, probability cueing effect, of 11 ms, in the first epoch of the test session (621 vs. 632 ms; $t(22) = -1.65$, $p = .057$, $d_z = 0.34$, 95% HPD [-21 ms, 0 ms], $BF_{10} = 1.317$), and there was no evidence of any effect for the second epoch (626 vs. 622 ms; $t(22) = 1.05$, $p = .848$, $d_z = 0.22$, 95% HPD [-6 ms, 0 ms], $BF_{10} = 0.12$).

Explicitness of learning. Across the two distractor conditions, 38% of the participants answered the distractor distribution question (four-alternative forced-choice, with equal option removed) correctly at the end of the learning session. For different-dimension distractors, the rate was 61% correct and differed significantly from chance, $\chi^2(1) = 7.26$, $p = .007$; this compares with a chance level rate of 17%, $\chi^2(1) = 0.14$, $p = .712$ for same-dimension distractors. Comparing the probability cueing effect between participants who had correctly versus incorrectly indicated the distractor distribution failed to reveal any significant differences: different-dimension distractors: 21 versus 24 ms, $t(15.04) = -0.11$, $p = .911$, $d = 0.05$, 95% HPD [−2 ms, 45 ms], $BF_{10} = 0.3871$; same-dimension distractors: 87 versus 103 ms, $t(8.01) = -0.56$, $p = .593$, $d = 0.2$, 95% HPD [59 ms, 135 ms], $BF_{10} = 0.4731$. Thus, again, there is no evidence for modulations of the distractor-location effect by awareness of the spatial bias in the distractor distribution.

After the test session, it was not possible for participants to indicate the correct (50/50) distribution as we did not reinstate the equal response option. Accordingly, an explicitness analysis could not be performed for this data set.

Discussion

Thus, overall, Experiment 2 essentially replicates Experiment 1 in virtually all respects. Most important, even with an immediate switch from the learning (uneven distractor distribution) to the test session (even distribution), there is no significant carry-over effect of the learned distractor distribution and no target location effect for the different-dimension condition. In other words, the mechanisms underlying different-dimension distractor suppression adapt more or less immediately to the changed distractor statistics. By contrast, although there is an element of unlearning (instigated by the changed distractor distribution) in the same-dimension condition (the distractor location effect is overall weaker in the test session compared with the learning session, and there is some evidence of a decrease in the effect across blocks in the former session), it is safe to conclude that it takes several hundred trials of exposure to the new distribution for the distractor location cueing effect to be completely abolished. Across the whole test session in the same-dimension condition, the cueing effect remained at 31 ms (and the target location effect at 36 ms), which compares with ~13 ms (and, respectively, 13 ms) for Blocks 1 to 4 in Experiment 1, in which the test session was conducted at least 24 h after the learning session. This comparison also suggests that there is actually little forgetting as a function of the time between learning and test (at least within a 1-day period), and "forgetting" is largely attributable to unlearning by exposure to the new statistical distractor distribution. The fact that, in contrast to same-dimension distractors, with different-dimension distractors the initially acquired cueing effect is rather shallow and almost instantaneously adapts to the changed distribution (some 60 to 120 distractor-present trials suffice for the effect to dissipate) provides further evidence that the underlying mechanism is (qualitatively) different from that in the same-dimension condition.

Experiment 3

In Experiments 1 and 2, carry-over of probability cueing from the learning to the test session (including carry-over of the target location effect) was observed only with same-dimension distractors, but not with different-dimension distractors. And for the latter, we had never observed a target location effect, in either the learning session[2] or the test session. Thus, given a total sample of 152 participants (Sauter et al., 2018, plus Experiment 2), we are reasonably confident that, in the different-dimension distractor condition, the significant distractor location (probability-cueing) effect is not normally associated with a target location effect that could be transferred from the learning to the test session.

On this background, Experiment 3 (that implemented a 24-plus hour gap between the learning and test sessions, similar to Experiment 1) was designed to examine for a new carry-over effect: participants were presented with same-dimension distractors in the learning session (90/10 distribution), followed by a switch to different-dimension distractors in the test session (50/50 distribution). Would there also be carry-over of distractor location probability learning, including carry-over of the target location effect, from same- to different-dimension distractors? As outlined in the beginning of the article, the answer has implications for the locus of the probability-cueing effect in the same-dimension condition. Assuming that what is learnt in the same-dimension condition is dimension-based suppression (i.e., stronger suppression of any orientation contrast signals in the frequent vs. the rare distractor region), we would not expect a carry-over of probability cueing from same-dimension (i.e., orientation-defined) distractors at learning to different-dimension (i.e., color-defined) distractors at test. Concretely, if participants learn to strongly suppress orientation signals in the frequent distractor area in the learning session, this acquired suppressive set should not influence the processing of color distractors in the test session (because participants had not learnt to suppress color signals). By contrast, carry-over would be expected if, with same-dimension distractors at learning, participants develop a strategy of spatially selective suppression operating at the level of the search-guiding overall-saliency map. That is, if, with same-dimension distractors, participants learn to (strongly) suppress any overall-saliency map signal in the frequent distractor area, this suppressive set—which Experiments 1 and 2 revealed is carried over to (at least the first block of) the test session—should (after the switch) also apply to signals originating from a different dimension. The reason is that, because of the summing of feature contrast signals across dimensions, overall-saliency coding is "feature-less" or "feature-blind": saliency signals only indicate that there is an object at a particular location that differs (to a certain degree) from the objects in its surround, but they do not indicate what constitutes the difference; for instance, whether it is a color difference (rather than an orientation difference) and, if so, whether the odd-one-out feature is "red" (rather than gray). Thus, carry-over of distractor probability cueing from same-dimension to different-dimension distractors, along with carry-over of a target location effect, would manifest only if the locus of the learning is the overall-saliency map (rather than learning being implemented at a dimension-specific level).

[2] Recall that the Bayes factors associated with the target location effect in different-distractor conditions of the various experiments (Sauter et al., 2018: 128 participants, $BF_{10} = 0.27$; Experiment 1: 24 participants (subsample of Sauter et al., 2018), $BF_{10} = 0.31$; and Experiment 2: 24 participants, $BF_{10} = 0.11$) support the null hypothesis.

Method

Participants. There were 48 observers (13 female, 27 male; all right-handed; all with normal or corrected-to-normal vision, including normal color vision; median age 27, range = 21–39, years) who participated in this experiment. All of them gave prior informed consent and received 8 € per hour for their service.

The number of participants in Experiment 3 was increased from 24 per distractor condition in the previous experiments to a total of (2 groups × 24 participants =) 48 participants (13 female, 27 male; all right-handed; all with normal or corrected-to-normal vision, including normal color vision; median age 27, range = 21–39, years; all giving prior informed consent, and all paid at a rate of 8 € per hour). The sample size was doubled to ensure the power to resolve any distractor location probability cueing (i.e., carry-over) effect with the changed, different-dimension distractors in the test session. This effect, if existent, was expected to be small for two reasons: first of all, it is anyway small with different-dimension distractors even in the learning session with an unequal, 90/10 distribution (21 ms in Experiment 1, 22 ms in Experiment 2); second, there is rapid unlearning when the distribution is switched to 50/50 (Experiments 1 and 2; see also Ferrante et al., 2018).[3]

Apparatus, design, stimuli, and procedure. The apparatus, the stimuli, and the design and procedure were exactly the same as in Experiment 1. The only difference to Experiment 1 was that distractors were consistently orientation-defined in the first, learning session (horizontal [gray] bar, differing from the vertical [gray] nontargets in the same dimension as the – 12° tilted [gray] – target bar), and consistently color-defined in the test session (red [vertical] bar, differing from the gray [vertical] nontargets in a different dimension to the [gray] 12° tilted target bar).

Results

Figure 8 presents the median correct RTs as a function of the distractor condition (in frequent area vs. in rare area vs. absent), for the learning session with same-dimension distractors and for the test session with different-dimension distractors. In the learning session, as in (the same-dimension condition of) Experiment 1, there is both distractor interference (i.e., slower RTs on distractor-present vs. distractor-absent trials) and probability cueing (i.e., relatively faster RTs, and less interference, with a distractor in the frequent vs. a distractor in the rare region). In the test session, there is also evidence of distractor interference (reduced relative to the learning session, because of the switch from same- to different-dimension distractors); however, across the whole test session, there is scant evidence of any distractor location probability-cueing effect. (These differential effects were confirmed by an RT ANOVA, with the factors distractor condition [in frequent area vs. in rare area vs. absent] and session [learning vs. test], which, besides the two main effects, revealed the interaction to be significant: distractor condition, $F(2, 94) = 260.17$, $p < .001$, $\eta_p^2 = 0.85$; session, $F(1, 47) = 70.54$, $p < .001$, $\eta_p^2 = 0.60$; interaction, $F(2, 94) = 167.01$, $p < .001$, $\eta_p^2 = 0.78$.) Given the possibility of relatively rapid unlearning of the previous distractor distribution (after the change from a 90/10 to a 50/50 distribution) and given the overall reduced interference with different-dimension distractors, carry-over effects would be expected to be obtained only (if at all) early during the test session. Given this, following the

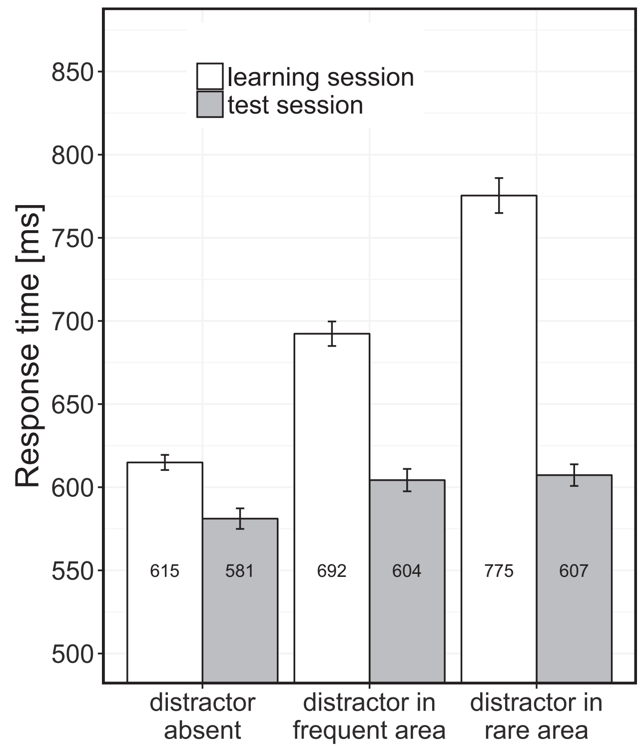

Figure 8. RTs as a function of the distractor condition (in frequent area vs. in rare area vs. absent) for both the learning session with same-dimension distractors and the test session with different dimension distractors. Error bars indicate the within-subject *SEM* (Morey, 2008).

confirmation of distractor interference and the establishment of probability cueing in the learning session, a more detailed examination of the test session will focus on the first block(s) only.

Distractor interference in the training session. A comparison of RTs on distractor-present trials versus those on distractor-absent trials revealed significant distractor interference: RTs were 85 ms slower overall when a distractor was present rather than absent (700 vs. 615 ms; $t(47) = 13.88$, $p < .001$, $d_z = 2$, 95% HPD [71.72 ms, 96.66 ms], $BF_{10} = 3.51 \times 10^{15}$). Furthermore, the probability-cueing effect was significant: RTs were 83 ms faster when a distractor was presented in the frequent area as compared with the rare area (692 vs. 775 ms; $t(47) = -12.97$, $p < .001$, $d_z = 1.87$, 95% HPD [−95.09 ms, −69.78 ms], $BF_{10} = 3.1 \times 10^{14}$). Given the same distractor-absent baseline, this also means that distractor interference in the frequent area (77 ms; $t(47) = 13.06$, $p < .001$, $d_z = 1.89$, 95% HPD [63 ms, 88 ms], $BF_{10} = 1.9 \times 10^{14}$) caused less interference than distractors in the rare area (161 ms; $t(47) = 16.91$, $p < .001$, $d_z = 2.44$, 95% HPD [142 ms, 182 ms], $BF_{10} = 3.36 \times 10^{18}$). Additionally, there was a signif-

[3] In fact, the increase in the sample size was implemented in response to a reviewer recommendation. That is, owing to the small (but, of note: significant) carry-over effects (from 90/10 distributed same- to 50/50 distributed different-dimension distractors) observed in the original sample of 24 participants, the reviewer advised us to replicate the effects by running a second group. As this yielded essentially the same pattern of results (there were no interactions involving the factor group), here we present the findings combined for the two groups.

icant target location effect, with targets being responded to slower in the frequent than in the rare region (671 vs. 637 ms; $t(47) = 4.5$, $p < .001$, $d_z = 0.65$, 95% HPD [17 ms, 47 ms], $BF_{10} = 960$).

Distractor interference in the test session. To examine whether traces of the probability-cueing effect established in the learning session would still be left after the change of the probability distribution (from 90/10 to 50/50) and the type of distractor (from same- to different dimension) in the test session, we focused our analysis on the first block of the second session. See Figure 9, which depicts the transition between the last block of the learning session (same-dimension distractors, 90/10 distribution) and the first block of test session (different-dimension distractors, 50/50 distribution). Again (different-dimension) distractors were found to generally cause interference: RTs were overall slower, by 44 ms, when a distractor was present as compared with absent (646 vs. 603 ms; (47) = 9.8, $p < .001$, $d_z = 1.41$, 95% HPD [33.56 ms, 51.74 ms], $BF_{10} = 2.7 \times 10^{10}$). In addition, there was still a significant probability-cueing effect: RTs were still faster, by 12 ms (642 vs. 654 ms; $t(47) = -1.88$, $p = .033$, $d_z = 0.27$, 95% HPD [−22.78 ms, −0.3592 ms], $BF_{10} = 1.53$), and distractor interference (relative to the distractor-absent baseline) remained reduced, when a distractor was presented in the frequent area compared with the rare area (net interference frequent area: 39 ms; $t(47) = 8.51$, $p < .001$, $d_z = 1.23$, 95% HPD [28.27 ms, 47.37 ms], 2.155×10^8; net interference rare area: 51 ms; $t(47) = 7.95$, $p < .001$, $d_z = 1.15$, 95% HPD [39 ms, 63 ms], $BF_{10} = 3.538 \times 10^7$). Additionally, there was a significant target-location effect, 638 versus 611 ms (27 ms; $t(47) = 2.83$, $p = .003$, $d_z = 0.41$, 95% HPD [7 ms, 44 ms], $BF_{10} = 11$).

Explicitness of learning. There were 13% of the participants who answered the distractor distribution question correctly after the first session, which is not different from chance, $\chi^2(1) = 1.20$, $p = .273$. Further, comparing the probability cueing effect between those who had indicated the distribution correctly versus those who had not revealed no significant difference: 86 versus 83 ms, $t(6.4) = 0.14$, $p = .892$, $d = 0.06$, 95% HPD [67 ms, 102 ms], $BF_{10} = 0.39$. After the second session, again 13% indicated the correct, now equal distribution.

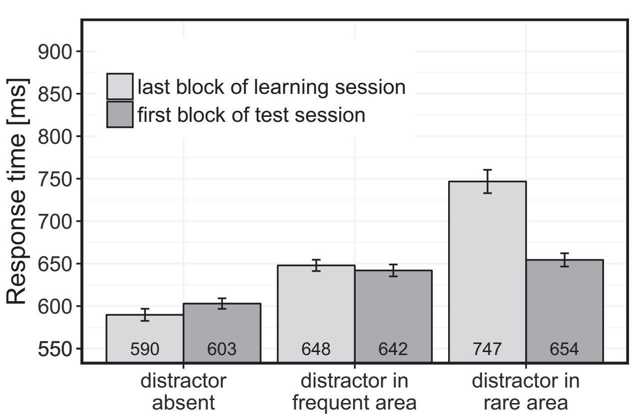

Figure 9. RTs as a function of the distractor condition (absent vs. frequent area vs. rare area) for the last block of the learning session (light gray) with same-dimension distractors and the first block of the test session (dark gray) with different-dimension distractors.

Discussion

Thus, Experiment 3 demonstrates that a probability-cueing effect established with same-dimension distractors in the learning session does carry over (after 24 plus hours) to the test session with different-dimension distractors, and this is accompanied by carry-over of a robust target location effect. This was the case even though distractors were equally likely to occur in each of the previously frequent and rare regions on the second day, that is, observers could not have learned the uneven distribution anew with different-dimension distractors. We take this to mean that a special space-based suppression strategy developed to deal with same-dimension distractors, namely: suppression of the frequent area at the level of the overall-saliency map, continues (at least initially) to be applied even to different-dimension distractors, even though the latter can, and would, normally be dealt with using a dimension-based suppression strategy—which, with different-dimension distractors, does not give rise to a target location effect (see Sauter et al., 2018, and Experiments 1 and 2).

General Discussion

The present results show that a distractor location probability-cueing effect developed during a learning session carries over to a test session (even when the latter is conducted about 24 h later) with same-dimension distractors, but not (reliably) with different-dimension distractors (Experiments 1 and 2). With same-dimension distractors, distractor interference in the test session remained significantly reduced for the (previously) frequent distractor area, compared with the (previously) rare area, even though distractors were distributed evenly in the test session—affording no opportunity for relearning of the previous (uneven) distribution. However, even with same-dimension distractors, the effect was reduced in the first block of the test session compared with the last block of the training session, indicative of relatively fast unlearning of the old (and new learning of the changed) distribution, though it took some 880 plus trials (i.e., 4 plus epochs) of practice with the changed distribution for the effect to be completely unlearnt (see Figure 4). We take this overall-pattern to indicate that practice with an uneven distribution of same-dimension distractors (that cause a greater degree of conflict) yields deeper—and, thus, better consolidated and persistent—probability learning effects than practice with different-dimension distractors.

Given the prior evidence for a target-location effect with same-dimension distractors and the evidence for the absence of such an effect for different-dimension distractors (only the former, but not the latter, was associated with slowed responding to targets in the frequent as compared with the rare region; see also Sauter et al., 2018), we hypothesized that the learning is not just of differential depth, but also implemented at a different level in the hierarchical architecture of search guidance: the superordinate overall-saliency map level (same-dimension distractors) as compared with the subordinate dimensional level (different-dimension distractors). The result pattern found by Sauter et al. (2018) did, however, not rule out the possibility that with same-dimension distractors, too, spatial learning is implemented at the dimensional level (i.e., the fact that the distractor location probability cueing effect was coupled with a target location effect could, in principle, also be explained by suppression of the orientation dimension, in which both the distractor and the target were defined). To identify the origin of spatial learning with same-dimension distractors, Experiment 3 examined for carry-over of (acquired) probability cueing from learning with same-dimension distractors to test with different-dimension distractors. If, with same-dimension distractors (with which there is carry-over of learning, as revealed by Experiments 1 and 2), the learning is implemented at the overall-saliency map level, then it should generalize to a new situation with a change in the type of distractor (to a different dimension) in the test session (Hypothesis A). The reason is that, because of the summing of feature contrast signals across dimensions, overall-saliency coding is feature-less or feature-blind: saliency signals only indicate that there is an object at a particular location that differs (to a certain degree) from the objects in its surround, without providing information about the dimension or specific feature(s) that constitute the difference (e.g., Liesefeld, Liesefeld, & Müller, in press; Töllner, Eschmann, Rusch, & Müller, 2014). Thus, if learned suppression continues to be applied to the (previously) frequent distractor area at the level of the overall-saliency map, any signal should be suppressed in this region whether it is defined in the same dimension as the target (that was tested and confirmed in Experiments 1 and 2) or in a different dimension (that was examined in Experiment 3). Alternatively, if the learning is dimension-specific (inhibiting feature contrast signals within the distractor dimension, more strongly so in the frequent than the rare area), there should be no carry-over when the dimension of the distractor is switched from learning to test: if one learns to specifically suppress orientation-defined distractors, one has not learned to suppress color-defined distractors (Hypothesis B). The results of Experiment 3 are in line with Hypothesis A: color-defined distractors continued to cause less interference, while orientation-defined targets persisted to take longer to be detected, in the (previously) frequent distractor area, when the initial learning had occurred with same-dimension distractors (Experiment 3), but not when learning occurred with different-dimension distractors (Experiment 1).

The interpretation offered above leaves open a number of questions, in particular:

1. Did we simply fail to find the (for our argumentation) critical carry-over effects, including a target location effect, with our different-dimension distractors because they generated too little interference?

2. Can we explain why the carry-over of distractor location probability cueing was weaker in Experiment 3 (same-dimension → different-dimension) than in Experiments 1 and 2 (same-dimension → same-dimension), while the target location effect was comparable in magnitude?

3. Why would suppression of same-dimension distractors operate at the overall-saliency map level when it could, in principle (on the dimension-weighting account, DWA), be equally implemented at the dimensional level?

4. Is the account offered here a general one, that is: does it extend to other dimensions of target- and distractor-defining features than those used in the present experiments?

Below, we consider these issues in turn.

1. One possible objection against the interpretation offered above, as pointed out by one of the reviewers, is as follows: Interference and, thus, acquired probability cueing was substantially weaker with different- than with same-dimension distractors, but a target location effect may become discernible only when the interference effect is sufficiently large. That is, a target location effect might also be found with different-dimension distractors provided they cause a similar-size interference effect to same-dimension distractors. Ultimately, we cannot rule out this possibility, and it is conceivable that different-dimension distractors may also (like same-dimension distractors) be suppressed at the overall-saliency map level (as has been argued by Ferrante et al., 2018, and Wang & Theeuwes, 2018, albeit with regard to paradigms in which a specific single location, rather than a whole region, was highly likely to contain a distractor).

However, in practice, it is virtually impossible to create different-dimension distractors that cause a similarly high interference to same-dimension distractors. In fact, this follows from a central assumption of the DWA, namely, that the former allows for highly effective, dimension-based suppression. That the existence of a dimensional boundary between the distractor and the target is a critical determinant of distractor interference has recently been shown by Liesefeld, Liesefeld, and Müller (in press). In this study, observers either looked for an orientation-defined target (one group) or a luminance-defined target (another group). Each type of target was combined, unpredictably across trials, with either an orientation-defined distractor or a luminance-defined distractor—with the distractors being exactly the same for the two groups. The results showed that exactly the same orientation distractor interfered more than the luminance distractor when searching for an orientation-defined target, and exactly the same luminance distractor interfered more than the orientation distractor when searching for a luminance-defined target. Thus, it cannot be a saliency difference between the distractors or differential suppressibility of the distractor-defining (orientation vs. luminance) features that explains this interaction. Rather, what drives the magnitude of the interference is the relation of the distractor- to the target-defining dimension, as predicted by the DWA: interference is low when distractors are defined in a different dimension to the target, but high when they are defined within the same dimension. As a consequence of this qualitative difference, same-dimension distractors also provide a higher incentive to learn to exploit any imbalance in the spatial distractor distribution and thus necessarily come to induce stronger distractor location probability cueing effects compared with different-dimension distractors.

As already stated, this does not rule out that if a different-dimension distractor could be made to interfere as strongly as a same-dimension distractor, it would produce a larger cueing effect and, associated with this, a target location effect. Critically, however, we would maintain that the latter would then also reflect a qualitative switch of the suppression strategy, from one operating at the (distractor-) dimensional level to one operating at the level of the (supradimensional) overall-saliency map. We are confident that the different-dimension distractor used here was suppressed on the dimensional level, because with this type of distractor (that was equated in terms of salience with the same-dimension distractor), we never observed a target location effect (the only exception being the test session of Experiment 3, which was, however, preceded by a learning session with same-dimension distractors). With a total sample size of 152 observers under this condition to date, we believe we would have resolved a target location effect had there been one, however small given the shallow (but highly significant) distractor location probability cueing effect.

2. Another question was raised by a reviewer in relation to the critical pattern of carry-over effects in Experiment 3: While being significant, why was the (same-dimension → different-dimension) carry-over of distractor location probability cueing weaker in Experiment 3 (12 ms) than the (same-dimension → same-dimension) carry-over effect in Experiments 1 and 2 (combined across the two experiments: 30 ms), while the target location effects were comparable (27 ms in Experiment 3 vs. ~24 ms in Experiments 1 and 2 combined)?

We believe the reason is a persistent spatial bias against the (previously) frequent distractor region at the level of the overall-saliency map, coupled with a relatively rapid instantiation of a (color-)dimension-based distractor suppression strategy in the test session. The switch of distractor type from same- (the orientation) to different- (the color) dimension—that affords the opportunity to operate dimension-based suppression—is more immediately apparent than the change in the distractor probability distribution from 90/10 to 50/50. Accordingly, dimension-based suppression would kick in relatively rapidly during the first block of the test session, and color distractors would be kept out of the search relatively efficiently and, importantly, without any spatial bias. That is, color-based suppression would be spatially equal for the (previously) frequent and rare distractor areas, as no spatial bias was acquired for the color dimension in the preceding learning session (with orientation distractors) and the current distractor distribution (50/50) is consistent with the default setting of spatially unbiased distractor suppression. This new, unbiased (color-) dimension-based filtering set might overlap for a while with the carried-over spatial bias at the (higher) level of the overall-saliency map (acquired in response to the 90/10 distributed orientation distractors in the learning session), which dissipates only slowly. However, as color distractors are now already largely filtered out at the (lower) dimension-based level, equally in both display regions, this carried-over bias will not add much with regard to reducing distractor interference: the more effective the filter at the lower level, the less the interference reduction brought about by an additional filter at a higher level. However, the carried-over bias would continue to harm the processing of the orientation-defined target when the target occurs in the previously frequent region (that continues to be suppressed at the overall-saliency map level). As a result, there would be a comparable target location effect across all experiments, along with a relatively weak distractor location effect when the distractor is switched in Experiment 3 compared with when it remains a same-dimension distractor in Experiments 1 and 2.

To illustrate, assume that the spatial suppression effect operating within the overall-saliency map scales with the strength of the distractor after dimensional down-modulation (i.e., its strength as it enters the stage of overall-saliency computation): if the same-dimension distractor (that is not dimensionally suppressed) has a hypothetical strength of, say, 1 (in some arbitrary units) and the suppressed different-dimension distractor a strength of 0.2 and both are spatially inhibited (linearly) in the (previous) frequent distractor region by a factor of 0.8, this results in a reduction of priority signaling of ($1 - 1 \times 0.8 =$) 0.20 for the same-dimension distractor, as compared with only ($0.23 - 0.3 \times 0.8 =$) 0.06 for the different-dimension distractor. Thus, even with the exact same amount of spatial suppression, one would expect the interference effect (that reflects the reduction of priority signaling because of spatial weighting) to be much weaker for the different-dimension than for the same-dimension distractor. This would explain why the distractor location effect was only 12 ms in the first block of the test session in Experiment 3 (different-dimension distractors), while it was larger in the relevant conditions (with same-dimension distractors at both learning and test) of the previous experiments. Further, it would explain why the target location effect remained as large in the test session of Experiment 3 as in the previous experiments with unchanged same-dimension distractors in the test session: since the target dimension (orientation) would not be suppressed, target priority signaling would be modulated only by the suppressive bias that persists at the level of the overall-saliency map—that is the same as in the previous experiments with same-dimension distractors at both learning and test. Thus, this effect pattern is entirely consistent with the DWA.

3. Why would suppression of same-dimension distractors operate at the overall-saliency map level, when it could, in principle, be equally implemented at the dimensional level? (Recall that the latter could also explain the target location effect with same-dimension distractors, while it fails to explain the carry-over effect from same- to different dimension distractors)? At present, only a speculative answer is possible (cf. Sauter et al., 2018): Perhaps, with same-dimension distractors, dimension-based suppression is a less viable strategy than overall-saliency map suppression, as any down-weighting of the orientation dimension would conflict with the task of finding the orientation-defined target. There would, thus, be a goal conflict with observers, at the same time, attempting to keep any signals from the orientation dimension out of the search and selectively enhancing the target orientation. Operating suppression at the overall-saliency map level would avoid such a goal conflict. Further work is required to examine the merits of this reasoning, along with answering whether the level of suppression is a strategic choice (in which case different observers might use different—optimal and nonoptimal—strategies under the same stimulus conditions), or selected automatically based on constraints intrinsic to the stimuli.

4. Is the account offered above—that is essentially a further development of the DWA—a general one? That is, is the present pattern of effects specific to the stimuli used in the present experiments (orientation-defined target coupled with an orientation-defined vs. color-defined distractor), or does it generalize to other dimensions of target- and distractor-defining features? While the present findings are

in line with the DWA (to our knowledge the only general account predicting a dissociation between same- and different-dimension distractors!), further work—for instance, with luminance-, color-, and motion-defined targets and distractors defined in either the same or one of the other dimensions—is necessary for the DWA to be established as a truly general account of the asymmetry revealed in the present study. In particular, would there be a location probability cueing effect, along with a target-location effect, with all kinds of same-dimension distractors, including color distractors? There is good evidence that, within the color dimension, salient singletons mismatching the target color (i.e., same-dimension distractors) may fail to capture attention (contingent-capture studies: e.g., Folk, Leber, & Egeth, 2002; Lien, Ruthruff, & Cornett, 2010; Lien, Ruthruff, & Johnston, 2010; additional-singleton studies: e.g., Gaspar, Christie, Prime, Jolicœur, & McDonald, 2016; Gaspar & McDonald, 2014). Even though there are exceptions consistent with the DWA (contingent-capture paradigm: Harris, Becker, & Remington, 2015; additional-singleton paradigm: Feldmann-Wüstefeld, Uengoer, & Schubö, 2015; Kadel, Feldmann-Wüstefeld, & Schubö, 2017), on the balance of evidence, it appears that the suppression of color distractors does involve an element of feature-based suppression (see also Gaspelin, Leonard, & Luck, 2015, and Gaspelin & Luck, 2018). This picture is actually consistent with previous studies of dimension weighting (with combinations of color, motion, and orientation targets), in which color proved to be special: it was the only dimension producing significant feature-specific intertrial priming and trial-wise precueing effects (e.g., Found & Müller, 1996; Müller et al., 2003; Weidner, Pollmann, Müller, & von Cramon, 2002), though with dimension-based effects outweighing feature-based effects even with color targets. To sum up: The differential carry-over effects between the distractor types (same-dimension: orientation; different-dimension: color) support our hypothesis that region-selective suppression of same-dimension distractors is based on different mechanisms than the suppression of different-dimension distractors. In particular, with same-dimension distractors, participants learn to (strongly) suppress any signal at the level of the overall-saliency map (in the frequent distractor area) and this suppressive set also applies to signals originating from a different dimension (after the switch from same-dimension to different-dimension distractors in Experiment 3). By contrast, with different-dimension distractors, the learning is dimension-specific: suppressing any feature contrast signals (exclusively) from the distractor-defining dimension.

In conclusion, we take our findings to show that when the probability cueing is learned through spatial suppression mechanisms on the overall-saliency map, it is more persistent over time and more resistant to un- or relearning. This is in contrast to the more shallow learning with different-dimension distractors, which is not implemented on the overall-saliency map, but on the feature contrast maps for specific dimensions.

References

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,* 422–430. http://dx.doi.org/10.1111/psyp.12019

Feldmann-Wüstefeld, T., Uengoer, M., & Schubö, A. (2015). You see what you have learned. Evidence for an interrelation of associative learning and visual selective attention. *Psychophysiology, 52,* 1483–1497. http://dx.doi.org/10.1111/psyp.12514

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. http://dx.doi.org/10.1016/j.cortex.2017.09.027

Folk, C. L., Leber, A. B., & Egeth, H. E. (2002). Made you blink! Contingent attentional capture produces a spatial blink. *Perception & Psychophysics, 64,* 741–753. http://dx.doi.org/10.3758/BF03194741

Found, A., & Müller, H. J. (1996). Searching for unknown feature targets on more than one dimension: Investigating a "dimension-weighting" account. *Perception & Psychophysics, 58,* 88–101. http://dx.doi.org/10.3758/BF03205479

Gaspar, J. M., Christie, G. J., Prime, D. J., Jolicœur, P., & McDonald, J. J. (2016). Inability to suppress salient distractors predicts low visual working memory capacity. *Proceedings of the National Academy of Sciences of the United States of America, 113,* 3693–3698. http://dx.doi.org/10.1073/pnas.1523471113

Gaspar, J. M., & McDonald, J. J. (2014). Suppression of salient objects prevents distraction in visual search. *The Journal of Neuroscience, 34,* 5658–5666. http://dx.doi.org/10.1523/JNEUROSCI.4161-13.2014

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

Gaspelin, N., & Luck, S. J. (2018). Distinguishing among potential mechanisms of singleton suppression. *Journal of Experimental Psychology: Human Perception and Performance, 44,* 626–644. http://dx.doi.org/10.1037/xhp0000484

Geng, J. J., & Behrmann, M. (2005). Spatial probability as an attentional cue in visual search. *Perception & Psychophysics, 67,* 1252–1268. http://dx.doi.org/10.3758/BF03193557

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. http://dx.doi.org/10.3389/fpsyg.2014.01195

Harris, A. M., Becker, S. I., & Remington, R. W. (2015). Capture by colour: Evidence for dimension-specific singleton capture. *Attention, Perception, & Psychophysics, 77,* 2305–2321.

Hickey, C., McDonald, J. J., & Theeuwes, J. (2006). Electrophysiological evidence of the capture of visual attention. *Journal of Cognitive Neuroscience, 18,* 604–613. http://dx.doi.org/10.1162/jocn.2006.18.4.604

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,* 1713–1730. http://dx.doi.org/10.1037/a0032251

Jiang, Y. V., Swallow, K. M., Rosenbaum, G. M., & Herzig, C. (2013). Rapid acquisition but slow extinction of an attentional bias in space. *Journal of Experimental Psychology: Human Perception and Performance, 39,* 87–99. http://dx.doi.org/10.1037/a0027611

Kadel, H., Feldmann-Wüstefeld, T., & Schubö, A. (2017). Selection history alters attentional filter settings persistently and beyond top-down control. *Psychophysiology, 54,* 736–754. http://dx.doi.org/10.1111/psyp.12830

Kiss, M., Grubert, A., Petersen, A., & Eimer, M. (2012). Attentional capture by salient distractors during visual search is determined by temporal task demands. *Journal of Cognitive Neuroscience, 24,* 749–759. http://dx.doi.org/10.1162/jocn_a_00127

Krummenacher, J., Müller, H. J., Zehetleitner, M., & Geyer, T. (2009). Dimension- and space-based intertrial effects in visual pop-out search: Modulation by task demands for focal-attentional processing. *Psychological Research, 73,* 186–197. http://dx.doi.org/10.1007/s00426-008-0206-y

Leber, A. B., & Egeth, H. E. (2006a). Attention on autopilot: Past experience and attentional set. *Visual Cognition, 14,* 565–583. http://dx.doi.org/10.1080/13506280500193438

Leber, A. B., & Egeth, H. E. (2006b). It's under control: Top-down search strategies can override attentional capture. *Psychonomic Bulletin & Review, 13,* 132–138. http://dx.doi.org/10.3758/BF03193824

Leber, A. B., Gwinn, R. E., Hong, Y., & O'Toole, R. J. (2016). Implicitly learned suppression of irrelevant spatial locations. *Psychonomic Bulletin & Review, 23,* 1873–1881. http://dx.doi.org/10.3758/s13423-016-1065-y

Lien, M. C., Ruthruff, E., & Cornett, L. (2010). Attentional capture by singletons is contingent on top-down control settings: Evidence from electrophysiological measures. *Visual Cognition, 18,* 682–727. http://dx.doi.org/10.1080/13506280903000040

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

Liesefeld, H. R., Liesefeld, A. M., & Müller, H. J. (in press). Distractor-interference reduction is dimensionally constrained. *Visual Cognition*.

Liesefeld, H. R., Liesefeld, A. M., Pollmann, S., & Müller, H. J. (in press). Biasing allocations of attention via selective weighting of saliency signals: Behavioral and neuroimaging evidence for the Dimension-Weighting Account. In T. Hodgson (Ed.), *Current topics in behavioral neurosciences: Processes of visuo-spatial attention and working memory*. Basel, Switzerland: Springer.

Liesefeld, H. R., Liesefeld, A. M., Töllner, T., & Müller, H. J. (2017). Attentional capture in visual search: Capture and post-capture dynamics revealed by EEG. *NeuroImage, 156,* 166–173. http://dx.doi.org/10.1016/j.neuroimage.2017.05.016

Liesefeld, H. R., Moran, R., Usher, M., Müller, H. J., & Zehetleitner, M. (2016). Search efficiency as a function of target saliency: The transition from inefficient to efficient search and beyond. *Journal of Experimental Psychology: Human Perception and Performance, 42,* 821–836. http://dx.doi.org/10.1037/xhp0000156

Mathôt, S., Schreij, D., & Theeuwes, J. (2012). OpenSesame: An open-source, graphical experiment builder for the social sciences. *Behavior Research Methods, 44,* 314–324. http://dx.doi.org/10.3758/s13428-011-0168-7

Morey, R. D. (2008). Confidence intervals from normalized data: A correction to Cousineau (2005). *Reason, 4,* 61–64.

Morey, R. D., Rouder, J. N., & Jamil, T. (2014). BayesFactor: Computation of Bayes factors for common designs. R package version 0.9. 8. Retrieved from https://cran.r-project.org/web/packages/BayesFactor/BayesFactor.pdf

Müller, H. J., Geyer, T., Zehetleitner, M., & Krummenacher, J. (2009). Attentional capture by salient color singleton distractors is modulated by top-down dimensional set. *Journal of Experimental Psychology: Human Perception and Performance, 35,* 1–16. http://dx.doi.org/10.1037/0096-1523.35.1.1

Müller, H. J., Heller, D., & Ziegler, J. (1995). Visual search for singleton feature targets within and across feature dimensions. *Perception & Psychophysics, 57,* 1–17. http://dx.doi.org/10.3758/BF03211845

Müller, H. J., Reimann, B., & Krummenacher, J. (2003). Visual search for singleton feature targets across dimensions: Stimulus- and expectancy-driven effects in dimensional weighting. *Journal of Experimental Psychology: Human Perception and Performance, 29,* 1021–1035. http://dx.doi.org/10.1037/0096-1523.29.5.1021

Nothdurft, H.-C. (1993). The role of features in preattentive vision: Comparison of orientation, motion and color cues. *Vision Research, 33,* 1937–1958. http://dx.doi.org/10.1016/0042-6989(93)90020-W

Open Science Collaboration. (2015). Estimating the reproducibility of psychological science. *Science, 349,* aac4716. http://dx.doi.org/10.1126/science.aac4716

Peirce, J. W. (2007). PsychoPy—Psychophysics software in Python. *Journal of Neuroscience Methods, 162,* 8–13. http://dx.doi.org/10.1016/j.jneumeth.2006.11.017

Plummer, M., Best, N., Cowles, K., & Vines, K. (2006). CODA: Convergence diagnosis and output analysis for MCMC. *R News, 6,* 7–11.

Rangelov, D., Müller, H. J., & Zehetleitner, M. (2013). Visual search for feature singletons: Multiple mechanisms produce sequence effects in visual search. *Journal of Vision, 13,* 22. http://dx.doi.org/10.1167/13.3.22

Rangelov, D., Müller, H. J., & Zehetleitner, M. (2017). Failure to pop out: Feature singletons do not capture attention under low signal-to-noise ratio conditions. *Journal of Experimental Psychology: General, 146,* 651–671. http://dx.doi.org/10.1037/xge0000284

R Core Team. (2014). R: A language and environment for statistical computing. *R Foundation for Statistical Computing,* Vienna, Austria. 2013.

Rouder, J. N., Speckman, P. L., Sun, D., Morey, R. D., & Iverson, G. (2009). Bayesian t tests for accepting and rejecting the null hypothesis. *Psychonomic Bulletin & Review, 16,* 225–237. http://dx.doi.org/10.3758/PBR.16.2.225

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. *Perception & Psychophysics, 80,* 622–642. http://dx.doi.org/10.3758/s13414-017-1477-4

Schneider, W., & Shiffrin, R. M. (1977). Controlled and automatic information processing: I Detection, search, and attention. *Psychological Review, 84,* 1–66. http://dx.doi.org/10.1037/0033-295X.84.1.1

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

Töllner, T., Eschmann, K. C., Rusch, T., & Müller, H. J. (2014). Contralateral delay activity reveals dimension-based attentional orienting to locations in visual working memory. *Attention, Perception, & Psychophysics, 76,* 655–662. http://dx.doi.org/10.3758/s13414-014-0636-0

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

Weidner, R., Pollmann, S., Müller, H. J., & von Cramon, D. Y. (2002). Top-down controlled visual dimension weighting: An event-related fMRI study. *Cerebral Cortex, 12,* 318–328. http://dx.doi.org/10.1093/cercor/12.3.318

Wykowska, A., & Schubö, A. (2011). Irrelevant singletons in visual search do not capture attention but can produce nonspatial filtering costs. *Journal of Cognitive Neuroscience, 23,* 645–660. http://dx.doi.org/10.1162/jocn.2009.21390

Zehetleitner, M., Goschy, H., & Müller, H. J. (2012). Top-down control of attention: It's gradual, practice-dependent, and hierarchically organized. *Journal of Experimental Psychology: Human Perception and Performance, 38,* 941–957. http://dx.doi.org/10.1037/a0027629

Zehetleitner, M., Koch, A. I., Goschy, H., & Müller, H. J. (2013). Salience-based selection: Attentional capture by distractors less salient than the target. *PLoS ONE, 8,* e52595. http://dx.doi.org/10.1371/journal.pone.0052595

Zellin, M., Conci, M., von Mühlenen, A., & Müller, H. J. (2013). Here today, gone tomorrow—Adaptation to change in memory-guided visual search. *PLoS ONE, 8,* e59466. http://dx.doi.org/10.1371/journal.pone.0059466

Zellin, M., von Mühlenen, A., Müller, H. J., & Conci, M. (2014). Long-term adaptation to change in implicit contextual learning. *Psychonomic Bulletin & Review, 21,* 1073–1079. http://dx.doi.org/10.3758/s13423-013-0568-z

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