Environmental Regularities Mitigate Attentional Misguidance in Contextual Cueing of Visual Search

Artyom Zinchenko[1], Markus Conci[1, 2], Hermann J. Müller[1, 2], and Thomas Geyer[1, 2, 3]

[1] Department Psychologie, Ludwig-Maximilians-Universität München
[2] Munich Center for Neurosciences–Brain & Mind, Ludwig-Maximilians-Universität München
[3] NICUM–Neuroimaging Core Unit Munich, Ludwig-Maximilians-Universität München

Visual search is faster when a fixed target location is paired with a spatially invariant (vs. randomly changing) distractor configuration, thus indicating that repeated contexts are learned, thereby guiding attention to the target (contextual cueing [CC]). Evidence for memory-guided attention has also been revealed with electrophysiological (electroencephalographic [EEG]) recordings, starting with an enhanced early posterior negativity (N1pc), which signals a preattentive bias toward the target, and, subsequently, attentional and postselective components, such as the posterior contralateral negativity (PCN) and contralateral delay activity (CDA), respectively. Despite effective learning, relearning of previously acquired contexts is inflexible: The CC benefits disappear when the target is relocated to a new position within an otherwise invariant context and corresponding EEG correlates are diminished. The present study tested whether global statistical properties that induce predictions going beyond the immediate invariant layout can facilitate contextual relearning. Global statistical regularities were implemented by presenting repeated and nonrepeated displays in separate streaks (mini blocks) of trials in the relocation phase, with individual displays being presented in a fixed and thus predictable order. Our results revealed a significant CC effect (and an associated modulation of the N1pc, PCN, and CDA components) during initial learning. Critically, the global statistical regularities in the relocation phase also resulted in a reliable CC effect, thus revealing effective relearning with predictive streaks. Moreover, this relearning was reflected in an enhanced PCN amplitude for repeated relative to nonrepeated contexts. Temporally ordered contexts may thus adapt memory-based guidance of attention, particularly the allocation of covert attention in the visual display.

Keywords: visual search, contextual cueing, N1pc, predictive coding, sequential structure

Humans display an impressive capability for detecting—and learning—statistical regularities in their current sensory environments (e.g., Jensen et al., 2011) and subsequently use these regularities to make predictions about upcoming events, thus increasing the efficiency of attentional processing. Recent progress in attention research has renewed interest in the behavioral and neural systems for the guidance of selective attention based on learned environmental structure, for instance, by employing statistical-learning paradigms in visual search or object recognition tasks (see Goujon et al., 2015; Sisk et al., 2019; Võ et al., 2019). Although this work has contributed significantly to our understanding of memory-guided visual search, relatively little is known about the attentional mechanisms involved in search guidance from established statistical long-term (LT) memories and the plasticity of such memories.

Correspondence concerning this article should be addressed to Artyom Zinchenko, Department Psychologie, Lehrstuhl für Allgemeine und Experimentelle Psychologie, Ludwig-Maximilians-Universität München, Leopoldstraße 13, 80802 München, Germany. Email: artyom.zinchenko@gmail.com

One example of how statistical regularities can facilitate behavioral—in particular, visual search—performance derives from the contextual cueing (CC) paradigm (Chun & Jiang, 1998). In a typical CC experiment, participants search for a target letter "T" embedded in a set of distractor letters "L." Unknown to participants, 50% of trials consist of repeated spatial distractor-target arrangements (i.e., the distractor configuration is predictive of the target location), while the other 50% of trials consist of nonrepeated, that is, random and thus nonpredictive arrangements of the distractors relative to the target. A host of studies using this paradigm has shown that visual search is expedited for targets embedded in repeated distractor "contexts," as compared to nonrepeated item arrangements—referred to as the CC effect. That the CC benefit is a LT spatial-memory effect is attested by the fact that it was demonstrable even 10 days after initial learning (van Asselen & Castelo-Branco, 2009; Zellin et al., 2014). Despite showing substantial reaction time (RT) benefits for repeated displays, participants, however, appear to be unable to reliably differentiate repeated from novel item arrangements in explicit-memory tests. Based on these findings, Chun and Jiang (1998) proposed that regularly encountered spatial distractor–target relations are extracted and encoded in some implicit spatial LT memory; then, upon reencountering a learnt arrangement, the acquired distractor–target associations are retrieved and "cue" attention to the target location (Schankin & Schubö, 2009; see also Zinchenko, Conci, Töllner, et al., 2020). In other words, the acquired associations are stored as spatial "templates" in LT memory, and if the current item arrangement matches such a

template, the template is activated, top-down raising the "attentional priority" of the target location within this arrangement and thus effectively guiding search toward the task-relevant item (Brady & Chun, 2007).

In typical CC experiments, a benefit in RTs develops relatively rapidly, requiring only a few (approximately three) repetitions of a distractor–target arrangement for facilitated search to emerge (Annac et al., 2019; Geyer et al., 2012; Zellin et al., 2014). However, if, after establishing a memory representation of a given (repeated) distractor–target arrangement, the target location is changed within an otherwise unchanged distractor layout, the updating of the representation requires a great deal of effortful practice with the relocated target. In fact, relocating a target to a new position within an already learnt context (in a relocation phase following an initial learning phase) immediately abolishes the RT benefit (see Annac et al., 2017, who reported a reduction by 97% in a meta-analysis of seven target-relocation studies) or may even produce a cost, such that the RTs to the repeated context become slower compared to nonrepeated contexts. And it may take some 80 repetitions of each repeated display to effectively reestablish a CC effect (Zellin et al., 2014; see also Yang et al., 2021). Thus, while contextual regularities are acquired fast and efficiently, established context memories are rather inflexible: They resist updating and prolonged practice is required for a new target location to be integrated within an existing representation (Conci & Zellin, 2022; Makovski & Jiang, 2010; Manginelli & Pollmann, 2009; Zellin et al., 2013; see also Geyer et al., 2021).

The inefficient adaptation to target-location changes is at least partly attributable to a persistent misguidance of (focal) attention to the originally learnt location, as recently shown by Zinchenko, Conci, Töllner, et al. (2020). Analyzing lateralized electroencephalographic (EEG) potentials in a CC experiment with an initial learning and a subsequent relocation phase, Zinchenko et al. found repeated displays to give rise to enhanced amplitudes of an enhanced early posterior negativity (N1pc) component, a negative-going deflection that peaks approximately 80–180 ms poststimulus onset contralateral to the target side of the display. This component is considered to reflect an initial, automatic orienting response to salient items in the display array (cf., Sänger & Wascher, 2011)—thus, in Zinchenko, Conci, Töllner, et al. (2020), essentially reflecting an early attentional bias toward the target location cued by the context. However, after the relocation of the target to a new position on the contralateral side of the display, the enhanced early N1pc for repeated (vs. nonrepeated) displays flipped and now exhibited a positive-going deflection. This N1pc flip may be taken to indicate some misguidance of attention to the initial (but now no longer valid) target location.

Apart from the N1pc, Zinchenko, Conci, Töllner, et al. (2020) also observed context-induced changes in the subsequent event-related potential (ERP) components: the posterior contralateral negativity (PCN) (also referred to as N2pc) and the contralateral delay activity (CDA) (also referred to as sustained posterior contralateral negativity). The PCN—a negative-going ERP at posterior electrode sites contralateral to the location of an attended item—is taken to index the allocation of focal attention to a target in visual search (Eimer, 1996; Luck & Hillyard, 1994; Töllner et al., 2015). EEG work predating Zinchenko, Conci, Töllner, et al. (2020) had already established the PCN to be enhanced in response to repeated (vs. nonrepeated) displays (Johnson et al., 2007; Schankin & Schubö, 2009, 2010), showing that learnt contexts can guide attentional selection in visual search. Finally, Zinchenko, Conci, Töllner, et al. (2020) found the CDA

component, a sustained negativity 400–800 ms poststimulus, to be more pronounced with repeated (vs. nonrepeated) displays. The CDA is thought to reflect postselective processing of already attended items, including the extraction of response-critical feature information and its matching against a target-identity "template" held in visual working memory (WM), to decide upon the required response (e.g., Mazza et al., 2007; Töllner et al., 2013; Woodman & Vogel, 2008). Accordingly, the increased CDA amplitude to repeated displays may be taken to reflect enhanced target processing, for instance, because the distractors in the vicinity of the target—which, in the typical CC paradigm, are invariant in terms of their "orientation" identity—may also contribute to target discrimination in repeated displays.[1]

Over and above these basic effects of learning and relearning in CC, we (Zinchenko et al., 2018) have recently shown that the build-up of contextual memories is expedited in statistically "rich" environments (see also Tseng et al., 2011; Zang et al., 2018; Zinchenko, Conci, Hauser et al., 2020): CC was found to develop more rapidly when the proportion of repeated (relative to nonrepeated) displays was 80%, as compared to 50% or only 20%. In fact, in the latter, statistically "poor" environment, CC failed to develop altogether. In addition, we found that context-based guidance of visual search was also modulated by manipulations of the temporal predictive context within which observers encountered individual repeated displays (Zinchenko et al., 2018; see also Richter et al., 2018; Turk-Browne et al., 2005). CC developed faster when repeated and, respectively, nonrepeated displays were presented in separate mini-blocks, or streaks, of trials (see, e.g., Geyer et al., 2006; Kristjansson et al., 2002). That is, rich statistical environments may promote learning about the frequencies or conditional probabilities of sensory events going beyond the immediately sensed contextual arrays, thereby facilitating statistical learning of co-occurring distractor-target patterns. Central to this proposal is the idea that CC reflects an active-perception mechanism that generates predictions for likely future events (e.g., Sauseng et al., 2015; Zinchenko et al., 2019) and thus takes into account the frequency distribution of statistical signals in the current search environment, such as the relative proportion of repeated and nonrepeated displays or the rate of change between these displays. For instance, while viewing the repeated arrays, participants may come to form hypotheses about regularities in the displays (or their absence) that then adjust learning, critically, and of relevance to the current study, also including the way they process target-location changes. Thus, a typical, "baseline" search experiment with, across trials, random presentations of repeated and nonrepeated displays may not lead to the impression of a "statistically rich" sensory world, as a result of which target position changes may rather be attributed to sensory noise than to reliable changes in the environment. In terms of perceptual inference, this would be equivalent to the maintenance of already established contextual expectations

---

[1] That is, the orientations of the (L-type) distractors are constant across repetitions, while the response-critical orientation of the (T-type) target itself is variable to prevent a given repeated display to be associated with a fixed response (see the Methods section for details). For instance, when the target is left-oriented, it may form a close configuration with adjacent (invariant) distractor items, and a different configuration would be rendered when the target is right-oriented. Learnt distractor orientations may then help target feature discrimination in repeated arrays by more effective matching of the focally attended item (the target T, including some distractor items in its immediate surround; e.g., Brady & Chun, 2007) against the left- versus right-oriented target-feature template held in WM, a process that is presumably indexed by the CDA.

(priors). Given this, a target location change in an environment with random ordering of repeated and nonrepeated displays, may leave observers with a strong tendency to search for the target at the initially encountered, that is, learned, target position. However, in stable search environments, in which repeated displays are presented across longer sequences of trials, target-relocation events may be highly informative, while at the same time, observers are more susceptible to the changing regularities. Thus, in a predictive environment, target location changes may be noticed more readily and integrated into the previously acquired context memory.

On this background, the goal of the present study was to examine whether global statistical, streak-related (temporal) regularities can facilitate the adaptation of acquired context representations following consistent target-location changes, using both behavioral measures (RTs) and corresponding evoked responses of the EEG: namely the N1pc, PCN, and CDA components, the latter permitting us to disentangle functionally distinct attentional processes and thus providing insights about how statistical contextual memories are updated after target relocation and how these are affected by a stable search environment.

To select the best conditions to demonstrate contextual adaptation behaviorally, the EEG experiment (Experiment 2) was preceded by a purely behavioral experiment (Experiment 1), in which we compared two "streak" variations in terms of their capacity to foster optimal relearning (Experiments 1a and 1b). Experiments 1a and 1b started with a learning phase comparable to standard CC experiments (i.e., repeated and nonrepeated displays were presented randomly). In the subsequent relocation phase of Experiment 1a, repeated and nonrepeated displays were presented in individual streaks of either repeated or nonrepeated trials presented in alternating order (e.g., repeated—nonrepeated—repeated etc.), which was essentially comparable to a previous study by Zinchenko et al. (2018) (which did, however not investigate CC relocation effects). In Experiment 1b, by contrast, the global predictability in the relocation phase was further increased by fixing the order of displays within the streaks (as well as the order of streaks themselves). We found the highly controlled temporal environment provided in Experiment 1b to yield significant CC adaptation, that is: this condition resulted in a relatively fast integration of the new target locations into the preestablished context representations in the target relocation phase. Next, in Experiment 2, we then employed the "successful" condition of Experiments 1b to determine the specific preattentive versus postselective contributions to context adaptation by examining the succession of lateralized ERPs.

Experiment 1

Method

Participants

Different groups of participants took part in each experiment: 16 participants in Experiment 1a (nine female; $M_{age} = 28.18$, $SD = 3.57$ years), and another 16 in Experiment 1b (eight female; $M_{age} = 27.37$, $SD = 3.37$ years). The sample size in the experiments was comparable to previous (EEG) studies that investigated CC effects (e.g., Schankin & Schubö, 2009, 2010; Zinchenko, Conci, Töllner, et al., 2020). Note, however, that the current experiments specifically aimed to test contextual adaptation; we compared CC in the initial learning phase to CC in the subsequent relocation phase. A modulation of CC by phase would thus be reflected in the statistical analyses in an interaction of the factors context (repeated, nonrepeated) and phase (learning, relocation). To provide a robust estimation of the required sample size to achieve this interaction, we conducted a meta-analysis on 24 published experiments that examined learning-relocation changes in CC in 31 different cases and for which sample sizes and F-statistics (or reported t-values) were available. We then computed Cohen's d effect-size scores for each study, and given the heterogeneity of individual effect sizes (see Figure 1), we conducted a meta-analysis on effect size scores using a random effects model. Based on the mean effect-size score of .75, which would, according to Cohen (1988), correspond to a "large" effect, a power analysis showed that to find a context by phase interaction on RTs with at least 80% power, a minimum sample size of $N = 16$ subjects was required.

Moreover, when assuming an effect size of only .61 (which would reflect the lower end of the 95% confidence interval from the meta-analysis: [.61–.88]), a sample of $N = 16$ participants would still achieve 65% power. Based on these estimates, our current sample size thus appears sufficient in terms of statistical power to detect a possible CC difference across phases in the current experiments. This study was not preregistered. All raw behavioral data and all individual subject means across conditions of the ERP components and critically also all analysis files are publicly accessible at https://osf.io/v89mz/?view_only=aa2bce929c1b413f9618b45337036f3e (Zinchenko, 2022).
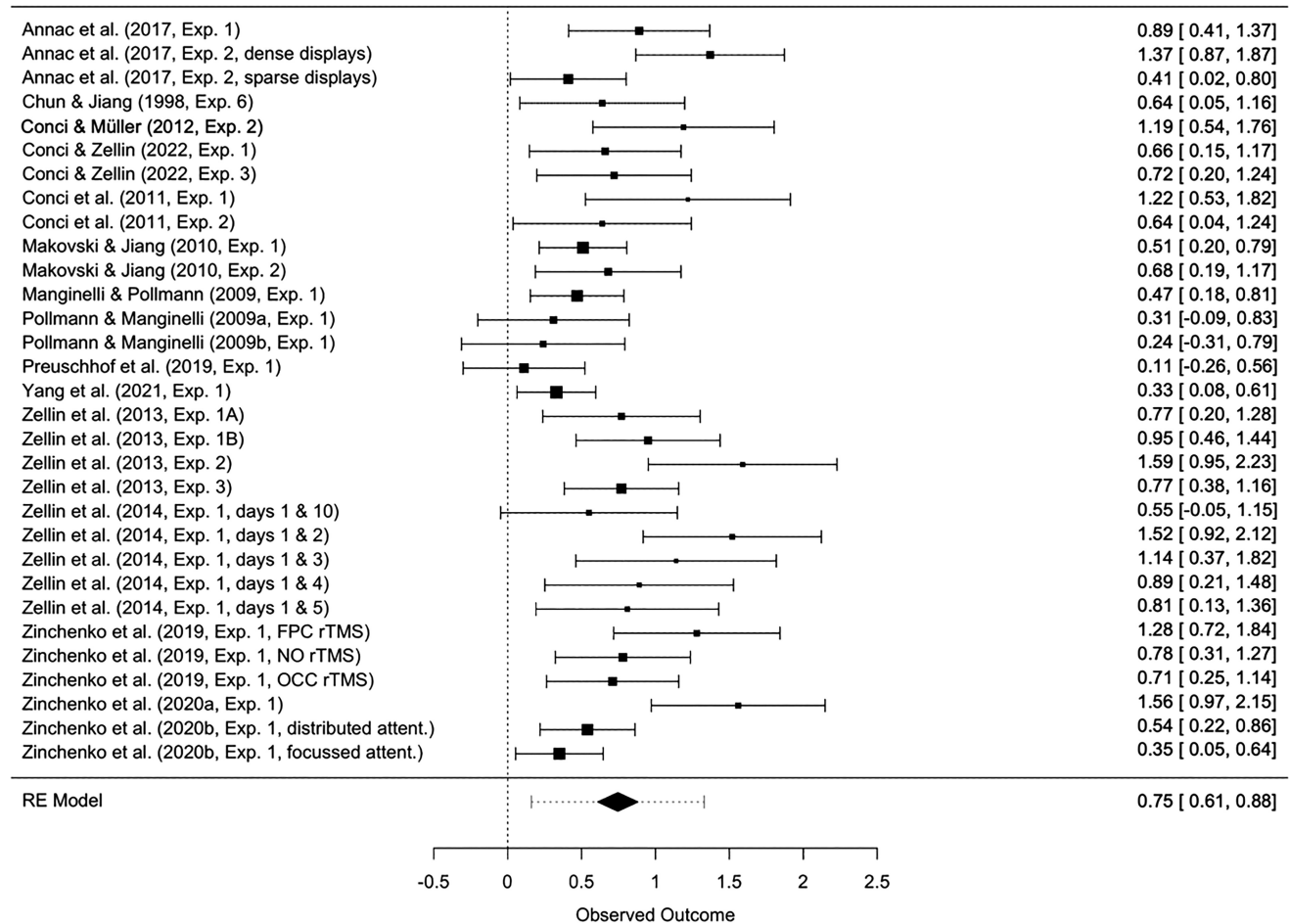
Apparatus and Stimuli

The experimental routine was programmed in MATLAB with Psychtoolbox extensions (Brainard, 1997; Pelli, 1997) and was run on a personal computer under the Windows 7 operating system. Participants were seated in a dimly lit room in front of a 23-inch liquid crystal display monitor (ASUS, Taiwan; refresh rate 60 Hz; display resolution: $1,920 \times 1,080$ pixels) at a viewing distance of approximately 80 cm (unrestrained). The search displays consisted of 12 gray items (luminance: 1.0 cd/m^2; one T-shaped target and 11 L-shaped distractors) presented against a black background (0.11 cd/m^2). All stimuli subtended 0.35° of visual angle in width and height. The items were arranged on three (invisible) concentric circles around the display center (with a radius of 1.74°, 3.48°, and 5.22°, for Circles 1 through 3, respectively). There were overall 24 possible target locations, eight of which were used for repeated displays with invariant distractor layout throughout the experiment (two in each quadrant). The other eight target locations (also two in each quadrant) were used for nonrepeated displays with random distractor arrangements. Finally, a third set of eight target locations (again, two in each quadrant) was used for repeated displays in the relocation phase. Importantly, for a given repeated display, the target would be presented in opposite hemifields during the initial learning and the subsequent relocation phase (i.e., the relocated target swapped its position with a distractor in the opposite hemifield, but the invariant layout of the other distractor items would remain otherwise unchanged; see Figure 2). Targets in both repeated and nonrepeated display layouts were presented at prespecified (and fixed) locations. For each type of display, two out of eight targets were placed on Circle 1 and three were presented on Circles 2 and 3 each, thus ensuring that target eccentricity was comparable across conditions.

The "T" target was rotated randomly by 90° to either the left or the right. The eleven remaining items were L-shaped distractors rotated randomly by 0°, 90°, 180°, or 270°. In both types of display

Figure 1

Cohen's d *Effect Sizes and 95% CIs of 24 Published Experiments That Investigate CC Adaptation in Altogether 31 Different Cases by Quantifying the Difference in RTs Between Repeated and Nonrepeated Search Layouts in an Initial Learning Phase Relative to a Subsequent Target Relocation Phase*

Study	Effect size [95% CI]
Annac et al. (2017, Exp. 1)	0.89 [0.41, 1.37]
Annac et al. (2017, Exp. 2, dense displays)	1.37 [0.87, 1.87]
Annac et al. (2017, Exp. 2, sparse displays)	0.41 [0.02, 0.80]
Chun & Jiang (1998, Exp. 6)	0.64 [0.05, 1.16]
Conci & Müller (2012, Exp. 2)	1.19 [0.54, 1.76]
Conci & Zellin (2022, Exp. 1)	0.66 [0.15, 1.17]
Conci & Zellin (2022, Exp. 3)	0.72 [0.20, 1.24]
Conci et al. (2011, Exp. 1)	1.22 [0.53, 1.82]
Conci et al. (2011, Exp. 2)	0.64 [0.04, 1.24]
Makovski & Jiang (2010, Exp. 1)	0.51 [0.20, 0.79]
Makovski & Jiang (2010, Exp. 2)	0.68 [0.19, 1.17]
Manginelli & Pollmann (2009, Exp. 1)	0.47 [0.18, 0.81]
Pollmann & Manginelli (2009a, Exp. 1)	0.31 [-0.09, 0.83]
Pollmann & Manginelli (2009b, Exp. 1)	0.24 [-0.31, 0.79]
Preuschhof et al. (2019, Exp. 1)	0.11 [-0.26, 0.56]
Yang et al. (2021, Exp. 1)	0.33 [0.08, 0.61]
Zellin et al. (2013, Exp. 1A)	0.77 [0.20, 1.28]
Zellin et al. (2013, Exp. 1B)	0.95 [0.46, 1.44]
Zellin et al. (2013, Exp. 2)	1.59 [0.95, 2.23]
Zellin et al. (2013, Exp. 3)	0.77 [0.38, 1.16]
Zellin et al. (2014, Exp. 1, days 1 & 10)	0.55 [-0.05, 1.15]
Zellin et al. (2014, Exp. 1, days 1 & 2)	1.52 [0.92, 2.12]
Zellin et al. (2014, Exp. 1, days 1 & 3)	1.14 [0.37, 1.82]
Zellin et al. (2014, Exp. 1, days 1 & 4)	0.89 [0.21, 1.48]
Zellin et al. (2014, Exp. 1, days 1 & 5)	0.81 [0.13, 1.36]
Zinchenko et al. (2019, Exp. 1, FPC rTMS)	1.28 [0.72, 1.84]
Zinchenko et al. (2019, Exp. 1, NO rTMS)	0.78 [0.31, 1.27]
Zinchenko et al. (2019, Exp. 1, OCC rTMS)	0.71 [0.25, 1.14]
Zinchenko et al. (2020a, Exp. 1)	1.56 [0.97, 2.15]
Zinchenko et al. (2020b, Exp. 1, distributed attent.)	0.54 [0.22, 0.86]
Zinchenko et al. (2020b, Exp. 1, focussed attent.)	0.35 [0.05, 0.64]
RE Model	0.75 [0.61, 0.88]

Observed Outcome (x-axis from -0.5 to 2.5)

Note. In addition, the bottom line of this table also provides the meta-analytic Cohen's *d* and CI, which was computed using a RE model. The size of each box representing the effect sizes for individual studies is proportional to the weight of the study in relation to the meta-analytical effect-size measure. Individual studies were identified by a search in Web of Science on Sunday, February 12, 2023, using these keywords and Boolean operators: (visual search) AND (contextual cueing) AND ((updating) OR (target location change) OR (flexibility) OR (adaptation)). Individual effect sizes were calculated using the R package "effectsize" (Ben-Shachar et al., 2020). The meta-analytical random effects model was computed using the R package "metaforest" (Van Lissa, 2020). CI = confidence interval; CC = contextual cueing; RT = reaction time; RE = random effects.

(repeated, nonrepeated), the distractors were placed randomly, but with the constraint that all search items were equally distributed across both hemifields (i.e., six items per hemifield) and circles (i.e., four items were placed on each of the three circles). Thus, the only difference between repeated and nonrepeated displays was that distractor locations (and distractor orientations) were fixed in the repeated context displays and always random in nonrepeated context displays.

There were two phases (learning, relocation) in each experiment. Each phase consisted of 16 blocks of 16 trials (thus, yielding 512 trials in total), with an equal number of repeated and nonrepeated display configurations presented in each block. In the learning phase (which was identical in Experiments 1a and 1b), repeated and nonrepeated displays were randomly intermixed across trials within a given block. That is, the learning phase followed the

standard design of CC experiments (e.g., Chun & Jiang, 1998), providing no statistically reoccurring regularities other than the repetition of the item arrangements in (temporally and sequentially nonpredictable) repeated-context displays. In contrast to the learning phase, in the relocation phases, repeated and nonrepeated displays were further subdivided in each block into separate streaks, or miniblock sequences, of trials (with eight trials per streak and two streaks [one of repeated and one of nonrepeated displays] per block). In Experiment 1a, the order of streaks (i.e., whether the eight repeated or the eight nonrepeated displays were presented first within a given block) was fixed (though the fixed order was random across participants), while the order of individual displays within streaks was random (see Zinchenko et al., 2018, for a comparable streak design). In Experiment 1b, the order of individual displays within the streaks was

Figure 2

Example of a Repeated-Context Search Display in the Learning and Relocation Phases of the Experiment

Learning   Relocation
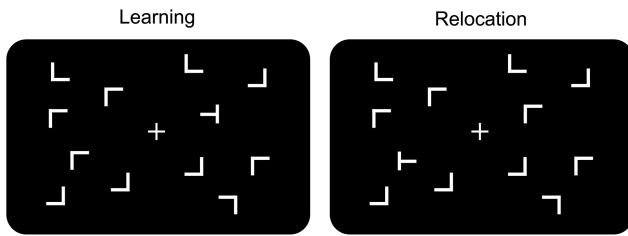
Note. Each display was presented with an initial target position during the learning phase; in the subsequent relocation phase, the target position then swapped with a distractor from the opposite hemifield, within an otherwise constant display layout. Note that the three dashed, concentric circles on which the search items were arranged were not shown in the actual search displays.

additionally fixed, thus providing a temporally and sequentially predictive learning environment. Of note, the order of displays was also fixed in the streaks of nonrepeated displays—though, in this case, the repetition was based solely on the target locations within the nonrepeated distractor layouts since the target locations were fixed not only in repeated but also in nonrepeated displays.

Trial Sequence

A trial started with presenting a fixation cross (size: 0.10° luminance: 1.0 cd/m²) for 500 ms, followed by a blank interval of 200 ms before the onset of the search display. Observers were instructed to respond as quickly and accurately as possible to the orientation of the "T" (left vs. right). Each search display stayed on the screen until the observer's manual choice response was registered. Observers responded to the left/right orientation of the "T" target by pressing the left/right arrow button on a computer keyboard with their corresponding index finger. Following an erroneous response, a red minus sign appeared on the screen for 1,000 ms. Each trial followed a blank (intertrial) interval of 1,000 ms.

Recognition Test

At the end of each experiment, we administered a yes/no recognition test to examine whether participants could explicitly remember the repeated configurations (and tell them apart from random, nonrepeated layouts). Observers were presented with eight repeated displays from the search task (note that a target was visible in these displays, specifically: A target was located at the position the target had occupied in the learning phase of the experiment), as well as eight newly composed displays, with all displays presented in random order. Their task was to indicate whether they had previously seen a given display. Repeated displays were selected from the learning phase because we assumed that these displays would be recognized more clearly, if at all. The recognition responses were nonspeeded, and no error feedback was provided. Of note, our analysis of recognition test performance combined the data from the individual Experiments 1a, 1b, and 2. This was motivated by a recent meta-analytical study showing that increasing test power can reveal above-chance recognition in CC (Vadillo et al., 2016; see also Geyer et al., 2020; Smyth & Shanks, 2008).

Results

Individual mean error rates in both Experiments 1a and 1b were below 3%, thus indicating that observers were very accurate in performing the task. Given that there were only few errors, no further statistical analyses were performed on these data. Mean RTs were calculated for each factorial combination. RTs above 5,000 ms and below 200 ms were removed from the data proper, leading to the elimination of <2% of all trials (the same procedure resulted in comparable exclusion rates in Experiment 2, see below). Trials with response errors were also removed from the RT analysis. In each experiment, individual mean RTs for each experimental condition were then submitted to a repeated-measures analysis of variance (ANOVA) with the factors phase (learning, relocation), context (repeated, nonrepeated), and epoch (1–4; with one experimental "epoch" combining the data across four consecutive trial blocks of 16 trials in each block). Greenhouse–Geisser corrected values are reported in case if Mauchley's test of sphericity was significant ($p < .05$). Significant interactions were further decomposed by least significant difference post hoc tests. Figure 3 depicts the mean RTs for repeated and

Figure 3

Mean RTs (in Seconds; With Associated SEs of the Mean) for Repeated and Nonrepeated Contexts (Solid and Dashed Lines, Respectively) as a Function of Epoch in the Learning and Relocation Phases of Experiments 1a (Top) and 1b (Bottom)
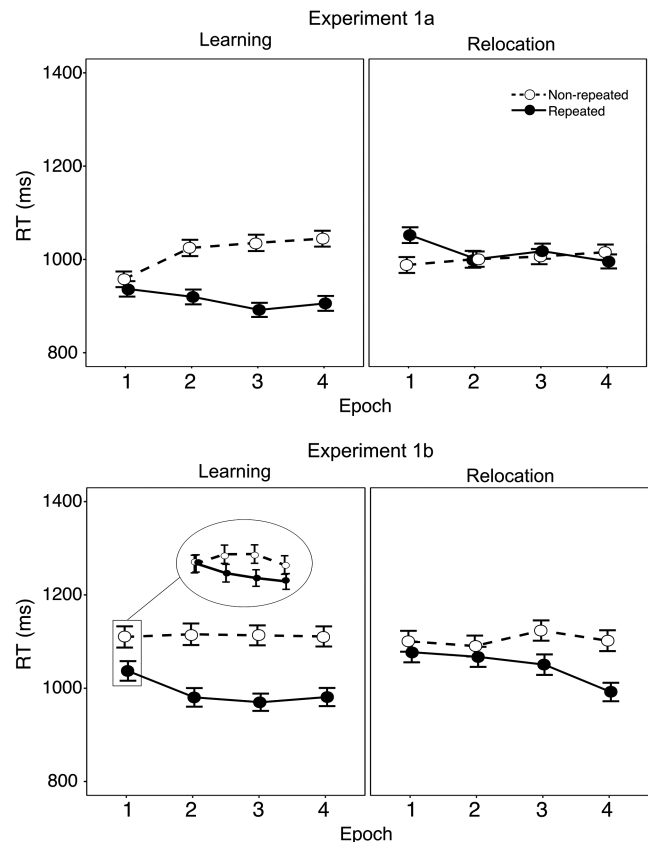
Note. In addition, in Epoch 1 of Experiment 1b, the mean RTs are additionally provided for each individual block to illustrate the onset of CC (see circular insertion). RT = reaction time; CC = contextual cueing.

nonrepeated displays across epochs in the learning and relocation phases of Experiments 1a (top) and 1b (bottom).

Experiment 1a

The analysis of Experiment 1a revealed a significant main effect of phase, with RTs being overall slower in the relocation phase (1,013 ms) than in the initial learning phase (967 ms), $F(1, 15) = 6.14$, $p = .026$, $\eta_p^2 = .29$. Moreover, there was a significant main effect of context: Participants responded overall faster to repeated (968 ms) relative to nonrepeated (1,013 ms) displays, $F(1, 15) = 8.11$, $p = .012$, $\eta_p^2 = .35$. In addition, the Context × Epoch interaction, $F(3, 45) = 9.31$, $p < .001$, $\eta_p^2 = .38$, and the theoretically important Context × Phase interaction, $F(1, 15) = 17.74$, $p = .001$, $\eta_p^2 = .54$, were significant, the latter being due to a reliable CC effect (faster RTs to repeated vs. nonrepeated displays) in the initial learning phase (CC effect = 105 ms), $t(15) = 4.16$, $p < .001$, Cohen's $dz = 1.04$, which was however abolished after the target-location change in the subsequent relocation phase (CC effect = −15 ms), $t(15) = 0.91$, $p = .37$, Cohen's $dz = -0.22$. The three-way interaction was not significant, $F(3, 45) = 1.28$, $p = .291$, $\eta_p^2 = .08$.

Experiment 1b

Experiment 1b again revealed a significant main effect of context, $F(1, 15) = 38.18$, $p < .001$, $\eta_p^2 = .72$, with faster RTs to repeated (1,025 ms) than nonrepeated (1,115 ms) displays. Similar to Experiment 1a, the CC effect in Experiment 1b was modulated by phase: There was an interaction of context and phase, $F(1, 15) = 4.55$, $p = .05$, $\eta_p^2 = .23$, suggesting that CC was overall more marked in the initial learning phase relative to the subsequent target relocation phase (CC effects of 127 and 52 ms, respectively). However, importantly, even though the CC effect was reduced during relocation, it nevertheless yielded a reliable difference, $t(15) = 2.16$, $p = .046$, Cohen's $dz = 0.54$, which shows that the repeated contexts continued to facilitate search even after target relocation. The three-way interaction did not reach significance, $F(3, 45) = 1.77$, $p = .166$, $\eta_p^2 = .11$.[2]

Comparison of Experiments 1a and 1b

In an additional comparison of Experiment 1a against 1b, we examined whether providing additional statistical regularities in the relocation phase of Experiment 1b did significantly facilitate contextual relearning. To this end, mean RTs in the learning and relocation phases were submitted to separate mixed ANOVAs with the within-group factors context (repeated, nonrepeated) and epoch (1–4), and the between-group factor Experiment (1a, 1b). As expected, the ANOVA of the learning-phase data revealed neither a main effect of experiment, $F(1, 30) = 1.36$, $p = .252$, $\eta_p^2 = .04$, nor an Experiment × Context interaction, $F(1, 30) = 0.44$, $p = .514$, $\eta_p^2 = .01$. However, there was a reliable main effect of context, $F(1, 30) = 48.26$, $p < .001$, $\eta_p^2 = .62$, which demonstrates that a comparable CC effect (of 116 ms averaged across Experiments 1a and 1b,) developed during the (identical) learning phases in both experiments. In addition the Context × Epoch interaction was significant, $F(3, 90) = 11.68$, $p < .001$, $\eta_p^2 = .28$, thus showing that CC emerged gradually in both experiments as the learning phase progressed (from 52 ms in Epoch 1 to 135 ms in Epoch 4).

In contrast, the analysis of the RT performance in the relocation phase only revealed a significant Experiment × Context interaction,

$F(1, 30) = 5.31$, $p = .028$, $\eta_p^2 = .15$: There was a reliable CC effect in Experiment 1b (CC = 52 ms), $t(15) = 2.16$, $p = .046$, Cohen's $dz = 0.54$, but not in Experiment 1a (CC = −15 ms), $t(12) = 0.91$, $p = .37$, Cohen's $dz = -0.22$. There were no other significant effects involving the factor Experiment (ps < .1). This again shows that, after the target location change, CC was reliable only when additional statistical regularities—namely predictable sequences of trials within streaks—were provided.

Discussion

Experiment 1 examined whether higher-order statistical regularities, that is, probability-based expectations about upcoming visual stimuli, can influence the adaptation of previously formed LT context memories. We found that presentation of repeated and nonrepeated displays in pure streaks of trials and with a fixed sequential order of individual repeated displays within streaks (in Experiments 1b) fostered contextual adaptation. In contrast, introducing streaks, with a randomized order of trial displays alone failed to promote successful adaptation (in Experiment 1a). Given this, we introduced the "optimal" memory-update conditions (in the relocation phase) of Experiments 1b in an EEG variant of this experiment in Experiment 2.

Experiment 2

Experiment 2 used EEG methods to elucidate at which specific processing stage(s) context adaptation is facilitated by higher order, temporal regularities, by examining lateralized ERP markers of (a) the initial, automatic biasing of attention by context memory (in the N1pc component), (b) the spatial orienting of attention and selection of the target (in the PCN component), and (c) the postselective processing of the target item in visual WM (in the CDA component). Thus, Experiment 2 was essentially an EEG-compatible variant (see Zinchenko, Conci, Töllner, et al., 2020) of Experiments 1b.

Method

Sixteen right-handed participants with normal or corrected-to-normal visual acuity took part in this study (11 female; M_{age}: 26.5 [age range: 21–33] years). All participants provided written informed consent and received 20 € for taking part in the experiment. All experimental parameters were comparable to the procedure described for Experiment 1b (see Zinchenko, Conci, Töllner, et al., 2020), and observers were instructed to fixate the central fixation cross throughout the trial and use peripheral vision to locate and identify the target. In order to confirm that participants did maintain central fixation, concurrent eye-tracking was performed using an

---

[2] An additional analysis revealed that CC was already reliable in Epoch 1 of the learning phase, $t(15) = 3.29$, $p = .004$, Cohen's $dz = 0.82$. Since a given epoch averages across the responses from four consecutive blocks, the resulting mean RTs per epoch might reveal a measure that is too coarse to map the time course of initial statistical learning. Given this, we compared the mean RTs to repeated versus nonrepeated displays across the first four blocks of Epoch 1 (see inset in Figure 3, bottom): CC revealed a certain numerical difference from Block 2 onwards, which however was fairly unstable: Block 1, $t(15) = 0.29$, $p > .7$, Cohen's $dz = -0.07$; Block 2, $t(15) = 2.16$, $p = .047$, Cohen's $dz = -0.53$; Block 3, $t(15) = 4.07$, $p = .001$, Cohen's $dz = -1.02$; Block 4, $t(15) = 1.58$, $p > .13$, Cohen's $dz = -0.39$. Thus, CC was not significant in Epoch 1 and stabilized only during the subsequent epochs of Experiment 1b.

EyeLink 1000 system (Ontario, Canada). Each search display was presented for 700 ms, after which all search items disappeared, leaving only the fixation cross, which stayed on-screen until a manual response was issued. Experiment 2 again consisted of a learning and relocation phase which presented 25 blocks of 16 trials each (thus, yielding 800 trials in total).

EEG Recording

The EEG was continuously sampled at 1 kHz using Ag/AgCl active electrodes (acti-CAP system; Brain Products Munich) from 64 scalp sites in accordance with the international 10–10 System. To monitor for blinks and eye movements, the electrooculogram was additionally recorded by means of electrodes placed at the outer canthi of the eyes and, respectively, the superior and inferior orbits. All electrophysiological signals were amplified using BrainAmp amplifiers (BrainProducts, Munich) with a 0.1- to 250-Hz bandpass filter. During data acquisition, all electrodes were referenced to FCz, and rereferenced offline to averaged mastoids. All electrode impedances were kept below 5 kΩ.

All EEG data analyses were performed in Brain Vision Analyzer (Version 2.2.2; Brain Products, Munich, Germany). Before segmenting, the raw data were visually inspected to remove nonstereotypical noise manually; subsequently, the data were bandpass-filtered using a 0.1- to 70-Hz Butterworth IIR filter (24 dB/Oct). Next, an infomax independent-component analysis was run to identify components representing blinks and horizontal eye movements and to remove these artifacts before backprojection of the residual components (1% of all trials were removed due to eye-movement artifacts). For the ERP analyses, the continuous EEG was epoched into 1,000-ms segments relative to a 200-ms prestimulus interval, used for baseline correction. Only trials with correct responses and without artifacts—any signal exceeding $\pm 60\ \mu V$, bursts of electromyographic activity (as defined by voltage steps/sampling points larger than $50\ \mu V$), and activity lower than $0.5\ \mu V$ within intervals of 500 ms (indicating dead channels)—were accepted for further analysis on an individual-channel basis before averaging the ERP waves. To extract the three components of interest (N1pc, PCN, CDA) from overlapping target selection-unspecific components, ERPs from parieto-occipital electrodes (PO7/8) ipsilateral to the target's location were subtracted from contralateral ERPs. The latencies of the components were defined individually as the maximum deflection in the time range 80–180 ms (N1pc), 180–350 ms (PCN), and 500–800 ms (CDA) poststimulus onset. We computed ERP amplitudes by averaging five sample points, respectively, before and after the maximum deflection, and in case of the CDA, by averaging activity over the 500- to 800-ms time window.

Results

Behavioral Results

Individual mean error rates and RTs were calculated for each factorial (Phase × Context × Epoch) combination. For the RT analysis, RTs above 5,000 ms and below 200 ms were removed from the data proper, leading to the removal of <2% of all trials (as in Experiment 1). Error trials were also removed from the RT analysis. Figure 5A depicts the mean RTs for repeated and nonrepeated displays across epochs in the learning and relocation phases.

The mean error rate in Experiment 2 was somewhat higher than in Experiment 1 (9.5% vs. 2.6%), but nevertheless comparable to a previous CC study that limited the display exposure time in order to prevent participants from making eye movements during the EEG recording (Zinchenko, Conci, Töllner, et al., 2020). Given that incorrect responses were considerably more frequent in Experiment 2 than in Experiment 1, we performed a repeated-measures ANOVA on the error rates, with the factors phase, context, and epoch. This analysis revealed a significant Context × Phase interaction, $F(1, 15) = 5.26$, $p = .037$, $\eta_p^2 = .26$: Fewer errors were committed with repeated than with nonrepeated contexts in the learning phase (8.3% vs. 11.2%), $F(1, 15) = 5.4$, $p = .035$, $\eta_p^2 = .26$, but this advantage disappeared in the relocation phase (9.3% vs. 9.5%), $F(1, 15) = 0.08$, $p = .785$, $\eta_p^2 = .01$. No other main effects or interactions reached significance (all $ps > .1$).

An analogous ANOVA on the RTs revealed a main effect of context, $F(1, 15) = 86.66$, $p < .001$, $\eta_p^2 = .85$, which showed that participants responded overall faster to repeated (827 ms) than to nonrepeated displays (881 ms). In addition, there was a decrease of RTs with increasing epoch from 910 ms in Epoch 1 to 807 ms in Epoch 5 (with the means aggregated across the two sequential phases); main effect of epoch, $F(4, 60) = 12.87$, $p < .001$, $\eta_p^2 = .46$. Moreover, responses were overall faster in the relocation (832 ms) than in the initial learning phase (876 ms), as revealed by a main effect of phase, $F(1, 15) = 9.75$, $p = .007$, $\eta_p^2 = .39$. Both effects are indicative of general procedural learning. This procedural learning effect was more marked in the initial learning phase (RT speed-up of 146 ms between Epochs 1 and 5) than in the subsequent relocation phase (60-ms speed-up)—as evident from a Phase × Epoch interaction, $F(4, 60) = 3.88$, $p = .007$, $\eta_p^2 = 0.21$. More importantly, the Context × Phase interaction turned out significant, $F(1, 15) = 5.74$, $p = .03$, $\eta_p^2 = .28$: There was a reliable, 79-ms benefit for repeated (vs. nonrepeated) displays in the learning phase, $t(15) = 6.63$, $p < .001$, Cohen's $dz = 1.66$, which reduced to (a still significant magnitude of) 28 ms in the relocation phase, $t(15) = 2.25$, $p = .039$, Cohen's $dz = 0.56$. Thus, despite a reduction in the CC effect during the relocation phase, participants successfully updated their initially formed contextual memory representations to incorporate the changed target location in the relocation phase, thus directly replicating Experiment 1b. No other interactions reached significance (all $ps > .7$).[3]

Electrophysiological Results

Individual mean amplitudes were calculated for each factorial combination, separately for each of the three ERP components. Mean amplitudes for each experimental condition were then submitted to repeated-measures ANOVAs with the factors phase and context. Figure 4B presents the ERP waves contralateral and ipsilateral to the target for nonrepeated (top) and repeated (bottom) contexts in the learning (left) and relocation phases (right). In addition, Figure 5 depicts the corresponding difference waves for the two phases.

---

[3] As can be seen from Figure 4A, a substantial CC effect was already evident in Epoch 1 of the experiment, $t(15) = 2.99$, $p < .01$, Cohen's $dz = 0.34$. To further examine the build-up of the CC-effect, we again compared the repeated and the nonrepeated contexts across the first five blocks of the experiment (see insertion in Figure 4A): CC was nonsignificant in Blocks 1, $t(15) = 0.34$, $p = .73$, and 4, $t(15) = 1.19$, $p = .25$, but significant in Blocks 2, 3, and 5 (all $ts > 2.4$; $ps < .05$). Thus, a CC-effect developed after only 2–3 encounters of the repeated contexts, showing a fast emergence of CC that is consistent with previous findings (e.g., Conci & von Mühlenen, 2009; Geyer et al., 2010; Zellin et al., 2011).

Figure 4

Reaction Times and Event-Related Potentials for Repeated and Nonrepeated Contexts During Learning and Relocation Phases
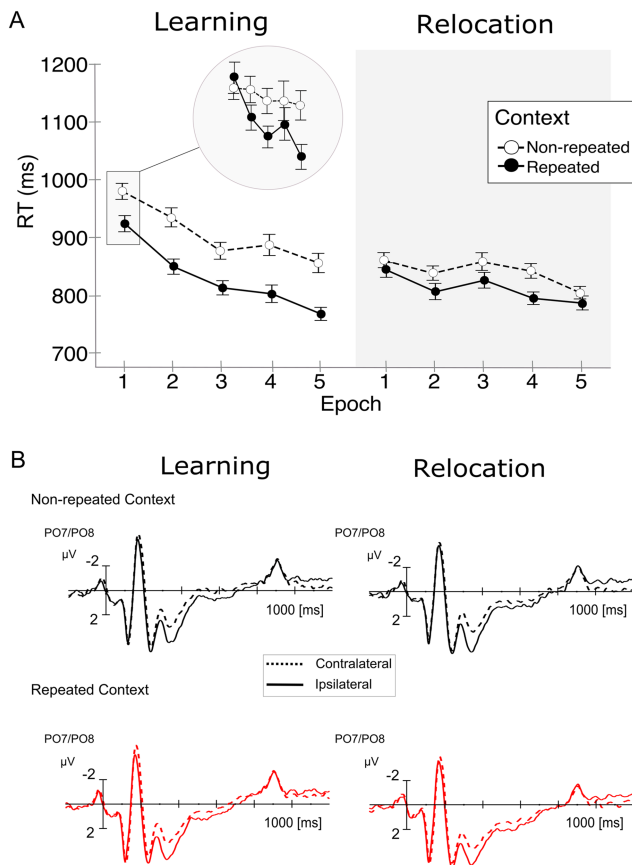
Note. A. Mean RTs, in milliseconds, with associated SEs of the mean for repeated and nonrepeated contexts (solid and dashed lines, respectively) as a function of epoch in the learning and relocation phases. In Epoch 1, the mean RTs are additionally provided for each block to illustrate the fast onset of CC (see circular insertion). B. Grand-average ERPs at electrodes PO7/PO8 contra- and ipsilateral to the target (dashed and solid lines, respectively) for nonrepeated (black) and repeated contexts (red) in the learning (left) and the relocation phase (right). Negative is plotted upward. RT = reaction time; CC = contextual cueing; ERP = event-related potential; PO7/PO8 = parieto-occipital electrodes. See the online article for the color version of this figure.

In an initial step, we compared the mean amplitudes of the difference waves in the baseline (200 ms before stimulus onset) with the N1pc amplitude in the learning and relocation phases using paired-sample t-tests. This analysis confirmed that the relatively small N1pc component differed from random fluctuations in the ERP data. The results showed that, compared to the baseline period, the N1pc exhibited a more negative amplitude deflection in the learning phase (N1pc $= -0.89\,\mu V$, baseline $= -0.0007\,\mu V$), $t(15) = 5.96$, $p < .001$, Cohen's $dz = -2.96$. In comparison, it became more positive in the relocation phase (N1pc $= 0.93\,\mu V$, baseline $= -0.0011\,\mu V$), $t(15) = 8.68$, $p < .001$, Cohen's $dz = 4.28$. Thus, there was a reliable N1pc that reversed in polarity from the learning to the relocation phase, comparable to the pattern observed previously (Zinchenko, Conci, Töllner, et al., 2020).

Next, the N1pc amplitudes were submitted to a Phase × Context repeated-measures ANOVA. This analysis revealed a marginal main effect of phase, with more negative amplitudes in the learning ($-0.19\,\mu V$) compared to the relocation phase (which actually yielded a positive-going deflection: $0.34\,\mu V$), $F(1, 15) = 3.84$, $p = .069$, $\eta_p^2 = .2$. Furthermore, the main effect of context was significant, due to more negative amplitudes for repeated ($-0.15\,\mu V$) versus nonrepeated displays ($0.29\,\mu V$), $F(1, 15) = 5.36$, $p = .035$, $\eta_p^2 = .26$. Finally, the Phase × Context interaction was also significant, $F(1, 15) = 6.44$, $p = .023$, $\eta_p^2 = .3$: For repeated (vs. nonrepeated) displays, there was an increased negative amplitude in the learning phase (repeated $= -0.63\,\mu V$, nonrepeated $= 0.24\,\mu V$), $t(15) = 4.67$, $p < .01$, Cohen's $dz = -1.17$, but this effect disappeared in the relocation phase in which both types of display gave rise to a positive-going deflection (repeated $= 0.35\,\mu V$, nonrepeated $= 0.33\,\mu V$), $t(15) = 0.03$, $p > .9$, Cohen's $dz = 0.009$ (see Figures 5 and 6A). Restated, for repeated displays, the N1pc polarity reversed from the learning to the relocation phase (mean amplitudes: -0.63 and 0.35, respectively), $t(15) = 2.31$, $p = .035$, Cohen's $dz = -0.58$, while nonrepeated displays yielded a positive-going deflection in both phases (learning phase $= 0.24$, relocation phase $= 0.33$), $t(15) = 0.49$, $p = .62$, Cohen's $dz = -0.12$. In sum, the N1pc showed a negative deflection (and an increased amplitude) contralateral to the target for repeated (vs. nonrepeated) displays during initial learning. Still, this difference reversed into a positive deflection following the target relocation to (the position of a distractor in) the opposite hemifield.

An analogous analysis of the subsequent PCN also revealed a significant main effect of context, characterized by more negative-going amplitudes for repeated versus nonrepeated displays (repeated $= -2.04\,\mu V$, nonrepeated $= -1.25\,\mu V$), $F(1, 15) = 17$, $p = .001$, $\eta_p^2 = .53$. Importantly, the Phase × Context interaction did not reach significance, $F(1, 15) = 1.95$, $p = .183$, $\eta_p^2 = .12$: repeated (vs. nonrepeated) displays elicited an increased PCN amplitude not only in the learning phase (repeated $= -2.36\,\mu V$, nonrepeated $= -1.34\,\mu V$), $t(15) = 4.05$, $p < .01$, Cohen's $dz = -1.01$, but also in the relocation phase (repeated $= -1.72\,\mu V$, nonrepeated $= -1.14\,\mu V$), $t(15) = 2.34$, $p = .033$, Cohen's $dz = -0.58$ (see Figures 5 and 6B). In other words, the PCN results revealed a consistently increased negativity for repeated displays, even following the repositioning of the target in the relocation phase.

Finally, the analysis of the CDA component yielded a significant main effect of context due to more negative-going amplitudes with repeated ($-0.76\,\mu V$) compared to nonrepeated displays ($-0.27\,\mu V$), $F(1, 15) = 9.93$, $p = .007$, $\eta_p^2 = .4$. Moreover, the Phase × Context interaction was again significant, $F(1, 15) = 7.54$, $p = .015$, $\eta_p^2 = .33$, owing to a more negative amplitude for repeated ($-1.17\,\mu V$) versus nonrepeated contexts ($-0.26\,\mu V$) in the learning phase, $t(15) = 4.53$, $p < .001$, Cohen's $dz = -0.935$, but not in the relocation phase (repeated $= -0.35\,\mu V$, nonrepeated $= -0.28\,\mu V$), $t(15) = 0.30$, $p = .76$, Cohen's $dz = -0.084$ (see Figures 5 and 6C). The CDA exhibited enhanced sustained negativity in the learning phase for repeated displays, which vanished in the relocation phase.

Correlational Analyses

An additional correlational analysis was performed, which revealed a nonsignificant numerical trend for the correlation of the N1pc

Figure 5

Contralateral Minus Ipsilateral Difference Waveforms for Repeated (Red) and Nonrepeated (Black) Contexts in the Learning (Upper Panel) and in the Relocation Phase (Lower Panel)
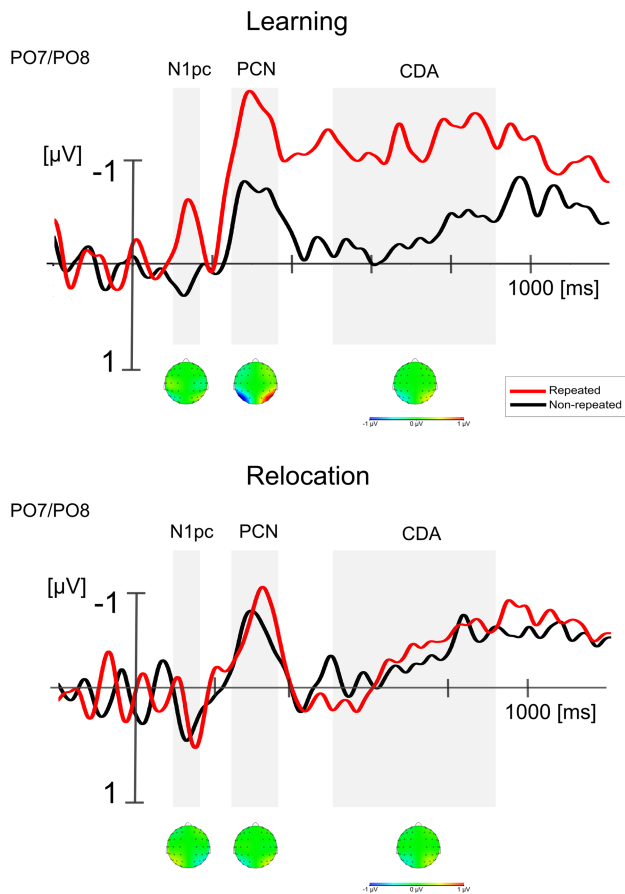
Note. The shaded, gray areas illustrate the timing of the N1pc, PCN, and CDA components, and each component is depicted with a corresponding scalp distribution. Negative is plotted upward. PO7/PO8 = parieto-occipital electrodes; N1pc = enhanced early posterior negativity; PCN = posterior contralateral negativity; CDA = contralateral delay activity. See the online article for the color version of this figure.

amplitude for repeated displays between the learning and relocation phases ($r = -.45$, $df = 14$, $p = .079$; see Figure 6D—notably, the correlation turns out significant, $r = -.57$, $df = 13$, $p = .02$, once the single outlier, that is, the filled circle in Figure 6D, is removed, which was more than four *SD*s above the sample mean. This indicates that the individual negative deflection during learning scaled with the polarity change (thus leading to a positive-going deflection) in the relocation phase. A significant positive correlation was also between the N1pc amplitude and the subsequent PCN in the relocation phase ($r = .64$, $df = 14$, $p < .01$; Figure 6E). That is the positive-going "misguidance" signal (toward the old target location) reflected in the N1pc scaled with more negative lateralization toward the new target side/location in the subsequent PCN, indicative of a possible PCN-related compensation of the earlier attentional misguidance effect.

Recognition Test

We compared the rate of hits (correct recognition of repeated displays as "repeated": 37.5%) to the rate of false alarms (erroneous recognition of nonrepeated displays as "repeated": 38.28%) across all experiments, using a mixed ANOVA with the within-group factor response type (hits, false alarms) and the between-group factor Experiment (1a, 1b, and 2). This ANOVA failed to reveal significant effects involving the factor response type: main effect, $F(1, 45) = 0.06$, $p = .809$, $\eta_p^2 = 0$, interaction of response type and experiment, $F(2, 45) = 0.55$, $p = .581$, $\eta_p^2 = .02$. In support of this, an analogous Bayesian ANOVA (implemented in the R package "BayesFactor"; Morey & Rouder, 2018) revealed a $BF_{10} = .21$ for the main effect of response type, which according to Jeffreys (1961) suggests that the data is 4.76 times more likely under the null hypothesis, of the hit rates being comparable to the false alarm rates and thus there is no explicit knowledge in CC. We nevertheless acknowledge that our Bayes factor is .21, so the evidence for the null hypothesis may be considered only as moderate (Dienes, 2014), probably because of the relatively low sensitivity of the specific, yes/no, recognition test (e.g., Geyer et al., 2020; Vadillo et al., 2016).

Discussion

Experiment 2 again replicated the behavioral results of Experiments 1b: a robust CC effect developed in the initial learning phase, which was then reduced, but nevertheless remained reliable in the target relocation phase. This confirms that context adaptation, that is, the integration of a new target location within an existing distractor representation, is facilitated when repeated displays are consistently encountered in a sequentially predictable order within a continuous streak of trials.

Moreover, the analysis of the ERP data revealed, for the early N1pc, a relocation-specific polarity reversal. Replicating previous findings (Zinchenko, Conci, Töllner, et al., 2020), this reversal can be interpreted as reflecting an automatic misguidance signal evoked by repeated displays, that is, an LT memory-driven bias in priority-signal computation toward the initially learnt (but, following the relocation, no longer relevant) target location. In contrast, the subsequent PCN showed a reliable negativity for repeated displays (relative to nonrepeated ones) not only in the learning phase, but also in the relocation phase. The latter may be taken to indicate that, over the course of contextual updating, focal–attentional target selection becomes decoupled from (or can overcome) the erroneous automatic biasing signal at the earlier processing stage (reflected in the N1pc). The next component, the CDA—which is thought to reflect postselective processes of target analysis for response—also exhibited an increased amplitude for repeated contexts in the learning phase, but this effect was not reestablished following the repositioning of the target in the relocation phase. Thus, it appears that contextual updating operates foremost on the stage of attentional target selection: The additional statistical regularities provided by sequentially predictive streaks of repeated displays brought about an improved deployment of attention to the new target location (reflected in the PCN), despite an attentional misguidance signal to the old location persisting at an earlier stage of priority computation (reflected in the N1pc). Moreover, postselective processes of target analysis (reflected in the CDA) never recovered to the same level of efficiency after, as compared to before the target relocation, which may contribute to the

Figure 6
Mean Peak Amplitudes in the N1pc (A), PCN (B), and CDA (C) Components for Repeated and Nonrepeated Contexts in the Learning and Relocation Phases
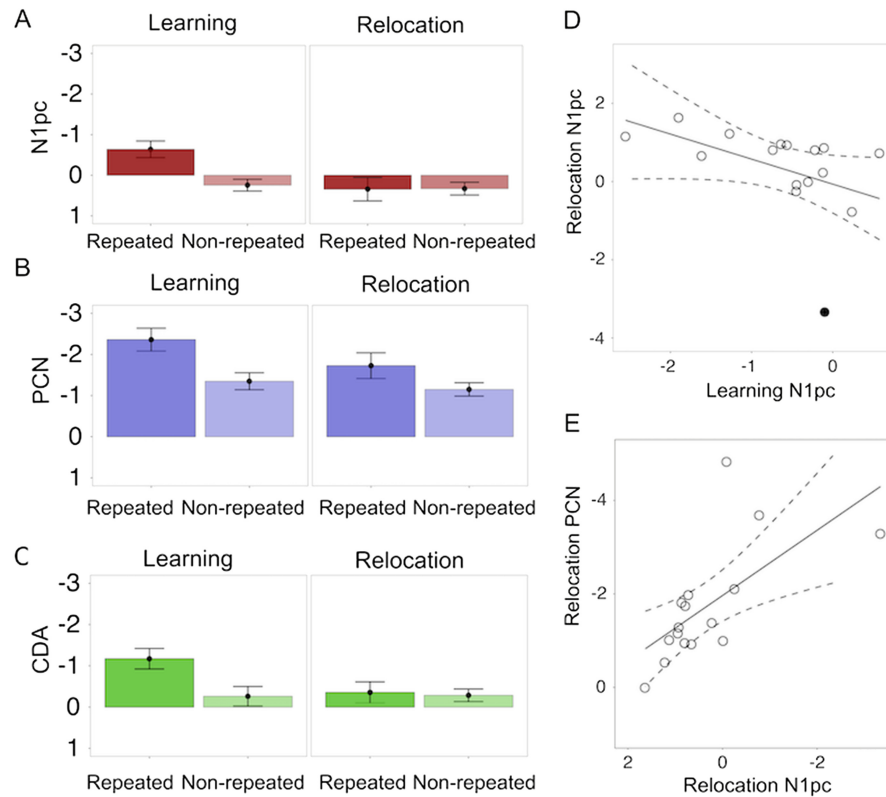
Note. Error bars denote 95% confidence intervals. Panels (D) and (E) show correlation plots of N1pc and PCN amplitudes for repeated displays. The graphs depict the correlation between the N1pc in the learning and relocation phases (D) and between the N1pc and PCN in the relocation phase (E). The dashed lines denote the 95% confidence interval. The filled circle in Figure 6D depicts an outlier that was greater than four *SD*s from the sample mean and was therefore removed from the correlational analysis. N1pc = enhanced early posterior negativity; PCN = posterior contralateral negativity; CDA = contralateral delay activity; PO7/PO8 = parieto-occipital electrodes. See the online article for the color version of this figure.

reduced behavioral CC effect despite the recovered attentional deployment (reflected in the PCN).

General Discussion

The present study aimed to investigate whether global statistical regularities can improve the adaptability of CC to changed distractor–target relations in otherwise unchanged search layouts. Previous studies had consistently shown pronounced costs in behavioral performance after repositioning a target to a new location within an already memorized context (Conci & Zellin, 2022; Geyer et al., 2023; Makovski & Jiang, 2010; Manginelli & Pollmann, 2009; Zellin et al., 2013, 2014). This pattern of findings was replicated in Experiment 1a, in which repeated distractor arrangements with the relocated target were presented in streaks of randomly intermixed trials of repeated or nonrepeated search displays. With these nonpredictive streaks, the CC effect was reduced by ∼100%—consistent with Annac et al.'s (2017) meta-analysis, which reported a reduction of ∼97% after a target-location change (in studies that did not present

trials in streaks). By contrast, when streaks were presented with a fixed, predictive display order in Experiment 1b, the additional global regularity improved the updating of acquired context representations after the change, as evidenced by a reliable CC effect both before and after the target-location change, even though CC after the change was still reduced to a certain extent. Thus, a sequentially predictive display order enhances the flexible updating of context memories.

In general agreement with a role of the predictability of repeated displays, previous work has shown that increasing the probability of repeated relative to nonrepeated displays, as well as presenting repeated and nonrepeated displays in streaks, expedited initial contextual learning, as evidenced by a faster development of the CC effect (Tseng et al., 2011; Zang et al., 2018; Zinchenko et al., 2018), while, however, not bringing about a generally stronger CC effect (Zinchenko et al., 2018). In other words, statistically regular environments increase the speed with which observers extract and store in spatial LT memory repeatedly encountered distractor-target relations. Going beyond previous work, the present study demonstrates that global statistical regularities can also facilitate the

integration of changed target locations, into already acquired and consolidated context representations, in a target-relocation phase—though only when the order of repeated displays within streaks is predictable, rather than when it is just predictable that a given trial display would be any "repeated" arrangement. This pattern of less effective contextual relearning with low- versus highly predictable streaks (Experiment 1a vs. Experiments 1b and 2) is also consistent with Bouwkamp et al. (2021), who found no advantage of structured over nonstructured sequences in initial contextual learning, in a study in which the cross-trial predictiveness within structured sequences was only low.

To account for the present findings, we suggest that CC is essentially an example of a predictive-coding mechanism (Geyer et al., 2021; Zinchenko et al., 2018, 2019) that takes into account the reliability of the prevailing sensory environment—in the present study: the ordered-streak structure of repeated search displays—for memory updating. Such a benefit for contextual updating might arise as a result of the additional statistical regularities as given by the predictable streaks, but it may also—in some sense—be explained in terms of a priming account. That is, the relocated target encountered on trial N may be associated with the target on trial $N + 1$, thereby facilitating the search for this target. Improved contextual adaptation given predictable trial sequences would result from learning sequences of predictable target locations (Jiménez & Vázquez, 2011). However, what is at odds with this proposal is that we kept constant trial order in the relocation phase for all types of display, that is, for both repeated and nonrepeated distractor-target configurations. Thus, any potential sequence effects arising from repeated target locations should have occurred with similar magnitude for both repeated and nonrepeated contexts—making this alternative idea of cross-trial, target-to-target, learning rather unlikely. The fact that we find a reliable RT difference between the repeated and nonrepeated contexts after target relocation with predictable trial sequences instead points to the important role of predictable distractor configurations on trial N as the source of the contextual facilitation effect on trial $N + 1$. This suggests that the predictable sequences facilitate memory updating only, when linked to streaks of repeated displays configurations.

The results of Experiment 1b clearly demonstrate that sequential display predictability aids contextual adaptation. However, these findings do not specify which processing stage is facilitated by this additional statistical regularity. This question was addressed in Experiment 2 by examining lateralized ERPs thought to reflect preattentive priority computations, attentional selection, and postselective processing of attended items, respectively. The behavioral results of Experiment 2 closely replicated our findings of Experiment 1b, showing a rapid acquisition of CC in the initial learning phase and, importantly, successful adaptation to the changed contexts in the target relocation phase (even though the reestablished CC effect was again reduced compared to the originally developed effect). In the learning phase, the ERPs exhibited enhanced N1pc, PCN, and CDA negativities for repeated relative to nonrepeated contexts, thus showing that CC is associated with an early (automatic) bias toward the target location, which then translates into enhanced attentional engagement of the target item and facilitated extraction of the response-relevant information from this item—thus, closely replicating previous findings (Zinchenko, Conci, Töllner, et al., 2020). In the relocation phase, the N1pc elicited by repeated displays was reversed in polarity, now reflecting an early bias toward the initially learnt target location—that is, a persistent

misguidance signal toward a previous target location which now presented a no longer task-relevant display item. Interestingly, however, the subsequent PCN again—as in the initial learning phase—showed an increased negativity for repeated displays, indicative of attentional allocation to the relocated target being enhanced in repeated displays. However, no such difference was evident in the subsequent CDA (in contrast to the CDA effect seen in the initial learning phase), indicative of a relatively inefficient extraction of the response-relevant information from the attended target.

Thus, it appears that a statistically highly predictable environment specifically improves the allocation of attention—as shown in the PCN—during contextual adaptation to the new target location, despite the persistent early, erroneous bias signal toward the old target location. This result somewhat contrasts with our previous study (Zinchenko, Conci, Töllner, et al., 2020), in which the PCN did not recover from the relocation-related cost. Thus, rich environmental regularities may particularly help search guidance to effectively "ignore" or "override" the automatic bias from the initially acquired context memory. This interpretation is further supported by the significant correlation between the amplitude of the N1pc and that of the subsequent PCN in the relocation phase (see Figure 6E), which implies that a stronger misguidance signal in the N1pc is associated with a stronger top-down compensatory signal in the PCN. In other words, the enhanced PCN amplitude for repeated over nonrepeated displays in the target relocation phase may reflect attentional facilitation toward the relocated target.

Finally, while CC was also reflected in the CDA component during initial learning, this was no longer the case after target relocation. In visual search, the CDA has been linked to postselective processing of the item in the focus of attention: establishing that the selected item is a searched-for target (in the present paradigm: a "T") and, if so, extracting the information required for the response (the orientation of the "T"; e.g., Mazza et al., 2007; Töllner et al., 2013; Woodman & Vogel, 2008). In line with this as well as previous CC studies (Kunar et al., 2007; Schankin & Schubö, 2009), the increased CDA to repeated displays would imply that contextual learning also enhances the processing of the target item at a postselective stimulus-analysis stage. As outlined in the introductory part, one idea how CC may aid postattentive processes is that the target template does not only contain information about the target itself, but also information from nearby distractors (see Sewell et al.'s, 2018, featural-learning account of CC)—given that not only the distractor locations but also their orientations were kept constant, and thus learnable, in repeated displays. In the relocation phase, the CDA for repeated displays was substantially reduced to a level comparable to the amplitude for nonrepeated displays (i.e., to the baseline level). This can be taken to indicate that the distractor-target templates for postselective decision making are not readily adapted after the target-location change, that is, as the target now appears in a changed local context of invariantly placed and oriented distractors, template tuning must start from scratch.

Summary and Conclusion

The present study shows that global statistical regularities can be successfully exploited to reduce the LT memory-based misguidance of attention following sudden (but consistent) target-location changes within an otherwise invariant context. Typically, relocation of the target largely abolishes the behavioral CC effect and interferes with subsequent relearning of the new location due to a persistent

contextual misguidance signal (to the old location), evidenced by an early positivity (relative to the new target location) at ~140 ms post-stimulus (N1pc). Interestingly, although the statistical regularities did not appear to abolish the automatic misguidance signal in the N1pc and to readily retune postattentional target identification processes (in the CDA), they did give rise to a modulation of the PCN amplitudes for repeated displays and concurrent behavioral CC benefits after the location change. We take this to reflect improved expectations about a stable and predictable sensory input to allow search guidance to (a) override the (initially acquired) automatic bias toward the previous target location and (b) effectively allocate attentional processing to the new target location.

References

Annac, E., Conci, M., Müller, H. J., & Geyer, T. (2017). Local item density modulates adaptation of learned contextual cues. *Visual Cognition*, 25(1–3), 262–277. https://doi.org/10.1080/13506285.2017.1339158

Annac, E., Pointner, M., Khader, P. H., Müller, H. J., Zang, X., & Geyer, T. (2019). Recognition of incidentally learned visual search arrays is supported by fixational eye movements. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, 45(12), 2147–2164. https://doi.org/10.1037/xlm0000702

Ben-Shachar, M. S., Lüdecke, D., & Makoski, D. (2020). Effectsize: Estimation of effect size indices and standardized parameters. *Journal of Open Source Software*, 5(56), Article 2815. https://doi.org/10.21105/joss.02815

Bouwkamp, F. G., de Lange, F. P., & Spaak, E. (2021). No exploitation of temporal sequence context during visual search. *Royal Society Open Science*, 8(3), Article 201565. https://doi.org/10.1098/rsos.201565

Brady, T. F., & Chun, M. M. (2007). Spatial constraints on learning in visual search: Modeling contextual cuing. *Journal of Experimental Psychology: Human Perception and Performance*, 33(4), 798–815. https://doi.org/10.1037/0096-1523.33.4.798

Brainard, D. H. (1997). The psychophysics toolbox. *Spatial Vision*, 10(4), 433–436. https://doi.org/10.1163/156856897X00357

Chun, M. M. M., & Jiang, Y. (1998). Contextual cueing: Implicit learning and memory of visual context guides spatial attention. *Cognitive Psychology*, 36(1), 28–71. https://doi.org/10.1006/cogp.1998.0681

Cohen, J. (1988). *Statistical power analysis for the behavioral sciences* (2nd ed.). Erlbaum.

Conci, M., & von Mühlenen, A. (2009). Region segmentation and contextual cuing. *Attention, Perception, & Psychophysics*, 71(7), 1514–1524. https://doi.org/10.3758/APP.71.7.1514

Conci, M., & Zellin, M. (2022). Stimulus-driven updating of long-term context memories in visual search. *Psychological Research*, 86(1), 252–267. https://doi.org/10.1007/s00426-021-01474-w

Dienes, Z. (2014). Using Bayes to get the most out of non-significant results. *Frontiers in Psychology*, 5, Article 781. https://doi.org/10.3389/fpsyg.2014.00781

Eimer, M. (1996). The N2pc component as an indicator of attentional selectivity. *Electroencephalography and Clinical Neurophysiology*, 99(3), 225–234. https://doi.org/10.1016/0013-4694(96)95711-9

Geyer, T., Baumgartner, F. J., Mueller, H. J., & Pollmann, S. (2012). Medial temporal lobe-dependent repetition suppression and enhancement due to implicit versus explicit processing of individual repeated search displays. *Frontiers in Human Neuroscience*, 6, Article 272. https://doi.org/10.3389/fnhum.2012.00272

Geyer, T., Müller, H. J., & Krummenacher, J. (2006). Cross-trial priming in visual search for singleton conjunction targets: Role of repeated target and distractor features. *Perception & Psychophysics*, 68(5), 736–749. https://doi.org/10.3758/bf03193697

Geyer, T., Rostami, P., Sogerer, L., Schlagbauer, B., & Müller, H. J. (2020). Task-based memory systems in contextual-cueing of visual search and

explicit recognition. *Scientific Reports*, 10(1), Article 16527. https://doi.org/10.1038/s41598-020-71632-4

Geyer, T., Seitz, W., Zinchenko, A., Müller, H. J., & Conci, M. (2021). Why are acquired search-guiding context memories resistant to updating? *Frontiers in Psychology*, 12, Article 650245. https://doi.org/10.3389/fpsyg.2021.650245

Geyer, T., Shi, Z., & Müller, H. J. (2010). Contextual cueing in multiconjunction visual search is dependent on color- and configuration-based intertrial contingencies. *Journal of Experimental Psychology: Human Perception and Performance*, 36(3), 515–532. https://doi.org/10.1037/a0017448

Geyer, T., Zinchenko, A., Seitz, W., Balik, M., Müller, H. J., & Conci, M. (2023). Mission impossible? Spatial context relearning following a target relocation event depends on cue predictiveness. *Psychonomic Bulletin & Review*. https://doi.org/10.3758/s13423-023-02328-9

Goujon, A., Didierjean, A., & Thorpe, S. (2015). Investigating implicit statistical learning mechanisms through contextual cueing. *Trends in Cognitive Sciences*, 19(9), 524–533. https://doi.org/10.1016/j.tics.2015.07.009

Jeffreys, H. (1961). *Theory of probability* (3rd ed.). Oxford University Press.

Jensen, M. S., Yao, R., Street, W. N., & Simons, D. J. (2011). Change blindness and inattentional blindness. *Wiley Interdisciplinary Review of Cognitive Sciences*, 2(5), 529–546. https://doi.org/10.1002/wcs.130

Jiménez, L., & Vázquez, G. A. (2011). Implicit sequence learning and contextual cueing do not compete for central cognitive resources. *Journal of Experimental Psychology: Human Perception and Performance*, 37(1), 222–235. https://doi.org/10.1037/a0020378

Johnson, J. S., Woodman, G. F., Braun, E. L., & Luck, S. J. (2007). Implicit memory influences the allocation of attention in visual cortex. *Psychonomic Bulletin & Review*, 14(5), 834–839. https://doi.org/10.3758/bf03194108

Kristjansson, A., Wang, D. L., & Nakayama, K. (2002). The role of priming in conjunctive visual search. *Cognition*, 85(1), 37–52. https://doi.org/10.1016/S0010-0277(02)00074-4

Kunar, M. A., Flusberg, S., Horowitz, T. S., & Wolfe, J. M. (2007). Does contextual cuing guide the deployment of attention? *Journal of Experimental Psychology: Human Perception and Performance*, 33(4), 816–828. https://doi.org/10.1037/0096-1523.33.4.816

Luck, S. J., & Hillyard, S. A. (1994). Electrophysiological correlates of feature analysis during visual search. *Psychophysiology*, 31(3), 291–308. https://doi.org/10.1111/j.1469-8986.1994.tb02218.x

Makovski, T., & Jiang, Y. V. (2010). Contextual cost: When a visual-search target is not where it should be. *The Quarterly Journal of Experimental Psychology*, 63(2), 216–225. https://doi.org/10.1080/17470210903281590

Manginelli, A. A., & Pollmann, S. (2009). Misleading contextual cues: How do they affect visual search? *Psychological Research*, 73(2), 212–221. https://doi.org/10.1007/s00426-008-0211-1

Mazza, V., Turatto, M., Umiltà, C., & Eimer, M. (2007). Attentional selection and identification of visual objects are reflected by distinct electrophysiological responses. *Experimental Brain Research*, 181(3), 531–536. https://doi.org/10.1007/s00221-007-1002-4

Morey, R. D., & Rouder, J. N. (2018). *Bayesfactor: Computation of Bayes factors for common designs* [Computer software manual]. https://richarddmorey.github.io/BayesFactor/

Pelli, D. G. (1997). The VideoToolbox software for visual psychophysics: Transforming numbers into movies. *Spatial Vision*, 10(4), 437–442. https://doi.org/10.1163/156856897X00366

Richter, D., Ekman, M., & de Lange, F. P. (2018). Suppressed sensory response to predictable object stimuli throughout the ventral visual stream. *Journal of Neuroscience*, 38(34), 7452–7461. https://doi.org/10.1523/JNEUROSCI.3421-17.2018

Sänger, J., & Wascher, E. (2011). The influence of extrinsic motivation on competition-based selection. *Behavioural Brain Research*, 224(1), 58–64. https://doi.org/10.1016/j.bbr.2011.05.015

Sauseng, P., Conci, M., Wild, B., & Geyer, T. (2015). Predictive coding in visual search as revealed by cross-frequency EEG phase synchronization.

Frontiers in Psychology, 6, Article 1655. https://doi.org/10.3389/fpsyg.2015.01655

Schankin, A., & Schubö, A. (2009). Cognitive processes facilitated by contextual cueing: Evidence from event-related brain potentials. *Psychophysiology*, 46(3), 668–679. https://doi.org/10.1111/j.1469-8986.2009.00807.x

Schankin, A., & Schubö, A. (2010). Contextual cueing effects despite spatially cued target locations. *Psychophysiology*, 47(4), 717–727. https://doi.org/10.1111/j.1469-8986.2010.00979.x

Sewell, D. K., Colagiuri, B., & Livesey, E. J. (2018). Response time modeling reveals multiple contextual cuing mechanisms. *Psychonomic Bulletin & Review*, 25, 1644–1665. https://doi.org/10.3758/s13423-017-1364-y

Sisk, C. A., Remington, R. W., & Jiang, Y. V. (2019). Mechanisms of contextual cueing: A tutorial review. *Attention, Perception, & Psychophysics*, 81(8), 2571–2589. https://doi.org/10.3758/s13414-019-01832-2

Smyth, A. C., & Shanks, D. R. (2008). Awareness in contextual cuing with extended and concurrent explicit tests. *Memory & Cognition*, 36, 403–415. https://doi.org/10.3758/MC.36.2.403

Töllner, T., Conci, M., & Müller, H. J. (2015). Predictive distractor context facilitates attentional selection of high, but not intermediate and low, salience targets. *Human Brain Mapping*, 36(3), 935–944. https://doi.org/10.1002/hbm.22677

Töllner, T., Conci, M., Rusch, T., & Müller, H. J. (2013). Selective manipulation of target identification demands in visual search: The role of stimulus contrast in CDA activations. *Journal of Vision*, 13(3), Article 23. https://doi.org/10.1167/13.3.23

Tseng, P., Hsu, T. Y., Tzeng, O. J. L., Hung, D. L., & Juan, C. H. (2011). Probabilities in implicit learning. *Perception*, 40(7), 822–829. https://doi.org/10.1068/p6833

Turk-Browne, N. B., Jungé, J. A., & Scholl, B. J. (2005). The automaticity of visual statistical learning. *Journal of Experimental Psychology: General*, 134(4), 552–564. https://doi.org/10.1037/0096-3445.134.4.552

Vadillo, M. A., Konstantinidis, E., & Shanks, D. R. (2016). Underpowered samples, false negatives, and unconscious learning. *Psychonomic Bulletin & Review*, 23(1), 87–102. https://doi.org/10.3758/s13423-015-0892-6

van Asselen, M., & Castelo-Branco, M. (2009). The role of peripheral vision in implicit contextual cuing. *Attention, Perception and Psychophysics*, 71(1), 76–81. https://doi.org/10.3758/APP.71.1.76

Van Lissa, C. J. (2020). Small sample meta-analyses: Exploring heterogeneity using MetaForest. In R. Van De Schoot & M. Miočević (Eds.), *Small sample size solutions: A guide for applied researchers and practitioners* (pp. 186–202). CRC Press. https://dspace.library.uu.nl/bitstream/handle/1874/414894/10.4324_9780429273872_16_chapterpdf.pdf?sequence=1

Võ, M. L. H., Boettcher, S. E., & Draschkow, D. (2019). Reading scenes: How scene grammar guides attention and aids perception in real-world environments. *Current Opinion in Psychology*, 29, 205–210. https://doi.org/10.1016/j.copsyc.2019.03.009

Woodman, G. F., & Vogel, E. K. (2008). Selective storage and maintenance of an object's features in visual working memory. *Psychonomic Bulletin & Review*, 15(1), 223–229. https://doi.org/10.3758/PBR.15.1.223

Yang, Y., Coutinho, M. V., Greene, A. J., & Hannula, D. E. (2021). Contextual cueing is not flexible. *Consciousness and Cognition*, 93, Article 103164. https://doi.org/10.1016/j.concog.2021.103164

Zang, X., Zinchenko, A., Jia, L., Assumpção, L., & Li, H. (2018). Global repetition influences contextual cueing. *Frontiers in Psychology*, 9, Article 402. https://doi.org/10.3389/fpsyg.2018.00402

Zellin, M., Conci, M., von Mühlenen, A., & Müller, H. J. (2011). Two (or three) is one too many: Testing the flexibility of contextual cueing with multiple target locations. *Attention, Perception, & Psychophysics*, 73(7), 2065–2076. https://doi.org/10.3758/s13414-011-0175-x

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(3), Article e59466. https://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(4), 1073–1079. https://doi.org/10.3758/s13423-013-0568-z

Zinchenko, A. (2022, January 25). *Environmental regularities mitigate attentional misguidance in contextual cueing of visual search*. https://osf.io/v89mz/?view_only=aa2bce929c1b413f9618b45337036f3e

Zinchenko, A., Conci, M., Hauser, J., Müller, H. J., & Geyer, T. (2020). Distributed attention beats the down-side of statistical context learning in visual search. *Journal of Vision*, 20(7), Article 4. https://doi.org/10.1167/jov.20.7.4

Zinchenko, A., Conci, M., Müller, H. J., & Geyer, T. (2018). Predictive visual search: Role of environmental regularities in the learning of context cues. *Attention, Perception, & Psychophysics*, 80(5), 1096–1109. https://doi.org/10.3758/s13414-018-1500-4

Zinchenko, A., Conci, M., Taylor, P. C., Müller, H. J., & Geyer, T. (2019). Taking attention out of context: Frontopolar transcranial magnetic stimulation abolishes the formation of new context memories in visual search. *Journal of Cognitive Neuroscience*, 31(3), 442–452. https://doi.org/10.1162/jocn_a_01358

Zinchenko, A., Conci, M., Töllner, T., Müller, H. J., & Geyer, T. (2020). Automatic guidance (and misguidance) of visuospatial attention by acquired scene memory: Evidence from an N1pc polarity reversal. *Psychological Science*, 31(12), 1531–1543. https://doi.org/10.1177/0956797620954815