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Original Article

QJEP

Quarterly Journal of Experimental Psychology
2025, Vol. 78(11) 2570–2582
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DOI: 10.1177/17470218251320540
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Eye on context: Individual differences reveal the mechanisms of statistical learning

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Abstract

If a searched-for target object is consistently encountered within repeating spatial distractor arrangements, target detection becomes more efficient relative to nonrepeated, that is, random arrangements (contextual cueing [CC] effect). However, target location changes within otherwise unchanged distractor arrays substantially weaken the cueing effect. Previous studies reported substantial variations in individual participants' abilities to learn and relearn invariant contexts. Therefore, the current study examined how individual differences in attentional control and focus, as indexed by the well-established Stroop and Navon tasks, respectively, relate to CC in a learning phase/relocation phase design. During the visual search, we recorded behavioural reaction times (RTs) and fixation locations, the latter permitting us to decompose search RTs into search- and motor-related substages. We could thus evaluate the processes responsible for CC and the lack thereof after target relocation while also testing whether search and motor components of CC are different for individuals depending on their Stroop/Navon scores. Repeated contexts yielded faster RTs (and reduced fixation numbers), though there was a substantial decrease in cueing from learning to adaptation, consistent with previous studies. Critically, contextual learning, but not relearning, varied across individuals: participants with high-Stroop interference displayed overall larger CC during early target search, while a more local Navon task bias was associated with increased CC during later processes of target response decisions. Our results demonstrate that analysing individual differences can help validate the processes responsible for CC in search tasks, particularly distinguishing between early search and later response-related mechanisms.

Keywords

Visual search; individual-differences research; statistical learning; selective attention; contextual cueing; global/local processing; cognitive control; Navon task; Stroop task

Received: 27 March 2024; revised: 22 January 2025; accepted: 27 January 2025

Introduction

Visual search is facilitated when the searched-for target is located within a repeating configuration of nontarget distractor items relative to a randomly generated layout of distractors. There are two accounts of this contextual-cueing (CC) effect (for reviews, see, for example, Goujon et al., 2015; Sisk et al., 2019). One assumes that display repetitions facilitate response selection and/or motor-execution processing stages when participants decide which motor (hand) effector is required for a correct response. The other attentional account assumes that CC arises because the

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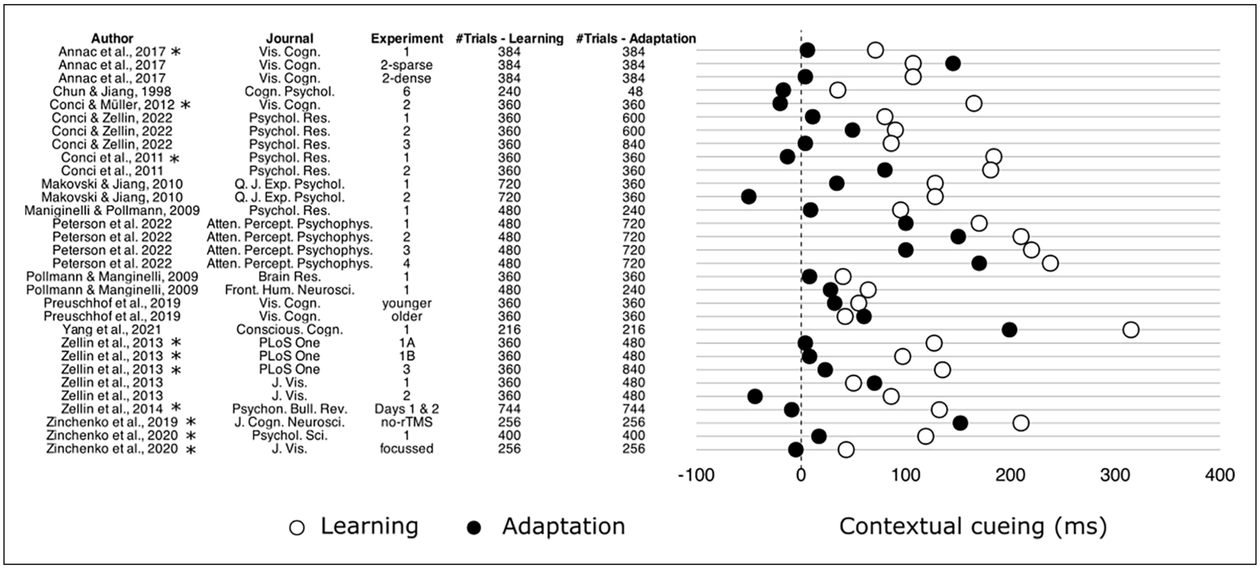
acquired target-distractor spatial associations (stored in long-term memory, LTM) come to guide search, predicting, or "cueing attention to" the target location.

Learning of such contextual regularities emerges rather quickly and without effort: participants require just a few repetitions (~3) to build an association between a repeated target location and the configuration of distractor items. On the other hand, relearning or adapting to a change of the target location within the previously learned and otherwise unchanged distractor context requires massive training on the relocated displays (e.g., Conci et al., 2011; Geyer et al., 2024; Geyer et al., 2021; Makovski & Jiang, 2009; Manginelli & Pollmann, 2009; Yang et al., 2021; Zellin et al., 2013; Zinchenko, Conci, Hauser, et al., 2020; Zinchenko, Conci, Töllner, et al., 2020; see also Preuschhof et al., 2019). For instance, each display may take 80 repetitions to effectively reestablish a CC effect (Zellin et al., 2014). Thus, although people can quickly and efficiently acquire contextual regularities, once established, these context memories become inflexible and resistant to updates following any changes—a phenomenon that is also reflected in everyday life examples. For example, location changes of grocery products require customers to spend ~20% of additional time to find their searched-for products, and this cost is particularly pronounced if they have previously been accustomed to the original placement (Croxton, 2012).

In lab settings, eye tracking and electrophysiological studies demonstrate that relocated targets within previously learned configurations of distractor items lead to a misguidance of attention to the no-longer-relevant target locations (Manginelli & Pollmann, 2009; Zinchenko, Conci, et al., 2024; Zinchenko, Conci, Töllner, et al., 2020). For instance, Manginelli and Pollmann (2009) demonstrated that, after target relocation, a significant proportion of initial saccades were made in the direction of the previous target location before relocation. Zinchenko and colleagues (Zinchenko, Conci, et al., 2024; Zinchenko, Conci, Töllner, et al., 2020) additionally reported that a change of the target location to the opposite hemifield reversed the early (80–180 ms poststimulus onset), lateralized N1pc event-related potential component, which appears to reflect a persistent misguidance of attention to the original target location early during visual search. Importantly, this misguidance effect does not arise from the item at the original target location being bottom-up, that is, physically salient, but rather because the previously acquired contextual long-term memories prioritise this location. This suggests that the observed adaptation cost is driven by attentional misguidance towards the learned, but no longer relevant, target item, with this bias emerging early after stimulus onset. In other words, once learned, repeated layouts trigger attentional-priority signals from memory that interfere with contextual relearning after target relocation in the adaptation phase.

Notably, the magnitudes of contextual learning and adaptation effects differ substantially across the existing studies. To gain a more systematic overview, we conducted a meta-analysis on 19 published studies identified by a Web-of-Science search that investigated CC across separate learning and adaptation phases in 31 cases/experiments (with altogether 669 participants). There was an average number of 407 trials (*SD* = 127) in the learning phase and 455 trials (*SD* = 199) in the adaptation phase. We found a mean CC effect of 123 ms (*SD* = 67 ms) in the learning phase and 41 ms (*SD* = 65) in the adaptation phase (see Figure 1). That is, the cueing effect was ~3 times smaller in the adaptation phase, but, at the same time, the relatively high standard deviations indicate that there is also a large variability of CC in both initial learning and subsequent adaptation phases. Corresponding results were obtained from an additional meta-analysis of individual CC scores in a subset of 10 (own) experiments for which individual data were available (142 participants). Here, the mean CC effect in learning was 121 ms (*SD* = 112), compared with a mean CC effect of 28 ms (*SD* = 99) in the adaptation phase. Once more, there was a clear reduction, with CC being even some ~4 times smaller in the adaptation than in the learning phase. Critically, SDs were again relatively high when analysing CC at the level of individual participants, indicating that individual differences may affect both the initial acquisition and later adaptation of statistical target-distractor memories.

Previous studies have already investigated individual variability in spatial context learning. For instance, Bellaera and colleagues (2014; see also Lleras & Von Muhlenen, 2004) used a Navon task to assess the extent to which individuals have an attentional bias towards processing information at a more global or local level. They then assessed how such a bias might affect the magnitude of CC. In the Navon task, participants were presented with hierarchical stimuli that consisted of several small shapes grouped into a single, larger shape (e.g., a large square composed of small triangles; note that the global and local shapes would always differ). Observers were asked to indicate whether a given target shape, defined at the beginning of each block, was present at the local or global stimulus level. Bellaera et al. found that individuals with a narrow attention focus, that is, those showing faster reaction times (RTs) in the Navon task for targets defined at a local compared with the global level, showed a larger CC effect in the search task than individuals with a wider attentional focus. These results thus indicate that an observer's preference to process information more strongly at a local level (i.e., with smaller attentional focus) significantly influences the ability to learn repeating context-to-target associations, which have also been suggested to rely largely on the association between the target and its local context of neighbouring distractors (see Brady & Chun, 2007). However, it remains unclear how a local



Author	Journal	Experiment	#Trials - Learning	#Trials - Adaptation
Annac et al., 2017 ∗	Vis. Cogn.	1	384	384
Annac et al., 2017	Vis. Cogn.	2-sparse	384	384
Annac et al., 2017	Vis. Cogn.	2-dense	384	384
Chun & Jiang, 1998	Cogn. Psychol.	6	240	48
Conci & Müller, 2012 ∗	Vis. Cogn.	2	360	360
Conci & Zellin, 2022	Psychol. Res.	1	360	600
Conci & Zellin, 2022	Psychol. Res.	2	360	600
Conci & Zellin, 2022	Psychol. Res.	3	360	840
Conci et al., 2011 ∗	Psychol. Res.	1	360	360
Conci et al., 2011	Psychol. Res.	2	360	360
Makovski & Jiang, 2010	Q. J. Exp. Psychol.	1	720	360
Makovski & Jiang, 2010	Q. J. Exp. Psychol.	2	720	360
Maniginelli & Pollmann, 2009	Psychol. Res.	1	480	240
Peterson et al. 2022	Atten. Percept. Psychophys.	1	480	720
Peterson et al. 2022	Atten. Percept. Psychophys.	2	480	720
Peterson et al. 2022	Atten. Percept. Psychophys.	3	480	720
Peterson et al. 2022	Atten. Percept. Psychophys.	4	480	720
Pollmann & Manginelli, 2009	Brain Res.	1	360	360
Pollmann & Manginelli, 2009	Front. Hum. Neurosci.	1	480	240
Preuschhof et al., 2019	Vis. Cogn.	younger	360	360
Preuschhof et al., 2019	Vis. Cogn.	older	360	360
Yang et al., 2021	Conscious. Cogn.	1	216	216
Zellin et al., 2013 ∗	PLoS One	1A	360	480
Zellin et al., 2013 ∗	PLoS One	1B	360	480
Zellin et al., 2013 ∗	PLoS One	3	360	840
Zellin et al., 2013	J. Vis.	1	360	480
Zellin et al., 2013	J. Vis.	2	360	480
Zellin et al., 2014 ∗	Psychon. Bull. Rev.	Days 1 & 2	744	744
Zinchenko et al., 2019 ∗	J. Cogn. Neurosci.	no-rTMS	256	256
Zinchenko et al., 2020 ∗	Psychol. Sci.	1	400	400
Zinchenko et al., 2020 ∗	J. Vis.	focussed	256	256

Figure 1. Results from 19 published studies that investigate contextual facilitation of visual search in 31 different experiments by quantifying the difference in RTs between repeated and nonrepeated search layouts (=contextual-cueing effect in milliseconds, ms) in the initial learning phase (white circles) and in the subsequent adaptation phase (black circles).

Individual studies were identified by a Web of Science search using these keywords and Boolean operators: (visual search) AND (contextual cueing) AND ((updating) OR (target location change) OR (flexibility) OR (adaptation)).

*—Studies for which we analysed CC at the level of individual participants.

attentional focus influences the subsequent adaptation of already-formed contextual memories. For instance, local biases may impose severe difficulties on contextual adaptation because established contextual memories are strongly activated (retrieved) during ongoing processing of the local display input and hence trigger strong attention misguidance towards the previous target position (Zinchenko, Conci, Töllner, et al., 2020; Zinchenko, Geyer, et al., 2024).

To overcome attentional misguidance by previously established yet outdated contextual memories, exerting attentional control may be crucial to facilitate reorienting and concurrently updating a previous context representation. Previous studies reported that prefrontal control structures are engaged during successful reorienting within previously learned contexts (Zinchenko et al., 2019; Zinchenko, Geyer, et al., 2024). Moreover, explicit cues to guide attentional reorienting (by a salient stimulus in the search display) were found to facilitate updating a misguidance signal from contextual memory (Conci & Zellin, 2022). The selection of a salient stimulus and the concurrent suppression of the (erroneous) contextual memory bias may thus crucially depend on (top-down) attentional control. One well-established task for measuring attentional control is the Stroop task (Stroop, 1935), in which participants are supposed to name the colour of the ink of a presented word while suppressing the word's meaning. For example, the word "blue" might be written in green ink (incongruent condition), which typically results in more effortful processing than a congruent word/ink combination (e.g., the word "blue" written in blue ink). This suggests the operation of (time-consuming) control processes in incongruent stimulus presentations: participants must inhibit automated reading responses when asked to respond to the ink colour. Applied to CC in a learning/relocation-phase design, adapting existing contextual memories may improve as individual participants become more adept at disregarding the previously learned, yet currently irrelevant, target and concentrating their processing on the new target location.

Therefore, the current study explored whether interindividual differences in attentional focus and concurrent control abilities could predict the success of contextual learning and the subsequent adaptation after a change in a typical CC visual search experiment that presented an initial learning phase and a subsequent adaptation phase while recording manual RTs and fixation locations (the latter indexing the locus of attention). Our analytical approach followed previous oculomotor investigations of visual search and CC in particular (e.g., Kroell et al., 2019; Tseng & Li, 2004; Watson et al., 2010). We divided each trial into two events based on saccadic measures, with each event reflecting cognitive processes that affect CC and thus may vary across individuals. First, the time required until the eyes first land at the target location, which may index the efficiency of visual search (henceforth referred to as target detection time). Second, the time between the first saccade to the target and the manual response to the target, which also includes fixations of other, nontarget, distractor objects until returning to the target and discriminating it (e.g., Godwin et al., 2017; Watson et al., 2010). This verification time may index the efficiency of target-response decisions. Accordingly, an eye-tracking-informed RT analysis can reveal the processes responsible for producing CC, and importantly, it can also include information about whether these processes are effective (or not) during adaptation.

Furthermore, our individual-difference approach has great potential to confirm, that is, validate these processes by showing converging evidence from other tasks: How CC in detection and verification times correlate with individual Stroop/Navon performance. The idea is that dissociations between individual search- and response-related measures of CC and individual Stroop/Navon task measures would suggest independence of underlying CC mechanisms (e.g., Vogel & Awh, 2008). Thus, we could provide converging evidence that CC has a search-and-response component by analysing statistical learning at the sample and individual levels. Moreover, our individual-difference approach would allow us to explain the variation in CC found in previous learning/adaptation studies.

After the search task, participants performed additional Stroop and Navon tasks. We applied a multiple-regression approach to test whether participants' performance on these two tasks could predict their context learning and adaptation effects (measured across all four epochs in target detection and verification times). Based on findings from Bellaera et al. (2014), who demonstrated a relationship between attentional focus and CC, we expected that participants with a local bias in the Navon task would show a larger CC effect during initial context learning. However, we predicted that a narrow focus on local parts would conversely harm performance in the subsequent adaptation phase. Specifically, we hypothesised that participants with a stronger local bias would show slower RTs when the target location changed within a repeated context, as their strong and locally biased contextual memories might continue to misguide attention to the initial target location.

Moreover, we predicted superiority in contextual adaptation for participants who show enhanced attentional control in the Stroop task as these participants may be able to overcome the attention bias arising from learned target positions and thus update existing memories of distractor-target associations, that is, incorporate the changed target position in the originally acquired contextual memory representation.

Methods

Participants

The sample size was motivated by previous contextual-adaptation studies, which tested ~50 participants per experiment (e.g., Geyer et al., 2024; Peterson et al., 2022). Based on the effect sizes reported in these studies, 50 volunteers participated in the present study (14 females, two left-handed, mean age = 25.16, *SD* = 2.46, range = 20–30). The data of four participants were removed due to high error rates ($>15\%$), which were more than 3 SDs above the mean error rate in the search task. Accordingly, the data analyses reported below are based on a sample of $N = 46$ participants.

Apparatus and stimuli

The experimental routine was programmed in MATLAB with Psychtoolbox extensions (Brainard & Vision, 1997; Pelli, 1997) and was run on an Intel PC under the Windows 10 operating system. Participants were seated in a dimly lit booth in front of a 19-inch CRT monitor (AOC, Amsterdam; display resolution 1024 × 768 pixels; refresh rate: 85 Hz) at a viewing distance of 60 cm (controlled by a chin rest). The search displays consisted of 12 grey items (luminance: 1.0 cd/m^2; one target and 11 distractors) presented against a black background (0.11 cd/m^2). All stimuli extended 0.35º of visual angle in both width and height. Figure 2 depicts the items placed on four (invisible) concentric rings around the display centre (with a radius of 1.74°, 3.48°, 5.22°, and 6.96° for Rings 1 through 4, respectively; Figure 2a). Two items were placed on each Ring 1 and Ring 3, while four items were placed on each Ring 2 and Ring 4. The minimal distance between any two items was 1.74°. There were always three items in each of the four display quadrants. Also, targets in both repeated and nonrepeated arrays appeared equally often in each of the four display quadrants. In repeated displays, the targets' locations and the locations and orientations of distractors were held constant across trials (cf. Chun & Jiang, 1998). In nonrepeated displays, distractor locations (and orientations) were generated anew on each trial. Overall, there were 12 possible target locations, four of which were used for repeated displays with invariant distractor layouts in the initial learning phase, and another four target locations were used for the repeated displays after target relocation in the subsequent adaptation phase. Finally, the last four target locations were used for nonrepeated displays with random distractor arrangements (presented across both phases).

All targets were presented on Ring 3. Note that for repeated displays, the targets in the adaptation phase were always presented in the contralateral hemifield relative to the initial learning phase. The "T" target was rotated randomly by 90° to either the left or the right. The 11 remaining items were L-shaped distractors rotated randomly at orthogonal orientations (0º, 90º, 180º, or 270º). With this display design, we followed a previous study of CC (Sewell et al., 2018) that also reduced the number of learnable, repeated target locations, as well as the number of target locations in nonlearnable, nonrepeated displays to four each, with one target location per display quadrant. This was meant to ensure that the memory signals for the

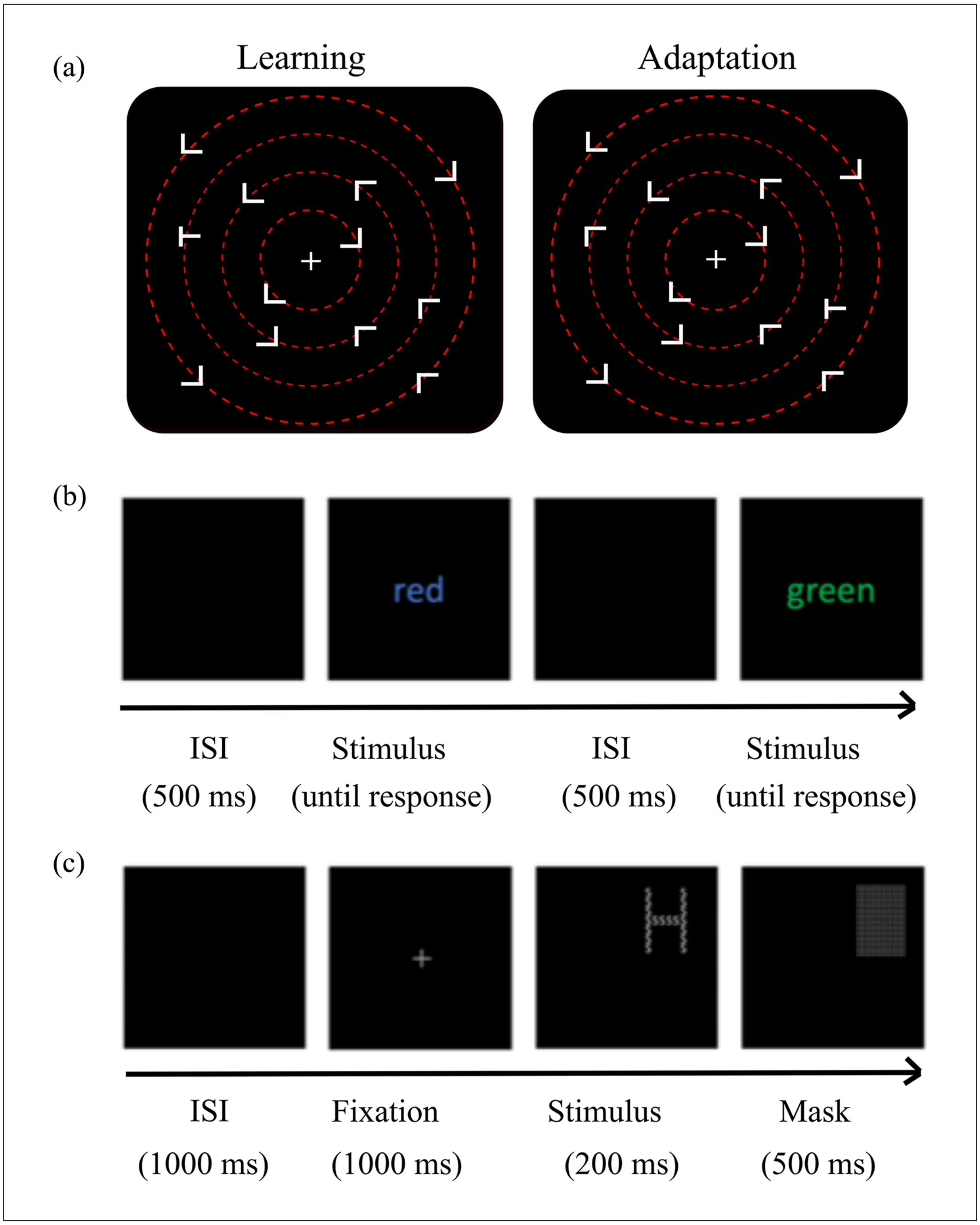


Figure 2. (a) Example search display that presents a repeated item configuration in the initial learning phase (left) and in the subsequent adaptation phase (right). Each display comprised a T-shaped target and 11 L-shaped distractors that were presented on three concentric rings (which are shown here for illustration purposes but were invisible in the actual experiment). In the initial learning phase, the target was presented at a given invariant location. In the subsequent adaptation phase, the target then swapped its location with a distractor from the opposite hemifield while the rest of the display remained unchanged. (b) Trial structure of the Stroop task. Participants identified the ink colour of the presented words ("RED," "GREEN," or "BLUE") as quickly and accurately as possible using predefined key responses. Congruent trials had matching word meanings and ink colours, while incongruent trials did not. (c) Trial structure of the Navon task. Participants identified a local letter (S or H) while ignoring the global letter structure, which could be congruent (e.g., both global and local levels show H) or incongruent (e.g., global H made up of local S). Each trial included a fixation cross, a briefly presented hierarchical stimulus, and a subsequent mask.

respective target location would have as little interference from other repeated displays as possible. As a result, CC should become more stable, that is, reliable, and thus, our display design should be able to capture individual differences in CC. To reinforce this, we also presented the same repeated and nonrepeated display arrangements to all participants. Using the same set of displays allowed us to control the perceptual content of the display set throughout the experiment, thus minimising confounds originating from, across participants, variably composed distractor-target configurations in repeated and nonrepeated displays. Figure 2 presents an example display layout of a repeated display across both experimental phases. The entire set of our repeated and nonrepeated displays is available at OSF: https://osf.io/bxm3y.

A video-based eye-tracker was used to monitor and record eye movements (EyeLink 1000; SR Research Ltd., Mississauga, Ontario, Canada; version 4.594). Eye-movement recordings were calibrated at the start of the experiment and after every four blocks (of 64 trials). Calibration was considered accurate when fixation positions fell within ~1° for all calibration points. The default psychophysical sample configuration of the eye-tracking system (i.e., saccade velocity threshold set at 35°/s, saccade acceleration threshold set at 9,500°/s^2) was adopted for the eye-data samples.

In our eye-tracking-informed RT analysis (cf. Watson et al., 2010), we first aligned target positions from the repeated and nonrepeated displays (measured in degrees of visual angle) with the eye-tracking data (measures in pixels) by performing a coordinate transformation. In doing so, we defined a circle with a radius of 5.22° (=273 pixels) centred at the origin (0, 0). The target angles, originally in degrees, were converted to radians. We then calculated the x and y coordinates of each target using the following formulas

$$x = \text{centerX} + \text{radius} * \cos(\text{angle})$$

$$y = \text{centerY} + \text{radius} * \sin(\text{angle})$$

where centerX and centerY were both set to 0 to maintain a centred coordinate system. The resulting coordinates were rounded to the nearest integer to align with pixel values. This transformation allowed us to express target positions in the same coordinate space as the fixation data, enabling direct comparisons between eye movements and target locations. Next, the *target detection time* was computed, which we defined as the time from the trial onset until the participants' gaze reached the point closest to the target. To calculate this measure, the Euclidean distance for each fixation in a trial was computed using the formula:

$$\text{distance} = (x1\text{-}x2)^2 + (y1\text{-}y2)^2$$

where (x1, y1) represents the coordinates of the fixation and (x2, y2) represents the coordinates of the target. The fixation with the minimum Euclidean distance to the target was then identified for each trial. Subsequently, the time to first target fixation was determined by summing the durations of all fixations from the trial onset (including initial saccadic latency) and up to and including the fixation closest to the target item. Our second eye-tracking-informed RT variable was the *target verification time*, which we defined as the time elapsed between the first fixation of the target and participants' responses (manual button presses). Target detection and verification RTs were aggregated across trials and participants for each (Epoch × Context × Phase) combination of our repeated-measures design.

Trial sequence

A trial started by presenting a central fixation cross (0.10° × 0.10°, luminance: 1.0 cd/m^2) for 500 ms, and which observers were required to fixate. Next, the fixation cross was removed from the screen, and a blank interval was presented for 200 ms, after which the search display was presented. Observers were instructed that they were allowed to move their eyes upon search display onset and to respond with a manual button press as quickly and accurately as possible to the orientation of the target "T" (left vs. right). Each search display stayed on the screen until a response was elicited. If the "T" was rotated to the right (left), observers responded by pressing the right (left) arrow button on the computer keyboard with their right (left) index finger. Following a response error, the word "Wrong" appeared on the screen for 1,500 ms. Each trial was followed by a blank inter-trial interval of 750 ms. Each phase (learning, adaptation) consisted of 16 blocks with 16 trials each, presenting the four repeated and nonrepeated displays with unique target positions twice (yielding 512 trials) with an equal number of repeated and nonrepeated display layouts. Participants were free to continue with the next block at their own pace. Before the experiment, participants performed one practice block of 16 trials (data not recorded). The experiment took ~50 min to complete.

Recognition test

At the end of the CC search experiment, participants were given a Yes/No recognition test to identify whether they had previously seen a configuration (cf. Chun & Jiang, 1998). They were shown four displays previously presented (with the original target positions) and four new ones and were asked to press a button indicating whether a given display was new or old. This was based on the assumption that explicit recognition of a given old context, if at all measurable, would be stronger for more reliably, that is, initially, learned context-target relations in a CC learning phase/relocation phase design (e.g., Zellin et al., 2014). Participants were presented with each repeated and nonrepeated display twice, yielding a total of 16 recognition trials to increase the accuracy and statistical power of the test (cf. Vadillo et al., 2016). Participants were not timed and were not given feedback on their responses.

Stroop task

After the search task, participants performed additional Stroop and Navon tasks, which were administered in counterbalanced order. In the Stroop task, three specific words, < RED >, < GREEN >, and < BLUE >, were employed, each appearing with an equal frequency in one of the three corresponding colours (Figure 2b). The experiment used RGB colour space with RED Colour: [1,−1,1], GREEN Colour: [−1,0.003,−1], and BLUE Colour: [−1,−1,1]. Subjects were asked to identify the ink colour as rapidly and accurately as possible using predefined arrow keys (left, down, right) with their primary hand. The association between the stimulus and the response was consistent for all participants (leftward arrow = RED, downwards arrow = GREEN, rightward arrow = BLUE). The items subtended 7.15° of visual angle in height and 1.72° in width. The displayed word remained visible until the participant responded. Following a response, a blank screen was presented for 500 ms before the next trial started (see Figure 2b). In total, 84 trials were presented, with an equal amount of congruent and incongruent trials, thus determining whether the semantic meanings of the word and their presented ink colours matched or mismatched, respectively. Congruent and incongruent trials were presented in random order. Before the main experiment, participants completed 12 practice trials to become acquainted with the procedure. During practice (but not during the main experiment), observers received feedback after each correct or incorrect answer by presenting the words "Correct" or "Incorrect" on the screen for 500 ms. We computed individual participants' Stroop interference by subtracting congruent RTs from incongruent RTs. Therefore, higher interference scores denote weaker attentional control in this task, as participants are more likely to read the word rather than name the ink colour.

Navon task

In the Navon task, participants were asked to identify a local letter, < S > or < H >, while ignoring either a congruent or incongruent global letter representation (Figure 2c). For example, an incongruent trial might display a large/global letter "S" composed of small letters "H," while in congruent displays, the letters at both local and global levels would be identical (e.g., large and small letters "H"). Note that only the letters S and H were used in the current task. Each trial started with a fixation cross presented for 1,000 ms followed by the hierarchical letter stimulus, randomly placed in one of four screen quadrants. After 200 ms, the stimulus was masked with white dots for 500 ms. Participants used "S" and "H" keyboard keys to respond as quickly and as accurately as possible to the presence of the target S or H, respectively. The items subtended 6.20° of visual angle in height and 3.82° in width. This part of the experiment presented 84 trials, with an equal amount of congruent and incongruent displays in random order and an equal frequency of the two letters at local and global levels. The main part was preceded by 16 practice trials, again providing feedback ("Correct" and "Incorrect," 500 ms). This task iteration diverges from traditional Navon experiments, which typically alternate between identifying letter identities at global or local levels. In our study, the task consistently focused on the local level. This modification was implemented for several reasons. The original Navon paradigm demonstrated the global precedence effect. Our study, however, aimed to explore the more challenging task of reporting local stimuli when the global stimulus was incongruent. Exclusively focusing on local stimulus features led to an identical number and duration of trials across the tasks and ensured uniform statistical analysis power. In addition, positioning the target letter unpredictably within screen quadrants required participants to expand their attentional spotlight to anticipate the target's appearance anywhere on the screen, engaging all in the global processing mode. In the Navon task, higher inconsistent minus consistent interference scores suggest that global letter information interferes more strongly with identifying local target letters, indicating a weaker attentional bias towards local scene elements.

Both the Stroop and Navon tasks yielded good split-half reliability in our sample: The Stroop task showed a Spearman–Brown-corrected $r = 0.63$, $p = .001$, the Navon task revealed a Spearman-Brown-corrected $r = 0.68$, $p < .0001$. This demonstrates sufficient psychometric properties of these measures in revealing the (hidden) processes of attentional control and attentional focus that may affect CC in learning and adaptation.

Results

Stroop and Navon tasks

In the Stroop task, incongruent trials resulted in longer RTs than congruent trials, $t(44) = 4.58$, $p < .001$ (incongruent = 849 ms, congruent = 766 ms; see Figure 3, upper panel), thus showing that mismatching word-colour stimuli resulted in enhanced processing interference. Moreover, in the Navon task, the inconsistent trials—where the global part of an image did not match its local constituents—also resulted in longer RTs than consistent trials, $t(44) = -9.21$, $p < .001$ (incongruent = 801 ms, congruent = 678 ms; see Figure 3, lower panel), which shows that local-object processing is slowed when the global level of representation provides information that interferes with task performance.

Contextual cueing task

Reaction times were analysed in three ways: First, we analysed the mean RTs, measured from trial onset until

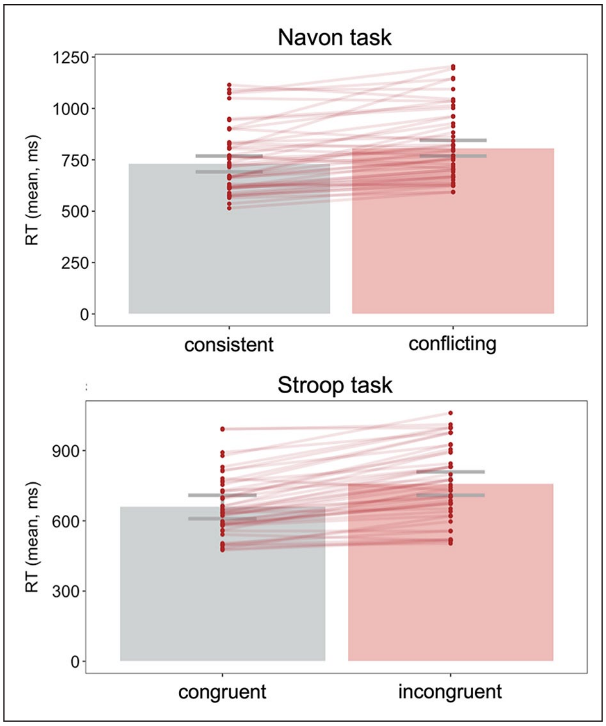


Figure 3. Mean reaction times (RTs, in milliseconds, with associated 95% confidence interval bars) for the consistent and inconsistent Navon conditions and congruent and incongruent Stroop conditions (upper and lower panels, respectively).
The lines connecting data points represent individual participants' reaction times across conditions, emphasising within-subject differences and illustrating the variability in the conflict effect (e.g., the RT difference between congruent and incongruent trials).

participants' responses (button presses). This was done to analyse and replicate CC in a learning phase/test phase design as in previous studies (e.g., Geyer et al., 2024; Zellin et al., 2014). Second, target detection RTs reflected the time from display onset until participants' first fixation of the target item. Third, target verification RTs indexed the time from the first target fixation until the participants' manual responses. Individual mean error rates and RTs were calculated for each factorial (Epoch × Context × Phase) combination. For the RT analyses, error trials and RTs above and below 3 standard deviations from the mean were excluded, leading to the removal of $<2\%$ of all trials. Mean values for each experimental condition were then submitted to a repeated-measures analysis of variance (ANOVA) with the factors Phase (learning, adaptation), Context (repeated, nonrepeated), and Epoch (1–4; one experimental "epoch" combining data across five consecutive trial blocks). Greenhouse–Geisser corrected values are reported in case Mauchly's test of sphericity was significant ($p < .05$).

Panel a of Figure 4 depicts the mean RTs for repeated and nonrepeated displays across epochs in the learning and adaptation phases. The average RT across all experimental conditions was 1,423 ms. The (Epoch × Context × Phase) repeated-measures ANOVA revealed a main effect of epoch and a main effect of context ($F\text{s} \geq 28.12$, $p\text{s} < 0.001$, $\eta_p^2 \geq 0.38$). Importantly, there was an interaction between context and phase, $F(1, 45) = 41.71$, $p < .001$, $\eta_p^2 = 0.48$, reflecting a substantial CC effect, that is, faster search RTs for repeated versus nonrepeated displays in the learning phase—207 ms, range: −136 to 465 ms; $F(1, 45) = 163.64$, $p < .001$, $\eta_p^2 = 0.78$; this compares with a (by 66%) reduced, but still significant CC effect during relocation—of 72 ms, range: −116 to 313 ms; $F(1, 45) = 27.57$, $p < .001$, $\eta_p^2 = 0.38$, thus showing that CC suffered from the target location change. Of note, the results from an analysis of the mean number of fixations are identical to the pattern of mean RT effects (see Figure 4: Panel b). The mean number of fixations until the target response was 8.68. Analysing this number by another (Epoch × Context × Phase) repeated measures ANOVA revealed all three main effects to be significant ($F\text{s} \geq 50.58$, $p\text{s} < 0.001$, $\eta_p^2 \geq .53$). The theoretically important Context × Phase interaction was significant, too, $F(1, 45) = 36.64$, $p < .001$, $\eta_p^2 = 0.45$. Fewer fixations were overall required to detect the target in repeated than in nonrepeated displays (7.29 vs. 8.13 fixations), but contextual facilitation in terms of eye movement savings was greater in the learning phase—CC effect: 1.2 fixations, $F(1, 45) = 136.96$, $p < .001$, $\eta_p^2 = 0.75$—than in the relocation phase (CC effect: 0.48 fixations; reduction: 60%), though CC again remained reliable in the latter phase, $F(1, 45) = 35.13$, $p < .001$, $\eta_p^2 = 0.44$.

For target detection RTs (Figure 4: Panel c), there was a significant main effect of epoch, $F(3, 135) = 15.4$, $p < .001$, $\eta_p^2 = 0.25$, suggesting that the time to the first target fixation progressively decreased across experimental epochs. Interestingly, the main effect of context was not significant, $F(1, 45) = 3.26$, $p = .078$, $\eta_p^2 = 0.07$, though inspection of Figure 4 indicates that CC was strongly modulated by phase (significant Context × Phase interaction, $F(1, 45) = 34.94$, $p < .001$, $\eta_p^2 = 0.44$.) That is, CC was reliable in the initial learning phase, $F(1, 45) = 5.52$, $p = .023$, $\eta_p^2 = 0.11$, though the effect reversed in the subsequent adaptation phase, in which target detection RTs were even slower for repeated compared with nonrepeated configurations, $F(1, 45) = 32.79$, $p < .001$, $\eta_p^2 = 0.42$, suggesting that learned, but no more relevant target locations, strongly interfere with processing of the actual, that is, changed, target location (e.g., Pollmann & Manginelli, 2009; Zinchenko, Conci, Töllner, et al., 2020).

Concerning target verification times (Figure 4: Panel d), the Epoch × Context × Phase repeated-measures ANOVA revealed all three main effects to be significant ($F\text{s} \geq 20.00$, $p\text{s} \leq .001$, $\eta_p^2 \geq 0.31$). Furthermore, there was a significant interaction between epoch and phase, $F(3, 135) = 13.56$, $p < .001$, $\eta_p^2 = 0.23$, as well as a significant interaction effect between context and phase, $F(1, 45) = 4.92$, $p = .032$, $\eta_p^2 = 0.1$. To explore the latter effect,

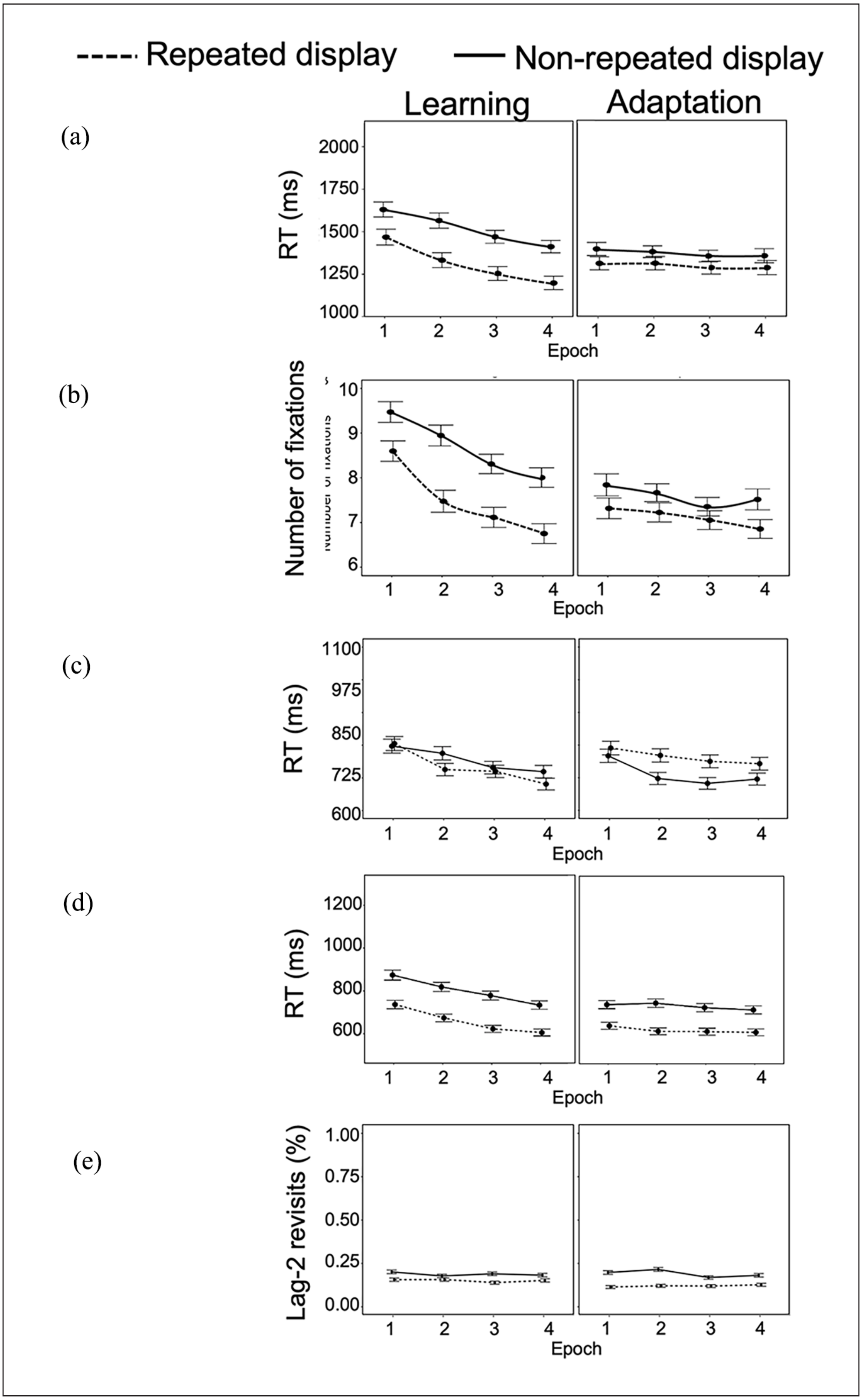


Figure 4. (a) Mean reaction times (RTs, in milliseconds) from display onset until participants' responses (button presses). (b) Corresponding mean fixation numbers. (c) Mean target detection times from display onset until first target fixation. (d) Mean target verification times from first target fixation until manual button presses. (e) Proportion of lag-2 revisits indicating one intervening, nontarget fixation between the first and final target fixation. All dependent variables are presented separately for repeated and nonrepeated contexts (solid and dashed lines) and for the learning and relocation phases. Associated error bars denote the 95% confidence intervals.

Table 1. Results from regression modelling.

Term	Phase	*B*	*SE*	*t*	*p*
Target detection RTs					
(Intercept)	Learning	−7.36	20.30	−0.36	.718
Stroop		0.44	0.17	2.53	.015**
Navon		−0.14	0.12	−1.17	.246
(Intercept)	Relocation	−46.35	18.50	−2.51	.016
Stroop		−0.07	0.16	−0.46	.642
Navon		−0.001	0.11	0.013	.988
Target verification RTs					
(Intercept)	Learning	141.82	16.05	8.83	.000
Stroop		0.17	0.13	1.23	.223
Navon		−0.23	0.10	−2.29	.026**
(Intercept)	Relocation	112.86	18.69	6.03	.000
Stroop		−0.14	0.16	−0.90	.370
Navon		0.19	0.11	1.68	.098

The provided estimates represent standardised Beta scores.
$^{**}p < .05$.

we analysed CC for each phase, which revealed significant contextual facilitation of 141 ms in the learning phase, $F(1, 45) = 268.11$, $p < .001$, $\eta_p^2 = 0.86$, and significant CC in the relocation phase, $F(1, 45) = 133.9$, $p < .001$, $\eta_p^2 = 0.75$, albeit with reduced magnitude (113 ms). Thus, the CC measure in target verification times was still functional in the target relocation phase. This suggests that target relocation is unlikely to affect CC arising at later stages of response decisions. In support of this, we also find that lag-2 revisits[1] to target objects (see Figure 4: Panel e) were overall lower for repeated compared with nonrepeated arrays—13.6% and 18.9%; main effect of context: $F(1, 45) = 35.51$, $p < .001$, $\eta_p^2 = 0.44$. Interestingly, contextual savings in lag-2 revisits were even larger in the subsequent adaptation phase (repeated displays: 12.1%, nonrepeated displays: 19.1%; savings: 7.0%) compared with the initial learning phase—15.2% versus 18.8%; savings: 3.6%; significant Context × Phase interaction, $F(1, 45) = 8.86$, $p = .005$, $\eta p^2 = 0.16$.

Regression modelling

We ran a series of four regression models in which we predicted CC measured in target detection and verification times and across learning and relocation by individual participants Navon/Stroop incongruence effects (i.e., differences in RTs between the incongruent minus congruent conditions in the respective task; see Figure 3). As shown in Table 1, individual variability in the Stroop task is associated with CC in the early portion of the search. Specifically, participants with high Stroop interference scores (indicating weak abilities to suppress a dominant Stroop response) display an overall larger CC effect until first arriving at the target item in the visual display. This contrasts with performance in the Navon task, which showed a systematic (negative) correlation with CC in later stages of search (of target verification) and suggested that participants with low Navon interference scores (indicating heightened perceptual capacities to focus processing on the local letter) benefit from contextual repetitions at the time of target response decisions. These results contrast with the relocation phase, in which no significant correlations between individual participants' Navon/Stroop interference scores and measures of CC were found in either target detection or target verification.

Recognition test

In the recognition test, the correct identification of repeated displays as "repeated" (hits) was compared with the erroneous identification of nonrepeated displays as "repeated" (false alarms) using a paired samples *t*-test. The results showed no significant differences between the hit and false alarm rates, $t(45) = 1.61$, $p = .11$. Overall, the hit rate was 53.8%, and the false alarm rate was 47.3%, thus revealing no evidence of explicit context memory in this experiment.

Discussion

Summary of findings and discussion

The current work addressed whether interindividual differences in attentional focus and attentional control abilities could be used to predict the pattern of statistical contextual learning and relearning in visual search. To this end, we performed a CC search experiment, which presented invariant, to-be-learned target-distractor configurations in an initial learning phase, followed by an unexpected change of the target location (within otherwise unchanged distractor contexts) in the subsequent adaptation phase. Besides RTs, we recorded fixation locations to track participants' overt focus of attention during initial learning and the subsequent adaptation. Specifically, we analysed RTs across the entire search trial but also relative to single trial events, which were identified by eye movements, such as the time from the onset of the search display until participants first fixated the target (=target detection RTs) or the time after fixating the target until responding to it (=target verification RTs). In doing so, we could track the psychological process/es responsible for producing the cueing effect during learning and relocation. Moreover, previous CC studies reported significant variability in CC during learning and adaptation. Accordingly, we used an individual-differences approach to explain this variability while providing converging evidence for the view that experience with repeated displays trains different—and independent—processes. This view is based on the idea that CC has a search-and-response component (e.g., Goujon et al., 2015).

We found that while participants could effortlessly and quickly learn the repeated target-distractor arrangements during the first half of the experiment, adapting this context representation to the changed target locations in the second half was more challenging. For instance, the contextual facilitation in mean RTs (and mean fixation number) was significant during initial learning but almost three times smaller after target relocation, while the cueing effect did not fully recover to baseline level even with extended practice on the relocated displays. Furthermore, for target detection RTs, contextual facilitation was reliable in the learning phase, but there was a significant negative CC effect in the relocation phase, suggesting that it took participants even longer to detect the target in the repeated displays, thus possibly reflecting attentional misguidance arising from previously learned target positions (e.g., Zinchenko et al., 2020). For target verification times, the CC effect was functional during both phases, albeit reduced during the relocation phase.

The results from our regression analyses, which showed a double dissociative pattern, are of theoretical interest. First, correlations between measures of CC and individual Stroop/Navon performance scores were found only for the learning, but not relocation, phase. Second, and concerning the learning phase, individual Navon/Stroop biases affected CC differently. While individuals with high-Stroop interference displayed elevated CC for target detection times, individuals with a local-Navon bias showed greater contextual learning for target verification times.

Our findings from the initial learning phase replicate the results of Bellaera et al. (2014), demonstrating that a local processing bias enhances context learning. Several studies have shown that CC is driven by learning the arrangement of the distractor items near the target (i.e., the local contexts; see Brady & Chun, 2007; Olson & Chun, 2002). Thus, it is not surprising that more locally biased participants also perform better in forming an association between the target and nearby distractor stimuli.

An unexpected finding was that participants with high Stroop interference scores had a larger cueing benefit in the initial learning phase, though Stroop task performance did not systematically relate to measures of CC obtained in the relocation phase. This may suggest that while the Stroop task measures executive functioning, this type of control may differ from the top-down attentional control required to overcome the learned target location during adaptation in the contextual array. Instead, Stroop interference scores may reflect stable individual differences in cognitive control rather than a distinction between active and passive search strategies (e.g., Smilek et al., 2006; Watson et al., 2010). As such, initial context learning benefits from more relaxed processing with less emphasis on attentional control. This idea is supported by Lleras and von Mühlenen's (2004) work, which found that participants instructed to perform a visual search task in a more passive mode showed comparably large CC effects. Statistical learning has also been found when search stimuli were initially only viewed passively and without explicit task (for review, see, for example, Theeuwes et al., 2022), further supporting a link between statistical learning and (reduced) attentional control.

Implications for CC

Our eye-tracking-informed RT analysis confirms that CC can enhance a series of psychological processes, which can be categorised as search- and response-related. Further support for this view comes from our correlation analysis, which found that individuals with a higher conflict effect on the Stroop task showed larger CC effects in search-related measures (i.e., target detection times), while participants who showed more of a local bias in the Navon task exhibited larger CC effects in response-related measures (i.e., target verification times).

Assuming now that the Stroop task indexes passive search and the Navon task reflects a perceptual effect, here: the ability to focus perceptual processing on the local (target) element, then the result of a significant correlation between local-Navon performance and CC in verification times might suggest that there is also a perceptual discrimination component to CC. That is, local-Navon participants would be able to more efficiently perceptually analyse the selected (i.e., focally attended) item to extract the response-critical feature—typically the orientation of target T—to decide on the appropriate motor reaction. Although the target orientation varies randomly in repeated search displays (to prevent the learning of stimulus-response couplings), the orientations of the L distractors (as well as their locations) are typically held constant (which is different from nonrepeated displays, in which both the distractor locations and orientations are randomly determined). It is thus possible that the repeated distractor orientations are learned (as well as their locations) and come to aid postselective target processing (see, for example, Sewell et al.'s [2018] perceptual-discrimination account of the CC effect). 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, local surround, for example, Brady & Chun, 2007) against the left- vs. right-oriented target-feature template.

One interpretation that follows from this scheme is that the local context of the display would not necessarily help with search guidance (e.g., Brady & Chun, 2007) but rather aids postselective processing of the target in repeated arrays by helping to exploit the local featural context provided by the consistent distractor orientations. This would argue for the need to consider lower-level learning mechanisms, such as implicit learning of local featural relationships, to understand the facilitated (postselective) processing of distractor-target (feature) relations in repeated arrays (Sewell et al., 2018).

This view would also be supported by the pattern of CC during the target relocation phase. We find a significant negative CC effect in target detection times (suggesting that it took individual participants longer to detect the target in the repeated arrays). However, relocation-CC was found in target verification times, albeit with reduced magnitude (compared with CC during learning). Assuming that verification times reflect an amalgamation of postselective and response-related processes, it is well possible that target relocation also affects the postselective processes of target discrimination. That is, the relocated target will be presented in a new local context of distractor elements (with new orientations), which will induce difficulties for participants in establishing new target-distractor featural associations (as previously established local feature target templates persist). Successful adaptation would then require that participants overcome these feature templates and spatial templates arising from previously established target-distractor spatial contextual associations. Accordingly, neither measures of Stroop (indexing passive search) nor Navon (indexing attention to local display elements) will correlate with CC when measured during the adaptation phase.

Future research should examine whether other individual differences in visual search, relating, for example, to intelligence, cognitive abilities, or habits/traits (for review, see Wagner et al., 2024), can account for CC in the relocation (and learning) phase. The data from the current experiment suggest that individual factors relating to interference in Navon and Stroop tasks do not adequately account for contextual adaptation.

Conclusion

The current work provides novel evidence that suggests that contextual learning, but not adaptation, depends on individual differences. While a robust local attentional bias in the Navon task is associated with a benefit in contextual learning during the late stages of target verification, participants with weak Stroop control show increased CC during the early stages of target detection. Overall, our results are compatible with a search-and-response account of CC that assumes that RT benefits during initial learning arise from more effective attentional scanning towards the target and more optimal target response decisions. Our individual-difference approach allowed us further to decompose the response component in CC and identify the contribution of a postselective perceptual process of target discrimination to the CC effect.

Declaration of conflicting interests

The author(s) declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

Funding

The author(s) disclosed receipt of the following financial support for the research, authorship, and/or publication of this article: The current work was funded by Deutsche Forschungsgemeinschaft (award number: GE 1889/4-1 and GE 1889/4-2 granted to Thomas Geyer and Markus Conci).

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Data accessibility statement

The data and materials from the present experiment are publicly available at the Open Science Framework website: https://osf.io/bxm3y/

Note

1. Lag-2 revisits occur when a participant fixates a target, moves to another object, and then rapidly returns to the target. We analysed only this measure as most revisits in visual search occur at this lag (e.g., Godwin et al., 2017). Technically, we (1) identified the minimal fixation distance to the target (cf. methods); (2) checked if any subsequent fixation had a higher distance to the target than the minimal distance fixation; and (3) verified that the next (final) fixation had a smaller distance to the target than the preceding fixation (to a nontarget object/empty display location). If this chain of events occurred, we marked a trial as a lag-2 revisit trial.

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