Assessing the impact of attention fluctuations on statistical learning

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Abstract

Attention fluctuates between optimal and suboptimal states. However, whether these fluctuations affect how we learn visual regularities remains untested. Using web-based real-time triggering, we investigated the impact of sustained attentional state on statistical learning using online and offline measures of learning. In three experiments (N=450), participants performed a continuous performance task (CPT) with shape stimuli. Unbeknownst to participants, we measured response times (RTs) preceding each trial in real time and inserted distinct shape triplets in the trial stream when RTs indicated that a participant was attentive or inattentive. We measured online statistical learning using changes in RTs to regular triplets relative to random triplets encountered in the same attentional states. We measured offline statistical learning with a target detection task in which participants responded to target shapes selected from the regular triplets and with tasks in which participants explicitly re-created the regular triplets or selected regular shapes from foils. Online learning evidence was greater in high vs. low attentional states when combining data from all three experiments, although this was not evident in any experiment alone. On the other hand, we saw no evidence of impacts of attention fluctuations on measures of statistical learning collected offline, after initial exposure in the CPT. These results suggest that attention fluctuations may impact statistical learning while regularities are being extracted online, but that these effects do not persist to subsequent tests of learning about regularities.

Keywords: statistical learning, visual regularities, sustained attention, attention fluctuations

Introduction

Regularities are prevalent in our everyday environment. We extract this potentially meaningful information over time via statistical learning. Statistical learning has been demonstrated in multiple sensory modalities including vision (e.g., Turk-Browne et al., 2005; Fiser & Aslin, 2002), audition (Conway & Christiansen, 2005; 2006), and language learning (Saffran et al., 1997), and has been observed across developmental stages (Krogh et al., 2013). As we navigate our environment, however, our attention also fluctuates between optimal and suboptimal states. Do these attentional state fluctuations impact the degree to which we are able to extract regularities?

Research has asked how another form of attention—*selective* feature-based and/or object-based attention—impacts statistical learning. Turk-Browne et al. (2005) tested this question by showing participants a sequence of shapes in two colors, where only one color was task-relevant. Participants were instructed to press a key whenever they observed an immediately subsequent repetition of a shape in that stream in relevant color. Results revealed that participants only learned regularities in the goal-relevant color stream, suggesting that goal-directed selective attention (i.e., attention to both color and shape) is required for visual statistical learning. Later work using a similar design, however, demonstrated learning of regularities in both the goal-relevant and irrelevant color streams, suggesting that selective attention may not be required to see offline evidence of statistical learning (Musz et al., 2015).

Importantly, attention is a multifaceted construct (Chun et al., 2011). Selection is only one of the fundamental aspects of attention. It is thus an oversimplification to assume that the downstream consequence of attention is all-or-none after selection. In fact, attentional state fluctuates within individuals over time, impacting information processing and thus has behavioral consequences in a wide range of cognitive tasks (Robertson et al., 1997; Sarter et al., 2001; Esterman et al., 2013; Esterman & Rothlein, 2019). Even after information is selected, task performance could vary with fluctuations in attentional state. The impact of *sustained attention* on how we learn regularities in an unsupervised manner via statistical learning is relatively unexamined in the literature.

How might sustained attention during initial exposure impact regularity-learning during acquisition and regularity representations after the fact? Work has asked analogous questions about the relationship between attention fluctuations and different forms of memory. deBettencourt et al. (2019) demonstrated that attentional state fluctuations co-vary with working memory performance as a whole-report memory task was *ongoing*. Attentional fluctuations during encoding also predicted *subsequent* memory for images when tested after the initial exposure, such that images encountered in high attentional states were better recognized (deBettencourt et al., 2018; Wakeland-Hart et al., 2022).

Analogously, we can evaluate the impact of attention fluctuations on statistical learning measured in two ways: *online* during initial exposure to regularities and *offline* after the initial exposure task is complete. Online measures, in which elements in a regular stimulus sequence are presented one after another in a cover task, primarily assess implicit knowledge. For example, in a serial response task in which participants repeatedly respond to a set of stimuli, learning is reflected in RT speeding (Hunt & Aslin, 2001; Kiai & Melloni, 2021; Siegelman et al., 2018). In a click-detection task in which participants respond to a click superposed on a stream of trisyllabic words (Gómez et al., 2011; Franco et al., 2015), learning is reflected in faster RTs to clicks presented at the boundary vs. in the middle of these regular trisyllabic words. On the other hand, offline measures are used to assess both implicit and explicit knowledge of regularity. The canonical offline test for implicit knowledge is the target detection task, which quantifies RT facilitation to targets in different positions within a previously presented regular sequence (Kim et al., 2009; Musz et al., 2015; Turk-Browne et al., 2005). RT facilitation, or faster responses to later items in the regular sequence, indicates learning. A classic offline test assessing explicit knowledge is the two-alternative forced choice (2AFC) task where participants are asked to choose the correct regular sequence from foils (Fiser & Aslin, 2002; Saffran et al., 1997). Studies examining the relationship between online and offline measures of statistical learning have largely revealed no association or only weak correlations between online and offline measures (Franco et al., 2015; Himberger et al., 2019; Kiai & Melloni, 2021; Siegelman et al., 2018).

Characterizing effects of sustained attention on both online and offline measures of statistical learning is important for two reasons. First, the lack of relationship between the two measures suggests that they involve different cognitive processes and capture different information about learning (Kiai & Melloni, 2021). Tasks assessing online learning may involve the extraction of stimulus properties and their regularities as well as the use of the extracted regularity. When tested offline, on the other hand, participants' focus shifts to applying the extracted temporal statistics in recognition tasks (Fiser & Aslin, 2002). Second, only examining statistical learning offline could miss insights about how information is *accumulated* in different attentional states. Examining both online and offline measures allows us to assess whether attentional fluctuations impact statistical learning when learning is happening on the fly and ask whether any effects of attentional state persist until knowledge of regularities is tested later.

To bridge this gap between sustained attention and statistical learning, we asked how moment-to-moment changes in sustained attentional state affect the degree to which we learn visual regularities. At first glance, it seems impossible to test this question because although we learn regularities across repeated pattern exposures, we may be attentive at one exposure but inattentive at the next. To overcome this challenge, we designed a task in which visual regularities are presented contingent on attentional state and aim to observe the downstream consequences of sustained attentional fluctuations on statistical learning.

In three web-based experiments (E1a, E1b, E1c), we systematically assessed the impact of attention fluctuations on online and offline measures of statistical learning. To do so, we combined a sustained attention task and a statistical learning task together within individuals. Participants performed a continuous performance task (CPT) with shape stimuli and were instructed to press a button in response to shapes from a frequent but not infrequent category. We measured correct-trial RTs in real-time, and inserted distinct shape triplets in the trial stream when RTs indicated that a participant was attentive (>1 standard deviation [SD] above the participant's mean RT) or inattentive (>1 SD below the participant's mean) (deBettencourt et al., 2018; 2019). In other words, participants saw one sequence of three shapes when they were attentive and another when they were inattentive. We assessed online learning by comparing changes in RT within regular triplet relative to those within control triplets that were encountered in similar attentional states but in random order. To assess learning offline, we first asked participants to perform a target detection task in which they responded to target shapes selected from the regular triplets. We then used two direct measures to examine different aspects of participants' knowledge. To measure knowledge about triplet group membership, we asked participants to select individual shapes that appeared in regular triplets among foils (E1b, E1c). To measure knowledge about the order of shapes within triplets, we asked them to explicitly re-create the regular shapes in a drag and drop task (E1a, E1b, E1c). In a fourth experiment (E2), participants only performed the target detection task without undergoing the initial attention-contingent exposure.

Results revealed that more participants than that would be expected by chance showed explicit knowledge for triplets learned in these experiments when asked to re-create the regular triplets. However, offline target detection results were mixed, and RT facilitation only differed between attentional states in one of the three triggering experiments. In contrast, online statistical learning measured from changes in RTs relative to control showed a consistent trend of high attentional states inducing more online changes in RTs across experiments. Evidence of sustained attention's impact on *online* statistical learning was found when we combined online learning data across our experiments (E1a, E1b, E1c). Thus, we find initial evidence for consequences of attentional state fluctuations on an online measure of visual statistical learning.

Experiment 1a

Methods

We conducted an web-based experiment using Prolific (www.prolific.co) to ask whether statistical learning varies as a function of sustained attentional state. In a cover task measuring sustained attention, we embedded visual statistical regularities on the fly contingent on attentional state. We assessed the degree to which participants learned statistical regularities embedded in the trial stream during better vs. worse attentional states. We predicted that participants would show more evidence of statistical learning for regularities encountered in the better attentional state.

Participants

We ran a power analysis on pilot data (η_p^2=0.01, power=0.8) using G*power (Faul et al., 2007), which suggested that 146 participants were needed to reach 80% power for an ANOVA interaction between triplet position and attentional state (Turk-Browne et al., 2005). We thus set our stopping rule as 150 usable participants after exclusion.

To meet our sample size obtained from the power analysis, 201 participants were recruited using Prolific (sex: 112 female, 89 male, 0 prefer not to say; mean age=26.94 years, SD=5.30, range=18–35; current country of residence: the United States; fluent language: English; normal vision; minimum approval rate >0.98; minimum previous submissions >=10). 38 participants were excluded due to a technical difficulty that resulted in missing data from the second part of the experiment, the target detection task. We defined a priori the minimum number of exposures to statistical regularities, excluding participants who saw five or fewer regular triplets in either the better or the worse attentional state during the CPT because so few exposures may not result in statistical learning. 11 participants were excluded because of five or fewer exposures to triplets in one of the two attentional states. We also decided a priori to exclude participants whose overall performance (A') on part one of the experiment, the CPT, fell more than two standard deviations from the group mean. Two participants were excluded based on this criterion (pre-exclusion group mean A'=0.86, SD=0.15, lower bound=0.56, upper bound=1.16).

Final analyses were performed on the remaining 150 participants (86 female, 64 male, mean age=26.98 years, SD=5.11, range=18–35). The study was approved by the relevant University of Chicago Institutional Review Board, and participants gave informed consent online and were compensated for their participation.

Continuous performance task

Our experiment included three phases. In the first phase, participants performed a CPT (e.g., Robertson et al., 1997) for approximately 29 minutes to assess visual sustained attention. Before the task began, participants were shown example shapes that they would see during the experiment, and instructed to press the 'spacebar' each time they saw a frequent-category shape (90% of non-triggered trials) but to withhold their response when they saw an infrequent-category shape ('L' shapes; 10% of non-triggered trials; **Fig. 1a**). At the start of each trial, a black shape appeared on the screen for 800 ms followed by a 200-ms intertrial interval (ITI). Responses were recorded while each stimulus was on the screen but not during the ITI[1]. A central gray fixation dot was present on the screen during the trial and ITI, disappearing when a participant made a response during stimulus presentation and reappearing at the start of each ITI. Stimuli were presented using jsPsych (de Leeuw, 2015).

Task stimuli matched those used in previous visual statistical learning studies (Fiser and Aslin, 2002; Turk-Browne et al., 2005; Zhao et al., 2013). 26 shapes were selected for all participants, and 12 were randomly assigned for each participant to serve as frequent-category shapes in the CPT. Six shapes were randomly divided into two groups of three shapes (i.e., two regular triplets). The remaining eight shapes served as rare control shapes (see the *Real-time regularity triggering* section for detail). Four "L" shapes served as the infrequent-category shapes (**Fig. 1a**).

[1] Shape stimuli were presented for 800 ms, and mean RT for frequent-category trials was 379.39 ms (SD=121.28 ms). Thus, the lack of RT recording during the ITI (800–1000 ms after stimulus onset) did not likely result in a large number of missed responses. Participants missed (i.e., failed to respond to) 2.96% frequent-category trials on average.

Real-time regularity triggering

We characterized participants' attentional states during the CPT using the speed of their RTs relative to an RT threshold (deBettencourt et al., 2018; 2019). On each trial *i*, we calculated the running mean (μ_i) and standard deviation (σ_i) of correct frequent-trial RTs in real-time. We also calculated the mean RT of the three frequent trials preceding *i* ($\overline{RT}_i$). When $\overline{RT}_i$ exceeded one standard deviation above the participant's running mean ($\overline{RT}_i > \sigma_i+\mu_i$)—that is, when participants were responding especially slowly, indicating a better attentional state (deBettencourt et al., 2018; 2019)—we inserted a triplet of a sequence of three regular shapes (e.g., ABC) into the trial stream. When $\overline{RT}_i$ fell more than one standard deviation below the participant's running mean ($\overline{RT}_i < \mu_i-\sigma_i$)—indicating fast responding and poor attention—we inserted a sequence of three different shapes (e.g., DEF) in the task (**Fig. 1b**). In other words, especially slow responding triggered the addition of one regular triplet and especially fast responding triggered the addition of another. No regular triplets were inserted in the first 80 trials to establish an RT range, in line with previous studies (deBettencourt et al., 2018; 2019). Shapes included in regular triplets were not presented during any other CPT trial. The set of frequent-category shapes that appeared in the regular triplets was randomized across participants.

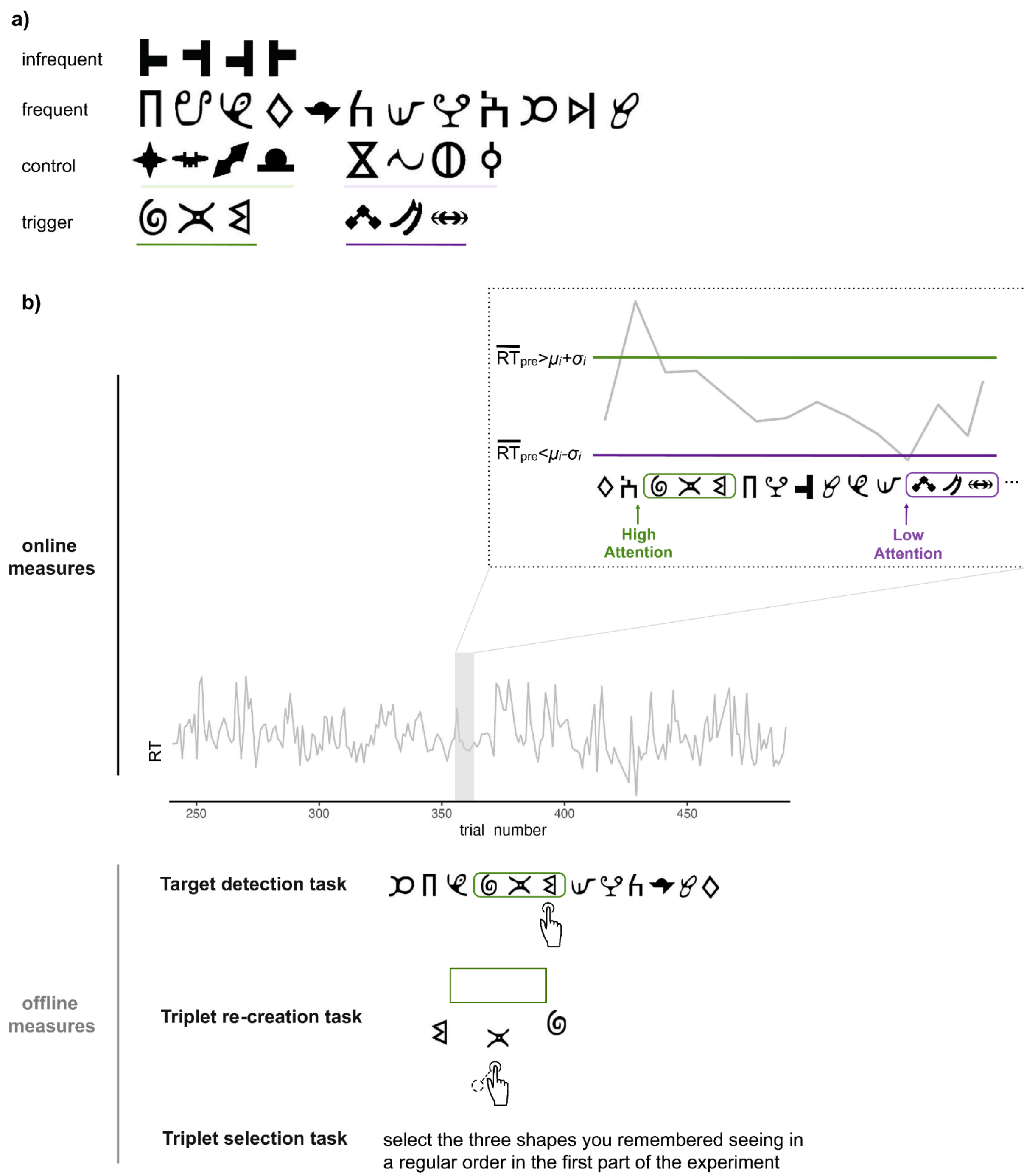

Figure 1. Task and stimuli. **(a)** Stimuli used in the tasks: The first four "L" shapes served as infrequent (10%) shape stimuli in the CPT. The other shapes served as frequent-category stimuli. Of these, 12 as non-triggered frequent-category shapes, 8 others were included in random control triplets, and 6 were included in regular triplets. Lighter green and purple underlines denote shapes included in random control triplets triggered by high and low attentional states, respectively. Darker green and purple underlines denote regular triggered triplets. The arrangement of all shapes other than the infrequent shapes was randomized for

each participant. **(b)** Task illustration. **Top panel**: CPT and online measures of statistical learning. Participants saw different regular triplets contingent on their attentional state. Darker green and purple arrows indicate when pre-trial RT is slower or faster than one SD from the running mean, respectively. Random control triplets are not shown in this plot due to limited space. **Bottom panel**: Offline measures of statistical learning. Participants completed the offline tasks in the order of the target detection task (E1a-c), triplet re-creation task (E1a-c), and triplet selection task (E1b-c).

We applied five constraints restricting when real-time triggering could occur. This allowed us to closely match the number of times a participant saw the two regular triplets despite the fact that they could have experienced more high than low attentional states or vice versa. Regular triplets could not be triggered within three trials following *(1)* an omission error (i.e., failure to press to a frequent-category shape); *(2)* an infrequent-category trial (an 'L' shape); or *(3)* another triggered regular triplet. In addition, *(4)* regular triplets could not be triggered if the previous three triggered regular sequences belonged to the same attentional state. This restriction helped ensure a roughly equal number of exposures to the better- and worse-attentional-state triplets and prevented participants from seeing four or more of the same sequence (e.g., ABC or DEF) in a row. Finally, *(5)* a regular triplet could not be triggered if doing so would cause the difference in the total number of triggered trials in the better vs. worse attentional state to exceed three.

These five restrictions resulted in some instances where regular triplets *could have* been triggered by especially fast or slow RTs but were not. To disentangle the effect of shape novelty (because triplet shapes were seen less frequently than other frequent-category shapes) and statistical learning on RTs in the CPT, we inserted triplets of rare shapes in random order at these positions in the trial stream. It is possible that introducing new control shapes could potentially lead to difference in novelty (i.e., how rare the shapes are relative to the frequent CPT stimuli shapes) between shapes in triggered and control trials. We thus roughly matched both the number of triggered and control triplets and individual triggered and control shapes. We inserted a maximum of 24 random triplets in the high and low attentional states, respectively, to approximately match the mean number of regular and random triplets with the number of regular triplets. Eight additional shapes thus served as control triplet shapes (**Fig 1a**). They were first randomly divided into two groups of four and then within each group arranged into 24 possible combinations of three shapes. One of the combinations was randomly interested into the CPT trial stream when a regular triplet *could have* been inserted due to a particularly high or low attentional state but was not because of one of the five restrictions. Thus, participants saw the random control triplet shapes approximately as often as they saw regular triplet shapes and under similar attentional states.

The CPT served not only as a cover task during which participants were initially exposed to statistical regularities but also as a measure of sustained attention fluctuations. This allowed us to selectively present regularities during either better or worse attentional states.

In this design, a trial could either be triggered or non-triggered. Non-triggered trials (1200 per participant) served as markers of sustained attention and included both frequent-category trials

(90% of all non-triggered trials) and infrequent-category trials (10% of all non-triggered trials). Triggered trials included regular triplets (ABC, DEF) as well as random sequences of novel control shapes. The number of non-triggered trials was fixed for all participants, whereas the number of triggered trials varied depending on how often each participant fell into high and low attentional states. Thus, participants saw different numbers of total trials during the CPT. The relative proportion of frequent- and infrequent-category shapes also varied across individuals because triggered shapes only came from the frequent category.

Target detection task

After participants completed the CPT, they performed a target detection task to assess their statistical learning (Turk-Browne et al., 2005). In this task, participants were instructed to respond to target shapes selected from the regular triplets embedded in the CPT (i.e., the initial exposure phase). The difference in RTs to the targets was then used as an offline measure of statistical learning. If participants learned the triplet sequence in the CPT, they should be able to make predictions about what shape is appearing next, and thus respond more quickly for later positions in the triplet.

On each trial, participants first saw a target shape along with text instructing them to press the 'spacebar' as quickly as possible when they see the target shape appear on the screen. The page commenced after the participant pressed 'enter'. Participants next saw a rapid serial presentation of 12 shapes. Each shape was on the screen for 300 ms separated by a 40-ms interstimulus interval. RT was calculated from the onset time of the target shape.

Shapes were drawn from the set of stimuli used during the CPT. Of the 12 shapes included in each target detection trial, nine were randomly drawn from the 12 frequent non-triggered shapes from the CPT and three were from one of the two regular triplets presented during the CPT. Each of the six shapes from the two regular triplets served as a target four times. The three shapes from the regular triplet could not be inserted in the first or the last three positions, resulting in six possible to-be-inserted positions for a shape and four for a triplet. Note that none of the control shapes were presented in this target detection task. As a result, there were 24 trials in the target detection task for each participant. We hypothesized that the RTs for shapes in later positions in the triplet will be faster, showing evidence for learning the sequence. Importantly, we predicted that this speeding will be *greater* for triplets learned under high vs. low attentional states. This result would suggest that visual statistical learning measured offline varies as a function of sustained attention.

Triplet re-creation

In the last part of the study, we assessed participants' knowledge about the order of the shapes within the triplets. Participants were presented with the three regular triplet shapes encountered in each attentional state during the CPT outside of a blank box. They saw the following instructions: "Some of the shapes you saw in the first part of the study in fact appeared in a regular order. Therefore, in this section, we will ask you to create groups of 3 shapes that you remember from the first part of the experiment. Now, click on "Next" to move on". Participants then dragged the shapes into the box to indicate the order that they believed the shapes appeared. After this task, we asked participants about their awareness of the regularities (**Supp Table 1**). Awareness data are not analyzed here.

Analysis approach

Assessing CPT performance

We assessed overall CPT performance using a non-parametric measure of sensitivity (A′), calculated as a combination of hit and false alarm rates (Smith, 1995). We next tested whether pre-trial RT was a valid index of attentional states in our online datasets. We predicted that faster RTs would precede incorrect than correct infrequent trials and assessed this prediction using a paired *t*-test.

Assessing statistical learning online

Participants were initially exposed to statistical regularities in the CPT. We thus asked if RT patterns indicative of statistical learning began to emerge during initial exposure. Specifically, we predicted that *(1)* participants would show greater RT differences from triplet position 1 to 3 for regular triplets vs. random control triplets, and *(2)* that these differences would be more evident in the high attentional state.

One potential challenge to this approach is that RTs tend to regress to the mean when they are especially fast or slow and triplets are triggered. That is, RTs usually do not get more extreme when already very fast or slow. To ask if regularity introduced changes in RT patterns above and beyond such regression to the mean, we took advantage of the "could-have-been-triggered" trials (random control triplets) that share similar high or low attentional states with the actual triggered trials but have no regularity. We tested if the triggered trials (regular triplets) showed more RT change compared to "could-have-been-triggered" trials (random control triplets) and if this facilitation varied across attentional states. This analysis was conducted using a mixed-effects model and contrast analyses to test the difference in RT patterns across trial types in the continuous performance task. The model was specified as follows:

CPT RT ~ shape position * attentional state * trial type + (1 + shape position + attentional state + trial type | participant)

where we included position in the triplet (1, 2, or 3), attentional state (high vs. low), and trial type (regular triplet vs. random control triplet) and their interactions as fixed effects, and participant as a random effect with random intercept and slope (see *Results* for model comparison). Trials with zero-averaging in three trials preceding a control were excluded from this analysis. (This only occurred for random control triplets, which could have been triggered within three trials of a non-response. Non-responses were erroneously averaged into the RTs as zeros when calculating the average of the three preceding trials. Non-responses were not averaged into the growing mean and SD RT as zeros.)

To examine the impact of attention on online statistical learning, we quantified an "online learning index" for each attentional state. Previous work quantified online statistical learning using measures reflecting the extent to which RTs speed up progressively within triplets (Franco et al., 2015; Gómez et al., 2011; Siegelman et al., 2018). However, since attention was not measured in these paradigms, patterns of within-triplet RTs across periods of attentional fluctuations were obscured. Here, since we are focusing on both tails (high and low) of participants' attentional states, the within-triplet RTs tend to vary in ways that reflect regression to the mean: under high attentional state where RTs start slow, within-triplet RTs tend to get progressively faster, while the opposite is true for low attentional state. Therefore, we do not have a strong theoretical reason to assume that learning leads to speeding of RTs across triplet positions under both attentional states. Instead, a more rigorous way to operationalize learning is to compare the patterns of RTs to control triplets with random order.

Our online learning index was thus operationalized as any impact of regularity on the change in RTs (regardless of direction) across triplet positions compared to control trials where triplet order was random. To calculate this index, we extracted the estimated marginal means from the above model by applying a contrast that compares the magnitude of the change in RTs from position 1 to 3 across trial type (regular vs. random) and across attentional state (high vs. low). Statistical significance of this contrast was determined by evaluating the post-hoc pairwise comparisons of estimated marginal means with *emmeans*. All analyses were conducted using RStudio (R version 4.2.2) and functions in the *lmerTest* (version 3.1.3; Kuznetsova et al., 2017) and *emmeans* (version 1.8.2; Lenth R, 2022) package.

Assessing statistical learning offline: Triplet re-creation

To test whether participants successfully re-created regular triplets, we compared the total number of individuals who re-created each triplet to a null distribution reflecting the number of participants expected to report the correct triplet order by chance. Specifically, we ran a non-parametric permutation test where, within each attention condition, we *(1)* randomly picked among the six possible shape arrangements within a triplet as the correct answer; *(2)* calculated the average number of participants whose answers matched the random answer, and *(3)* ran 5000 iterations of steps *(1)* and *(2)*. This process resulted in a null distribution of 5000 participant counts per attention condition. Statistical significance was then assessed using the following formula:

one-tailed p = (1+ number of null participant counts >= observed participant count) / 5001

Assessing statistical learning offline: Target detection task

We then asked if participants learned the statistical regularities overall. Replicating the approach applied in previous work (Turk-Browne et al., 2005; Musz et al., 2015), trials with RTs greater than three standard deviations above or below each participant's individual mean were excluded from analysis. We predicted that there would be more facilitation in the triplet encountered in the high compared to the low attentional state, indicating better learning under the higher attentional state.

We ran a mixed-effects model to allow RT facilitations to vary in each individual to reveal systematic differences in RTs across the three triplet positions and to obtain interpretable numerical estimates of the amount of facilitation (Kiai et al., 2021). The final model is specified as follows:

target detection RT ~ attentional state * shape position + (1 + attentional state + shape position | participant)

where we included attentional state (high and low) and position in the triplet (factor levels: 1, 2, 3) and their interaction as fixed effects and participant as a random effect with both random intercept and slope (see *Results* for model comparison).

Previous work has pointed out a potential confound of shape position in the trial stream (Himberger et al., 2019), such that participants tend to detect target shapes presented later in the stream faster than those presented earlier. To address this point, we regressed out the variance explained by stream position using a mixed-effects model with stream position (factor levels: 4-9) as the fixed effect and a random intercept for each participant. We conducted the same analyses described above on the residuals of this regression.

Results

Overall CPT performance

Mean CPT A' across participants was 0.88 (SD=0.06; chance=0.5; **Fig. 2a**). We next tested whether pre-trial RT was a valid index of attentional states in our web-based sample. Replicating previous work (deBettencourt et al., 2018; 2019), RTs averaged from three correct frequent trials preceding an error on an infrequent trial ('L' shape) were faster than that preceding a correct infrequent trial ($t(149)=23.78$, two-tailed $p<0.001$, Cohen's $d=1.02$, mean difference [correct – incorrect]=47.03 ms, 95% CI=[43.12,50.94]) (**Fig. 2b;** see **Supp Fig. 4a** for CPT RT distribution). In line with previous literature (deBettencourt et al., 2018, 2019; Robertson et al., 1997), these results confirmed that pre-trial RT was a valid index of attentional state, such that faster pre-trial RTs correspond to a worse attentional state.

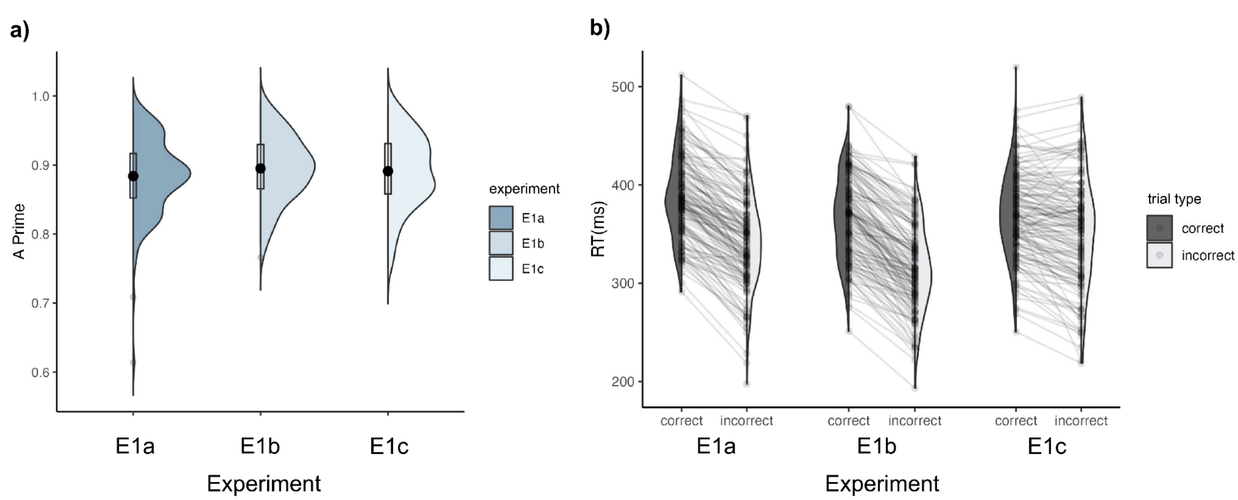

Figure 2. Continuous performance task performance. (a) Distribution of overall A' values. (b) Pre-trial RTs predicted accuracy on infrequent trials. Lines correspond to individual participants. Error bars correspond to s.e.m.

Real-time triggering of regularity based on attentional state

On average, participants saw 17.85 regular triplets (SD=6.10, range=6–36) under high attentional states and 18.10 (SD=6.00, range=6–36) under low attentional states (see **Supp Fig. 1a** and **Supp Fig. 4b** for their position). The number of regular triplets encountered in the high vs. the low attentional state did not systematically differ across participants (mean difference [high-low]=-0.25, mean absolute difference [condition with more - condition with fewer]=2.00, SD=2.25, range=-3,3; $t(298)=-0.35$, $p=0.72$, Cohen's $d=0.04$, 95% CI=[-1.62,1.13]) (**Supp Fig. 1c**).

We inserted random control triplets at "could-have-been-triggered" positions to investigate the impact of regularity on CPT RTs while controlling for shape novelty. On average, participants saw 17.83 random control triplets (SD=6.79, range=2–24) under high attentional states and 23.80 random control triplets (SD=1.24, range=13–24) under low attentional states **(Supp Fig. 1b**).

Online measure of statistical learning

In the CPT, we introduced regular triggered shape triplets and random control shape triplets when participants' RTs were especially fast or slow to test if RTs to these two different trial types differ. Did participants show evidence of online statistical learning for regular triplets during this initial exposure phase?

A mixed-effects model using triplet position, attentional state, and trial type to predict CPT RT revealed a significant three-way interaction ($\chi^2(2, N=150)=10.98$, $p<0.01$, Type II; **Fig. 3a**). To examine the impact of attention on online statistical learning, we quantified an "online learning index" for each attentional state. The online learning index was calculated by comparing how much RT changed across triplet positions in triggered relative to control trials. We then compared this index across attentional states. Online statistical learning was not significantly different across attentional states (estimated marginal mean for online learning index, high attention=11.11ms, estimated marginal mean for online learning index, low attention=8.17ms, estimated difference in online learning index=2.95ms, SE=5.92, $p=0.62$; **Fig. 3e**). Regularity impacted RTs relative to control within both attentional states. Under high attentional states, RTs to regularity were significantly faster than random shapes encountered in the same state (estimated marginal mean for online learning index, high attention=11.11ms, SE=4.28, $p=0.01$). Under low attentional states, RTs to regularity were significantly slower than random shapes encountered in the same state (estimated marginal mean for online learning index, low attention=8.17ms, SE=4.09, $p=0.04$).

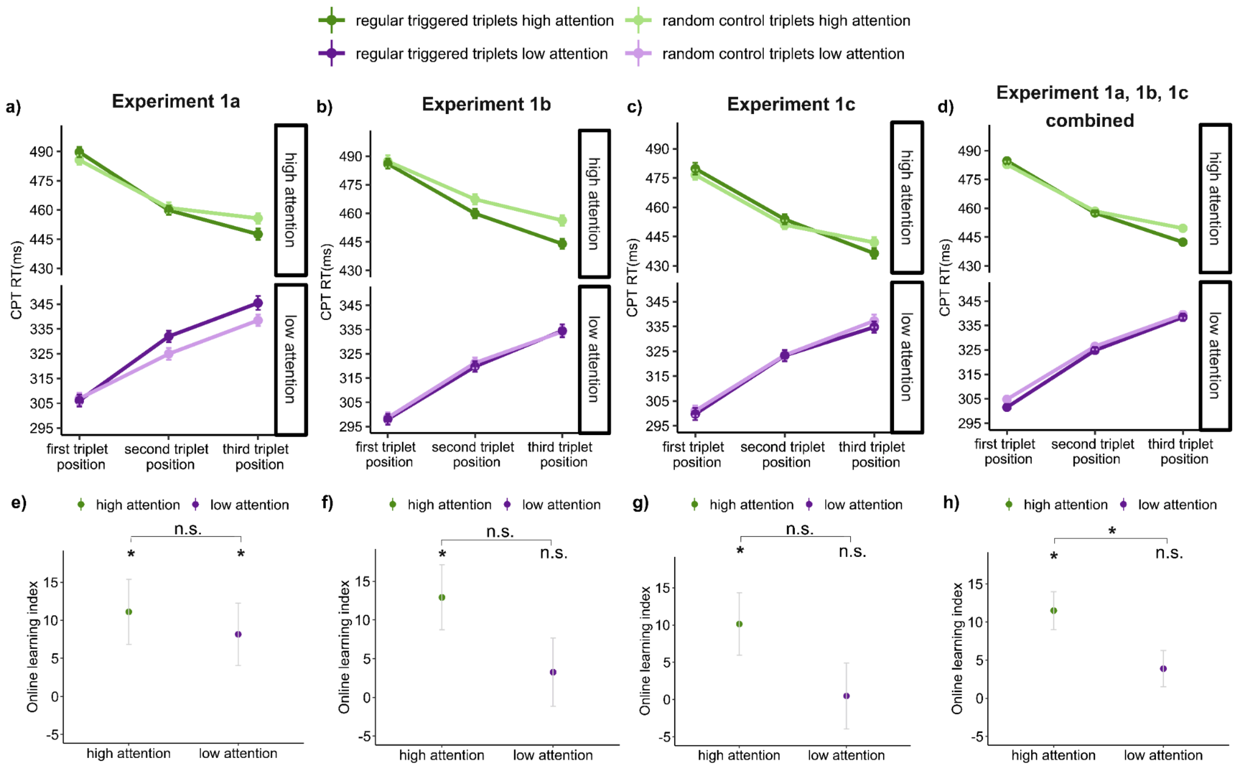

Figure 3. **Panels A–D:** RTs in the continuous performance task in E1a, E1b, E1c, and data compiled from all three experiments. RTs in the high attentional state are in upper panels. RTs under low attentional state are in lower panels. Error bars correspond to the s.e.m. **Panels E–H:** online learning index measured in the continuous performance task in E1a, E1b, E1c, and data compiled from all three experiments. The *y*-axis represents the online learning index quantifying the impact of regular triplets vs. random triplets on RTs, where higher values indicate more impact of regularity on RTs.

Offline measures of statistical learning: Triplet re-creation

To assess whether participants' showed knowledge about the order of the triplet shapes, we asked them to re-create the triplets they remembered seeing in the CPT. In E1a, 34/148 participants (22.97%) successfully recreated full triplets encountered in high attentional states (null mean=24.60, one-tailed p<0.05 [effect larger than 96.90% of 5000 random permutations]). 40/148 participants (27.03%) successfully recreated the triplet encountered in the low attentional state (null mean=24.66, one-tailed p<0.05 [effect larger than 99.99% of 5000 random permutations], **Supp Fig. 2a-b**). The number of participants who correctly re-created the triplet was not significantly different between the two attentional states (diff=-6.0, null diff=-0.13, two-tailed p=0.37, **Supp Fig. 2c**). In other words, more participants than expected by chance showed explicit memory for regular triplets. At the group level, participants did not better remember regular triplets encountered in one of the attentional states. We next asked whether there is a difference in the number of shapes that participants positioned at the correct location within a triplet. A linear regression accounting for the number of times the regular triplet was encountered in the CPT revealed no difference in the number of shapes correctly positioned in the triplet re-creation task between attentional states (β=-0.10, p=0.44, CI=[-0.36,0.16]). Of note, participants performed the triplet re-creation task after the target detection task in which they saw rapid presentation of each regular triplet 12 times (**Fig 1b, bottom**). This extra exposure, independent of attentional state, may have impacted the difference between high-attention and low-attention triplet re-creation in this task.

Offline measures of statistical learning: Target detection task

We assessed whether participants learned the embedded regularities using data from the post-CPT target detection task. We found a main effect of shape position (χ^2(2, N=150)=17.90, p<0.001, Type II Wald Chi-square test) but not attentional state, (χ^2(2, N=150)=1.35, p=0.25, Type II), on target detection RT (see **Supp Fig. 5a** for target detection RT distribution). Overall target detection RT did not differ as a function of the attentional state in which participants originally encountered the target shape (**Fig 3a**). 1.74% trials were excluded based on the trial exclusion criterion (>±3*SD from each participant's individual mean RT) described in the methods (Turk-Browne et al., 2005; Musz et al., 2015).

Participants learned regular triplets embedded in the CPT. Did sustained attention fluctuations impact how well they learned the regularities? To ask this question, we compared the degree to which RTs in the target detection task were facilitated in the triplets encountered in high and low attentional states.

We compared two models with participants as the random effect: one with a random intercept for each participant, and the other with both a random intercept and slope for each participant. Model comparison was conducted using Akaike Information Criterion (AIC). The model including a random intercept and slope for each participant (AIC=34435) performed better than the model with only random intercept (AIC=34588).

The mixed-effects model with target position and attentional state as fixed effects and random intercepts and slopes for participant revealed a significant interaction between attentional state and shape position within-triplet (χ^2(2, N=150)=10.98, p<0.01, Type II). This result shows more RT facilitation within-triplet (i.e., position 1, 2, and 3) for the triplet encountered in a higher attentional state, indicating better statistical learning (**Fig. 4a**).

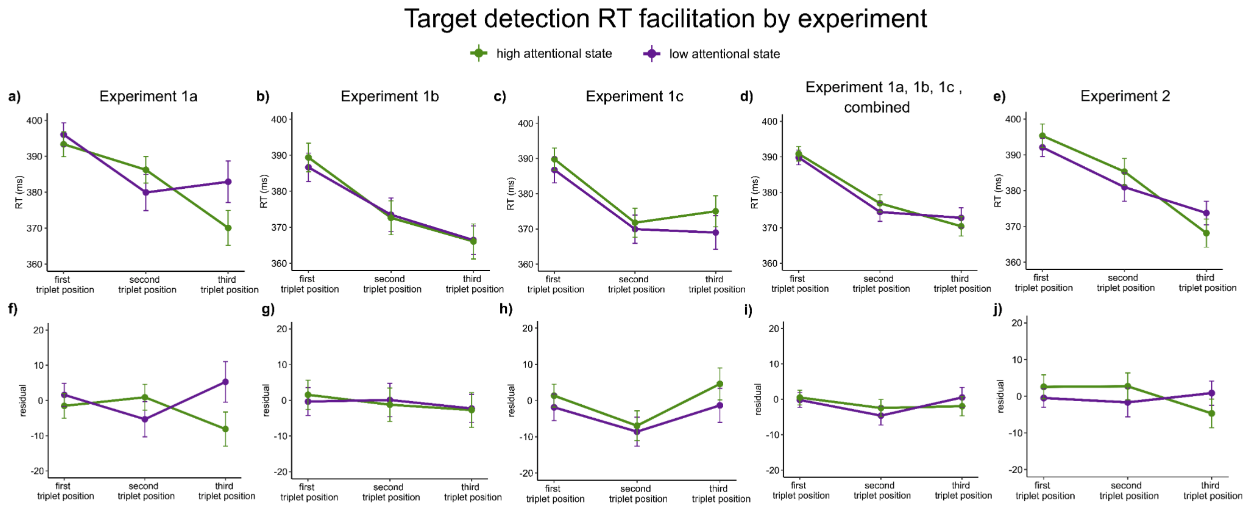

Figure 4. RTs in the target detection task. Green and purple bars show RTs for triplet encountered under high and low attentional state in the CPT, respectively. **Panels A–E:** RTs for triplets in the target detection task in E1a, E1b, E1c, and E2. **Panels F-J:** Residualized RTs for triplets in the target detection task after regressing out the effect of shape position in the test stream in E1a, E1b, E1c, and E2. Error bars correspond to the s.e.m.

It is possible that participants tended to respond faster towards the later part of the target detection stream (Himberger et al., 2019). To address the influence of target position in the test stream, we regressed out the amount of variability explained by position in the trial stream and performed the mixed-effects model using residuals as the predicted variable. The interaction between attentional state and shape position within-triplet remained significant (χ^2(2, N=150)=12.07, p<0.01, Type II), such that the amount of facilitation from early to later positions was larger under high than low attentional states (**Fig. 4f**). However, the main effect of triplet position was not significant (χ^2(2, N=150)=0.32, p=0.85, Type II).

Dividing participants into those who explicitly reported at least one (learners) or none (non-learners) of the regular triplets in the triplet re-creation task revealed no significant difference in target detection RT facilitation between the two groups (median chi-squared value: learners=13.98, non-learners=4.57, 93.70% of chi-squared values for learners are more extreme than those for non-learners, one-tailed p=0.06, Cohen's d=1.54; **Supp Fig. 6a-c**).

Individual differences in sustained attention and statistical learning

We predicted that individuals who performed more successfully on the CPT overall would also show more evidence of offline statistical learning, measured with accuracy in the triplet re-creation task and RT facilitation in the target detection task. Two participants were excluded from this analysis because data from the re-creation task were not recorded.

We ran a linear regression model to test the relationship between performance in the CPT and target detection task. We accounted for the fact that not every participant has the same number of trials in the CPT, which led to small differences in the ratio of infrequent to frequent trials (mean infrequent trial percentage=8.38%, SD=0.27%) and could in theory result in difference in task difficulty. Supporting our hypothesis, CPT A' score was associated with the amount of target detection RT facilitation from position one to three across individuals (β=0.18, $t(147)$=2.16, p=0.03; **Fig. 5**). Thus, participants who paid more attention in the CPT also tended to have a greater amount of RT facilitation when their statistical learning was tested in the target detection task. There was also a non-significant positive relationship between A' and facilitation from position one to two (β=0.05, $t(147)$=0.62, p=0.54) and two to three (β=0.13, $t(147)$=1.60, p=0.11). These relationships were not significant when running the same linear regression model separating attentional states (within triplet position 1-3, 1-2, 2-3: high attention β=0.17, 0.14, 0.06, $t(147)$=1.92, 1.74, 0.62, p=0.06, 0.08, 0.54; low attention β=0.13, 0.03, 0.13, $t(147)$=1.60, -0.38, 1.55, p=0.11, 0.71, 0.12). No relationship was observed between CPT A' and triplet re-creation performance (β=0.14, $t(145)$=1.67, p=0.10; **Supp Fig. 7a**).

These results show that participants who were more attentive during the initial exposure tended to have stronger evidence for statistical learning as measured with RT facilitation in the target detection task.

Experiment 1b

In E1a we found that, compared to random control triplets encountered under the same attentional states, RTs to regular triplets got significantly faster under high attentional states and slower under low attentional states. We observed evidence for a difference in target detection task RT facilitation due to attentional fluctuations in E1a.

In E1b, we aimed to replicate the findings in E1a and test the impact of attentional states on a different measure of offline statistical learning. Previous work suggests that statistical learning can be measured in different gradations. While we did not observe a difference in the offline re-creation task, using a more liberal measuring criteria for learning might reveal more information. We thus asked participants to select the regular triplet shapes they remembered seeing in the CPT from all frequent shapes.

Methods

Participants

To keep our sample size consistent with that of E1a (N=150), 186 participants were recruited using Prolific (sex: 93 female, 93 male, 0 prefer not to say; mean age=27.43 years, SD=4.86, range=19–35; all other criteria consistent with E1a). 21 participants were excluded due to a technical difficulty that resulted in missing data from either the CPT or target detection task. Exclusion criteria were consistent with E1a. 12 participants were excluded because their overall CPT A' fell more than two standard deviations from the group mean (pre-exclusion group mean

A'=0.88, SD=0.07, lower bound=0.75, upper bound=1.01). Three additional participants were excluded because they saw five or fewer regular triplets in one of the two attentional states.

Final analyses were performed on the remaining 150 participants (69 female, 81 male, mean age=27.52 years, SD=4.82, range=19–35). The study was approved by the relevant University of Chicago Institutional Review Board, and participants gave informed consent online and were compensated for their participation.

Continuous performance task and real-time regularity triggering

All CPT procedures were consistent with those in E1a.

Target detection and triplet re-creation tasks

All target detection and triplet re-creation task procedures were consistent with those in E1a.

Triplet selection

Statistical learning can be measured in different gradations. For example, participants may be able to identify the shapes in a regular triplet (i.e., group membership) despite being unable to order those regular shapes correctly (Forest, et al., 2020). Thus, in E1b, we added a triplet selection task to assess participants' knowledge about the group membership of shapes in the regular triplets. Participants answered two triplet-selection questions, one for the triplet learned under each attentional state. In each question, all frequent-category shapes (six shapes in the regular triplet, eight control shapes used to create the random triplets, and 12 shapes that were not involved in any triplet but served as the frequent shapes in the CPT) were presented on the screen. Participants were instructed to select the three shapes they remembered seeing in a regular order in the CPT and were required to make exactly three selections to be able to proceed. This selection thus assesses participants' knowledge about single shapes they remembered being presented in a regular order, regardless of other higher level organizations (Forest et al., 2022; Liu et al., 2023) like how these shapes were grouped (e.g., as a whole triplet encountered in high vs. low attentional state) or ordered within a group (e.g., the position and transition probability of shapes in a triplet under a given attentional state).

Analysis approach

Analyses of CPT performance, online measures of statistical learning, and target detection and re-creation task performance were consistent with E1a.

To analyze triplet-selection performance we scored each of the two selection trials based on the number of regular triplet shapes selected. For each participant, we first assigned trial labels—one high- and one low-attention triplet—to the two selection trials in the way that would maximize their score. Score for each trial was then counted as the number of shapes that match with the trial label selected on that trial (see **Supp Fig 3**. for a description of the full approach used to assign trial labels). To assess the significance of the scores, we calculated a chance score for each attentional state by simulating the experiment with 150 participants 1000 times where on each trial three shapes were picked randomly. The same set of scoring criteria were used as described above. We then calculated the average score for each attentional state. We compared the number of shapes participants correctly selected from each attentional state to this chance value using a one sample *t*-test. To assess selection task performance across attentional states, we ran a linear regression model predicting the number of shapes correctly selected using attentional state while controlling for the number of triggered trials encountered in the CPT.

Results

Overall CPT performance

Mean A' across participants was 0.90 (SD=0.05; chance=0.5; **Fig. 2a**). Replicating E1a, RTs averaged from three correct frequent trials preceding an error on an infrequent trial ('L' shape) were faster than that preceding a correct infrequent trial ($t(149)=22.27$, two-tailed $p<0.001$, Cohen's $d=1.14$, mean difference [correct – incorrect]=48.10 ms, 95% CI=[43.83,52.37]) (**Fig. 2b;** see **Supp Fig. 4c** for CPT RT distribution). These results confirmed that pre-trial RT was a valid index of attentional state in this sample.

Real-time triggering of regularity based on attentional state

On average, participants saw 17.46 regular triplets (SD=5.59, range=6–33) under high attentional states and 17.50 (SD=5.60, range=6–34) under low attentional states (see **Supp Fig. 1d** & **Supp Fig. 4d** for their position). The number of regular triplets encountered in the high vs. the low attentional state did not systematically differ across participants (mean difference [low – high]=0.04, mean absolute difference [condition with more – condition with fewer]=1.80, SD=2.12, range=-3,3; $t(298)=-0.23$, $p=0.82$, Cohen's d=0.01, 95% CI=[-0.38,0.30]) (**Supp Fig. 1f**). On average, participants saw 18.41 random control triplets (SD=6.80, range=1–24) under higher attentional states and 23.18 random control triplets (SD=3.21, range=0–24) under lower attentional states (**Supp Fig. 1e**).

Online measure of statistical learning

We hypothesized that regularity learning is more pronounced under higher attentional states. A mixed-effects model consistent with E1a built using triplet position, attentional state, and trial type to predict CPT RT revealed a significant three-way interaction ($\chi^2(2, N=150)=7.63$, $p<0.05$, Type II). We did not observe significant evidence for the impact of attention on online statistical learning quantified by online learning index (estimated marginal mean for online learning index, high attention=12.93ms, estimated marginal mean for online learning index, low attention=3.26ms, estimated difference in online learning index=9.67ms, SE=5.89, $p=0.10$; **Fig. 3f**), though the direction of this effect aligns with our hypothesis. Regularity impacted RTs relative to control only under high attentional states, where RTs to regularity got significantly faster over time compared to random shapes encountered in the same state (estimated marginal mean for online learning index, high attention=12.93ms, SE=4.23, $p<0.01$). Under low attentional states, RTs to regularity were not significantly different from random shapes encountered in the same state (estimated marginal mean for online learning index, low attention=3.26ms, SE=4.10, $p=0.43$).

Offline measures of statistical learning: Triplet selection and re-creation

We examined two explicit measures of offline statistical learning. In the selection task, we asked participants to select the three regular shapes they remembered seeing from all non-infrequent shapes (non-"L" shapes) in the CPT. We examined whether participants selected more correct shapes from among all the shapes than expected by chance. Participants on average correctly selected 0.98 high-attention state shapes (chance=0.58, $t(149)=4.84$, SD=1.01, range=0,3, $p=0.00$, Cohen's d=0.40, 95% CI=[0.82,1.14]) and 0.86 low-attention shapes (chance=0.58, $t(149)=3.35$, SD=1.02, range=0,3, $p=0.00$, Cohen's d=0.28, 95% CI=[0.69,1.03]). A linear regression accounting for the number of times the regular triplet was encountered in the CPT revealed no difference in the number of correct shapes chosen in the selection task between attentional states ($\beta=-0.11$, $p=0.34$, CI=[-0.35,0.12]). These results mean that participants selected shapes in the regular triplets above chance in both attentional states, providing evidence that participants, on average, had knowledge about what shapes constitute the regular triplets, while the selection performance did not differ significantly across attentional states.

E1b participants showed above-chance performance in the triplet re-creation task only for the high attention triplets, suggesting explicit knowledge of the regularities in some participants. 41/150 participants (27.33%) successfully recreated full triplets for the high attentional states (null mean=24.87, one-tailed $p<0.01$ [effect larger than 99.98% of 5000 random permutations]). This number was 29/150 participants (19.33%) for triplets in the low attentional state (null mean=25.08, one-tailed $p=0.22$ [effect larger than 78.34% of 5000 random permutations], **Supp Fig. 2d-e**). The number of participants who accurately reproduced the triplets did not significantly differ between the two attentional states (diff=12, null diff=0.01, two-tailed $p=0.08$, **Supp Fig. 2f**). These results suggest that, at the group level, participants showed evidence of explicit knowledge of the regularities for triplets learned under high attention state. There was no difference in the number of shapes correctly positioned in the triplet re-creation task between attentional states after controlling for CPT exposures ($\beta=0.17$, $p=0.18$, CI=[-0.08,0.41]).

Offline measures of statistical learning: Target detection task

Inconsistent with E1a, we did not observe an interaction between within-triplet position and attention state on the raw RT data ($\chi^2(2, N=150)=0.27$, $p=0.87$, Type II; **Fig. 4b;** see **Supp Fig. 5b** for RT distribution) or the residualized RT ($\chi^2(2, N=150)=0.39$, $p=0.82$, Type II; **Fig. 4g**). In other words, RT facilitation did not differ by attentional state.

Dividing participants into those who explicitly reported at least one (learners) or none (non-learners) of the regular triplets in the triplet re-creation task revealed no significant difference in target detection RT facilitation between the two groups (median chi-squared value: learners=3.10, non-learners=4.10, 37.6% of chi-squared values for non-learners are more extreme than those for learners, one-tailed $p=0.62$, Cohen's $d=-0.23$; **Supp Fig. 6d-f**).

Individual differences in sustained attention and statistical learning

A linear regression model testing the relationship between CPT A' and RT facilitation in the target detection task revealed no relationship between A' and the amount of target detection RT facilitation from position one to three, one to two, and two to three across individuals (all $|\beta|$<=0.06, $|t|$<=0.68, p>=.50). These relationships were not significant when running the same linear regression model separating attentional states (all $|\beta|$<=0.10, $|t|$<=0.121, p>=.23). No relationship was observed between CPT A' and triplet re-creation performance (β=-0.12, $t(147)$=-1.49, p=0.14; **Supp Fig. 7b**).

Experiment 1c

In E1a and E1b, we demonstrated that pre-trial RT was a valid index of attentional state and successfully triggered regular and control triplets based on participants' attentional states in real time. We observed a consistent difference in online statistical learning measured from changes in regular triplet RTs relative to random triplet control under high attentional states. However, this effect was not different across attentional states. We did not, however, observe consistent effects of attentional state on offline measures of statistical learning. Given this, we sought to replicate E1b with one change to the triggering procedures to better match regular and random control triplets.

Methods

Participants

To keep our sample size consistent with that of previous experiments, 210 participants were recruited online using Prolific (sex: 104 female, 105 male, 0 prefer not to say, demographic information was missing from one participant due to a technical difficulty; mean age=26.97 years, SD=4.69, range=18–35; all other criteria consistent with E1a and E1bs). 46 participants were excluded due to a technical difficulty that resulted in missing data from either the CPT or the target detection task. Exclusion criteria were consistent with E1a and E1b, six participants were excluded since their overall performance (A') on part one of the experiment, the CPT, fell more than two standard deviations from the group mean (pre-exclusion group mean A'=0.88, SD=0.07, lower bound=0.75, upper bound=1.02). Eight participants were further excluded because of fewer than or equal to five exposures to triplets in one of the two attentional states.

Final analyses were performed on the remaining 150 participants (77 female, 73 male, mean age=27.03 years, SD=4.59, range=18–35). All participants gave informed consent online and were compensated for their participation.

Continuous performance task and real-time regularity triggering

All CPT procedures were consistent with those in E1a and E1b, with one change. In E1a and E1b, control triplets could have been triggered within three trials of a non-response. Importantly, all control triplets preceded within three trials of a missing response were excluded from analysis. In E1c, control triplets (like regular triplets) could only be triggered after three consecutive responses. This change ensures that trailing RT mean calculation was consistent across regular trigger and random control trial types.

Offline measures of statistical learning

Target detection and triplet re-creation task procedures were consistent with those in E1a and E1b. Triplet selection task procedures were consistent with those in E1b.

Analysis approach

All analyses were consistent with E1a and E1b, except that there were no control triplets with a missing response one, two, or three trials before so no trial exclusion was performed.

Results

Overall CPT performance

Mean A' across participants was 0.89 (SD=0.05; chance=0.5; **Fig. 2a**). Replicating E1a and E1b, RTs averaged from three correct frequent trials preceding an error on an infrequent trial ('L' shape) were faster than that preceding a correct infrequent trial ($t(149)=8.15$, two-tailed $p<0.001$, Cohen's $d=0.34$, mean difference [correct – incorrect]=17.40ms, 95% CI=[13.18,21.61]) (**Fig. 2b;** see **Supp Fig. 4e** for CPT RT distribution).

Real-time triggering of regularity based on attentional state

On average, participants saw 17.15 regular triplets (SD=4.94, range=6–34) under high attentional states and 17.56 (SD=4.95, range=6–36) under low attentional states (see **Supp Fig. 1g** and **Supp Fig. 4f** for their position). The number of regular triplets encountered in the high vs. the low attentional state did not differ across participants (mean difference [low – high]=0.41, mean absolute difference [condition with more – condition with fewer]=1.85, SD=2.12, range=-3,3; $t(298)=-0.72$, $p=0.47$, Cohen's d=0.08, 95% CI=[-1.54,0.71]) (**Supp Fig. 1i**). On average, participants saw 19.91 random control triplets (SD=6.11, range=2–24) under high attentional states and 23.05 random control triplets (SD=3.45, range=5–24) under low attentional states (**Supp Fig. 1h**).

Online measure of statistical learning

A mixed-effects model using triplet position, attentional state, and trial type to predict CPT RT revealed a significant three-way interaction ($\chi^2(2, N=150)=3.10$, $p=0.21$, Type II). Consistent with previous experiments, we calculated one online learning index for each attention state and tested the significance between them using the post-hoc pairwise comparisons on estimated marginal means. The impact of attention on online statistical learning was not significant but was in line with the directions in E1a and E1b (estimated marginal mean for online learning index, high attention=10.132ms, estimated marginal mean for online learning index, low attention=0.483ms, estimated difference in online learning index=9.65ms, $SE=6.11$, $p=0.11$; **Fig. 3g**). Regularity impacted RTs relative to control only under high attentional states. In high attentional states, RTs to regularity were significantly faster than random shapes encountered in the same state (estimated marginal mean for online learning index, high attention=10.13ms, SE=4.44, $p=0.02$). In low attentional states, RTs to regularity were not significantly different from random shapes encountered in the same state (estimated marginal mean for online learning index, low attention=0.483ms, SE=4.20, p=0.91).

Offline measures of statistical learning*: *Triplet selection and re-creation

In the selection task, we asked participants to select the three regular shapes they remembered seeing from all non-infrequent shapes (non-“L” shapes) in the CPT. Participants on average correctly selected 0.74 high-attention state shapes (chance=0.58, $t(149)=2.18$, SD=0.90, range=0,3, p=0.03, Cohen’s d=0.18, 95% CI=[0.59,0.89]) and 0.93 low-attention shapes (chance=0.58, $t(149)=4.47$, SD=0.95, range=0,3, p=0.00, Cohen’s d=0.37, 95% CI=[0.77,1.08]). A linear regression accounting for the number of times the regular triplet was encountered in the CPT revealed no difference in the number of correct shapes chosen in the selection task between attentional states (β=0.20, p=0.06, CI=[-0.01,0.41]). These results mean that participants showed knowledge about what shapes were in the regular triplets under both attentional states, although this knowledge did not differ significantly across attentional states.

In the triplet re-creation task, 29/150 participants (19.33%) successfully recreated full triplets in the high attentional states (null mean=24.92, one-tailed p=0.21 [effect larger than 78.62% of 5000 random permutations], **Supp Fig. 2g-h**). This number was 33/150 participants (22.00%) for the triplets in low attentional states (null mean=25.05, one-tailed p=0.05 [effect larger than 94.52% of 5000 random permutations]). Accuracy between the two attentional states was not significantly different (diff=-4.0, null diff=0.10, two-tailed p=0.59, **Supp Fig. 2i**). In line with E1a and E1b, no difference in the number of shapes correctly positioned in the triplet re-creation task between attentional states was observed after controlling for CPT exposures (β=-0.05, p=0.67, CI=[-0.30,0.19]).

Offline measures of statistical learning: Target detection task

We did not observe an interaction between within-triplet position and attention state on the raw RT data (χ^2(2, N=150)=0.15, p=0.93, Type II; **Fig. 4c**; see **Supp Fig. 5c** for RT distribution) or the residualized RT (χ^2(2, N=150)=0.22, p=0.90, Type II; **Fig. 4h**).

Dividing participants into those who explicitly reported at least one (learners) or none (non-learners) of the regular triplets in the triplet re-creation task revealed no significant difference in target detection RT facilitation between the two groups (median chi-squared value: learners=2.02, non-learners=1.42, 64.70% of chi-squared values for learners are more extreme than those for non-learners, one-tailed p=0.35, Cohen’s d=0.38; **Supp Fig. 6g-i**).

Individual differences in sustained attention and statistical learning

We did not observe a relationship between CPT A’ and target detection RT facilitation from across individuals (all $|\beta|$<=0.06, $|t|$<=0.71, p>=0.48). Relationships were not significant when running the same linear regression model separating attentional states (all $|\beta|$<=0.13, $|t|$<=1.65, p>=0.10). No relationship was observed between CPT A’ and triplet re-creation performance (β=-0.07, $t(147)=-0.86$, p=0.39; **Supp Fig. 7c**).

Across-experiment analyses

Since E1a, E1b and E1c followed a similar design, we combined the data from all three experiments and assessed the evidence for a relationship between attentional state fluctuation and statistical learning using all available data (N=450). Analyses replicated those performed in E1a, E1b, and E1c.

Online measure of statistical learning

We ran the following mixed effects model:

CPT RT ~ shape position * attentional state * trial type + (1 + shape position + attentional state + trial type | experiment/participant)

using triplet position, attentional state, and trial type to predict CPT RTs, while including experiment and participant as random effects. The model revealed a significant three-way interaction (χ^2(2, N=450)=20.05, *p*<0.001, Type II). Consistent with previous experiments, we calculated one online learning index for each attention state and tested the significance between them using the post-hoc pairwise comparisons on estimated marginal means. We observed evidence for the impact of sustained attention on online statistical learning, such that RT changes due to statistical regularity are more pronounced under high compared to low attentional states (estimated marginal mean for online learning index, high attention=11.48ms, low attention=3.90ms, estimated difference in online learning index=7.61ms, SE=3.45, *p*=0.03; **Fig. 3h**). Regularity impacted RTs relative to control only under high attentional states, where RTs to regularity were significantly faster than random shapes encountered in the same state (estimated marginal mean for online learning index, high attention=11.50ms, SE=2.49, *p*<0.0001). Under low attentional states, RTs to regularity were not significantly different from random shapes encountered in the same state (estimated marginal mean for online learning index, low attention=3.88ms, SE=2.38, *p*=0.10). This result suggests that sustained attention impacts statistical learning when learning is assessed when regularity is unfolding.

Offline measure of statistical learning

We examined the interaction between within-triplet position and attention state in data compiled from E1a, E1b, and E1c using a mixed effects model including experiment as an additional random effect. We did not observe a significant interaction in target detection task RT facilitation when looking at raw RT (χ^2(2, N=450)=3.50, *p*=0.17, Type II; **Fig. 4d**) or residualized RT (χ^2(2, N=450)=2.88, *p*=0.24, Type II; **Fig. 4i**).

Experiment 1 Discussion

In a series of three experiments, we indexed sustained attentional state in real time based on the average RT preceding each trial. We replicated previous findings that pre-trial RT is a valid index of sustained attentional state, such that participants are more likely to make an error when pre-trial RTs are faster.

In E1a, we first confirmed that more participants than that would be expected by chance showed explicit knowledge about the order of shapes in the regular triplets through the offline triplet re-creation task. Next, we observed mixed evidence for the impact of attentional fluctuations on online and offline measures of statistical learning. We did not see evidence for a difference in online learning across states. However, there was evidence that, under both high and low attentional states, RT changed due to regular triplets significantly more than that due to random control triplets. While target detection task performance differed across attention states, explicit drag and drop task performance did not differ as a function of attentional state.

In E1b, we aimed to replicate the findings in E1a and examine a more liberal criteria for offline learning—knowledge about group membership of shapes in regular triplets—by asking participants to select regular shapes among foils. At the group level, participants did show evidence of learning for the triplet shapes in each attentional state in the selection task and the high-attention triplet order in the re-creation task, although there were no differences across attentional states. We saw evidence for online learning in the high attention state but no difference across states. Interestingly, inconsistent with E1a, we did not find evidence for the impact of attention in the offline target detection task.

In E1c, we implemented a slightly different triggering criteria so that the regular and random triplets were embedded under more similar attentional states. At the group level, participants showed evidence of learning for the triplet shapes in each attentional state in the selection task. In contrast to E1a and E1b, they did not show explicit knowledge of either triplet order in the re-creation task. We observed no significant evidence for a difference in online index of learning across attentional states, although in line with E1a and E1b, we observed significant impact of regularity on RT under high attentional states. None of the offline measures revealed differences in learning across attentional states.

Combining E1a, E1b, and E1c data, we observed evidence for the impact of attentional state fluctuations on online measures of statistical learning, where the impact of regularity on RTs was significant under high attentional states and significantly greater in high vs. low attentional states. There was no evidence for an impact of sustained attention on offline measures of learning. Overall, these results demonstrate the successful implementation of web-based real-time triggering. They also suggest that attention may impact statistical learning while regularities are being extracted online. However, when knowledge about regularity is assessed in subsequent tests, performance may no longer depend on the initial attentional states during extraction.

Experiment 2

How much is the facilitation in the offline target detection task due to regularity learning? Himberger et al. (2019) raised the possibility that RT facilitation in offline target detection tasks may result from RT speeding to later shapes in the test stream rather than learning alone. Another interesting question about the amount of exposure needed for learning is whether participants would learn statistical regularities from the target detection task on its own. To address these questions, in E2, we tested participants' RTs facilitation even when they were *not* *exposed* to regularities in the CPT before being tested in the target detection task. We achieved this in a yoked control experiment where participants only performed a target detection task. In other words, participants in E2 saw the same stimuli in E1a offline target detection task but the regular triplets were no longer contingent on attention since there was no CPT. This control experiment allowed us to obtain a baseline measure of how RT changes within triplet position when no attentional states fluctuations were involved.

Methods

We predicted that there would not be an interaction between “pseudo” attentional state and shape position when regularity presentation was no longer contingent on attention. We conducted a separate experiment in which participants did not perform the CPT and only completed a target detection task and a triplet re-creation task. Importantly, participants saw the *exact same visual sequences* and were instructed to respond to the exact same matched targets as those in E1a. In other words, E2 is the exact same with E1a except that here participants were not asked to perform a CPT. Using this design, we took the trial and stimuli sequences each participant saw in E1a and presented those sequences to a matching participant in E2 by collecting data from one participant at a time.

Participants

To match our sample with that of E1a, 148 participants were recruited online using Prolific (sex: 77 female, 70 male, 1 prefer not to say; mean age=28.20 years, SD=4.84, range=18–35; all criteria are the same as E1a and E1b) to match the number of participants with complete data from the E1a target detection and triplet re-creation tasks. We asked one attention check question (i.e., a multiple choice question asking “What is the rule of the first part of the study?”) at the end of the study and decided a priori to exclude participants that answered this question incorrectly. No participants were excluded based on this criterion.

Target detection task

The target detection task followed the exact procedure described in E1a. Each participant in E2 saw the same visual stream and targets as one of the participants in E1a.

Triplet re-creation

After the target detection task participants were asked to re-create the two shape triplets following the exact procedure and stimuli from E1a.

Awareness question

We asked participants about their strategies to complete the target detection task and awareness of the regularities both after the target detection task and the triplet re-creation task (**Supp Table 1**).

Analysis approach

All analyses matched those in E1a except that there was no CPT.

We applied a non-parametric analysis to investigate whether attention-dependent regularity exposure in the CPT in E1a led to more target-detection RT facilitation across attentional states (two-way interaction between shape position and attentional state) compared to E2. Note that attentional states in E2 were “pseudo” because they were neither measured nor manipulated but matched to the initial states participants learned the regular triplets in E1a. We then conducted non-parametric analyses. For each experiment, we generated 1000 bootstrap samples of size 148. We ran the same model specified in the target detection task section for each to obtain 1000 chi-squared values of the two-way interaction term (attentional state * shape position). We then compared the two distributions of bootstrapped chi-squared values to obtain an effect size (Cohen’s *d*) measure. Next, we assessed statistical significance by comparing the median of the bootstrapped distribution of E1 to the distribution of E2. (The E2 distribution essentially serves as a “null” or “control” distribution of two-way interaction values reflecting differences in facilitation across attentional states when there is no initial exposure.)

one-tailed *p* = (1+ bootstrapped chi-squared values in E2 >= median of E1 bootstrap distribution) / 1001

Results

RT facilitation when exposure was not attention-contingent

We observed a significant main effect of triplet position (χ^2(2, N=148)=46.96, p<0.001, Type II; **Fig. 4e;** see **Supp Fig. 5d** for RT distribution) but no significant interaction between triplet position and pseudo-attentional state (matched with E1a) on the raw RT (χ^2(2, N=150)=3.64, p=0.16, Type II; **Fig. 4j**). We then followed the same procedure in previous experiments to regress out the effect of stream position. The main effect of triplet position was not significant (χ^2(2, N=148)=1.30, p=0.52, Type II). The two-way interaction (shape position * pseudo attentional state) was not significant in E2 (χ^2(2, N=148)=3.82, p=0.15, Type II). This result indicates that unlike E1a, here in E2 without initial exposure to regularities and when exposure to regularities was not attention-contingent, the extent to which target detection RT was facilitated did not differ across regular shape triplets (**Fig. 3c-d**).

A non-parametric bootstrapping approach to formally assess the difference between the two experiments revealed a significant difference between the bootstrap distributions of the two experiments (median of E1a=15.37, median of E2=4.83, 96.60% of chi-squared values in E1a are more extreme than those in E2, one-tailed p=0.03, Cohen’s d=1.61), indicating that the extent to which RT facilitation differed across attentional states is different between the two experiments (**Fig. 5**).

We next asked to what extent the target detection task RT facilitation of E1b and E1c differed from E2. No significant difference in the bootstrap distributions was revealed when comparing E1b and E2 (median of E1b=1.49, median of E2=4.83, 20.7% of chi-squared values in E1b are more extreme than those in E2, one-tailed p=0.79, Cohen’s d=-1.09), or E1c and E2 (median of E1c=1.53, median of E2=4.83, 20.6% of chi-squared values in E1b are more extreme than those in E2, one-tailed p=0.79, Cohen’s d=-1.10).

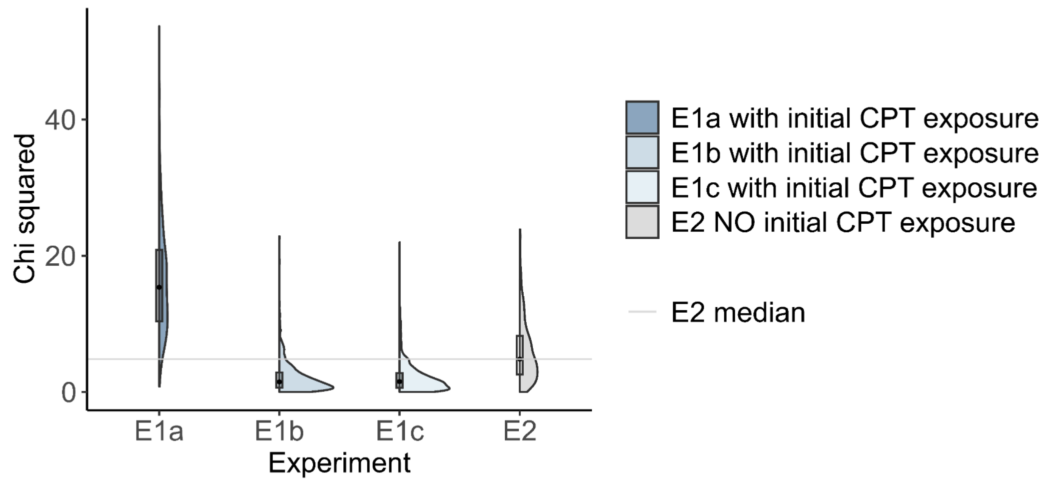

Figure 5. Bootstrap permutation results. Distributions for 1000 bootstrap samples of chi-squared values of the two-way interaction term (attentional state * shape position) in E1a, E1b, E1c, and E2. Gray line represents the median of the bootstrapped distribution of chi-squared values in E2.

Offline statistical learning: triplet re-creation

E2 participants were presented with the exact same target detection sequences as participants in E1a but did not perform the CPT. Interestingly, E2 participants still showed above-chance performance in the triplet re-creation task for both types of triplets, suggesting explicit knowledge of the regularities in some participants. 38/148 participants (25.68%) successfully recreated full triplets for the pseudo high attentional states (null mean=24.58, one-tailed $p<0.01$ [effect larger than 99.68% of 5000 random permutations]). This number was 37/148 participants (25.00%) for triplets in the pseudo low attentional states (null mean=24.61, one-tailed $p<0.01$ [effect larger than 99.32% of 5000 random permutations], **Supp Fig. 2j-k**). Accuracy between the two pseudo attentional states was not significantly different (diff=1.0, null diff=0.10, two-tailed $p=0.94$, **Supp Fig. 2l**). These results suggest that, at the group level, participants showed evidence of explicit knowledge of the regularities even with 12 rapid regularity exposures.

Experiment 2 Discussion

In E2, we showed participants the same target detection task stimulus sequence, which included the regular triplets, seen by participants in E1a. Interestingly, more participants than that would be expected by chance successfully re-created the regular triplet from these 12 exposures, demonstrating that there is regularity-learning during the target detection task itself. In addition, we observed speeding in RTs in the target detection task in raw RTs, while the extent to which the RTs were facilitated did not depend on attentional state.

General discussion

Attentional state fluctuates within an individual from moment to moment and impacts information processing. The information we extract and retain from our environment is likely to be influenced by this fundamental, dynamic process as well. For example, in a stream of information, regularly repeating patterns across space and time contain helpful information. We thus process and extract this information through statistical learning. Here we explored the behavioral consequences of attentional state fluctuations for our ability to pick up on visual temporal regularities.

In our series of experiments (E1a, E1b, E1c), we implemented a web-based real-time triggering design where to-be-learned statistical regularities were presented contingent on attentional states. We first used a behavioral index of attentional state to show that in the CPT, when participants were responding especially fast, they tended to make more errors and were thus likely in attentional lapses. We measured explicit knowledge of the regular triplets by asking participants to recreate the triplets in order (E1a-c and E2) and select regular triplet shapes from foils (E1b and 1c). Participants successfully selected shapes in the regular triplets encountered under both attentional states in E1b and E1c. On the group level, more participants than that would be expected by chance re-created both regular triplets in order in E1a and E2 and the high-attention triplet in order in E1b.

Our results revealed mixed evidence for the impact of sustained attention on statistical learning. We observed a consistent difference in online statistical learning measured from changes in regular triplet RTs relative to random triplet control under high attentional states. However, this effect only significantly differed across attentional states when collapsing across experiments E1a–c (n=450) and was not significant in any one experiment alone (n=150). We observed no consistent evidence of statistical learning measured offline after initial familiarization through CPT. Thus, these results suggest that attention fluctuations may impact the extraction of regularities online, but that these effects do not persist when learning of regularities were tested subsequently.

The current study innovates on past work in three ways. First, we looked at the role of moment-to-moment fluctuations in sustained attentional state on statistical learning. Second, unlike most previous work, we monitored attentional state without manipulating it. Third, we collected RTs to regularities during initial exposure, which enabled us to measure learning both online and offline. These steps allowed us to observe the consequence of sustained attention fluctuations both during and after familiarization. We next discuss each of these points, address the implications of this work, and offer future directions for work bridging sustained attention fluctuations and statistical learning.

Examining the impact of sustained attention on statistical learning

To the first point, attention to stimuli was required to perform the CPT. However, participants could perform the task without overt awareness of the regularities themselves. Our results suggested that participants nonetheless showed evidence of learning, replicating previous work using a cover task (Turk-Browne et al., 2005; Musz et al., 2015; Zhao et al., 2013; Kiai et al., 2021; but see Himberger et al., 2019 for contradicting results). We further raised the hypothesis that the role of attention in statistical learning is not all or none. Rather, when in a more engaged attentional state, people might be more likely to register the regularities. Examining this hypothesis adds to a growing list of cognitive processes impacted by attention fluctuations, including inhibitory control (Robertson et al., 1997), working memory capacity (but not precision; deBettencourt et al., 2019; Hakim et al., 2020), and long-term memory (deBettencourt et al., 2018; Wakeland-Hart et al., 2022).

Previous work demonstrated the role of attention in statistical learning, assessing distinct aspects of attention (e.g., attention as a selection mechanism, object-based attention). To effectively integrate the interaction between attention and statistical learning, it is crucial to clearly operationalize which aspect of attention is being examined (Frost et al., 2019). Indeed, the impact of one's intrinsic fluctuations of attentional state on learning was largely unexamined in previous literature. We argue here that state-like fluctuations in attention might also contribute to our ability and efficiency of extracting regularity from the environment.

Monitoring rather than manipulating sustained attention

We examined the role of sustained attention in statistical learning by monitoring attentional state rather than manipulating or biasing it directly. We instead manipulated what the participants saw and learned contingent on their attentional states. The stream of shapes that comprised the CPT trials, embedded regular triggered trials and random control trials were sampled from the same set of visual stimuli and thus came from a shared visual category (Fiser & Aslin, 2002; Turk-Browne et al., 2005; Zhao et al., 2013; Musz et al., 2015). This manipulation makes an interleaved cover task an uninterrupted serial response task, which feels subjectively more continuous from the participants' view. This design then allowed us to assess whether sustained attention impacts statistical learning in a graded manner.

Measuring RTs during the learning phase

Online measures of statistical learning have gained less attention than offline measures. Yet online measures of extraction of regularities have been found to be largely uncorrelated with offline measures, revealing that the former process might reflect the extraction of regularity, while the latter might reflect the deployment of extracted information (Fiser & Aslin, 2002). In a typical statistical learning paradigms, the learning phase could involve passive viewing without explicit tasks (Fiser & Aslin, 2002), responding only to a selectively attended visual stream (Turk-Browne et al., 2005), or responding only to a target (Kiai et al., 2021).

To assess online statistical learning during extraction, a serial reaction task is an ideal method, since repeated response to a set of stimuli, including the regular stimuli, is needed. Participants' knowledge of the regularity can then be assessed by observing how RTs change within the regular sequence. To this end, a few studies have examined online statistical learning using tasks that require serial motor responses to a visual stream (Hunt & Aslin, 2001), a click-detection task that compares RTs of clicks to a target that is presented at the boundary of vs. within regular trisyllabic words (Gómez et al., 2011), and pressing a button to advance in a self-paced manner to familiarize with a visual stream (Siegelman et al., 2018). Similarly, in our studies, the use of a CPT enabled us to both observe trends in RTs during initial exposure and compare the trends when regularity is present vs. not. Specifically, our cover task required a response for most trials and a response inhibition for rare (i.e., "L"-shaped) trials. Since RTs to regular triplet shapes were recorded, we could examine RTs as participants are gradually extracting regularities.

Examining the impact of attention on online vs. offline measurements of statistical learning

Statistical learning tasks involve extracting and storing the regular information during the study phase and retrieving it during the test phase. Two potential scenarios could explain why, when data were collapsed across experiments, attentional state during encoding affected online but not offline measures of statistical learning. First, sustained attention during the online study phase could have only weakly affected learning, such that the effect was apparent during the learning itself but did not persist to the offline test phase. Second, attentional state could have affected the rate of statistical learning but not the maximum strength of the learned representation. Participants could have learned the high-attention triplet sooner but learned both triplets equally well by the end of the task. In this case, regularities seen in both states would have reached the plateau by the end of the initial familiarization phase and online learning measures would differ but offline learning measures would be matched. Therefore, if online and offline assessments of learning tell us different information about how we learn statistical regularity, we need to empirically assess the impact of attention on statistical learning measured from these two phases separately. Here we raised the possibility that sustained attention might impact online extraction of regularity, a property that cannot be revealed with only offline measures.

Limitations.

Our novel task design introduced a few methodological constraints. First, it is possible that our online measure of statistical learning was limited by the amount of variance in RTs and was thus not optimally sensitive to learning. To this point, future work could consider making the predictiveness of the shapes in the regular triplet more beneficial for task performance (e.g., adjusting the frequent-infrequent trial ratio, although there is a tradeoff between taxing attention and facilitating learning) to allow more room for responses to vary. Second, across three experiments we found that participants on average were exposed to the two triggered triplets around 18 times. The small number of exposure trials and of the triplet group (i.e., one triplet for each attentional state) might constrain our power to detect online effects. In fact, we demonstrated a consistent trend in the effect of attention on online measures of learning and a significant effect when we compiled data across experiments. However, the small number of exposure trials were a result of the restriction criteria crucial to our task that ruled out other factors potentially impacting learning above and beyond our variable interest-attentional state. Therefore, neural or physiological signatures of attention can be utilized to increase the possible number of triggered trials under each attentional state.

Second, we observed significant interaction between attentional state and trial type in RT facilitation online only when compiled across the three experiments, an analysis that was not planned a priori. Recent discussion raised concerns about the validity of internal meta-analysis when each experiment bears the risk of generating false-positives and when experimenters selectively choose which internal experiments to analyze (Vosgerau et al., 2019). Although our experiments were not formally preregistered, the current analysis fits criteria for non-problematic internal meta-analysis in that we used rigorous operationalization and rationale for the online learning analysis consistent across experiments and included all experiments conducted (E1a-c) in the analysis without choosing.

Lastly, in our series of offline tasks, participants first completed the target detection task that indirectly measured learning and then the selection and triplet re-creation tasks that measured learning more directly. There could be potential interference between the direct and indirect measures in a within-subject design. Results from E2 suggest that learning may occur during the target detection task itself, which could bring learning of high and low attention triplets to the same level. Similar results were observed in Himberger et al. (2019) where participants performed two-alternative forced choice and triplet creation tasks with above-chance accuracy when there was no initial exposure to regularity before the target detection task. It is possible that additional learning during the target detection task bolstered learning and thus interfered with knowledge retained from *online* learning.

Future directions.

Our work motivates suggestions for research on attention fluctuations and statistical learning. First, research may benefit from including both online and offline measures of learning, which may reflect different information about participants' knowledge of regularities. Second, to avoid the potential interference between indirect and direct measure of learning, between-subjects designs in which separate groups of participants complete the indirect and direct offline tasks may be preferable. Finally, future work should prioritize indirect and/or direct offline assessment tasks that are less prone to attentional fluctuations during measurement to avoid obscuring potential effects of attentional state on learning during initial exposure.

Our results also motivate future work on attentional state and statistical learning using a wider range of measurements of both attention and learning. For example, an index of attentional state other than reaction time (e.g., pupillometry and functional brain networks predicting CPT performance using functional neuroimaging techniques; Rosenberg et al., 2020) can be utilized to decrease the extent to which the timing of presented regularity is dependent on RTs, allowing for a more sensitive and statistically powered measure of *online* statistical learning. On the statistical learning side, the index of learning can be identified neurally using fMRI (Schapiro et al., 2012, 2013, 2014, 2017; Turk-Browne et al., 2009) and electroencephalography (EEG; Batterink & Paller, 2017; Tóth et al., 2017), which also has the benefit of quantifying learning when it happens online.

Future work could also explore the opposite causal direction: the role of statistical regularities on sustained attention. Studies have shown that regularities bias attention, such that attention could be captured by both a spatial location where temporal regularities occurred, and by features (i.e., color or dimension) of the regular stimuli (Zhao et al., 2013; Wang & Theeuwes, 2018). These observations leave open the interesting question of whether regularities affect different aspects of attention, such as sustained attention, differently. The impact of attention on statistical learning is not unitary and future work would benefit from using and developing paradigms that monitor multiple facets of attention and their downstream impacts on statistical learning.

Conclusions.

We introduced a new task for studying the impact of sustained attention on statistical learning. Whereas in typical tasks participants may be more and less attentive when presented with regularities, we presented regularities contingent on attentional state measured in real-time. This allowed us to assess the ongoing and downstream effects of sustained attentional fluctuations on statistical learning. We saw greater evidence for online statistical learning in engaged attentional states when combining data across experiments, although the effect of attentional state at encoding did not affect offline measures of learning. Looking ahead, our web-based triggering task can be applied to characterize the consequences of attention fluctuations for other forms of learning as well.

Acknowledgements

We thank Jiaying Zhao for sharing the task stimuli. We also thank Omid Kardan for his analysis suggestions. This work was supported by National Science Foundation BCS-2043740 (M.D.R.) and resources provided by The University of Chicago Research Computing Center.

Data and Code Availability

Data and code are available at
https://osf.io/46grb/?view_only=53d7f6d3e5374a02a30021444b1ebee0.

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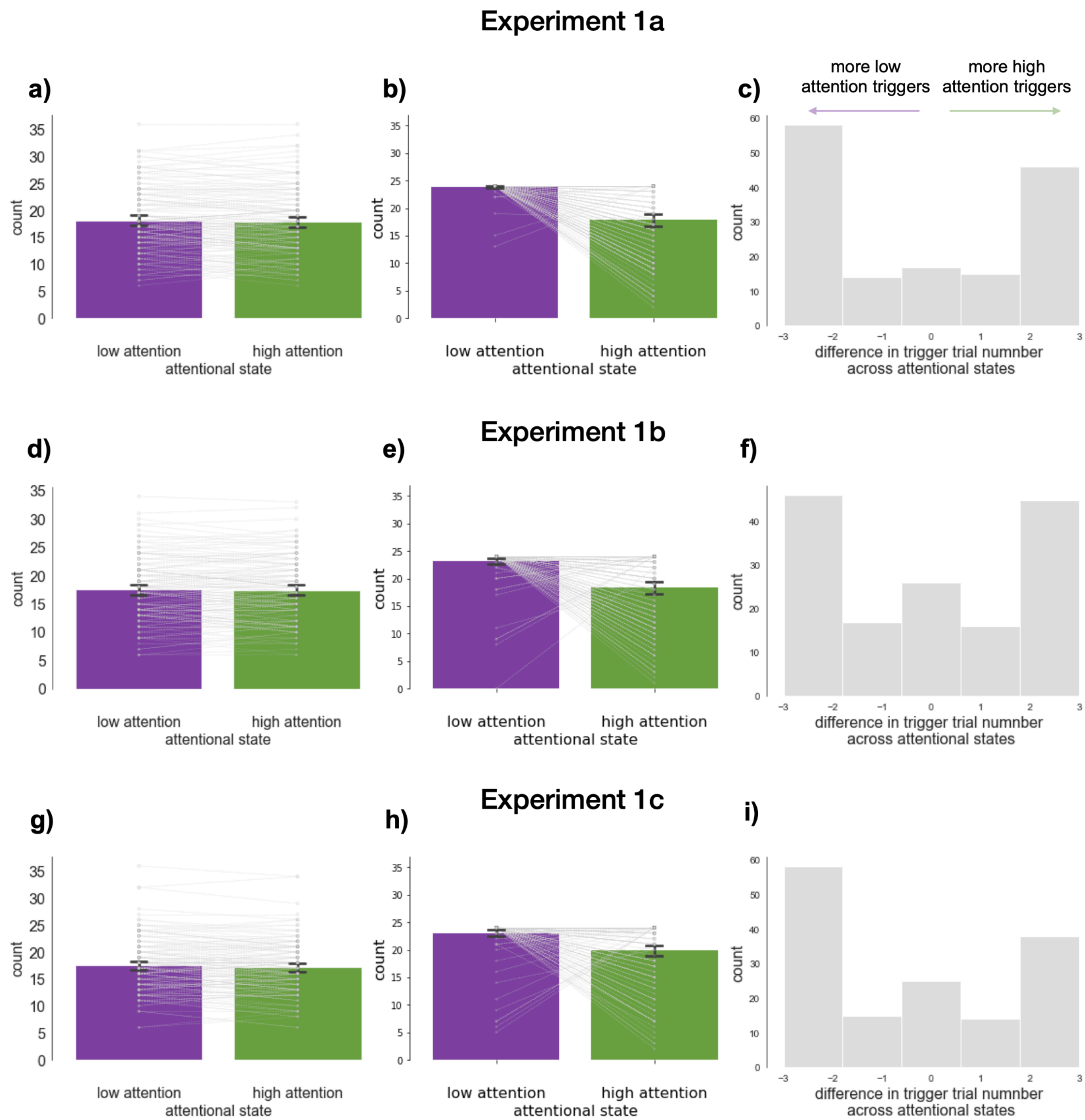
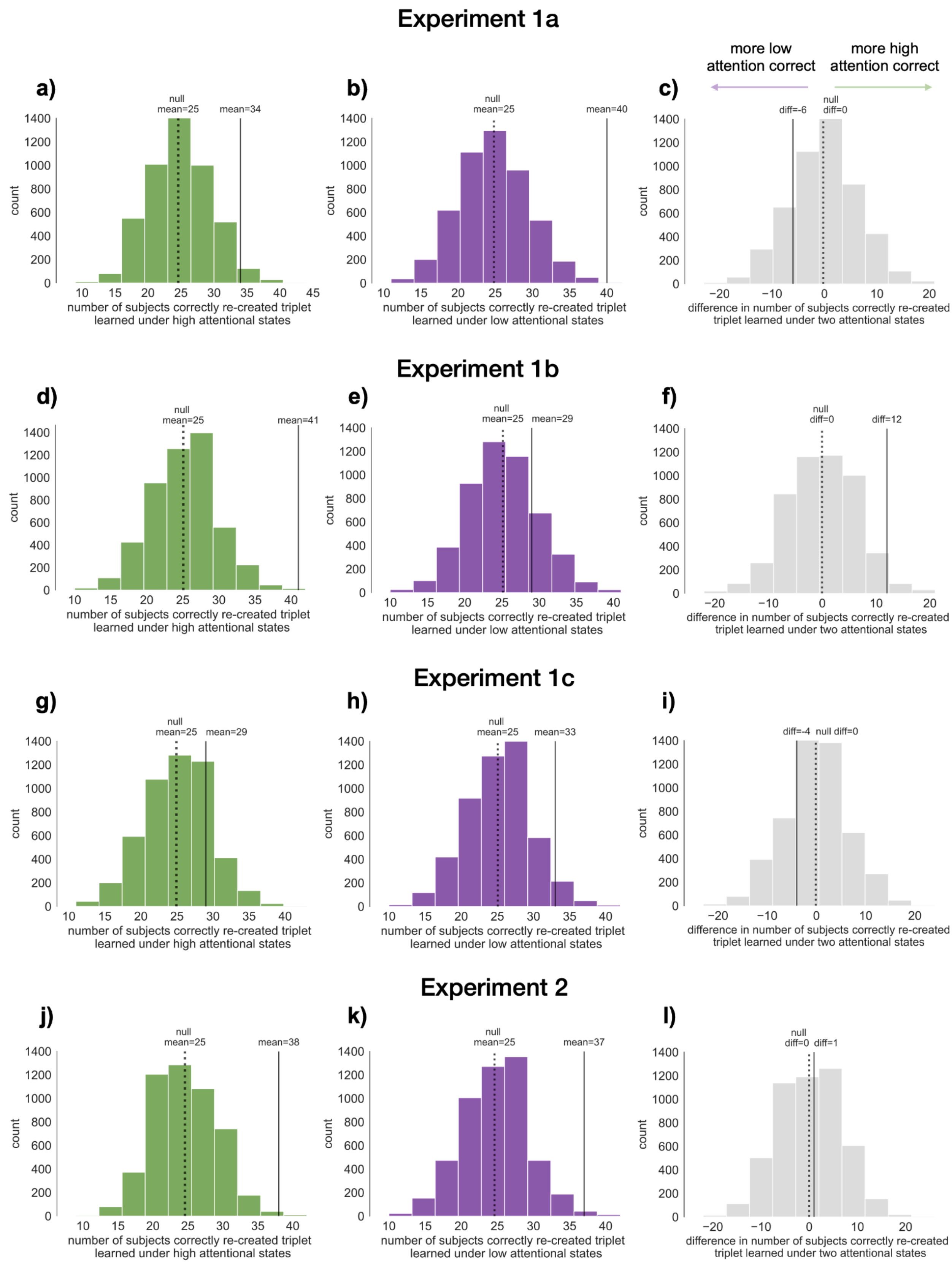
Supplemental Materials

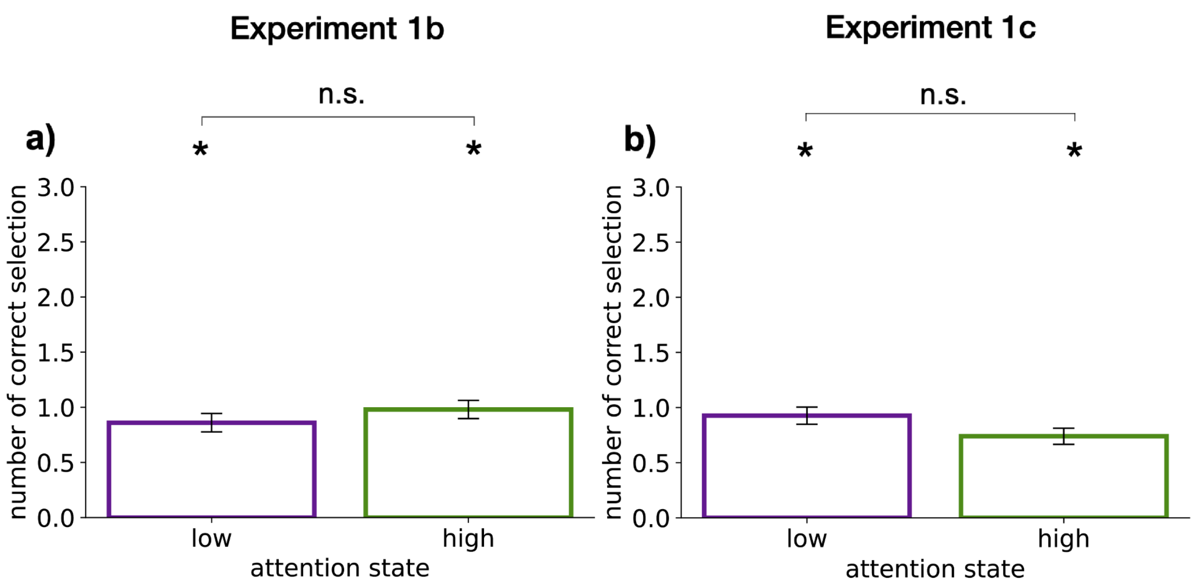


Supp Figure 1. Number of triggered and control trials. (a), (d), (g) Number of triggered trials (regular triplets) for E1a, E1b, E1c. (b), (e), (h) Number of control trials (random triplets) for E1a, E1b, E1c. (c), (f), (i) Difference in the number of triggered trials (low-high attentional state) across attentional states for E1a, E1b, E1c. Error bars correspond to 95% confidence intervals.



Experiment 1a
a)
null mean=25
mean=34
count
number of subjects correctly re-created triplet learned under high attentional states
b)
null mean=25
mean=40
number of subjects correctly re-created triplet learned under low attentional states
c)
more low attention correct
more high attention correct
diff=-6
null diff=0
difference in number of subjects correctly re-created triplet learned under two attentional states
Experiment 1b
d)
null mean=25
mean=41
e)
null mean=25
mean=29
f)
null diff=0
diff=12
Experiment 1c
g)
null mean=25
mean=29
h)
null mean=25
mean=33
i)
diff=-4
null diff=0
Experiment 2
j)
null mean=25
mean=38
k)
null mean=25
mean=37
l)
null diff=0
diff=1

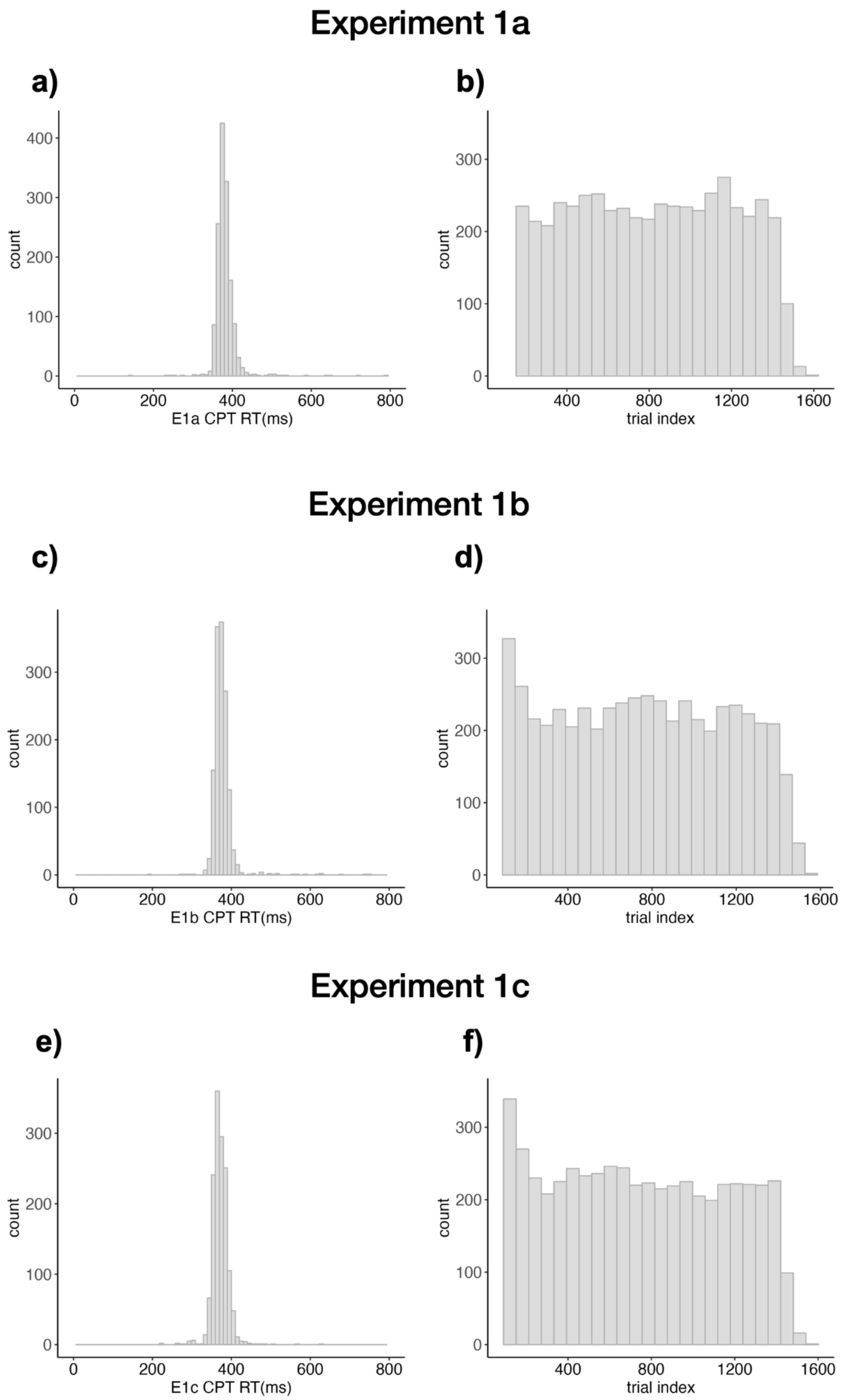
Supp Figure 2. Non-parametric permutation test results for the triplet re-creation task. Green and purple colored bars represent null distributions obtained from counting the number of participants that match with a randomly generated answer in 5000 iterations. Dotted gray lines denote the mean of each null distribution. Solid gray lines denote the true number of participants that answered correctly under each attentional state. Results for triplets encountered under high attention shown in E1a (a), E1b (d), E1c (g), and “pseudo” high attention in E2 (j); Results for triplet encountered under low attention shown in E1a (b), E1b (e), E1c (h), and “pseudo” low attention in E2 (k); Distribution of the difference (high-low attentional state) between two attentional states shown in E1a (c), E1b (f), E1c (i), and E2 (l).



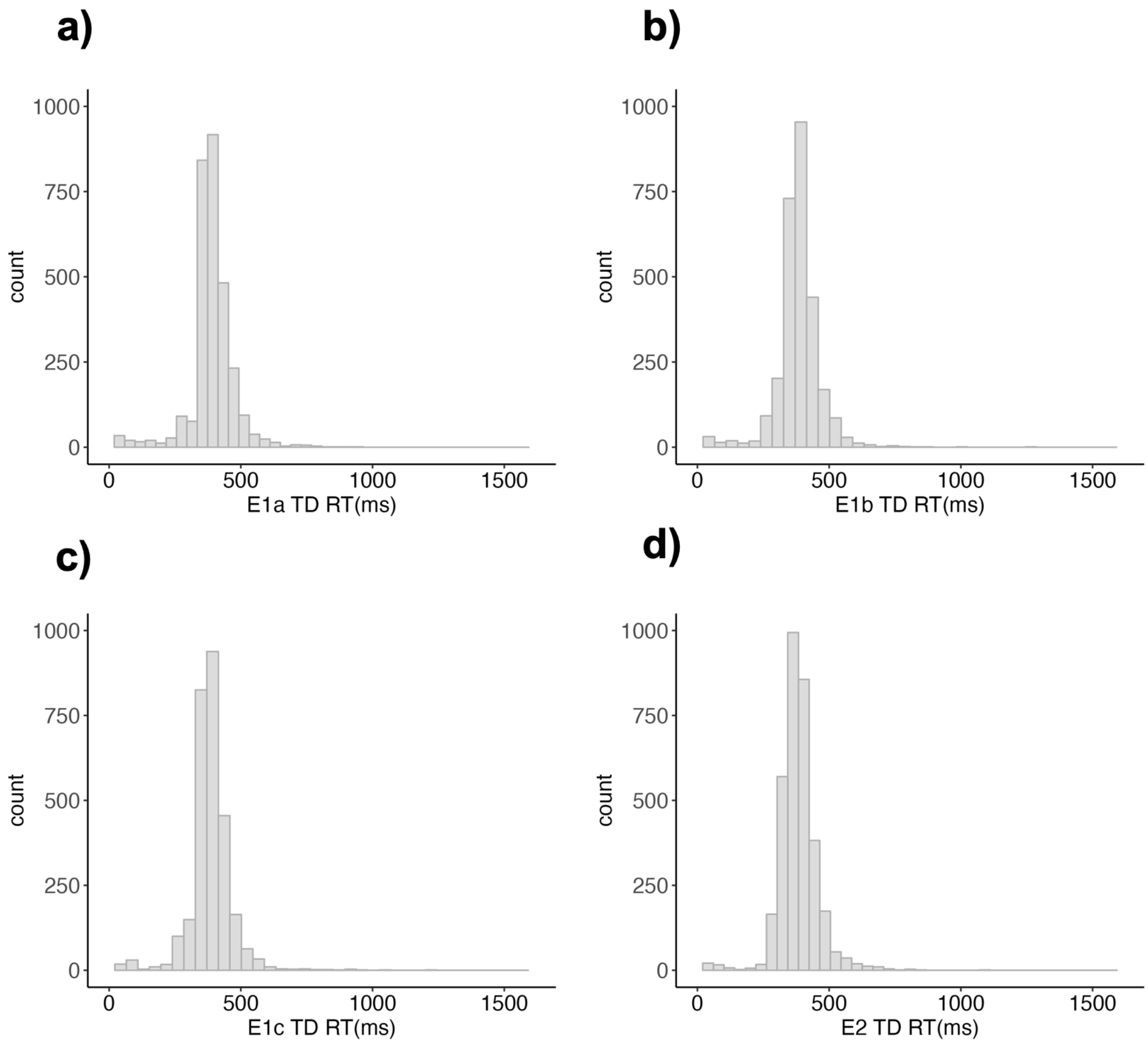
Supp Figure 3. Triplet selection results. Selection scores for low vs. high attentional states in E1b (a), and E1c (b). Error bars represent s.e.m. Scoring criteria were calculated in an interactive approach. Specifically, we listed all ten possible combinations of three shapes here (HHH, HHL, HLL, HHR, HRR, LLL, LLR, LRR, HLR, RRR), where H, L, R stand for shape from high-attention, low-attention, and random triplet. For each participant, we assigned trial labels—one high- and one low-attention triplet—to the two selection trials in the way that would maximize their score using an iterative approach. Score for each trial was counted as the number of shapes that match with the trial label selected on that trial. This is the iterative scoring approach:

1. Assign unambiguous trial labels first. Trials with 2 or 3 shapes from the same triplet are unambiguous. In this step, HHH, HHR, and HHL trials are labeled high attention and LLL, LLR, and LLH trials are labeled low attention. If both of a participant's trials are unambiguous, move to step 4.
2. If only one trial is unambiguous, assign the opposite label to the other trial. For example, if a participant responded HHR and LHR or HHR and RRR, the first triplet would be labeled high attention in step 1 and the second trial would be labeled low attention in this step.

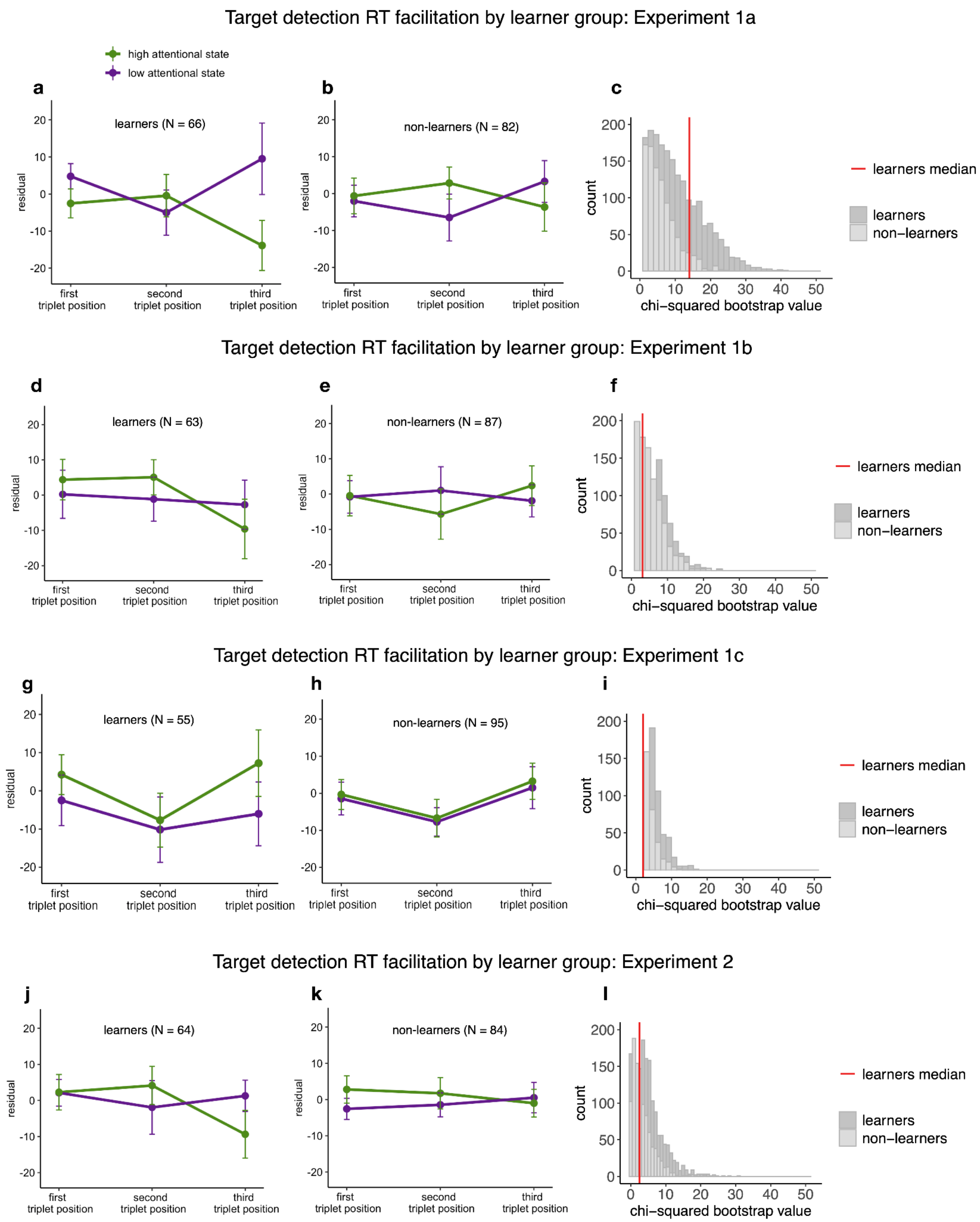
3. If both trials are ambiguous, assign labels with another iterative process.
    a. If one trial has one triplet shape and the other includes only random shapes, assign the corresponding label to the first trial and the other label to the random-only trial. For example, for a participant who provided LRR and RRR, trial one would be labeled low attention and trial two would be labeled high attention.
    b. If both trials are unambiguously from the same triplet (HHR and HHL), assign labels randomly.
    c. If both trials have one shape from each triplet (LHR and HLR), assign labels randomly.
    d. If both trials are random-only (RRR and RRR), assign labels randomly.
    e. If one trial has two triplet shapes and the other includes only random shapes (LHR and RRR), this participant gets a score of 1 for high attention and 1 for low.
    f. For all remaining trials, assign labels in the way that would maximize the participant's score. For example, for a participant who responded HRR and LHR, trial one would be labeled high attention and trial two would be labeled low attention.
4. Score each triplet from 0-3 based on the number of correct shapes provided. When both triplets were scored, we conducted a *t*-test assessing learning for each attentional state and a linear regression model to assess the difference between attentional states.



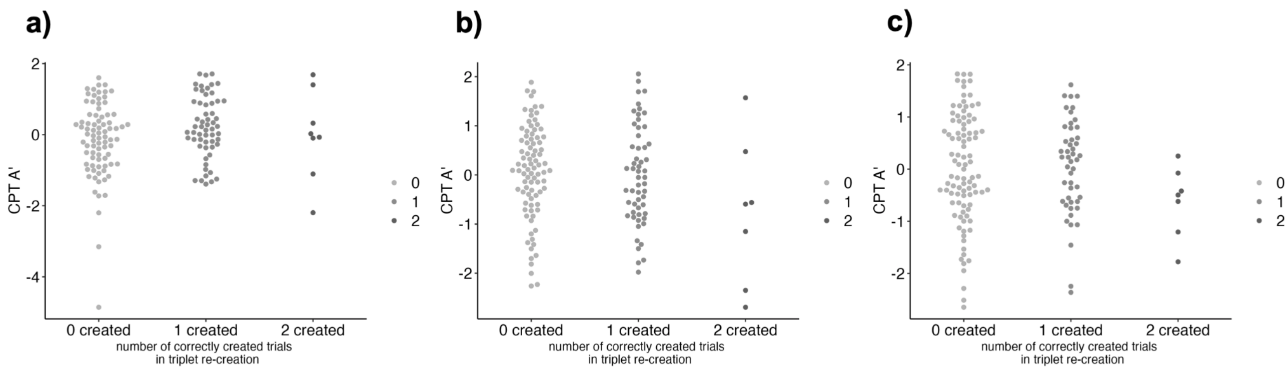
Supp Figure 4. RT distribution for the CPT and trial indices of triggered trials in the CPT. **Panel a,c,e**: CPT RT distribution in E1a-c. The y-axis shows trial count. The x-axis shows the CPT RT averaged across subjects. **Panel b,d,f**: Distribution of where the triggered trials appeared in E1a-c. The y-axis shows trial count and the x-axis shows trial indices.



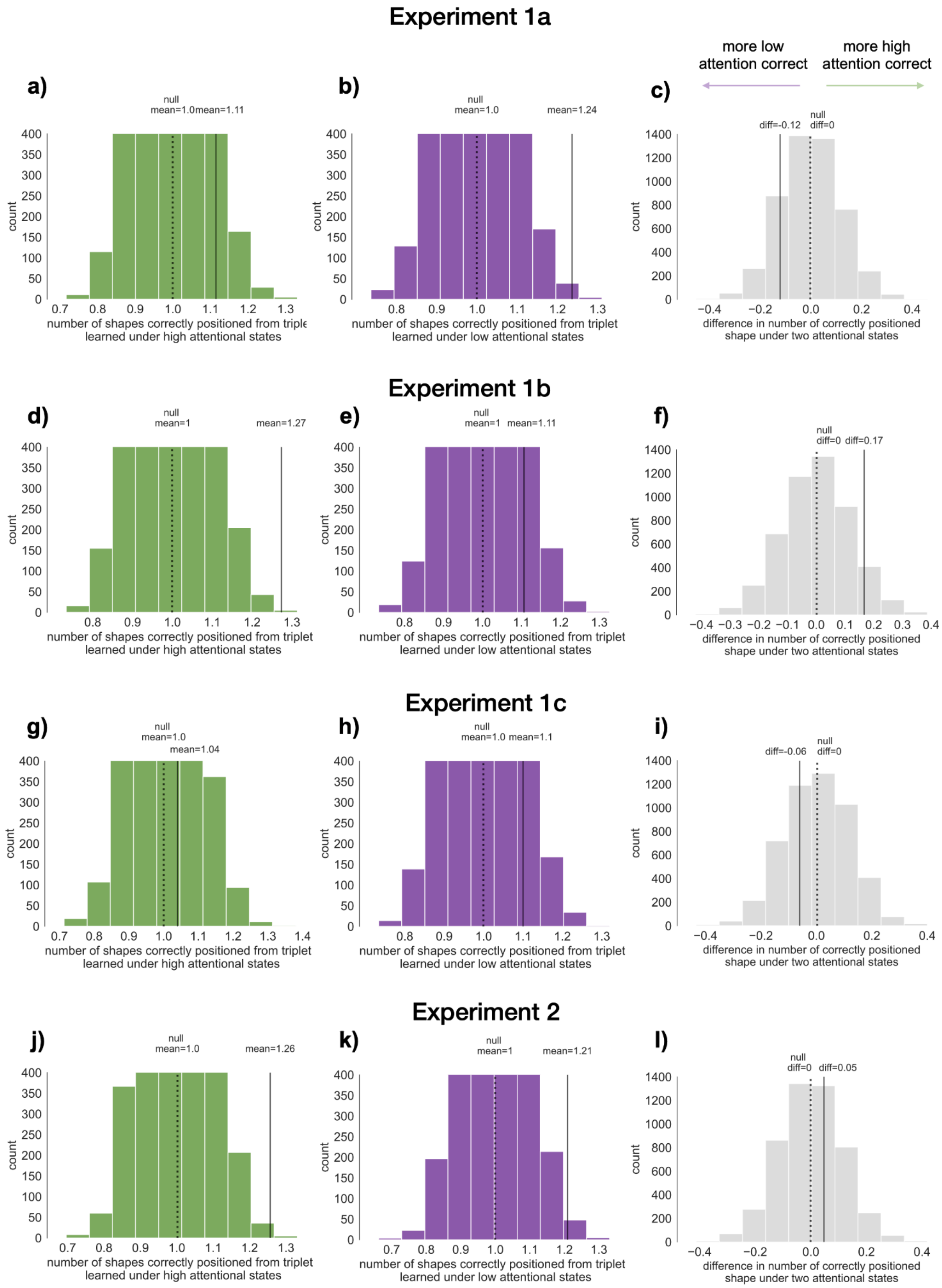
Supp Figure 5. RT distribution for the target detection task. The y-axis shows trial count and the x--axis shows the target detection task RT for all subjects. (a) E1a. Mean RT=388.34ms, SD=87.37ms. (b) E1b. Mean RT=379.84ms, SD=88.77ms. (c) E1c. Mean RT=382.53ms, SD=86.40ms. (d) E2. Mean RT=382.57ms, SD=79.97ms.



Supp Figure 6. Target detection RT facilitation by learners vs. non-learners (determined by drag-and-drop task performance). Green and purple bars show RTs for the triplet encountered under high and low attentional states in the CPT, respectively. Target detection RT facilitation of participants who correctly created at least one of the triplets in the triplet re-creation task (learners) in E1a (a), E1b (d), E1c (g), and E2 (j). RT facilitation for those who correctly created none (non-learners) in E1a (b), E1b (e), E1c (h), and E2 (k). The y-axis shows residualized RTs and the x-axis shows shape positions within the triplet. Error bars correspond to the s.e.m. Distributions for 1000 bootstrap samples of chi-squared values of the two-way interaction term (attentional state * shape position) for learners (dark gray) and non-learners (light gray) in E1a (c), E1b (f), E1c (i), and E2 (l). The median of the bootstrapped distribution of chi-squared values for learners (red line) is plotted relative to the distribution of chi-squared values for non-learners. Statistical significance was assessed using one-tailed *p* = (1+ bootstrapped chi-squared values for non-learners >= median of learners bootstrap distribution) / 1001.



Supp Figure 7. The relationship between E1a CPT A' and triplet re-creation task accuracy for E1a (a), E1b (b), and E1c (c).



Supp Figure 8. Non-parametric permutation test results for the number of shapes correctly positioned at the given location in the triplet re-creation task. Green and purple colored bars represent null distributions obtained from counting the number of participants that match with a randomly generated answer in 5000 iterations. Dotted gray lines denote the mean of each null distribution. Solid gray lines denote the true number of participants that correctly positioned the shape in a regular triplet under each attentional state. Results for triplets encountered under high attention shown in E1a (a), E1b (d), E1c (g), and “pseudo” high attention in E2 (j); Results for triplet encountered under low attention shown in E1a (b), E1b (e), E1c (h), and “pseudo” low attention in E2 (k); Distribution of the difference (high-low attentional state) between two attentional states shown in E1a (c), E1b (f), E1c (i), and E2 (l). On average, E1a participants placed 1.11 high-attention shapes in the correct position and 1.24 low-attention shapes in the correct position. The number of correctly positioned shapes (diff (high-low)=-0.12, null diff=0, two-tailed p=0.29) were not significantly different. The results for replication E1b, and E1c, are high-attention: 1.27, 1.04; low-attention: 1.11, 1.10; diff (high-low): 0.17, -0.06. None of the two experiments showed a significant difference between the two attentional states (two tailed p=0.15, 0.61). E2 participants placed 1.26 pseudo-high-attention shapes in the correct position and 1.21 pseudo-low-attention shapes in the correct position. The difference (diff (high-low)=0.05) was not significant (two tailed p=0.67).

	Question	Position	Type
E1			
	"Did you notice regular sequences of 3 shapes in the first part of the study, before the instructions told you that they were present? Please describe in as much detail as you can. If you are not sure, please share your best guess."	after the triplet re-creation task	free response
E2			
	“Did you use any strategies to complete the first part of the study? Please describe in as much detail as you can. If you are not sure, please share your best guess.”	after the target detection task	free response
	“Did you notice any patterns in the shapes in the first part of the study? Please describe in as much detail as you can. If you are not sure, please share your best guess.”	after the target detection task	free response
	"Did you notice regular sequences of 3 shapes in the first part of the study, before the instructions told you that they were present?"	after the triplet re-creation task	multiple choice
	"What is the rule of the first part of the study?"	after the triplet re-creation task	multiple choice

Supp Table 1. Attention check and awareness questions.