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Learned States of Preparatory Attentional Control

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Individuals regularly experience fluctuations in the ability to perform cognitive operations. Although previous research has focused on predicting cognitive flexibility from persistent individual traits, as well as from spontaneous fluctuations in neural activity, the role of learning in shaping preparatory attentional control remains poorly understood. Across 3 experiments, we manipulated the statistical regularities of an attentional orienting paradigm to examine whether individuals modulated attentional flexibility, the readiness to perform a spatial shift of attention, across learned contexts. We found evidence of learning-based modulations in preparatory attentional control settings when the probability of shifting the focus of attention differed based on temporally or color-defined contexts. Furthermore, in the case of color-defined contexts, these modulations in preparatory control persisted even after a change in the underlying statistical properties. Our results indicate that dynamic adjustments in preparatory attentional control are sensitive to the underlying statistical regularities of an environment. This finding has implications for understanding disordered patterns of attentional control and how these patterns might be modified with training.

Keywords: attentional flexibility, preparatory cognitive control, statistical learning

Attention, the process by which we select from among competing stimuli those that will receive preferential mental representation, shapes our awareness of the world around us, influencing the actions we perform and the memories we store (Desimone & Duncan, 1995; Rensink, O'Regan, & Clark, 1997; Reynolds, Chelazzi, & Desimone, 1999; Yantis & Johnston, 1990). Individuals selectively attend to stimuli that have salient physical characteristics or are relevant to behavioral goals (Chiu & Yantis, 2009; Folk, Remington, & Johnston, 1992; Serences & Yantis, 2006; Theeuwes, 1992; Yantis & Egeth, 1999). As task demands change, individuals must be able to flexibly update goal-related attentional priorities accordingly. Although the behavioral consequences and neural correlates of goal-oriented shifts of spatial attention have been a popular topic of research, the factors influencing moment-by-moment changes in preparatory attentional control states remain less understood. In the current series of experiments, we test whether the preparedness to shift or maintain the current focus of attention is sensitive to the statistical regularities of an environment.

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Preparatory attentional control may be thought of as falling along a continuum ranging from states in which individuals are prepared to maintain attentional focus (attentional stability), to states in which they are prepared to rapidly perform a shift of attention (attentional flexibility). In addition to varying in their baseline levels of cognitive flexibility (e.g., Heatherton & Wagner, 2011; Nolan, Bilder, Lachman, & Volavka, 2004; see Cools, 2008, for a review), individuals also regularly fluctuate over time in their moment-by-moment readiness to perform a cognitive switch, such as an update of task set or a shift of spatial attention. These changes over time in task preparation and attentional control have been linked to spontaneous fluctuations of neural activity in frontoparietal cortical control regions, as well as in medial cortical areas comprising the default-mode network (Christoff, Gordon, Smallwood, Smith, & Schooler, 2009; Esterman, Noonan, Rosenberg, & Degutis, 2013; Leber, 2010; Leber, Turk-Browne, & Chun, 2008; Weissman, Roberts, Visscher, & Woldorff, 2006; Weissman, Warner, & Woldorff, 2009). Together, these studies help to explain between- and within-individual variability in attentional flexibility that is independent of learning and experience. Here, we focus on the aspects of preparatory attentional control that are sensitive to learning. In particular, we examine adjustments of control according to learned expectations concerning the changing demands of the environment.

Reinforcement learning serves as one mechanism through which previous experiences have been shown to influence future states of cognitive control (Sali, Anderson, & Yantis, 2013). Participants in a recent study selected among four objects to uncover hidden rewards across training and test phases in which targets were defined by color or location, respectively. Over the course of training, the reward contingencies either remained consistent such that one colored object contained the hidden reward (regardless of its location) on the majority of trials, or changed periodically without any indication or warning. Participants who experienced consistent reward contingencies during training demonstrated more stable selection behavior in the subsequent test phase compared with participants who had received changing reward contingencies; this finding indicates that reward history can have a broad influence on how quickly an individual is willing to shift selection strategies (Sali et al., 2013).

Environmental factors regularly place unique demands on the attentional control system. For example, while a stable state of preparatory attentional control may be most useful when attempting to block out distractions, such as when reading in a noisy room, flexible control over attention is advantageous for situations in which there are frequently changing sources of important information, such as driving a vehicle down a busy street. Given our ability to effectively deploy attention across a wide range of contexts, each with differing demands, learning may play an important role in the adjustment of preparatory attentional control settings. In particular, preparatory attentional control may be sensitive to the statistical regularities of an environment, such that individuals enter into a flexible state when they have learned to expect frequent shifts of attention and a stable state when there is a need to maintain focus. In line with this idea, context cues associated with the likelihood of task switching modulate shift costs such that these costs are larger in contexts for which switching is unlikely (Crump & Logan, 2010; Leboe, Wong, Crump, & Stobbe, 2008). The degree to which similar learning may influence the preparedness to shift the focus of spatial attention is unknown. Given the potential for dynamic changes in preparatory attentional control as the result of statistical learning, we conducted a series of experiments in which we manipulated the statistical structure of an attentional orienting paradigm and tested for corresponding modulations of preparatory control states.

Statistical Learning and Visual Cognition

Evidence stemming from multiple domains of cognition suggests that the brain uses the statistical properties of an environment to guide behavior. For example, statistical regularities in the order of phonemes play a role in language acquisition in infants (Saffran, 2003; Saffran, Aslin, & Newport, 1996). Statistical learning is present from an early age in humans (e.g., Aslin, Saffran, & Newport, 1998; Fiser & Aslin, 2002b; Saffran, Johnson, Aslin & Newport, 1999) and is also found in nonhuman primates (Newport, Hauser, Spaepen, & Aslin, 2004). One well-studied domain in which statistical regularities influence cognition is vision.

When passively viewing visual displays, individuals extract statistical regularities and are able to use these representations to guide future judgments, a phenomenon known as visual statistical learning (VSL). For example, individuals learn the spatiotemporal regularities of dynamic visual objects (Fiser & Aslin, 2002a), as well as regularities in recursively embedded visual shape combinations (Fiser & Aslin, 2005). A hallmark of VSL is the ability of statistical structure to influence behavior outside of conscious awareness of these regularities. Although VSL requires attentional selection of the relevant stimuli, it operates implicitly and without intent (Baker, Olson, & Behrmann, 2004; Turk-Browne, Jungé, & Scholl, 2005) and is highly related to statistical summary perception (Zhao, Ngo, McKendrick, & Turk-Browne, 2011). Furthermore, researchers have identified several constraints on VSL. Perceptual biases such as those governing the perception of objects passing or colliding behind an occluder influence which statistical regularities are learned (Fiser, Scholl, & Aslin, 2007), and the covariance of stimulus features determines whether VSL is object-based (Turk-Browne, Isola, Scholl, & Treat, 2008). Taken together, these studies provide evidence that the visual system is sensitive to statistical regularities and that perception and attentional selection constrain which of many potentially present regularities in an environment an individual may learn.

In addition to merely learning visual statistical structure, individuals use these regularities to guide the deployment of attention (see Hutchinson & Turk-Browne, 2012, for a review). For example, visual search is speeded when the configuration of distractor items in a search array carries predictive information about the location of the target, a phenomenon known as contextual cuing (Chun & Jiang, 1998, 1999). Despite showing an improvement in visual search based on the statistical properties of the task, participants lack explicit knowledge of this structure (Chun & Jiang, 2003). Rather, implicit knowledge about the configuration of search array items allows for faster visual search than under comparable conditions that lack predictable structure.

More recently, researchers have shown that both spatial and feature-based attention are spontaneously biased toward statistical regularities in an environment (Zhao, Al-Aidroos, & Turk-Browne, 2013). In one experiment, Zhao and colleagues (2013) presented four continuous streams of objects surrounding a central fixation point. Periodically, a visual search task appeared with a single target and three distractors in the location of the object streams. Critically, one of the object streams had a reliable statistical structure such that triplets of objects were presented in a fixed order; the remaining three streams consisted of randomly generated objects only. Participants detected visual search targets appearing at the location of the structured stream more rapidly than those appearing in the random streams, even though they lacked conscious awareness of the statistical structure. Similarly, in two follow-up experiments, participants viewed a continuous stream of either red and green shapes or red and green line segments. As before, only stimuli of a particular color or orientation contained a predictable statistical structure. When presented with a visual search array, participants were more slowed by the presence of a singleton distractor appearing either in the same color or orientation as the previously presented structured items than in the color or orientation associated with the unstructured items. These findings suggest that attention is biased toward stimuli with predictable statistical structures, and that visual search displays are processed more efficiently when their statistical structure has been learned.

Statistical Structure Influences Attentional Priority

In addition to biasing attention to a particular location (Chun & Jiang, 1998, 1999; Zhao et al., 2013) or stimulus feature (Zhao et al., 2013), statistical structure may also influence future settings of attentional priority, even when these regularities are no longer present. When searching for a target that is defined by a unique feature, individuals may adopt an attentional set for any salient visual feature in the search array (singleton-detection mode). Under this particular attentional control setting, the most physically salient item appearing in the array involuntarily captures attention (e.g., Bacon & Egeth, 1994; Folk & Anderson, 2010). However, capture by salient distractors is overridden when individuals instead search for a target with a particular featural identity (feature-search mode), suggesting that individuals may effectively limit attentional selection to a particular set of goal-relevant features (Bacon & Egeth, 1994; Folk & Anderson, 2010; Folk et al., 1992; Folk, Leber, & Egeth, 2002; Leber & Egeth, 2006).

Attentional priority varies across learned contexts. Cosman and Vecera (2013) paired trials requiring singleton-detection mode and those requiring feature-search mode with city/nature scene context cues. Following training, participants completed a test phase visual search task in which either singleton-detection or feature-search modes were viable strategies for locating the target. In support of learning-based modulations of attentional priority, a singleton distractor captured attention only for test phase trials in which the context was previously associated with salience-based visual search (Cosman & Vecera, 2013). Context has also been shown to modulate value-based attentional priority (see Anderson, Laurent, & Yantis, 2011a, 2011b). Using a similar city/nature scene context manipulation, Anderson (2014) conducted an experiment in which the context indicated which target color would result in a reward if selected. In a subsequent test phase, a previously reward-associated color only captured attention when it appeared in the context in which it was rewarded during training.

Individuals may also implicitly develop attentional priorities for specific stimulus features as a result of statistical learning. When searching for a target of a particular color, distractors appearing in that color involuntarily capture the focus of attention, whereas distractors appearing in a different color do not (e.g., Folk et al., 1992). In one recent study, researchers manipulated the frequency of red and green targets in a standard contingent capture task such that some participants received a majority of red targets while others received a majority of green targets (Cosman & Vecera, 2014). Critically, behavioral performance was measured after an unannounced change in the color asymmetry such that participants received an equal number of red and green targets. The magnitude of the difference in response time (RT) between validly and invalidly cued targets was greatest for stimuli appearing in the previously more likely target color than in the previously less likely target color. The previous results therefore demonstrate that feature-based attentional sets as well as search modes are sensitive to the underlying regularities of a task.

Overview of the Current Study

Given the evidence that attentional priorities are sensitive to the statistical regularities of the environment, we investigated whether statistical learning modulates moment-by-moment adjustments in preparatory goal-oriented attentional control. In particular, although previous research has indicated that statistical regularities shape attentional sets, thereby influencing attentional priority for particular stimulus features, the degree to which environmental regularities determine our ability to shift the current focus of attention remains unknown. We sought to apply recent ideas concerning statistical learning and attention to how we understand states of attentional flexibility, which to date have been ascribed exclusively to persistent individual traits and spontaneous fluctuations. Evidence in favor of learning-based modulations of preparatory attentional control would suggest that attentional flexibility is to some degree plastic and adaptively adjusted to accommodate changing task demands. Therefore, in a series of experiments, we manipulated shift and hold cue frequency across temporally and color-defined contexts. Converging evidence across these experiments suggests that statistical learning serves as a powerful mechanism for determining preparatory attentional control settings.

Experiment 1

A defining feature of any environment is temporal structure. One method of preparing a particular cognitive operation such as a spatial shift of attention is to predict when this action will be necessary (see Grondin, 2010, for a review). Anticipation of future events is advantageous for goal-directed cognitive control, and deficient time perception has been associated with a variety of neuropsychological and psychiatric disorders, such as schizophrenia (e.g., Carroll, O'Donnell, Shekhar, & Hetrick, 2009), Parkinson's disease (e.g., Smith, Harper, Gittings, & Abernethy, 2007), and attention-deficit/hyperactivity disorder (ADHD; e.g., Gilden & Marusich, 2009). Attentional selection has also been shown to influence the perception of time such that attended events seem longer than they really are (Tse, Intriligator, Rivest, & Cavanagh, 2004; see Brown & Merchant, 2007). Furthermore, it has been suggested that time perception depends on the synchroniticity of oscillations in attentional selection with the temporal structure of the environment, suggesting that attentional control and time perception are closely linked (Jones & Boltz, 1989).

Given the relationship between attention, cognitive control, and time perception, we first tested whether preparatory attentional control is sensitive to temporal expectations arising from statistical regularities. Participants completed a rapid serial visual presentation (RSVP) task in which they shifted or held attention in response to visual cues. Critically, we manipulated the temporal structure of the task such that within each trial the probability of receiving shift and hold cues changed as participants waited for the cue onset. Behavioral responses to target digits appearing in the cued stream served as an index of attentional flexibility. In particular, we compared the magnitude of the difference in RT for trials requiring a spatial attention shift minus those in which participants held attention at a single location, referred to here as a *shift cost*, for each temporal interval. Large shift costs are indicative of a stable preparatory state of attentional control, whereas small costs indicate a preparatory state of flexibility.

To test whether temporal statistical regularities play a modulatory role in preparatory attentional control, we manipulated the likelihood that participants would receive cues to shift or hold attention across three temporal intervals during which they monitored a stream of digits for the onset of the cue. For one-third of the participants, we set the cue type probabilities such that shifting attention was more likely at a short delay while holding attention was more likely at a long delay. Another group of participants experienced the opposite relationship between cue and time delay. A final group received an equal number of shift and hold cues at all intervals. If participants were able to use the statistical structure of the task to guide preparatory attentional control, we predicted that those participants who received mostly shift cues at the shortest interval and mostly hold cues at the longest interval would have increasingly large shift costs as a function of the time delay. Conversely, participants who received the opposite mapping would demonstrate decreasing shift costs as a function of the time delay. Alternatively, if participants were unable to guide preparatory attentional control based on the temporal regularities of the task, we would find no difference in shift costs across time as a function of experimental group. In the current experiment and throughout the article, we remain agnostic as to whether a change in shift costs stems from either a modulation of hold trial or shift trial RTs across contexts, because either outcome reflects a change in preparatory attentional control.

Method

Participants. Fifty-five adults (37 women) ranging in age from 18 to 30 years (M = 19.3, SD = 2.03) participated in the study in exchange for course credit or monetary compensation. One participant did not report age. All participants signed a consent form approved by the Johns Hopkins University Institutional Review Board prior to participation. Seven participants were excluded from all analyses for responding correctly on fewer than 75% of all trials, for having recently completed a pilot experiment on statistical learning and preparatory attentional control in our lab, or for not finishing the experiment. The RT results and conclusions remain the same when those participants excluded based on accuracy or previous participation were included in the analyses. Participants were randomly assigned to one of the three cue probability groups.

Apparatus. All stimuli were displayed on an Asus VE247 LCD monitor that was connected to a Mac Mini computer and was positioned approximately 76 cm away from the participant. Stimulus presentation was controlled by the Psychophysics toolbox for Matlab (Brainard, 1997). Fixation was not enforced. Participants made all responses with a standard computer keyboard that was positioned directly in front of them on a table.

Stimuli. Participants viewed displays consisting of eight synchronous RSVP streams of alphanumeric characters with the central streams positioned approximately 4.15° (center-to-center) to the left and right of a central crosshairs (0.60°x0.60°) and along the vertical meridian (Figure 1). All streams were rendered in white and presented against a black background. Each of the flanking streams was positioned approximately 1.51° above, below, and to the outside of the two central streams (center-to-center). Each frame was presented for 250 ms (no gap). The two central streams consisted of randomly generated digits ranging from 1–8 (approximately 0.68° × 0.91°), except for the appearance of cue and target stimuli as described in the Procedure, whereas the flanking streams consisted of randomly generated letters (excluding E, F, H, I, N, O, S, T, U, A, K). The same digit or letter never repeated in two successive frames. Participants were instructed to restrict attention to the two central streams and were informed that they should always ignore the flanking streams.

Procedure. As illustrated in Figure 1, each trial began with a flashing asterisk (0.53° × 0.53°) in the location of the to-be-attended RSVP stream for a total of 1,500 ms. Following the offset of the asterisk, the eight RSVP streams appeared and began to change every 250 ms. A cue signaling participants to either shift or hold attention appeared embedded within the attended stream after a delay of either 1,000, 3,000, or 5,000 ms. During this distractor interval, random digits appeared in both of the task-relevant streams. The letter "A" signaled participants to hold attention at the same stream, while the letter "K" signaled participants to shift attention as rapidly as possible to the opposite stream. Participants performed a digit parity categorization task immediately after detecting the attention cue. For a period of 2,000 ms following the cue onset, all stimuli within the to-be-attended location were generated with the same parity. At the to-be-ignored location, digits were randomly generated during the response window. Participants responded based on the first target digit identified by pressing the "Z" key if the digit was odd and the "M" key if the digit was even. The entire 2,000-ms target digit sequence was displayed regardless of the participant's behavioral response. We enforced a response deadline of 2,000 ms with reference to the onset of the first target digit; any responses occurring after this deadline were not counted and the trial was scored as an incorrect trial. A constant inter-trial-interval of 1,000 ms followed the final target digit frame. Participants completed 6 blocks of 60 trials each with a self-paced break between blocks. Behavioral accuracy feedback was displayed on the screen following each block.

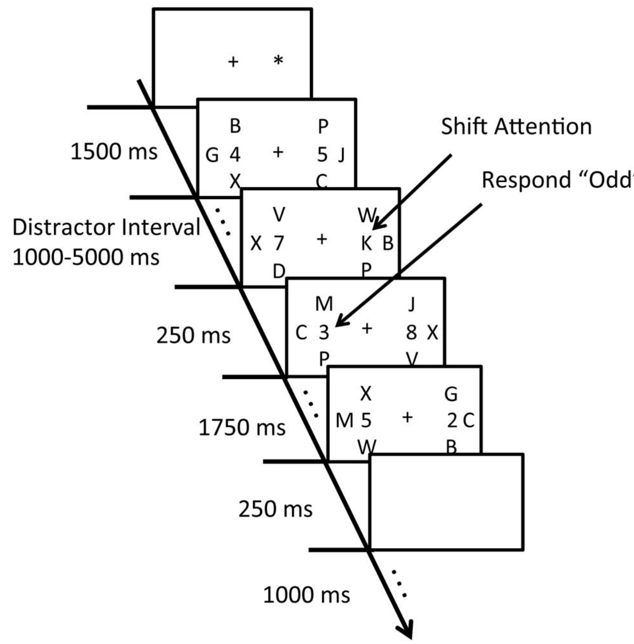

Figure 1. Behavioral task for Experiment 1. Participants monitored one of two central rapid serial visual presentation (RSVP) streams for the appearance of a letter cue ("A" = hold attention, "K" = shift attention). Immediately after the onset of the cue, participants made a parity judgment for target stimuli appearing in the cued stream.

We manipulated, between-subjects, the probability of receiving a shift or hold cue at the three potential distractor intervals. For all participants, there was an equal probability on each trial of receiving a shift or hold cue at the 3,000-ms interval. However, the likelihood of shifting or holding attention at the remaining intervals varied across subjects. For one third of the participants, 80% of cues appearing at the 1,000-ms delay signaled a shift of attention, while 80% of cues appearing at the 5,000-ms delay signaled participants to hold attention. Another third of participants received the opposite set of contingencies. The remaining participants received an equal number of shift and hold cues at all three distractor intervals to serve as a baseline from which to compare any evidence of learning in the other two groups. Within each block, there were a total of 20 cues presented at each of the three intervals, such that over the course of the block, participants experienced each distractor interval an equal number of times.

Debriefing. Following completion of the task, participants in the two probability manipulation groups answered a series of questions to assess explicit knowledge of the temporal statistical structure. Participants read the questions on index cards one at a time and filled out responses on a separate response sheet. We first asked participants, "Was there any way to predict when you would receive a cue ('A' or 'K') to shift attention (K) versus when you would receive a cue to hold attention at a single location (A)? If yes please explain." After writing a response, participants flipped over a second card and read the following prompt: "One cue type (either shift or hold cues) tended to appear closer in time to the previous cue than the other. For which cue type did the interval between cue presentations tend to be the shortest?" Participants indicated their response by circling shift or hold on a response sheet.

Data analysis. We trimmed all RTs greater than 3 *SD*s above or below the mean of each condition for each participant, resulting in a reduction of less than 2% of trials with a correct response. Here and throughout the paper, within-subject analyses were Geisser-Greenhouse corrected for violations of the sphericity assumption where appropriate.

Results

Behavioral performance. We first tested whether the magnitude of the cost associated with shifting attention varied as a function of the temporal statistics of the environment with a $3 \times 2 \times 3$ mixed-design analysis of variance (ANOVA) with factors of experimental group (expect shift at short interval, expect shift at long interval, or equal probabilities), cue type (shift vs. hold), and distractor interval (1,000, 3,000, or 5,000 ms). There were significant main effects of both cue type, $F(1, 45) = 290.10$, $p < .001$, $\eta_p^2 = .866$, and distractor interval, $F(2, 90) = 19.80$, $p < .001$, $\eta_p^2 = .306$, such that participants were slower for attention shift trials than for those in which they held attention and faster at longer intervals. Critically, there was a significant three-way interaction between experimental group, cue type, and distractor interval, $F(4, 90) = 15.97$, $p < .001$, $\eta_p^2 = .415$ (Figure 2).

To further explore the nature of the three-way interaction, we computed the two-way interaction of cue type by distractor interval for each of the three between-subjects probability conditions individually, as well as the three-way interactions comparing the pattern in the baseline condition to that of each of the probability manipulation conditions (i.e., computed by removing the other probability manipulation condition from the ANOVA model). The two-way interaction of cue type by distractor interval was statistically significant for both the expect shift at short interval, $F(2, 30) = 8.43$, $p = .002$, $\eta_p^2 = .360$, and the expect shift at long interval, $F(2, 30) = 18.38$, $p < .001$, $\eta_p^2 = .551$, groups, but not for the equal probability control group, $F(2, 30) = 2.09$, $p = .147$. Participants in both the expect shift at short interval and expect shift at long interval groups had decreasing shift costs as a function of shift trial likelihood, reflecting learned adjustments of preparatory attentional control. Importantly, participants in both the expect shift at short interval, $F(2, 60) = 8.32$, $p = .001$, $\eta_p^2 = .217$, and the expect shift at long interval, $F(2, 60) = 11.50$, $p < .001$, $\eta_p^2 = .277$, groups showed significantly different patterns in RT in comparison to the equal probability baseline group. All other main effects and interactions in the full factorial model failed to reach statistical significance Fs < 0.93, ps $> .402$.

Although the order of presentation of shift and hold cues was randomized, participants' behavior may have varied based on whether they were asked to repeat the same cognitive operation at either the same or a different moment within a trial. To the degree that such priming occurred, it might partially explain the observed modulation in shift costs over time, as our manipulation made high probability combinations of cue type and distractor interval more likely to repeat on consecutive trials than other combinations (and thus more frequently subject to priming). We therefore tested for the presence of any trial-by-trial carry-over effects that were modulated by distractor interval. Specifically, we examined whether there was a significant difference in RT for trials in which the cue type (shift or hold) repeated but at a different distractor interval versus those trials in which the same cue type occurred at the same distractor interval for two consecutive trials. We collapsed across experimental group since any trial-by-trial priming would influence behavior regardless of the underlying statistical regularities of the environment. RTs did not significantly differ between trials in which distractor interval repeated (shift trials: $M = 998.30$, $SD = 132.86$; hold trials: $M = 821.34$, $SD = 118.89$) and those in which distractor interval changed (shift trials: $M = 1003.06$, $SD = 120.94$; hold trials: $M = 825.45$, $SD = 118.07$) for shift trials, $t(47) = 0.62$, $p = .538$, or for hold trials, $t(47) = 0.69$, $p = .493$. The observed evidence of learned flexibility in RT is therefore not attributable to differential carry-over effects of cue type and interval repetitions, as repeating the same cognitive operation had equivalent effects on performance regardless of whether the interval at which this operation was performed also repeated.

Next, we conducted the same $3 \times 2 \times 3$ mixed-design ANOVA on behavioral accuracies, with experimental group, cue type, and distractor interval as factors. There was a significant main effect of distractor interval, $F(2, 90) = 7.90$, $p = .002$, $\eta_p^2 = .149$, such that accuracies were greater for hold than for shift trials and the interaction between distractor interval and experimental group approached significance, $F(4, 90) = 2.28$, $p = .082$, $\eta_p^2 = .092$. The three-way interaction between experimental group, cue type, and distractor interval also reached statistical significance $F(4, 90) = 2.86$, $p = .031$, $\eta_p^2 = .113$. The three-way interaction between experimental group, cue type, and distractor interval failed to reach statistical significance when comparing only the two probability manipulation groups, $F(2, 60) = 0.62$, $p = .533$; the critical RT differences reported above between the expect shift cue at short interval and expect shift cue at long interval groups are therefore not the result of a speed–accuracy trade-off (Table 1).

Debriefing. Only two participants reported noticing the temporal statistical regularities of the task when asked the free response question. However, when forced to guess whether shift or hold cues appeared at the short distractor interval most frequently, 26 out of 32 participants responded correctly ($p < .001$ vs. 50% chance), indicating some knowledge of the statistical structure.[1]

[1] The participants who responded correctly on the debriefing measure did not significantly differ in mean shift costs ($M = 164.68$, $SD = 64.92$) from those who did not respond correctly ($M = 153.54$, $SD = 57.25$), $t(30) = 0.39$, $p = .702$.

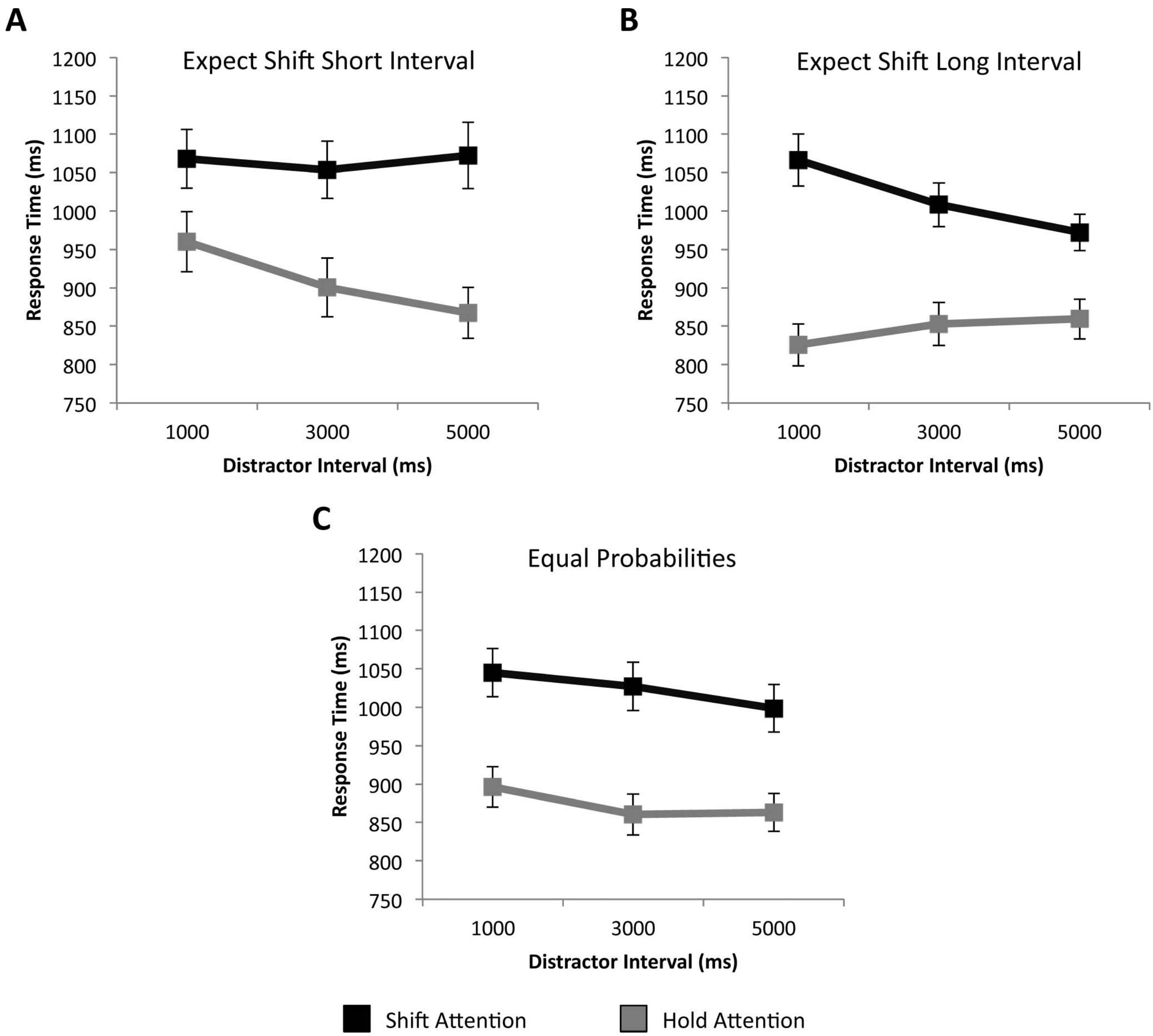

Figure 2. Behavioral results for Experiment 1. Response time as a function of cue type and distractor interval for participants who received mostly shift cues at the short interval (A), mostly shift cues at the long interval (B), and an equal number of shift and hold cues at all intervals (C). Error bars denote 1 between-subjects *SEM*.

Discussion

Experiment 1 provides evidence that the statistical regularities of an environment serve a modulatory role in the setting of preparatory attentional control states. In particular, participants demonstrated a greater preparation to shift attention (attentional flexibility) at distractor intervals for which they predominantly received shift cues in the past and less preparation to shift attention (attentional stability) at distractor intervals for which they received predominantly hold cues. The main effect of cue type confirms that participants were shifting attention as directed by the cues, as do the high accuracies in the task. The modulation of the cost associated with shifting attention across the different distractor intervals indicates that the preparedness to perform a shift of attention varied based on the associated probability that such a shift would be required.

The results from the current experiment cannot be explained by intertrial priming of cue type or temporal delay. The temporal structure predicted which cue would appear as time progressed within a single trial, but there was no trial-by-trial predictive structure regarding either cue type or temporal delay. Neither the timing nor type of cue on one trial could be predicted by what occurred on the prior trial. For example, although participants in the probability manipulation groups were more likely to shift or hold attention at certain distractor intervals than at others, they

Table 1
Behavioral Accuracies for Experiment 1

	Cue type					
	Expect shift 1,000 ms		Expect shift 5,000 ms		Equal probabilities	
Interval	Hold	Shift	Hold	Shift	Hold	Shift
1,000 ms	90.63 (9.68)	89.72 (9.59)	94.01 (4.36)	93.23 (5.67)	92.92 (5.92)	91.04 (7.09)
3,000 ms	93.13 (5.44)	91.77 (7.76)	95.62 (3.04)	92.19 (5.30)	93.33 (6.08)	95.42 (5.92)
5,000 ms	93.62 (7.22)	93.49 (7.29)	93.23 (5.02)	93.69 (4.23)	94.58 (4.89)	94.06 (5.27)

Note. The error terms, in parentheses, reflect *SD*.

remained equally likely to shift or hold attention on a trial-by-trial basis. Furthermore, we found no evidence of carry-over effects in RT when comparing those trials in which both cue type and distractor interval repeated to those in which cue type repeated at a different distractor interval. Our findings suggest that individuals are able to dynamically update attentional flexibility based on the learned structure of an environment and that this learning takes place outside of explicit instructions to prepare to shift or maintain the focus of attention.

Experiment 2

Experiment 1 demonstrated that preparatory attentional control processes are sensitive to temporal statistical regularities. An unresolved question remains the extent to which these learned modulations of preparatory attentional control state persist even in the face of new probability learning. In the context of visual search, learned contextual knowledge continues to guide attention even after a salient change in the shape of distractor stimuli (Chun & Jiang, 1998). We sought to determine whether learned temporal expectations would similarly continue to influence behavior even after the introduction of a competing temporal structure. In Experiment 2, participants first completed a training phase identical to Experiment 1. However, immediately following this training phase, the probability structure changed for all participants without warning such that shift and hold cues became equally likely to appear at each interval tested. Participants received no explicit notification that the probabilities had changed. Experiment 2 therefore tested whether preparatory attentional control is persistently modulated as the result of previously learned statistical regularities or whether control settings may quickly adjust to a change in the underlying statistical structure of the task.

Method

Participants. Sixty adults (45 women) ranging in age from 18–27 years (M = 20.0, SD = 1.99) completed the study in exchange for course credit or monetary compensation. As in Experiment 1, we adopted an accuracy threshold of 75% as an inclusion criterion for all analyses. Ten individuals were excluded from the analyses because of low behavioral accuracies, or for having previously completed a similar experiment with a temporal cue probability manipulation. All participants signed a consent form approved by the Johns Hopkins University Institutional Review Board.

Apparatus. The apparatus was identical to that used in Experiment 1.

Stimuli. The stimuli were identical to those used in Experiment 1.

Procedure. The experimental procedures of both the training and test phases were identical to Experiment 1 except as noted below. Participants completed an initial 6 blocks of 60 trials each (training phase) in which the likelihood of receiving shift and hold cues differed at the 1,000- and 5,000-ms distractor intervals as in Experiment 1. The equal probability control group from Experiment 1 served as a no-learning baseline. Beginning with the seventh block of the task, the cue probabilities switched without any notification such that shift and hold cues became equally likely at all intervals. Participants completed a total of 2 blocks of 60 trials each (test phase) in which they were equally likely to shift and hold attention at each interval.

Debriefing. As in the first experiment, participants viewed two debriefing prompts written on individual index cards, one at a time, and made responses on a separate sheet. Participants first read: "On some trials you had to shift attention from one stream to the other. On other trials, you held attention at a single stream. Could you predict when you would be asked to shift attention and when you would be asked to hold attention? If yes, how?" Next, participants read: "One cue type (either shift or hold cues) tended to appear closer in time to the previous cue than the other. An example of a shift cue would be a "K" appearing in the right stream while an example of a hold cue would be an "A" appearing in the left stream. For which cue type (shift or hold) did the interval between the presentations tend to be the shortest? Circle your answer. Rate your confidence." Participants made a response by circling shift or hold on the response sheet. They then rated their confidence in their judgment on a 7-point Likert-type scale ranging from 1 "Very Unconfident" to 7 "Very Confident." Participants answered the debriefing questions following completion of the test phase of the experiment.

Data analysis. As in Experiment 1, we again trimmed RTs that were 3 *SD*s above or below the mean of each condition for each participant, resulting in a loss of less than 2% of correct responses in the training phase and less than 1% of correct responses in the test phase.

Results

Training phase. First, we sought to replicate our finding from Experiment 1 that temporal cue probability statistical structure influenced preparatory attentional flexibility. A 2 × 2 × 3 mixed-design ANOVA with factors of experimental group (expect shift at short interval vs. expect shift at long interval), cue type (shift vs. hold), and distractor interval (1,000, 3,000, or 5,000 ms) revealed that there was a significant main effect of cue type, $F(1, 48) = 245.06$, $p < .001$, $\eta_p^2 = .836$, as well as a significant main effect of distractor interval, $F(2, 96) = 10.75$, $p < .001$, $\eta_p^2 = .183$, such that participants made faster responses on hold trials and at the longest distractor interval. Furthermore, there was a significant cue by experimental group interaction, $F(1, 48) = 6.88$, $p = .012$, $\eta_p^2 = .125$, and the distractor interval by experimental group interaction approached statistical significance, $F(2, 96) = 2.44$, $p = .100$, $\eta_p^2 = .048$. Critically, in replication of Experiment 1, there was a significant three-way interaction, $F(2, 96) = 14.44$, $p < .001$, $\eta_p^2 = .231$ (Figure 3, A and B). As in Experiment 1, we followed up the significant three-way interaction by testing the cue type by distractor interval interaction separately for both groups. The interactions for both the expect shift at short interval, $F(2, 48) = 3.78$, $p = .034$, $\eta_p^2 = .136$, and the expect shift at long interval, $F(2, 48) = 14.30$, $p < .001$, $\eta_p^2 = .373$, groups reached statistical significance. In replication of Experiment 1, shift costs were again smaller at the interval that was associated with shifting attention than at the interval that was associated with holding attention for participants in both training groups. All other main effects and interactions in the full factorial model failed to reach statistical significance, Fs < 1.21, ps $> .302$. Last, we compared the RTs of participants in each group against the performance of participants in the equal probability group from Experiment 1. The expect shift at long interval group displayed a different pattern in RT as a function of cue type and distractor interval than did the equal probability group, $F(2, 78) = 4.77$, $p = .013$, $\eta_p^2 = .109$,

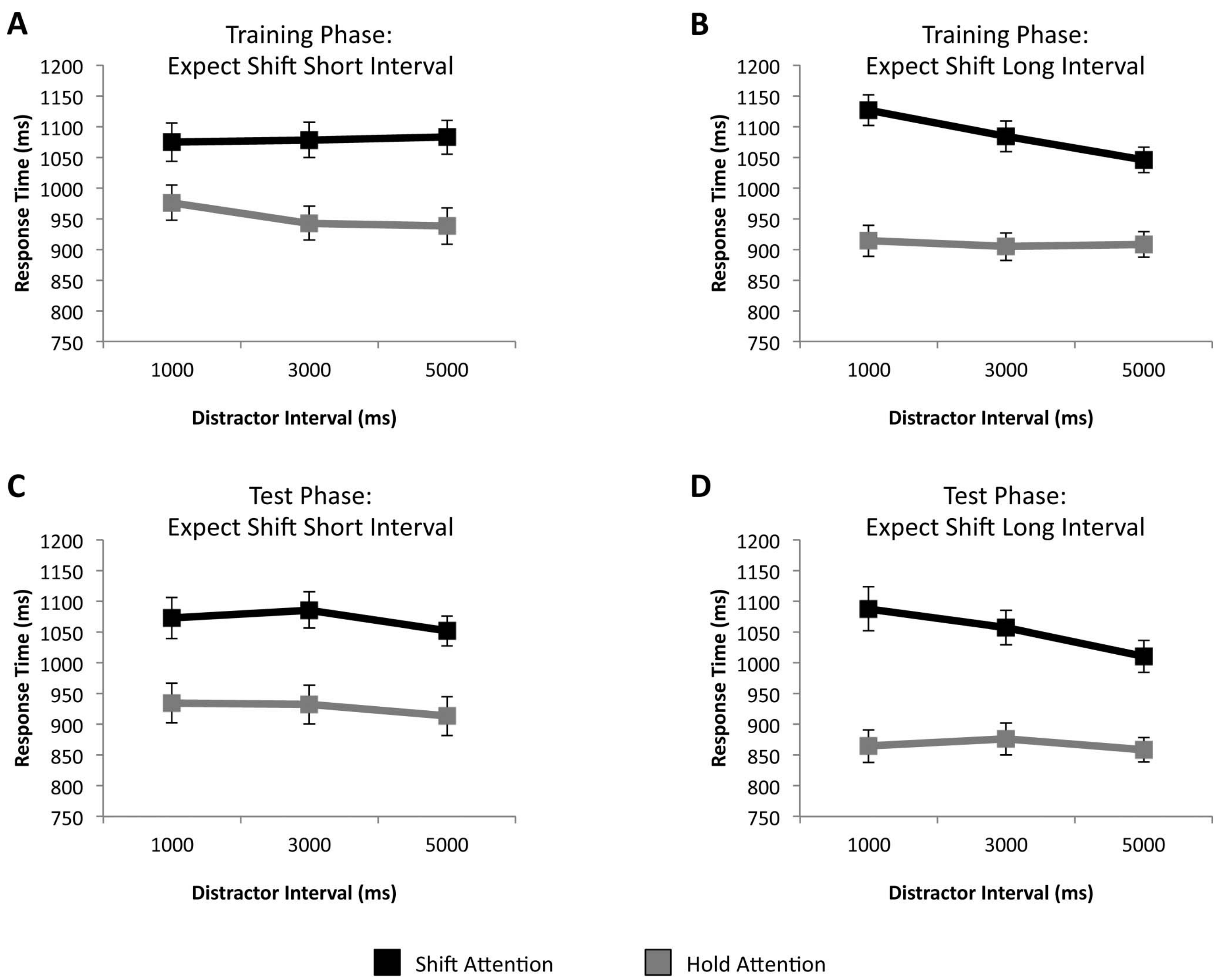

Figure 3. Behavioral results for Experiment 2. Training phase response time as a function of cue type and distractor interval for participants who received mostly shift cues at the short interval (A) and mostly shift cues at the long interval (B). Test phase response time as a function of cue type and distractor interval for participants who previously received mostly shift cues at the short interval (C) and mostly shift cues at the long interval (D). Error bars denote 1 between-subjects *SEM*.

while a similar trend existed for the expect shift at short interval group, $F(2, 78) = 2.86$, $p = .067$, $\eta_p^2 = .068$.

To rule out the possibility of a speed–accuracy trade-off accounting for the current findings, we next tested the training phase behavioral accuracies with an identical $2 \times 2 \times 3$ mixed-design ANOVA (Table 2). There were significant main effects of both cue type, $F(1, 48) = 7.97$, $p = .007$, $\eta_p^2 = .142$, and distractor interval, $F(2, 96) = 8.47$, $p = .001$, $\eta_p^2 = .150$. No other main effects or interactions reached statistical significance, $F\text{s} < 1.77$, $p\text{s} > .180$.

Test phase. We examined the test phase RT data for evidence of persistent modulations in preparatory attentional control following a change in the task's underlying statistical structure. As in the training phase, a $2 \times 2 \times 3$ mixed-design ANOVA revealed that there were significant main effects of cue type, $F(1, 48) = 228.24$, $p < .001$, $\eta_p^2 = .826$, and distractor interval, $F(2, 96) = 7.35$, $p = .001$, $\eta_p^2 = .133$ (Figure 3, C and D). Furthermore, the cue type by experimental group interaction, $F(1, 48) = 3.68$, $p = .061$, $\eta_p^2 = .071$, as well as the cue type by distractor interval interaction, $F(2, 96) = 2.87$, $p = .069$, $\eta_p^2 = .056$, approached statistical significance. Last, the critical three-way interaction between cue type, distractor interval, and experimental group was marginally significant, $F(2, 96) = 3.23$, $p = .051$, $\eta_p^2 = .063$, suggesting that there was only limited transfer of learning from the training phase to the test phase. There was a significant two-way interaction between cue type and distractor interval for participants in the expect shift at long interval condition, $F(2, 48) = 7.09$, $p = .004$, $\eta_p^2 = .228$, but the same interaction did not reach statistical significance for participants in the expect shift at short interval condition, $F(2, 48) = 0.29$, $p = .723$. Together these findings suggest that learned preparatory states of attentional flexibility may, under some circumstances, rapidly reconfigure following a change in environmental structure. All other main effects and interactions of the full factorial model failed to reach statistical significance, $F\text{s} < 1.12$, $p\text{s} > .295$.

As in the training phase, we also examined behavioral accuracies for evidence of modulations in preparatory attentional control using an identical mixed-design ANOVA (Table 3). There was a significant main effect of distractor interval, $F(2, 96) = 3.97$, $p = .026$, $\eta_p^2 = .076$, while all other main effects and interactions failed to reach statistical significance, $F\text{s} < 2.56$, $p\text{s} > .116$.

Debriefing. We had usable debriefing data from 48 of the 50 participants; answers for two participants were not collected because of experimenter error. Unlike Experiment 1, no participants described an explicit awareness of the temporal statistical structure following the free response prompt. Furthermore, only 25 of the 48 participants selected the correct item for the forced choice prompt (confidence ratings for accurate selections: $M = 3.96$, $SD = 1.46$). The debriefing data from Experiment 2 suggests that participants lacked explicit awareness of the underlying temporal statistical structure. Completion of the debriefing questions took place following the equal-probability test phase blocks. As a consequence, we cannot rule out the possibility that participants did have an explicit awareness of the temporal structure prior to completion of the test phase but that this awareness extinguished over time.

Table 2
Behavioral Accuracies for the Training Phase of Experiment 2

	Cue type			
	Expect shift 1,000 ms		Expect shift 5,000 ms	
Interval	Hold	Shift	Hold	Shift
1,000 ms	90.67 (7.82)	88.46 (8.62)	91.37 (4.95)	88.00 (8.95)
3,000 ms	92.40 (7.33)	91.87 (6.32)	92.20 (5.35)	91.67 (4.71)
5,000 ms	93.09 (5.57)	90.33 (8.48)	92.67 (6.17)	92.29 (4.69)

Note. The error terms, in parentheses, reflect *SD*.

Table 3
Behavioral Accuracies for the Test Phase of Experiment 2

	Cue type			
	Expect shift 1,000 ms		Expect shift 5,000 ms	
Interval	Hold	Shift	Hold	Shift
1,000 ms	93.20 (7.34)	91.60 (10.07)	91.80 (7.34)	90.80 (9.09)
3,000 ms	97.20 (5.22)	95.20 (4.89)	92.60 (5.61)	92.60 (8.43)
5,000 ms	94.60 (6.76)	95.40 (5.94)	93.00 (9.68)	92.40 (9.26)

Note. The error terms, in parentheses, reflect *SD*.

Discussion

As in Experiment 1, we found evidence of learning-based modulations of preparatory attentional flexibility when cue probabilities differed across distractor intervals. Participants were the least prepared to shift attention, as indexed by large shift costs, at the time interval for which they received relatively few shift cues and the most prepared to shift attention at the interval for which they frequently received shift cues.

The results from the test phase, in which cue probabilities were equated across temporal delays, provided only limited evidence of a persistent modulatory influence of previous statistical learning on preparatory attentional control. Rather, individuals may have adjusted to the change in the underlying statistical structure such that there was a decrease in the reliability of a performance difference based on training history. Together, these findings suggest that temporal statistical structure influences preparatory attentional control, and that such learning may only have a limited influence following a change in the underlying statistical regularities of the environment.

Experiment 3

Given the evidence of learning-based modulations of attentional flexibility in the first two experiments, we next sought to determine whether such learning is restricted to the domain of temporal expectations, or rather, whether other forms of statistical structure may also influence preparatory attentional control settings. As in the first two experiments, participants received cues to shift or hold attention between two RSVP streams and made parity categorizations of targets appearing in the cued stream. In Experiment 3, we manipulated context by alternating the color of the RSVP stimuli. Specifically, participants received predominantly shift cues when the stimuli were one color and predominately hold cues when the stimuli were a second color. As in the first two experiments, we defined attentional flexibility as the magnitude of the cost in RT associated with shifting attention in comparison to holding attention. Furthermore, we again tested whether previously learned statistical structure may influence future preparatory attentional control settings after a change in the underlying structure of the task. In support of Experiments 1–2, we predicted that shift costs would be larger for the color context in which participants frequently held attention than in the context in which they frequently shifted attention.

Method

Participants. Twenty-one adults (12 women) ranging in age from 18–22 years ($M = 19.6$, $SD = 1.12$) completed the study in exchange for course credit. All participants completed a consent form approved by the Johns Hopkins University Institutional Review Board prior to participation in the experiment. One participant was excluded from all analyses for having a behavioral accuracy below 75%.

Apparatus. The apparatus was identical to that used in Experiment 1.

Stimuli. All aspects of the task were identical to the first two experiments except where noted below. Participants monitored one of the central RSVP streams for 1,000, 1,500, 2,000, 2,500, or 3,000 ms prior to the onset of a letter cue ("A" or "K") embedded within the attended stream. Unlike the earlier experiments, both shift and hold cues appeared, on average, with equal frequency at each of these intervals. Cue type and target digit parity were randomly selected on each trial with the constraint that participants could receive no more than three consecutive cues of the same type (shift vs. hold) and parity (odd vs. even) combination in a row. A constant inter-trial-interval of 1,000 ms followed the final target digit frame.

Procedure

Training phase. We varied the probability that participants would receive cues to shift or hold attention across two color-defined contexts. All of the RSVP stimuli in a given trial were either red or green (Figure 4). Color remained constant throughout blocks of 60 trials each. Following each block, the color alternated. The first block was green for all participants and participants completed a total of 2 green and 2 red blocks. For 11 of the participants, 80% of all cues were shift cues when the stimuli were red and 80% of all cues were hold cues when the stimuli were green. The remainder of the participants received the opposite context-probability mapping. Participants received accuracy feedback during breaks occurring between each of the blocks.

Test phase. After completing four blocks of 60 trials each (2 blocks for each color context), we changed the probability structure of the task without notifying participants. For a remaining four blocks of 60 trials each, shift and hold cues appeared equally often in both contexts. All aspects of the test phase were identical to the training phase, except for this change in cue probabilities.

Debriefing. Immediately following completion of the study, we assessed the degree to which participants had conscious awareness of the cue-probability manipulation. Participants first read: "Did you notice anything about the color changes in the experiment?" and wrote their response on a separate sheet. Next participants read: "During the first half of the experiment, you had to shift attention more often when the stimuli appeared in one of the colors and hold attention more often when the stimuli appeared in the other color. Which color do you think was associated with more frequent attention shift cues (i.e., the letter 'K')?" Participants circled either "red" or "green" on a response sheet to indicate their response.

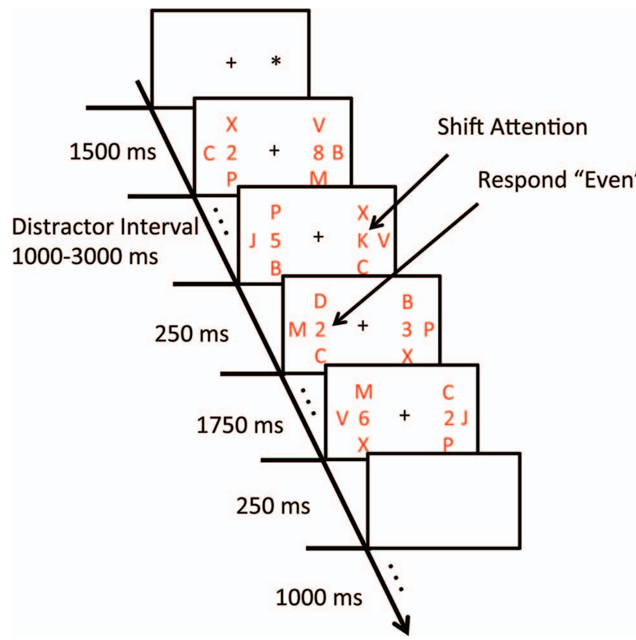

Figure 4. Behavioral task for Experiment 3. Participants monitored one of two rapid serial visual presentation (RSVP) streams for the appearance of a letter cue ("A" = hold attention, "K" = shift attention). Immediately after the onset of the cue, participants made a parity judgment for target stimuli appearing in the cued stream. During training, cue probabilities were asymmetric such that one color (either red or green) was associated with 80% shift cues while the other color was associated with 80% hold cues. During test, shift and hold cues were presented with equal frequency for both color contexts. See the online article for the color version of this figure.

Data analysis. As in Experiments 1 and 2, we removed trials with RTs greater than 3 *SDs* above or below the mean of each condition for each participant. This procedure resulted in a loss of less than 1% of training phase and less than 2% of test phase trials in which participants made a correct response. When examining RTs separately for the first and second half of the test phase, this procedure also resulted in the loss of less than 2% of trials with an accurate response.

Results and Discussion

Training phase. First, we tested whether RT for shift and hold attention trials varied as a function of cue probabilities. A 2 × 2 repeated measures ANOVA with factors of cue type (shift vs. hold) and context (mostly shift cues vs. mostly hold cues) yielded a significant main effect of cue type, $F(1, 19) = 58.66$, $p < .001$, $\eta_p^2 = .755$, such that participants made slower responses for shift attention trials than for hold attention trials. There was no significant main effect of context, $F(1, 19) = 0.69$, $p = .415$. A significant interaction of cue type and context, $F(1, 19) = 137.11$, $p < .001$, $\eta_p^2 = .878$, revealed that participants did modulate shift costs in response to changes in the underlying statistical properties of the environment. As illustrated in Figure 5A, shift costs were

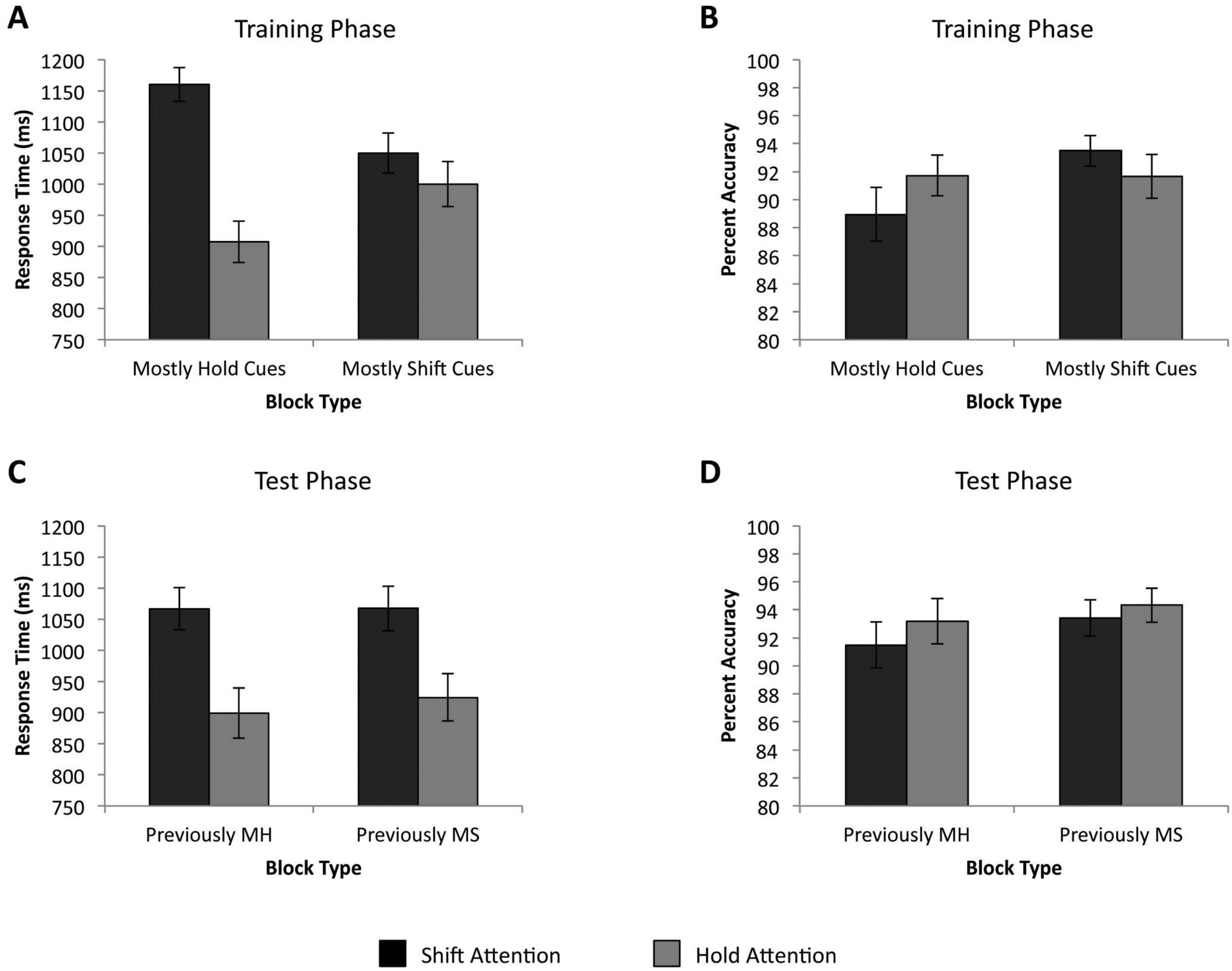

Figure 5. Behavioral results for Experiment 3. Response time (A) and behavioral accuracies (B) as a function of cue type and context for the training phase. Response time (C) and behavioral accuracies (D) as a function of cue type and context for the test phase. Error bars denote 1 between-subjects *SEM*.

larger for the context in which participants received mostly hold cues than that in which they received mostly shift cues.

We next examined behavioral accuracies across both cue types and contexts with an additional repeated measures ANOVA. The main effect of cue type, $F(1, 19) = 0.16$, $p = .695$, failed to reach statistical significance. However, there was a significant main effect of context, $F(1, 19) = 5.31$, $p = .033$, $\eta_p^2 = .218$, such that participants were less accurate in the mostly hold cue context than in the mostly shift cue context. Furthermore, the cue type by context interaction approached statistical significance, $F(1, 19) = 4.25$, $p = .053$, $\eta_p^2 = .183$, mirroring the pattern in RT (Figure 5B).

Test phase. Intertrial priming provides one potential account of the significant interaction in RT observed during the training phase of Experiment 3. Because there were mostly cues of one type in each block, the more frequent cue was more likely to be repeated across consecutive trials. To address this concern, we tested for behavioral modulations based on context when shift and hold cues were equally likely in the test phase. As in the training phase, we ran a 2 × 2 ANOVA with factors of cue type (shift vs. hold) and context (previously mostly shift cues vs. previously mostly hold cues) to test for differences in RT across conditions. Because shift and hold cues were equally likely in both contexts in the test phase, any observed differences in shift costs across contexts would be the result of learning from the training phase.

As in the training phase, participants had slower RTs for shift attention trials than for hold attention trials, $F(1, 19) = 83.70$, $p < .001$, $\eta_p^2 = .815$, but there was no significant main effect of context, $F(1, 19) = 0.91$, $p = .353$. Critically, there was a significant interaction of cue type and context, $F(1, 19) = 6.40$, $p = .020$, $\eta_p^2 = .252$, such that participants continued to have larger shift costs for the context previously associated with mostly hold cues than the context previously associated with mostly shift cues (mean difference in shift cost = 24.33 ms; Figure 5C). Learned modulations of attentional flexibility therefore persisted into the test phase.

It is possible that the significant interaction we observed when collapsing across the entire test phase was driven primarily by early performance before participants were able to adjust to the new probabilities. To investigate this possibility, for each subject, we computed the magnitude of the shift cost in each block of test phase trials. We compared shift costs in the first test-phase presentation of each context against those in the second presentation of each context with a 2 × 2 ANOVA with factors of context and half. There was no significant main effect of test phase half, $F(1, 19) = 0.82$, $p = .376$. It is important that the half by context by cue type interaction was not statistically significant, $F(1, 19) = 0.51$, $p = .485$, suggesting that the observed modulations of attentional control showed little evidence of extinction during the duration of the test phase.

Last, we tested behavioral accuracies in the test phase with an additional 2 × 2 repeated measures ANOVA. There were no significant main effects of cue type, $F(1, 19) = 3.32$, $p = .084$, or context, $F(1, 19) = 2.38$, $p = .140$, nor was the interaction between cue type and context significant, $F(1, 19) = 0.32$, $p = .580$ (Figure 5D).

The results of Experiment 3 provide converging evidence that individuals are able to use the statistical regularities of an environment to guide preparatory attentional control settings. Participants demonstrated differing levels of readiness to perform a spatial shift of attention as the result of statistical learning, even when there was no asymmetry in cue frequencies. Our results therefore cannot be attributed to intertrial priming effects. We observed more robust transfer of learning to the test phase of Experiment 3 than in Experiment 2. It is possible that the color-defined contextual manipulation was more salient than the temporally defined contexts of Experiments 1 and 2 and that the resultant learning was therefore more robust to a change in the underlying statistical structure. Similarly, blocking the stimuli during training may have strengthened the representation of the original underlying statistical regularities. Such persistence of preparatory attentional control modulations suggests that context-dependent statistical regularities may continue to influence behavior even after a change in the underlying statistical properties of the environment.

Debriefing. Three participants reported an explicit awareness of a relationship between stimulus color and cue probabilities. However, only 10 out of the 20 participants correctly identified the color that was associated with mostly shift cues during the training phase of the experiment following the forced choice prompt.

General Discussion

The stability of the focus of attention is known to vary across individuals (e.g., Cools, 2008). However, the need to flexibly update the focus of attention differs across situations and tasks. Differences in the efficacy with which individuals are able to maintain the focus of attention in the face of competing sensory information profoundly influence behavior (e.g., Barkley, 1997). Here, we provide the first evidence that the flexible control of attention can be modulated within an individual through learning, allowing for dynamic adjustments in preparatory attentional control settings to meet changing task demands.

Across multiple domains of statistical learning, we found that participants were more flexible (i.e., more ready to perform a shift of attention) when shifting attention was more likely than was holding attention. We found evidence of these learning-based modulations following less than 400 trials of training in Experiments 1–3, suggesting that statistical learning for preparatory attentional control states occurs much more rapidly than perceptual learning, which often occurs after thousands of trials of exposure (e.g., Kyllingsbaek, Schneider, & Bundesen, 2001; Roelfsema, van Ooyen, & Watanabe, 2010; Shiffrin & Schneider, 1977). In addition, in the case of color-defined contextual learning, we found evidence of a persistent influence of the previous statistical regularities even after shifting and holding attention became equally likely to occur in both contexts. Furthermore, there was a similar trend toward a persistent influence of previous learning following the temporal cue expectation manipulation in Experiment 2. Our results therefore suggest that statistical learning serves as an additional mechanism, along with trait-level individual variability and spontaneous fluctuations in neural activity, which shapes preparatory attentional control states.

Our findings are consistent with a growing body of research linking statistical learning to cognitive control. In particular, individuals modulate preparatory control for overcoming interference based on the statistical properties of an environment. Participants demonstrate greater Stroop interference for stimuli appearing in a location of the screen that was previously associated with a majority of congruent stimuli (Crump, Gong, & Milliken, 2006; Crump, Vaquero, & Milliken, 2008; Crump & Milliken, 2009). Similarly, interference is reduced in the Eriksen flanker and Stroop tasks when the relative frequency of conflicting stimuli is increased, providing evidence of conflict adaptation (Botvinick, Braver, Barch, Carter, & Cohen, 2001; Jiménez & Méndez, 2013). Researchers have also demonstrated that the probability of receiving conflicting flanker stimuli in different contexts, such as location on a computer screen, modulates preparatory cognitive control in a context-specific fashion. Participants showed greater flanker compatibility effects for stimuli appearing in a context previously associated with infrequent conflict (Corballis & Gratton, 2003; Lehle & Hübner, 2008; Vietze & Wendt, 2009). Furthermore, in a flankers task, individuals are able to implicitly learn that visual cues predict stimulus compatibility or the likely concordance, whether both stimuli tend to be either congruent or incongruent, of successive trials and adjust cognitive control settings accordingly (Ghinescu, Schachtman, Stadler, Fabiani, & Gratton, 2010; Zhao, Karbowicz, & Osherson, 2014). Our results provide converging evidence that contextual information guides preparatory control processes, extending these previous findings to the control of spatial attention.

The current experiments are also consistent with recent findings regarding statistical learning and attentional priorities. Individuals preferentially attend to target features that have previously appeared with greater frequency in a particular context (Cosman & Vecera, 2013, 2014). Our findings suggest that learned representations of the statistical regularities of an environment also influence how prepared an individual is to shift or maintain the current focus of attention. In particular, individuals are capable of dynamically updating such preparatory attentional flexibility according to expectations of cue frequency across contexts.

Our observed evidence of learned attentional flexibility converges with studies in the domain of task set switching. The cost associated with switching tasks is reduced when contextual cues such as the location on a computer display are associated with the likelihood of performing a particular task (Mayr & Bryck, 2007). Relatedly, contextual cues also facilitate task switching when these cues predict the likelihood of a task switch, rather than a particular task itself (Crump & Logan, 2010; Leboe, Wong, Crump & Stobbe, 2008). Our results provide evidence for the role of learning in shaping individuals' readiness to shift the focus of spatial attention, complementing and extending these prior demonstrations.

An important question for future research concerns the neural bases of dynamic adjustments in attentional flexibility according to learned statistical regularities. Researchers have identified genetic markers of persistent trait differences in cognitive flexibility (e.g., Cools, 2008). Specifically, concentrations of dopamine within the prefrontal cortex (PFC) as well as the striatum, mediated by polymorphisms of the catechol-O-methyltransferase (COMT) and dopamine transporter (DAT) genes, respectively, serve as a predictor of individual differences in cognitive flexibility (e.g., Bédard et al., 2010; Bertolino et al., 2006; Nolan et al., 2004). Furthermore, spontaneous fluctuations in neural activity correlate with, and may contribute to, moment-by-moment fluctuations in cognitive flexibility and preparatory attentional control (Leber, 2010; Leber et al., 2008). The neural mechanisms of contextually modulated preparatory control resulting from statistical learning remain less understood. In one recent study, activity in the medial superior parietal lobule (mSPL) served as a correlate of context-specific interference resolution in an Eriksen flanker task (King, Korb, & Egner, 2012). Given the role of mSPL in goal-directed switches in attentional selection (e.g., Chiu & Yantis, 2009; Esterman, Chiu, Tamber-Rosenau, & Yantis, 2009; Yantis et al., 2002; see also Serences & Yantis, 2006), further research should explore how posterior parietal cortex may be implicated in contextual modulations of attentional flexibility.

An additional unresolved question in the study of learning-based modulations of attentional flexibility is the degree to which individuals possess explicit knowledge of the underlying statistical structure. Previous studies of VSL have found that while VSL requires attentional selection, participants lack explicit knowledge of the learning (e.g., Turk-Browne, Jungé, & Scholl, 2005). In the current experiments, our measure of explicit awareness revealed that only a few participants self-reported knowledge of the statistical structure. Furthermore, when given a two-alternative forced-choice follow-up question, only participants in Experiment 1 selected the correct answer at a rate that was significantly above chance. Given our goal of studying the role of environmental structure in shaping preparatory attentional control, we did not design the current experiments to provide a rigorous test of explicit awareness. As a consequence, because of the somewhat crude nature of our debriefing measures, we refrain from making any strong claims regarding the degree to which participants had explicit awareness of the statistical manipulations. Future research is needed to more fully characterize the relationship between explicit knowledge of the underlying statistical structure and the learning-based modulations of preparatory attentional control identified in the present study.

Future research is also needed to explore the mechanisms behind the learned states of attentional flexibility that we observed across multiple manipulations. In particular, it is possible that the benefits we observed when individuals have learned to expect to shift attention in a particular context are because of a change in the breadth of attentional selection in addition to an increased readiness to perform a spatial attention shift. For example, the spread of attention is variable such that at some moments selection encompasses a comparatively narrow or broad region of space (e.g., Castiello, & Umiltà, 1990; Jefferies, Gmeindl, & Yantis, 2014). It is therefore possible that individuals broaden the spread of attentional selection when in contexts in which shifting attention is more likely than is holding attention. Alternatively, participants may be able to divide attentional selection in contexts in which shifting attention is likely (e.g., Jans, Peters, & De Weerd, 2010).

The domain generality of learned flexibility remains unknown. In particular, such flexibility may be specific to a single task context or cognitive operation (e.g., shifting spatial attention), or may involve broader modulations that apply to other contexts and domains of cognition. Since contextual learning also modulates preparatory control over an individual's readiness to update task sets and resolve response conflict (e.g., Crump et al., 2006; Crump & Logan, 2010), learned flexibility in each of these domains may share a common mechanism and consequently tend to fluctuate together in response to environmental regularities. Alternatively, learned states of preparatory control within a particular domain may change independently in accordance with uniquely associated alterations in environmental regularities.

The current study demonstrates that the statistical properties of an environment dynamically shape the adjustment of preparatory attentional control settings. Differences in the probability of shifting or holding attention across temporally or color-defined contexts modulated attentional flexibility such that individuals were most flexible in contexts for which shifting was highly probable. Our results therefore suggest that preparatory attentional control is sensitive to statistical regularities and that previously learned representations of statistical properties can evoke associated states of cognitive flexibility. We provide an account of how individuals rapidly and effortlessly modulate the focus of attention across a wide range of environments, each with different demands on the nature of information processing. More broadly, the present study suggests that the stability of the focus of attention can be (at least to some degree) learning-dependent, which has implications for how we understand both healthy and disordered fluctuations in attentional control.

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