SELECTION HISTORY:
A THIRD SOURCE OF BIAS IN ATTENTIONAL CONTROL?

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ABSTRACT

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Researchers have long posited that attention is controlled through two modes: a bottom-up mode in which attention is directed automatically to items based on their physical salience and a top-down mode in which the observer exerts volitional influence to prioritize information relevant to current task goals. Recently, however, others have begun to question the validity of this model and suggest that attention is also driven by prior experience. The current work investigates how this third mechanism, called selection history, is implemented in visual search. We conducted a series of experiments to investigate the conditions under which observers could learn to prioritize a frequently selected feature. Participants searched for a target horizontal or vertical line, which appeared in one of two possible colors, among diagonal distractors and made a judgement about the target (i.e. length or orientation). Each experiment began with a training phase, during which targets were presented more frequently in one of the two possible colors (called the "high probability color"), followed by a test phase in which targets appeared equally often in both colors. We predicted that participants would continue to respond more quickly to targets presented in the high probability color in the test phase, and that this learning would occur implicitly and thus be distinguishable from top-down control. In addition to this question, Experiments 1 and 2 examined whether color must be bound to other defining features of a stimulus (i.e. the lines must appear in colored font) for participants to implicitly develop a lingering bias toward the high probability color in the line length judgement task.

The results of these experiments indicated that participants implicitly learned to prioritize the high probability color regardless of whether color was inherently bound to the stimulus. The remaining experiments tested whether implicit learning that leads to a lingering bias attributable to selection history occurs automatically when specific features are encountered more frequently and are diagnostic of outcomes. Specifically, we predicted that implicit learning would be modulated by the amount of attention devoted to the task and whether perceptual load permitted the passive processing of irrelevant but predictive color. Experiments 3 and 4 tested this prediction by manipulating the selection difficulty (the ease of distinguishing a target from distractors). In both tasks, participants prioritized the high probability color overall, but this effect was driven by participants who explicitly recognized the high probability color. Finally, Experiment 5 manipulated the perceptual difficulty of distinguishing the stimuli from the background by comparing the performance of participants who viewed the stimuli in a high contrast white font (Experiment 5a) to those who viewed the stimuli in a low contrast dark gray font against the black background (Experiment 5b). Although the participants in the low contrast condition responded more slowly overall, both groups showed evidence of implicit learning associated with a lingering bias for the high probability color. We conclude that implicit learning, beyond simple repetition priming, is not a process that occurs automatically when features are encountered repeatedly or diagnostic of outcomes, but may require an optimal level of task difficulty to ensure that attention is devoted to the task and free to process color.

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CHAPTER 1

GENERAL INTRODUCTION

The visual environment is overflowing with information that the limited-capacity attention system is unable to process simultaneously. To ensure efficient encoding, one must select and prioritize only the most relevant items from amongst competing inputs, where they can be encoded into working memory and used to serve current goals. This process is called selective attention, and has long been a central topic in the study of human cognition. However, despite a wealth of attention literature, how objects in the environment compete to gain attentional priority remains a topic of active study and speculation. The items in the environment that compete most effectively for attention can change depending on internal states of the observer, the environment, the task, and the stimuli. Current theories posit that attention is controlled volitionally, based on internal control settings and task goals, and automatically based on salient or novel properties in the environment that capture attention. For example, to read this manuscript requires deliberate coordination of voluntary attention. If a fire alarm were to sound, however, attention would be drawn automatically to its loud sound and bright flashing light alerting of potential danger. These two categories of attentional control, known as top-down and bottom-up, respectively, are thought to represent the sources of information that can bias competition for limited attentional resources to select the most important or relevant stimuli from the environment.

The top-down and bottom-up dichotomy gained widespread acceptance, in part, because there is evidence that the two sources of attentional bias operate under separate neural and cognitive mechanisms. Investigators have suggested that top-down and bottom-up attention are distinct “modes” of attentional control, and that these signals are associated with unique patterns of neural activity in frontal and parietal cortices (Buschman & Miller, 2007). Results from human neuroimaging studies have corroborated these findings, identifying largely distinct fronto-parietal brain networks that support top-down and bottom-up attention (Corbetta & Shulman, 2002; Corbetta, Kincade, Ollinger, McAvoy, & Shulman, 2000; Downar, Crawley, Mikulis, & Davis, 2000). Furthermore, although top-down and bottom-up attention both influence attentional selection, their effects on selection may be distinct. Top-down attention benefits attentional selection for items consistent with goals, but bottom-up attention may help to encode items that were previously unattended but may be behaviorally relevant. For example, Prinzmetal, Park, and McCool (2005) argued that bottom-up, or involuntary attention, is a reflexive orienting response that can help bias attention to respond quicker to a cued location, whereas the voluntary mechanism of attention enhances the representation of information. They demonstrated that bottom-up attention could improve reaction time, but that only the allocation of voluntary attention could improve accuracy. Thus, the authors demonstrated two separate mechanisms for top-down and bottom-up attention. Recently, Ravizza, Uitvlugt, and Hazeltine (2016) replicated this finding with working memory encoding. They found that top-down attention was more effective than bottom-up attention at improving memory for cued items during a change detection task, but that bottom-up attention could help bias selection to encode cued items first and benefit memory via primacy effects. Top-down and bottom-up attention may likewise affect selection on different timescales. Early deployment of attention is thought to reflect only bottom-up influences, with top-down attention implemented later (Theeuwes, 2010; Theeuwes, Atchley, & Kramer, 2000).

Together, top-down and bottom-up biases draw attention to encode information that is consistent with goals or inherently salient, novel, distinct, or otherwise attention-grabbing. Some investigators have argued that what captures attention, even automatically, is determined largely by the observer's current goals and internal control settings relative to the properties of the stimulus (Folk, Remington, & Johnston, 1992; Folk, Remington, & Johnston, 1993; Bacon & Egeth, 1994; Wolfe, 1994; Folk, Leber, & Egeth, 2008; Eimer & Kiss, 2008). Conversely, others have suggested a more substantial role for low-level features in controlling attention automatically despite task goals or internal settings (Yantis, 1993; Theeuwes & Godijn, 2002; Theeuwes, 2004). The optimal selection of relevant information, however, is thought not to rely on one source over the other, but rather to depend on optimized, dynamic interactions and integration of biases from both modes (Corbetta & Shulman, 2002; Serences, Shomstein, Leber, Golay, Egeth, & Yantis, 2005; Asplund, Todd, Snyder, & Marois, 2010; Connor, Egeth, & Yantis, 2004; Navalpakkam & Itti, 2006; Theeuwes, 2010).

Despite the prominence of the top-down and bottom-up attention dichotomy, however, it may not adequately encompass all factors that influence selection. One important question regarding the characterization of attention into a top-down and bottom-up dichotomy is the boundary between the two sources. Katsuki and Constantinidis (2014) define bottom-up attention as "an externally induced process in which information to be processed is selected automatically because of highly noticeable features of stimuli," (p. 509) and top-down attention as "an internally induced process in which information is actively sought out in the environment based on voluntarily chosen factors" (p. 509). These definitions illustrate a fundamental issue with the top-down and bottom-up dichotomy: the terms "top-down" and "goal-driven" are frequently used interchangeably to describe any influence on attention that cannot be attributed to salient or novel properties of the stimulus itself. This nomenclature raises the question of whether attention can be categorized as "top-down" if an observer cannot willfully control it based on task goals, or as “bottom-up” if a stimulus captures attention in an automatic way without being inherently salient or distinct.

It is problematic to equate top-down attention and goal-driven attention because internal settings are not always under volitional control, and they do not always affect attention in a manner that is beneficial to goals. For example, attention can be automatically and robustly drawn to stimuli that have been associated with reward or frequent selection. Indeed, when attention is biased toward behaviorally relevant items, previously learned associations between stimuli and outcomes can facilitate selection of goal-relevant information (Gong & Li, 2014; Jiang, Sha, & Remington, 2015). However, in other circumstances, attention is persistently and robustly biased to features or locations that have been previously selected even when they are neither goal relevant, nor inherently salient, at times rendering their selection contrary to current task goals (Della Libera & Chelazzi, 2006; Anderson, Laurent, & Yantis, 2011a; Sali, Anderson, & Yantis, 2014). The traditional dichotomous approach to attentional control places these situations in the same category as volitionally attending a goal-relevant stimulus, defining them as instances of top-down control stemming from learned regularities in the environment (Navalpakkam & Itti, 2006; Baluch & Itti, 2011; Jiang et al., 2015). However, because this type of selection is influenced by internal settings, occurs in an automatic way outside of voluntary control, and cannot be attributed to inherently noticeable features of the stimulus, it does not conform to the traditional top-down and bottom-up dichotomy of attentional control in which top-down attention is equated with goal-driven attention (Awh, Belopolsky, & Theeuwes, 2012).

There are a number of attentional phenomena within these “gray areas” of attentional selection, which several investigators have attempted to resolve by broadening the definition of top-down attention to extend beyond goal-driven selection (Baluch & Itti, 2011; Jiang et al., 2015). Others, however, have begun to consider additional sources of attentional bias beyond the traditional top-down and bottom-up dichotomy. Awh, Belopolsky, and Theeuwes (2012) suggested a mechanism of selection history that accounts for prior experience with a stimulus or feature. Through selection history, attention may be biased to continue to select stimuli that have been previously attended. The authors suggest that selection history, in addition to goals and salience, can influence attentional priority when items are repeatedly selected or associated with reward.

In the following sections, I discuss several phenomena in which attention is biased outside of voluntary control and in the absence of inherently salient features. These phenomena include statistical learning, repetition priming, and reward learning. I then discuss evidence supporting an integrated model of attentional control, as suggested by Awh and colleagues (2012) that includes selection history as a third source of attentional bias. Finally, I discuss the potential mechanisms of selection history, arguing that despite its relative novelty as a source of attentional bias, considering the role of selection history in attentional control follows intuitively from what is already known about the role of learning in perception and attention.

Statistical Learning

There are many situations where attention can be biased to encode information based on selection history without volitional, goal-driven control or highly noticeable features. For example, attention can be influenced by regularities in the environment or patterns in stimulus presentation. Through this type of learning, called statistical learning, observers can automatically learn to exploit nonrandom, predictive (statistically regular) patterns. Statistical learning can occur incidentally and implicitly regardless of explicit recognition of these meaningful structures (Perruchet & Pacton, 2006). The idea that human observers are adept at statistical learning as an algorithm to automatically interpret the world has existed for decades. Early vision scientists acknowledged the preposterous nature of a theory of perception that assumes a random selection process, asserting that the visual system must account for statistical regularities and reduce redundancies in order to process information efficiently (Helmholtz, 1925; Field, 1987). Similarly, Gibson (1979) acknowledged the importance of "education of attention," which depends on experience and learning from environmental regularities. These early investigators demonstrated that natural visual environments are teeming with regularities and meaningful structures that can provide context to enhance the efficiency of selection, which human observers are adept to detect and exploit (for a review, see Barlow, 2001).

Several investigators have found behavioral and neural evidence of this type of incidental statistical learning, which has been demonstrated regardless of whether participants are explicitly aware of statistical regularities. Using fMRI, Turk-Browne, Scholl, Chun, and Johnson (2009) found evidence of statistical learning in participants who viewed a set of 24 glyphs. Half of these stimuli were presented in a structured set, where sets of 3 glyphs were always presented in the same order (a total of 4 triplets), whereas the remaining 12 glyphs were presented in random order. Participants identified "jiggles" in the stimuli, which were characterized by brief rapid motion of the glyph occurring at random intervals throughout the experiment. Afterward, participants completed a familiarity test, which revealed that nearly all of the participants were unaware of the repeated patterns in the stimuli. The authors found activation in brain regions such as the striatum and medial temporal lobe, which are implicated in other forms of associative learning (Liljeholm & O'Doherty, 2012; Mayes, Montaldi, & Migo, 2007; Burgess, Maguire, & O'Keefe, 2002; Schapiro, Turk-Browne, Norman, & Botvinick, 2016).

Chun and Jiang (1998) further illustrated this concept in visual search, showing that participants implicitly learned to locate targets faster when they were presented in repeated configurations across blocks regardless of explicit recognition of these patterns. In a later study, Jiang and colleagues (2015) again illustrated a role for implicitly learned regularities predictive of target location in guiding attention. Participants searching for a target letter "T" among L-shaped distractors located the target faster when it was presented more frequently in one quadrant of the screen (50% of trials versus 16.7% in the remaining 3). Importantly, participants developed these biases in the absence of explicit awareness of the structure and continued to locate targets in the previously high probability quadrant faster even when target was presented equally often in each quadrant. Thus, the authors demonstrated that participants could learn and exploit regularities to prioritize a region of space even when it was no longer advantageous to attend one quadrant over the others. Although the authors considered the competitive advantage of the high probability quadrant and development of a premotor attention "habit" a driver of top-down attention, they acknowledged that it is separate from goal-driven selection.

Repetition Priming

In addition to statistical learning, which is thought to occur automatically when features, locations, or configurations are more predictive of targets, Jiang and colleagues (2015) proposed a role for repetition priming in facilitating the selection of frequently repeated targets. Repetition priming occurs when features or locations that are selected repeatedly are selected more efficiently. Similar to the guidance of attention through statistical learning, priming occurs automatically and outside of volitional control. Maljkovic and Nakayama (1994) found that participants still showed robust effects of repetition priming (i.e. responded faster to repeated targets than switched targets) even when they were explicitly instructed or given a consistent, alternating pattern of target presentation. The authors concluded that priming is an automatic process that cannot be willfully overcome, and that despite observer knowledge and predictability between trials, this knowledge could not be used to improve task performance.

There has been debate among scientists about how priming fits into the top-down and bottom-up dichotomy. Maljkovic and Nakayama's (1994) conclusions suggest that priming is not "top-down" because it is not under the observer's volitional control, but should be considered bottom-up because it is an automatic process (Leonard & Egeth, 2008). However, Wolfe, Butcher, Lee, and Hyle (2003) describe this type of priming as an implicit form of top-down guidance, suggesting that because priming occurs independently of salience, prior knowledge, even implicit, is better characterized as a form of top-down attentional bias. Again, however, "top-down" biases from priming are distinct from goal-driven influences, making repetition priming another attentional phenomenon that does not fit clearly into the goal- versus stimulus-driven account of the top-down and bottom-up attention dichotomy.

Contingent Capture

Another example of an attentional phenomenon that defies clear classification into top-down or bottom-up sources and further illustrates the need to expand theories of attention beyond the traditional dichotomy is contingent capture. Previously described as a hybrid between top-down and bottom-up biases, contingent capture occurs when items that share a feature with a target capture attention in an involuntary manner but are not inherently salient (Folk et al., 1992; Serences et al., 2005; Folk et al., 2008; Eimer & Kiss, 2008). Folk and colleagues have argued that attentional capture is not purely "bottom-up", as they showed evidence that what captures attention is often related to current task goals and previously selected information. However, although contingent capture of attention for items sharing target features relates to goal-driven processing, contingent salience often distracts from task goals and is thus not necessarily best characterized as top-down in a model that assumes top-down and goal-driven are synonymous. Additionally, other contingent capture experiments using fMRI have shown evidence that the same brain regions, including the temporo-parietal junction and the ventral frontal cortex, that are active when stimulus-driven attention is captured (see Corbetta & Shulman, 2002) are likewise activated under conditions of contingent capture (Serences et al., 2005).

Furthermore, Belopolsky, Schreij, and Theeuwes (2010) demonstrated that attentional capture could occur independent of top-down goals. The authors found that when targets changed between trials, both task-relevant and irrelevant properties captured attention despite participants being informed of the target on the upcoming trial and therefore provided with the opportunity to adopt a top-down set. Consistent with Malikovic and Nakayama (1994), the authors argued that many findings attributing contingent capture to top-down control are confounded by intertrial priming from repeated selection that is largely outside of top-down control. Thus, rather than being seen as the intersection between top-down and bottom-up attention, it may be useful to characterize contingent capture as a history effect, wherein stimulus properties capture attention because they have been previously selected.

Attentional Bias from Reward Learning

Repeated selection or detection of regularities in stimulus properties or configurations represents one potential category of selection history effects on attention, through which context, nonrandom structure, and repeated selection influence the efficiency of attention. A second category emerges from the study of reward learning. Reward is a powerful tool to shape behavior and influence task motivation. It has been associated with enhanced attention, perhaps due to functional coupling between reward-sensitive brain regions and attentional networks

(Mohanty, Gitelman, Small, & Mesulam, 2008; Stănişor, van der Togt, Pennartz, & Roelfsema, 2013). Recent evidence has shown that stimulus-reward associations can alter attentional priority, such that when specific locations or features are associated with stronger reward value, these stimuli compete more effectively for limited attentional resources independent from goals and salience (Anderson et al., 2011a).

Della Libera and Chelazzi (2006) first demonstrated the effect of prior reward association on attention. Using a negative priming paradigm, the authors found that when participants were highly rewarded for ignoring a particular stimulus, selection for that stimulus was impaired on subsequent trials. Conversely, stimuli associated with low reward were selected more quickly during subsequent trials, suggesting that low value distractors were not inhibited as strongly as high value distractors. The authors interpreted this finding to suggest that the low reward feedback, indicative of suboptimal performance, led to a more rapid resetting of attentional control, whereas the inhibition of stimuli previously associated with high reward persisted. It has since been established that attention can be robustly guided to features that have previously been associated with higher reward value (Della Libera & Chelazzi, 2009; Anderson et al., 2011a; Camara, Manohar, & Husain, 2013; Chelazzi et al., 2014; Gong & Li, 2014; Bucker, Silvis, Donk, & Theeuwes, 2015).

Anderson and colleagues (2011a) demonstrated this concept using a paradigm in which participants implicitly learned to associate a particular color with a high reward. In these experiments, participants completed a training phase, during which the target was defined as either a red or a green circle, and made a judgment about the target (i.e. orientation of a line segment contained within the circle). One color was associated with an 80% chance of receiving a high reward, and the other was associated with an 80% chance of receiving a low reward.

Importantly, participants were not informed of these contingencies, but they learned them implicitly over hundreds of trials. Following the training phase, participants completed a separate test phase in which the color became irrelevant (i.e. the target was now defined as a shape singleton, for example, a diamond among circles). Some trials included a circle of the high reward color, and some included a circle of the low reward color. Anderson and colleagues found that participants responded slower to the target on trials that included a high-value distractor, suggesting that their attention was still drawn to the rewarded color even when this was contrary to goals. The authors interpreted these findings to suggest that stimuli previously associated with high reward captured attention automatically. Critically, the low-reward color did not influence attention in the same manner as the high reward color, a result that Anderson and colleagues attributed to a unique influence of reward beyond the frequent presentation of specific colors. The authors termed this phenomenon value-driven attention capture (Anderson, 2013; Anderson, 2016). This paradigm has since been replicated and extended, further illustrating that high-value stimuli continue to compete for attention even when reward contingencies are no longer enacted (Anderson, Laurent, & Yantis, 2011b; Anderson, Laurent, & Yantis, 2014; Anderson et al., 2017; Qi, Zeng, Ding, & Li, 2013).

In addition to selection, reward may also influence perceptual representation of an item and subsequent memory. Gong and Li (2014) used a similar training task wherein participants identified a canonically oriented line and responded to its orientation. The line was surrounded by a red or green circle, with one color associated with a high probability of receiving a high reward and the other associated with a high probability of receiving a low reward. In the test portion of this experiment, however, participants performed a change detection task. The authors found that participants remembered stimuli presented in the high reward color more accurately than the low reward or unrewarded colors, suggesting that reward can modulate both attentional capture and perceptual representation. Interestingly, when stimuli in the change detection task were also made salient (i.e. a bolded bar), memory for these items was not improved. In a follow-up experiment, Gong and Li replaced reward feedback with performance feedback, simply indicated whether participants responded correctly. Similar to Anderson (2011a), performance feedback did not influence attentional capture to items that were previously selected in the absence of reward feedback.

Critically, these studies demonstrate that reward can influence attention in the absence of explicit awareness and separate from salience and goals. In support of the notion that goal-driven attention operates separately from reward-related changes to attention, Jiang and colleagues (2015) included an experiment in which participants were informed of reward contingencies and thus encouraged to use top-down attention in attempt to maximize reward outcomes. The authors utilized a target detection task in which participants searched for a letter "T" among L-shaped distractors while one quadrant of the screen was associated with a higher reward. In some of these experiments, participants were explicitly told to maximize reward by identifying and prioritizing the high reward quadrant. Participants who were successfully able to determine the high reward quadrant showed the strongest attentional bias toward that location (i.e. faster RT to stimuli presented in the high reward quadrant), suggesting that top-down bias from explicit instruction controlled attention more strongly than implicit learning. Furthermore, Anderson, and colleagues (2011b) dissociated this effect from salience-driven attentional capture, demonstrating that high reward associated features captured attention more robustly than salient, unrewarded distractors.

An Integrated Model of Attentional Control

Thus, attention can be elicited in a habitual manner when stimuli have been selected frequently or associated with reward. This type of habitual attention can persist even when selection is contrary to current task goals and even when the selected features or stimuli are not inherently salient, distinct, novel, or otherwise attention-grabbing. These points raise a key issue with current models of attentional selection: although the terms "top-down" and "goal-driven" are used synonymously, investigators cannot classify phenomena that are neither goal-driven nor inherently salience-driven without reformulating their definitions of what is considered "top-down" and "bottom-up." Neither bottom-up nor top-down attention, as defined formerly (Katsuki and Constantinidis, 2014), adequately describes automatic attention to learned features, stimuli, and patterns.

If automatic guidance outside of the observer's control is the criterion for attention to be bottom-up, then the characterization of these phenomena as a source of top-down bias is inherently contradictory. Although these circumstances arguably originate from internal "top-down" sources, they are not goal-driven and therefore should not be placed in the same category of biases as goals, as current models suggest. Conversely, if a stimulus must be selected purely based on the novelty or distinctness of its features to elicit bottom-up attention, then it is no more accurate to classify the former situations as a bottom-up manner of guiding attention. Some investigators have attempted to resolve this inconsistency by expanding the definition of top-down attention to encompass any influence on attention from internal control settings, knowledge, or biases of the observer, even one that occurs automatically or outside of willful control. For example, Baluch and Itti (2011) distinguished between two separate top-down mechanisms: a volitional top-down process that is directly modulated by willful and deliberate attention and a mandatory top-down mechanism that modulates attention automatically.

Although a broader definition of top-down attention is reasonable, current iterations of the top-down and bottom-up dichotomy rarely make the distinction between processes that are under volitional control and processes that may be "top-down" but are not "goal-driven." Instead, a more comprehensive model of attention should make allowances for circumstances under which attention is controlled through lingering biases to attend familiar information. The mechanism of selection history, as suggested by Awh and colleagues (2012) provides a framework to accomplish this. Selection history is defined as any bias to attention related to learning and experience with a stimulus or feature. This includes biases from learning of consistent, regular patterns in stimulus presentation, repeated encounters with stimuli or features, and reward history. In this framework, attentional biases from selection history are distinct from goal-driven and stimulus-driven influences.

Although selection history is a relatively recent addition to theories of attentional selection, the idea that prior experience can modulate selection is well established. In addition to goals and physical salience, recent theories of attention suggest that this experience makes its own unique contribution to attentional priority. Awh and colleagues (2012) suggested an integrative framework by which distinct categories of selection bias are integrated via a priority map to determine how various items compete for attention. In this framework, rather than selection occurring because of current goals, physical salience, or selection history per se, biases from each of the three sources contribute to determining an item's overall attentional priority.

The priority map hypothesis of attention provides a plausible framework to integrate biases from a variety of sources. This theory proposes that each item in the visual environment possesses a variety of physical qualities that can affect its salience or relation to current task goals. These qualities may be encoded by distinct feature maps, but are integrated in a singular priority map that represents a combination of distinctiveness and relevance of each item. When multiple items compete for attention, the item that is represented most strongly in the priority map is selected (Fecteau & Muno, 2006). Current theories suggest that an efficient attentional selection mechanism should be able to integrate information from multiple sources, typically top-down and bottom-up, such that information can flow back and forth between the priority map and sensory regions to bias low-level perception in favor of a highly competitive stimuli or features (Ptak, 2012). Awh and colleagues (2012) proposed that, in addition to goals and salience, this priority map can also represent information from previous encounters and learned value.

Recent work has begun to provide support for Awh and colleagues' (2012) notion that selection history effects are likewise exerting influence on attentional priority. Chelazzi and colleagues (2014) found that reward-based training produced changes in attentional priority, such that participants were able to detect targets more quickly and accurately in spatial locations that were previously associated with a high reward. These changes were still apparent four days after training, suggesting that spatial priority maps were altered based on the reward structure learned in the training portion of this experiment. Klink, Jentgens, and Lorteije (2014) suggested that different priority signals from goals, salience, and value might originate in different brain regions, such as the frontal cortex, visual cortex, and midbrain structures such as the striatum, respectively. Inputs from these regions may then be integrated elsewhere in the brain, such as the frontal eye fields, to form the integrated priority map utilizing information from goals, salience, and value to determine how well a given item will compete for attention.

These findings and theories are likewise consistent with proposed neural mechanisms of the attentional priority map. This priority map is thought to exist in the posterior parietal cortex (PPC), a region involved in attentional selection (Behrmann, Geng, & Shomstein, 2004; Corbetta et al., 2000; Malhortra, Coulthard, & Husain, 2009; Bisley & Goldberg, 2010). The PPC, along with the frontal eye fields (FEF), is part of the dorsal frontoparietal attention network (Corbetta & Shulman, 2002; Stanton, Bruce, & Goldberg, 1995), which is modulated by both top-down and bottom-up attention, thus making this region a viable candidate for integration of biases from multiple sources. Furthermore, Jarbo and Verstynen (2015) found that the caudate nucleus and the putamen, brain regions implicated in associative learning, each contain projections from orbitofrontal, dorsolateral prefrontal, and parietal brain regions. Thus, it is likely that the connections between these regions and attention networks support contributions from associative learning to attentional priority.

The Selection History Mechanism

The integrated priority map hypothesis provides a clearer view of how different sources of information can be integrated to determine how effectively items compete for attentional resources. Like the top-down and bottom-up dichotomy, this model acknowledges the role of current goals and physical salience in determining an item's priority, but it adds the third category of selection history to account for the role of learning and prior experience. Although the term "selection history", as it relates to attentional control, was defined recently (Awh et al., 2012), there are a number of well-established concepts in cognitive psychology that, when viewed through the lens of selection history, reveal the intuitive nature of considering the role of past experience in attentional selection. Broadly speaking, the mechanisms of selection history may alter attention in one of two ways: brief changes in attentional bias, such as inter-trial influences from repetition priming, and persistent bias from learning and memory. Both can alter attentional priority for previously selected items, but each may have different implications for the duration of changes in attention (Sha et al., 2017).

In a recent study, Sha and colleagues (2017) dissociated the conditions under which brief and persistent changes in attention toward previously selected features emerged. In these experiments, participants searched for a target (vertical or horizontal line among diagonal distractors) that could appear in one of two possible colors. In some experiments, the target was presented in one color more frequently than the other (75% versus 25% of trials), but only one color was presented in a given trial and always corresponded with a target. Thus, each time an item was presented in one of the two possible colors, it had a 100% chance of being a target despite the probability that it would be presented. In these experiments, participants responded faster to the high probability color during the training phase of the experiment. However, during the final block (test phase), when the two possible target colors were presented equally often, participants failed to show a bias toward the high probability color. The authors interpreted these results to suggest that faster RT to the high probably color could be attributed to repetition priming alone, and that although priming represents a rapid accumulation of information that can alter attention on a short timescale, longer changes require more than repetition alone.

Conversely, in other experiments, the authors presented both colors concurrently during each trial, but during the training phase, one was a target 75% of the time, and a distractor the other 25%. These values were reversed for the second color, such that it was a target only 25% of trials and a distractor on 75%. With this method, the high probability color became more predictive of the target than the low probability color, creating a statistical regularity that participants learned implicitly, which the authors termed “diagnostic value.” The high probability color competed for attention more strongly even in the test phase when it no longer benefited participants to prioritize one color over the other. Unlike the rapid and short-term changes from repetition priming, manipulating the diagnostic value of a feature produced a stronger association that persisted throughout the duration of the experiment. Thus, although priming can lead to faster attention to repeated stimuli, persistent changes to habitual attentional control are thought to occur because of associative learning mechanisms and will not develop unless some reward contingencies or specific features are more predictive of a target (Sali et al., 2014; Sha et al., 2017).

Repetition priming may influence attention on a brief timescale by accumulating information between trials about the likelihood that a target will occur in a given location or feature because visual search is facilitated when features or locations are repeated between trials because features remain in an activated state and thus maintain a lower activation threshold (Kristjansson & Campana, 2010; Dobbins, Schnyer, Verfaellie, & Schacter, 2004). Priming is characterized by reductions in cortical activity across several brain regions in response to repeated stimuli (Wig, Grafton, Demos, & Kelley, 2005; Thiel et al., 2005). Early visual areas show decreased responses to repeatedly presented stimuli, but these changes in activation are not correlated with behavioral priming effects (Schacter, Wig, & Stevens, 2007). Greater reduction in activity in frontal regions associated with priming is correlated with increased behavioral switch costs when targets do not repeat, which indicates that reduction in brain activity may represent a decreased reliance on controlled processing for repeated items. When the target is switched, however, control processes must be reactivated (Dobbins et al., 2004). These findings support the hypothesis that priming occurs outside of controlled processing and may thus fit better within a history-driven rather than top-down category of attentional control. Furthermore, some attention researchers have argued that effects such as contingent capture and apparent top-down guidance in visual search from information held in working memory can be explained by repetition priming (Theeuwes, Reimann, & Mortier, 2006).

Priming can be characterized both as a type of selection history, which results in short-term prioritization of features that are repeatedly selected, and a mechanism through which longer-term learning leading to persistent lingering biases toward frequently selected features can develop. Logan (1990) proposed that priming and automaticity share a common underlying mechanism through which "instances" in which a stimulus was encountered are recalled when they are encountered again. Repeated associations between stimuli and outcomes are likewise a key component to learning (Poldrack, Selco, Field, & Cohen, 1999; Hauptmann & Karni, 2002). It is possible that priming effects account for a portion of the attentional biases seen in previously selected stimuli, but that recollections must be committed to long-term memory via an alternative mechanism to affect persistent changes in attentional priority. Hauptmann and Karni (2002) found that consolidation to long-term memory was related to priming processes. However, they suggested that it was not priming itself, but rather the saturation of priming effects, that may help induce learning processes and consolidation.

Although priming may automatically change attentional priority on a short timescale and potentially contribute to long-term learning given enough trials, priming is not the only mechanism through which environmental regularities can be learned and exploited. Other associative learning mechanisms may be dissociated from priming, through which attention is habitually shifted to locations or features that are attended most frequently in an automatic "procedural" form of attention (Jiang, Swallow, & Capistrano, 2013; Jiang et al., 2015). Because the visual environment is not completely random, humans are sensitive to statistical regularities and adept to learn associations between stimuli and outcomes. Rescorla and Wagner (1972) proposed that the amount of associative learning depends on the strength of the association between stimuli. When there are strong associations between a feature and an outcome, for example, the outcome can be predicted based on the stimulus. The more often a particular feature is associated with a particular outcome, the stronger these associations become.

Associations between stimuli and outcomes are learned over time as they are consistently paired. Through this incidental learning mechanism, attention is involuntarily drawn to regularities in the environment, which can influence expectations about future encounters. Expectations can modulate behavior and neural signals, thereby facilitating decision-making about objects that have been previously encountered (Summerfield & de Lange, 2014; Sallet et al., 2007). Expectations can similarly bias selective attention. Cheadle and colleagues (2014) found that human observers showed the greatest bias toward information that was consistent with expectations from previous stimuli, and that this bias was evident in behavioral and physiological measures, including pupillometric signals, fMRI, and electroencephalography (EEG). They suggested that bias toward recent and consistent information represent a mechanism to control the gain of sensory information by strengthening representations of information that is expected in a given context and thereby facilitating perception and attention to environmental regularities. Nonhuman primate work further supports this hypothesis. For example, neurons in macaque cortex begin to increase firing associated with a more probable response prior to the presentation of a stimulus (Hanes & Schall, 1996; Gold & Shadlen, 2007). In this way as an observer learns to associate a particular feature or location with a higher reward or greater chance of predicting a target, which influences attention separate from goal and physical salience in a manner that is consistent with Awh and colleagues' (2012) category of selection history.

A Unitary Mechanism?

Of note, the question of whether learning from reward structure and statistical learning are best characterized under the same class of attentional guidance remains open. Awh and colleagues (2012) characterized both of these types of learning as instances of selection history. There are a number of reasons for this assumption. First, both reward and statistical learning are characterized by implicit recognition and exploitation of learned regularities that guide attention robustly in the absence explicit knowledge. Second, factors other than monetary reinforcement such as performance feedback (Ravizza, Goudreau, Delgado, & Ruiz, 2012; Ravizza & Delgado, 2014) can effectively increase task performance. Levy and Glimcher (2012) suggested that neurons represent various types of value as a “common neural currency” by which attention is influenced, suggesting that value may be represented in a domain-general manner. Successful completion of goals, which can be enhanced by predictive environmental factors, may generate internal reward signals that reinforce attention to particular features. Similar neural reward signals may underlie the enhancement of attention to other factors predict favorable outcomes, such as positive feedback and more accurate task performance gained from exploiting environmental regularities. Finally, there is evidence that brain regions such as the striatum and modulation of early visual cortex are involved in both types of learning (Turk-Browne et al., 2009; Anderson et al., 2014).

Alternatively, other evidence suggests the contrary, namely that history effects from prior selection may involve completely separate cognitive and neural processes that are distinct from reward-driven processing. Anderson and colleagues (2011a), and Gong and Li (2014) demonstrated that simply presenting a color more frequently did not enact changes in attentional priority in the absence of reward feedback. This may suggest that there are differences between attentional effects from repeated selection and from reward history. However, given that Sha and colleagues (2017) recently provided evidence that the repetition of features alone produced only transient changes in attention that could be attributed to priming, this finding may simply reflect a lack of diagnostic information available in these selected features. Furthermore, Anderson, Chiu, DiBartolo, and Leal (2017) demonstrated that although value-driven attention capture was blunted in depressed individuals, attentional biases related to unrewarded selection history remained robust. The authors interpret this as further evidence that value-driven attention and selection history related to repeated, unrelated encounters with specific stimuli or features are best characterized as separate influences on attention. It is possible that there is a common learning mechanism underlying changes to attention from both selection and reward history, but that reward history includes additional emotional components that relate specifically to reward processing. Conversely, Wingard and colleagues (2015) found evidence that this type of hippocampal-dependent response learning was dissociated from the gradual "habit" learning processes of the striatum. Thus, it is also possible that statistical learning depends more on hippocampal learning mechanisms and reward learning depends more on striatal learning mechanisms.

Abnormal reward processing has been implicated in clinical conditions including depression and anhedonia (Ravizza et al., 2016; Anderson, Chiu, DiBartolo, & Leal, 2017). On the other extreme, heightened sensitivity to reward has been associated with increased attentional biases to rewarded stimuli and other conditions such as addiction and risk-taking behavior (Anderson, Faulkner, Rilee, Yantis, & Marvel, 2013; Hickey, Chelazzi, & Theeuwes, 2010). Individual differences in susceptibility to attentional capture from previously rewarded stimuli may help explain why some individuals develop disorders such as depression and addiction.

Furthermore, understanding the relationship between attention and clinical conditions such as depression and addiction may serve to clarify the relationship between reward-related attentional capture and other forums of selection history (Anderson, Chiu, DiBartolo, & Leal, 2017). In a more recent study, Kim and Anderson (2019) directly compared the neural mechanisms of reward learning to those of repeated selection in the absence of reward feedback. The authors found that only reward learning was associated with dopaminergic regions such as the caudate tail, whereas capture effects of stimuli selected repeatedly were only associated with changes in visual areas. Thus, although reward and statistical learning through frequent repetitions of features or patterns are both ways that previous experience can change attention, and thus fall under the broader category of selection history, it is likely that these processes rely on separate underlying mechanisms.

Summary

Although the top-down and bottom-up dichotomy has remained a prominent theory of attentional control, the lack of clear distinction between "top-down" and "goal-driven" processes has led some to consider alternative sources of information that can bias attention. The third category of selection history, as proposed by Awh and colleagues (2012), includes repetition priming, statistical learning, and reward learning. Through repeated selection and associative learning mechanisms, which are well established in psychological research, selection history accounts for the natural ability of the visual system to detect and exploit nonrandom, predictive structures in the environment to efficiently direct attention. In addition to goals and salience, selection history is thought to affect how information competes for limited resources. The priority map hypothesis argues that any given item in the environment can have a value in each of the three categories, and items that have the greatest activation in this priority map compete most strongly for attention. This approach provides a clearer framework for understanding how information competes for attention than the traditional top-down and bottom-up dichotomy.

CHAPTER 2

PREDICTIONS FOR SELECTION HISTORY VIA STATISTICAL LEARNING

In recent years, a number of attention researchers have begun to accept the priority map hypothesis and consider the role of selection history in attentional control. Despite the surge of acceptance for selection history, however, it remains a relatively new area of study and thus warrants further investigation to understand how and when it can affect attentional priority. Previously, we have discussed selection history including both reward and statistical learning. However, given the likelihood that there are distinct cognitive and neural mechanisms underlying these effects, the remainder of the current work will focus on selection history from frequent selection in the absence of reward. Furthermore, although statistical learning can bias attention toward predictive locations (Jiang et al., 2015), temporal presentations (Turk-Browne et al., 2009), and spatial configurations (Jiang et al., 1998), we limited our assessment of statistical learning to predictive features, specifically color, particularly because there is evidence detailing some of the specific conditions under which predictive features lead to persistent, implicit statistical learning (i.e. diagnostic value; Sha et al., 2017).

Here, we will investigate two questions about how statistical learning biases attention. First, can statistical learning bias attention separate from goal-driven attention, or are these effects driven by participants who become explicitly aware of predictive values and thus confounded by goal-driven attention? Second, is statistical learning a passive phenomenon that occurs automatically when features are encountered repeatedly, or can it be modulated by task conditions? To test these questions, we designed a series of experiments based on the paradigm developed by Sha et al. (2017) because it allowed us to test our research questions using small variations in the presented stimuli. Furthermore, the original results provided evidence for statistical learning that occurred separate from goal-driven control, which is important to establish before testing other predictions about implicit statistical learning. In the task, participants searched for a target horizontal or vertical line among diagonal distractors. Each line in the display could be short (1° visual angle) or long (2° visual angle), and participants reported the length of the target line. Targets were presented in two possible colors with unequal probability (75% in the high probability color and 25% in the low probability color) during a training phase. In the final blocks of the experiment, however, targets appeared equally often in both colors. Participants continued to respond faster to targets presented in the high probability color even when it was no longer beneficial to prioritize one color over the other. Thus, this paradigm demonstrated statistical learning for a frequently selected color that was predictive of a target.

Implicit Statistical Learning vs. Goal-Driven Attention

One aspect of the traditional top-down and bottom-up dichotomy that contributed to its prominence is the ability to dissociate the psychological and physiological contributions of top-down and bottom-up modes of attention (for a review, see Corbetta & Shulman, 2000). The priority map hypothesis suggests that a combination of relevance to current goals, physical salience, and previous experience determine an item's relative competitiveness for limited attentional resources (Theeuwes, 2019). However, with this approach, the ability to parse out contributions from different sources of attentional bias remains important to understanding how the most relevant information is selected from the environment. Specifically, if including selection history, along with goals and salience, provides a more accurate view of attentional control than the prominent dichotomous model, it is critical to demonstrate that learning can influence selective attention independent from goals and salience.

Although there is some debate over the amount of goal-driven control that one can exert using explicit knowledge to guide visual search (Theeuwes et al., 2006; Theeuwes, 2018), Jiang and colleagues (2015) demonstrated that when participants were told that one region of space would be associated with a higher reward, they were able to use this knowledge to find targets in the high reward quadrant more efficiently. In this way, it is possible that explicit recognition confounds goal-driven attention with selection history. Selection history may still be involved when regularities are explicitly recognized, but a key assumption of this model is that learning can occur implicitly and bias attention outside of explicit awareness and contrary to goals. Although some experimenters have found this type of result in statistical learning (Sha et al., 2017; Jiang et al., 2015), given their small sample sizes, they lack the statistical power necessary to detect the possible contributions of explicit awareness to their results.

Importantly, approximately half of the participants in the experiments conducted by Sha et al. (2017) were considered explicitly aware of the probability differences between colors, which might have falsely inflated the effect attributed to implicit learning. Thus, one purpose of the current work was to replicate these findings using a larger sample size and to examine the contribution of explicit recognition of environmental regularities to effects previously attributed to selection history in statistical learning. Experiment 1 tested this question by replicating Sha and colleagues' (2017) original experiment using a larger sample size to test whether the implicit learning effect that the authors found would replicate and to examine potential effects of explicit awareness in this task. Participants were tested for explicit awareness through self-report questions administered following the completion of the task. Although this question was particularly important for Experiment 1, the role of explicit awareness was examined in all of the experiments in this work.

Statistical Learning and Task Difficulty

A second question of interest to the present work concerns the conditions under which statistical learning can occur and lead to lingering biases capable of enacting changes to attention. Statistical learning might not occur automatically when some features are encountered more often or are more predictive of targets than others. For example, several investigators have found that simply presenting a stimulus repeatedly does not always lead to persistent changes in its relative priority beyond intertrial repetition priming effects (Sha et al., 2017; Gong & Li, 2014; Anderson et al., 2011a); however, given enough trials, it is possible for an observer to develop a persistent bias to attend a frequently selected color through repetition alone (Anderson et al., 2017; Kim & Anderson, 2019). Generally, however, statistical learning is thought to rely on more than repetition priming to persistently change attention.

One example is the learning of diagnostic features, as suggested by Sha and colleagues (2017). Specifically, when the high and low probability colors were presented separately, the authors argued that both colors were equally predictive of targets during the trials in which they appeared. However, when both possible target colors were presented simultaneously in each trial, the high probability color became more predictive of the target, whereas the low probability color became more predictive of a distractor. Thus, participants developed a persistent bias to attend the high probability color under the latter condition, but not the former. Because Sha and colleagues demonstrated in multiple experiments that diagnostic features are important to the development of persistent attentional biases from statistical learning, we included both the high and low probability color in each trial in all of the current experiments. Keeping diagnostic features consistent across experiments allowed us to test other factors that might likewise influence statistical learning.

In addition to stronger predictive relationships between stimuli and outcomes from diagnostic features, other task factors might also influence whether observers can implicitly learn to prioritize features that are selected repeatedly. First, statistical learning might be influenced by whether the predictive feature is bound to other defining features of the target. Previous studies have demonstrated that binding can modulate attention. For example, in the Stroop task, during which participants are instructed to name the font color while ignoring a color word, interference between incongruent color/word pairs (i.e. the word 'blue' presented in red font) is reduced when font color is separated from color words (Risko, Stolz, & Besner, 2005), or when only one letter of a word is presented in an incongruent color font (Besner & Stolz, 1999). Thus, the ability to attend the font color and ignore the distracting word is modulated by binding.

Binding between a predictive feature and other defining features of a target might likewise influence statistical learning. Sha and colleagues (2017) used colored lines for the stimuli in their experiments testing whether participants would learn to prioritize a color in which targets appeared more frequently. Although the targets were defined based on orientation (vertical/horizontal targets versus diagonal distractors) and judged based on length (long versus short lines), it is possible that the inherent binding of stimulus color with these features contributed to participants' ability to learn associations between color and probability of finding a target. If the color is separated from the defining features of the target (e.g. the target is surrounded by a colored box instead of presented in colored font), then participants may pay less attention to color and thus learn these associations less often. Alternatively, if separating color from the defining features of the stimulus reduces attention to color, observers may still learn to prioritize a predictive color, but be less likely to become explicitly aware of its predictive value. Experiment 2 tested the role of binding color with other defining features of the stimuli in statistical learning by presenting the lines in white font surrounded by colored font rather than presenting colored lines.

Another factor that may affect statistical learning in a visual search paradigm is the difficulty of the task. Task difficulty might influence statistical learning by modulating the amount of attention allocated to the task. Previous studies have demonstrated that when predictive features are ignored, implicit learning does not occur (Jiang & Chun, 2001). When a visual task is simple and relatively efficient, an observer is generally able to find a target quickly, accurately, and with relatively little cognitive effort. Under these conditions, an observer is likely to devote less attention to the task, which might reduce their ability to implicitly learn even in the presence of diagnostic features if these are largely unattended. Furthermore, an easier task during which performance is already efficient might be insensitive to measure implicit learning effects. However, when task difficulty increases, search becomes less efficient and would require increased allocation of attentional resources to locate a target (Huang & Pashler, 2005). This allocation of task-related attention might be a necessary component to statistical learning. If this is true, then statistical learning may only occur when a task is difficult enough to engage attention.

Alternatively, the role of task difficulty in statistical learning could be explained by attentional load theory (Lavie, Hirst, Fockert, & Viding, 2004; Lavie, 2005). Load theory predicts that different types of load affect an observer's susceptibility to distracting information in different ways. Increased perceptual load is thought to reduce interference from distractors when perceptual capacity is exhausted with the processing of relevant information. Alternatively, increased load on working memory or other cognitive control functions is thought to affect frontal control processes responsible for maintaining task goals. When cognitive load becomes too great, these processes fail to maintain task goals and the observer becomes susceptible to distractor interference. Because targets in Sha and colleagues' (2017) experiment were defined by orientation and judged on length, participants should have seen color as an irrelevant feature. Thus, increased perceptual load from a more difficult task might exhaust attentional resources to process relevant information (i.e. orientation, which is the defining feature of the target) and prevent processing of irrelevant features (color). Alternatively, the task of judging the target's length requires an extra processing step and might load on working memory, which would explain why participants in this task were able to learn to prioritize the high probability color. The higher working memory load of the length judgment task might have allowed attention to drift to the irrelevant color information, and this passive processing might be necessary for statistical learning.

Experiments 3 through 5 in the present work focused on the role of perceptual difficulty in statistical learning. To keep working memory load constant in these tasks, participants performed a simplified task during which they were instructed to locate the target defined by its orientation and to report the orientation. Two manipulations of perceptual load were employed. First, targets are easier to locate when they are more distinct from distractors, which may occur because visual search is thought to rely on matching visual information to an internally maintained target template and this process becomes more difficult when targets and distractors are not easily distinguished (Duncan & Humphreys, 1989). We refer to this as selection difficulty, meaning the difficulty of distinguishing between targets and distracting stimuli. Experiments 3 and 4 tested the effects of selection difficulty on statistical learning by manipulating the distinctness of the target from the distractors. Second, visual search tasks are also more difficult when stimuli are lower contrast or more difficult to distinguish from the background. We refer to this as perceptual difficulty, which should likewise increase perceptual load. Experiment 5 tested the effect of perceptual difficulty on selection history by manipulating the contrast of the stimuli against the background.

It was hypothesized that selection and perceptual difficulty would both increase perceptual load and thus affect statistical learning similarly. Changing task difficulty was expected to modulate implicit statistical learning by affecting the amount of processing allocated to color. First, if increasing task difficulty leads participants to pay more attention to the task overall and this increased task-related attention leads to implicit learning, then participants should develop a bias to attend the high probability color regardless of explicit awareness. Conversely, decreasing task difficulty should not engage task-related attention and implicit learning should be less likely to occur. If the data support this prediction, then participants should only implicitly learn to prioritize the high probability color in the more difficult conditions. Importantly, if participants become explicitly aware of the predictive value of the color, then they may volitionally prioritize targets in the high probability color regardless of task difficulty. This effect, however, would not be attributable to implicit statistical learning, but would be confounded with goal-driven attention because aware participants may purposely devote more attention to the high probability color if they recognize its predictive value. Instead of viewing color as an irrelevant feature, these participants are likely to incorporate color into their search template in a top-down manner.

Alternatively, if the role of task difficulty is not a function of attention but is consistent with load theory, then increasing task difficulty by imposing a greater perceptual load might prevent processing of color, which should not be prioritized as a relevant feature to locating a target that is defined by its orientation. If high perceptual load prevents the processing of color without explicit awareness, then only aware participants should show a bias to attend the high probability color in both the training and the test phase. Unaware participants, on the other hand, should not prioritize the high probability color in either phase of the experiment if the task is too difficult to allow processing of the seemingly irrelevant feature of color. Similarly, decreasing task difficulty by presenting highly distinct targets and distractors or high contrast stimuli would result in a decreased perceptual load, which may allow for increased processing of color. If more attentional resources are available to process seemingly irrelevant features such as color, then all participants should prioritize the high probability color under easier task conditions regardless of explicit awareness.

Finally, statistical learning might require an optimal level of task difficulty if both task-related attention and load theory reflect components of statistical learning. If this prediction is supported, then implicit statistical learning should not occur when task difficulty is too high to allow attention to irrelevant features, as predicted by load theory. Conversely, in an easier task, although attention would be allocated to color, without sufficient task-related engagement of attention, persistent and implicit learning would not occur. Thus, unaware participants in the easier conditions would be expected to process color only passively and show a transient bias toward the high probability color during the training phase that would dissipate quickly and not persist into the test phase. Because high probability color targets appear more frequently, participants should show this effect because of repetition priming if attention is devoted to color (Sha et al., 2017). Furthermore, with more attention freed to process color and without goal-driven strategy to bias performance, the behavior of unaware participants might be more strongly driven by the implicit regularities in the task. Thus, these participants might be better able to adapt to the changing predictive values of color in the training and test phases of the task even if they are not explicitly aware of these contingencies.

CHAPTER 3

IS STATISTICAL LEARNING SEPARATE FROM GOAL-DRIVEN ATTENTION?

Experiment 1

The purpose of Experiment 1 was to test whether implicit, statistical learning can occur separate from goal-driven attention. This task was a direct replication of the experiment developed by Sha and colleagues (2017), which was designed to ensure that we could reproduce the same implicit learning effect and test whether this effect could be attributed to goal-driven attention via explicit awareness. Because Sha and colleagues found that approximately half of participants in each of their experiments explicitly recognized the high probability color, it is possible that these effects were driven by the aware participants and that the unaware participants did not implicitly learn to prioritize the high probability color. If this is true, then the effect attributed to implicit statistical learning might be confounded with goal-driven attention because it is likely that aware participants volitionally prioritized the high probability color. This is especially problematic because of the small sample sizes used in the original experiment (~12 participants per experiment). Thus, we replicated this task using a larger sample size to increase statistical power to detect any effect of explicit awareness.

We expected the results of Experiment 1 to mirror those of the original paper, namely that participants would develop a persistent bias to prioritize the high probability color, which would be evidenced by faster response times to high probability color targets. We expected this bias to be present during both the training phase, where targets occurred more frequently in the high probability color, and during the test phase, where probabilities are equal and it was thus no longer beneficial to prioritize one color over the other. Furthermore, consistent with the original experiment, we predicted that approximately half of participants would be able to explicitly recognize the high probability color, but a bias to prioritize the high probability color during the test phase would occur consistently regardless of whether participants became explicitly aware of probability differences between colors. In other words, we predicted an overall main effect of color that would not be overshadowed by an interaction between color and awareness.

Method

Participants

Data were collected from 53 participants, who were students at Michigan State University (ages 18-30). The task was completed in a single, 1-hour session. Participants were recruited using Michigan State University's Human Subjects Pool (SONA) and received one hour of course credit for their participation in this experiment. Participation was voluntary. All procedures were approved by the Human Research Protection Program at Michigan State University, and written informed consent was obtained from all participants before beginning the experiment. Of the 53 participants, data from four were excluded from analysis – three participants were removed for performing at chance level accuracy (~50% correct trials), and one was removed for a high proportion of removed trials after the exclusion of extreme RT trials (< 150 ms or > 3 standard deviations above the individual's mean RT). This left 49 participants for the final analysis.

Stimuli

Stimuli for this experiment included a set of colored lines (red, yellow, cyan, magenta, blue, and lime) that were oriented horizontally, vertically, or diagonally (45° clockwise and counter clockwise). There were long (2° visual angle) and short (1° visual angle) versions of each line stimulus. Participants responded to the stimuli using a standard keyboard and all responses were collected using E-Prime software.

Procedure

This experiment was designed to replicate Experiment 2 from Sha et al. (2017). In this task, participants searched for a target horizontal or vertical line and reported its length (long or short). The target was always either a red or a green line, and the high probability color was be counterbalanced between subjects. The task comprised of a training phase and a testing phase. During the training phase, the target was presented more frequently in one of the possible target colors (75% of trials) and less frequently in the other (25%). During the test phase, the target appeared equally often in both colors. Both possible target colors appeared in each trial to ensure that the high probability color gained a greater diagnostic value (Sha et al., 2017).

The general trial layout for these experiments is illustrated in Figure 1. Each began with the presentation of a fixation dot for a period of 400, 500, or 600 ms (jittered), followed by the presentation of the stimulus. The stimulus consisted of an array of six line stimuli (see Figure 1A). One was the target horizontal or vertical (red or green) line and the rest were long and short diagonal distractors presented in the remaining five colors. Importantly, participants were instructed to find the target based on its orientation and were not informed that the target was only presented in two possible colors. The stimulus remained on the screen until participants made a response and were followed by a 1000ms feedback display indicating whether the participant responded correctly. If their response time was longer than 1000 ms, they received a message asking them to respond faster.

Participants completed 16 blocks of this experiment with 48 trials each. The first 12 blocks comprised the training phase, and the testing phase included the remaining four. At the end of the task, participants were asked two questions to measure their explicit recognition of the high probability color: "Do you think that the target was presented with equal frequency in either color, or do you think that one color was presented more frequently than the other?", "The target was presented more frequently in one color than the other. On the next screen, each possible target color will be numbered (1 and 2). Please press the key on the number pad corresponding to the color that you think contained the target more frequently. If you are unsure, please guess." On the following screen, participants received a forced choice between red and lime and indicated which one they believed to be the high probability color. Responses to these questions were collected and participants who reported that one color was presented more frequently than the other and correctly guessed the high probability color were considered explicitly aware.

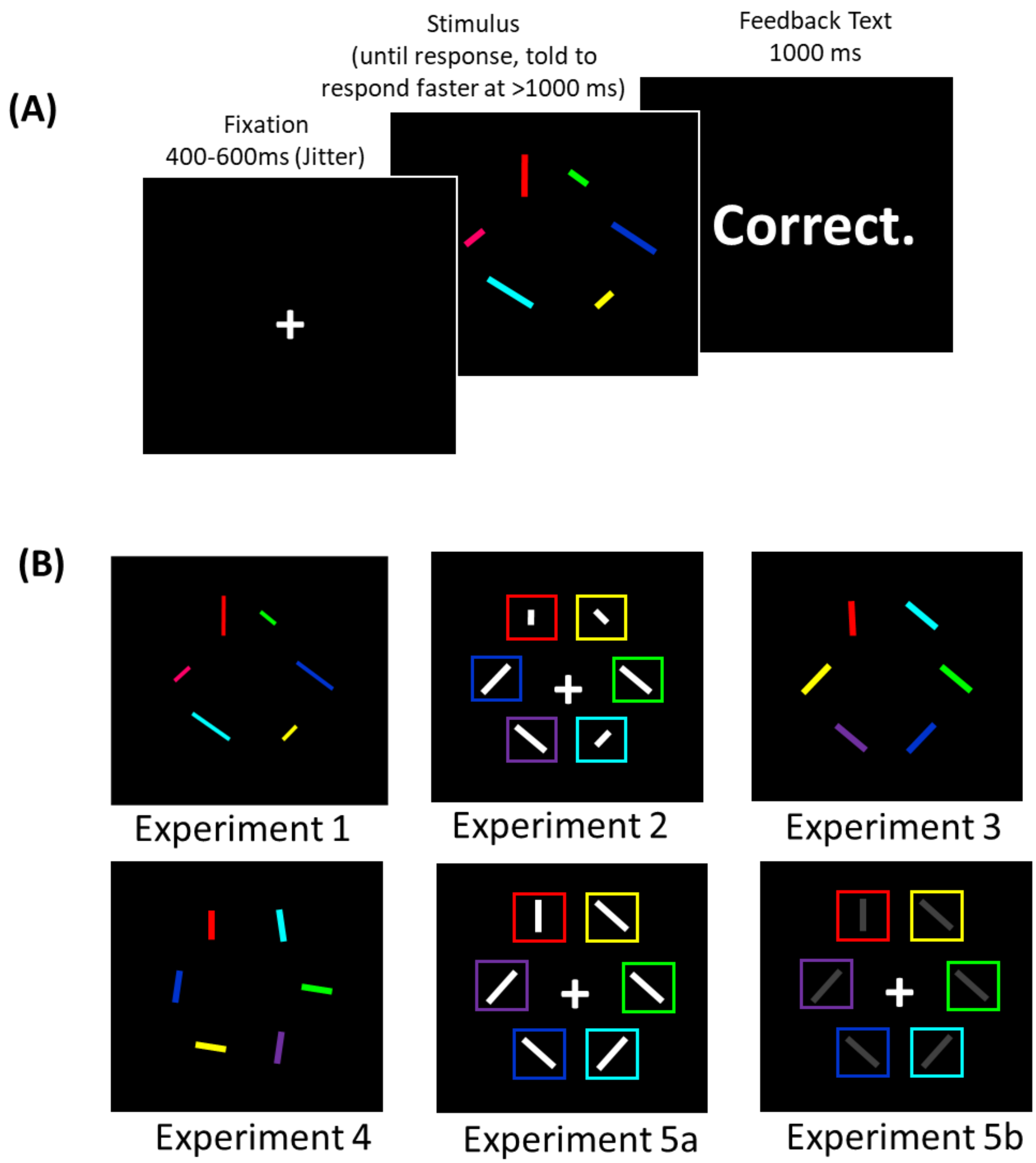

Figure 1. General trial layout (A) and an example of a stimulus for each experiment (B). In each experiment, participants searched for a target defined by its orientation (the horizontal or vertical line amongst diagonal distractors) and reported either the length or the orientation of the target. Targets occurred more frequently in one color during the training phase (Blocks 1 – 12) and occurred equally in both possible colors during the test phase (Blocks 13 – 16).

Results

Average accuracy was relatively high (M = .82, SD = .12), but substantially lower than in the original study, in which average accuracy for this task exceeded 90% (Sha et al., 2017). Participants were significantly more accurate for targets presented in the high probability color (M = .85, SD = .11) relative to those presented in the low probability color (M = .78, SD = .15), $t(48) = -4.72$, $p < .001$. Following the original study, we focused the remainder of the analyses on the RT data. Before examining RT data, trials were removed during which participants responded extremely quickly (< 150 ms) or extremely slowly (> 3 standard deviations above the individual's mean RT). The average number of kept trials was high (M = .97, SD = .07). Thus, we removed less than 3% of trials, retaining 97% for analysis. From these retained trials, only correct trials were included in the RT analysis.

To recapitulate, this experiment consisted of a training phase (blocks 1-12), in which targets were presented more frequently in one color, and a test phase (blocks 13-16) in which targets were equally likely to appear in both possible colors. To test the effect of color over time during the training phase, we conducted a Block (1-12) by Color (low and high probability color) repeated-measures ANOVA. This analysis revealed substantial main effects of both Block, $F(11,528) = 19.59$, $p < .001$, $\eta_p^2 = .29$, and Color, $F(1,48) = 48.40$, $p < .001$, $\eta_p^2 = .50$. There was no interaction between Block and Color, $F(11,528) = .80$, $p > .1$, $\eta_p^2 = .02$. In the training phase, participants consistently responded more quickly to the high probability color and became faster overall as the task progressed (Figure 2A). For the test phase, we conducted a second Block (13-16) by Color (low and high probability color) repeated-measures ANOVA. There was a main effect of Color, $F(1,48) = 20.93$, $p = .012$, $\eta_p^2 = .30$, but no main effect of Block, $F(3,144) = .59$, $p > .1$, $\eta_p^2 = .01$, and no interaction, $F(3,148) = .07$, $p > .1$, $\eta_p^2 = .002$. Thus, participants continued to respond faster to the high probability color during the test phase of this experiment when the target was presented in the two colors with equal frequency.

Finally, we examined whether these results were dependent upon explicit awareness. Of the 49 participants included in the final analysis, 31 noticed that one color was more likely to be a target and were able to identify the high probability color. Thus, in this particular sample, more than half of participants were considered aware (~ 63%). To test whether the results were dependent upon explicit awareness, we repeated the analyses of both the training and test phases including Awareness as a between subjects factor to see if there was a significant interaction between Awareness and Color. The Condition X Awareness interaction term was not significant in the training phase, $F(1,47) = .46$, $p = .50$, $\eta_p^2 = .01$, or the test phase, $F(1,47) = 3.00$, $p = .09$, $\eta_p^2 = .06$, indicating that the results of were not dependent upon explicit awareness (Figure 3).

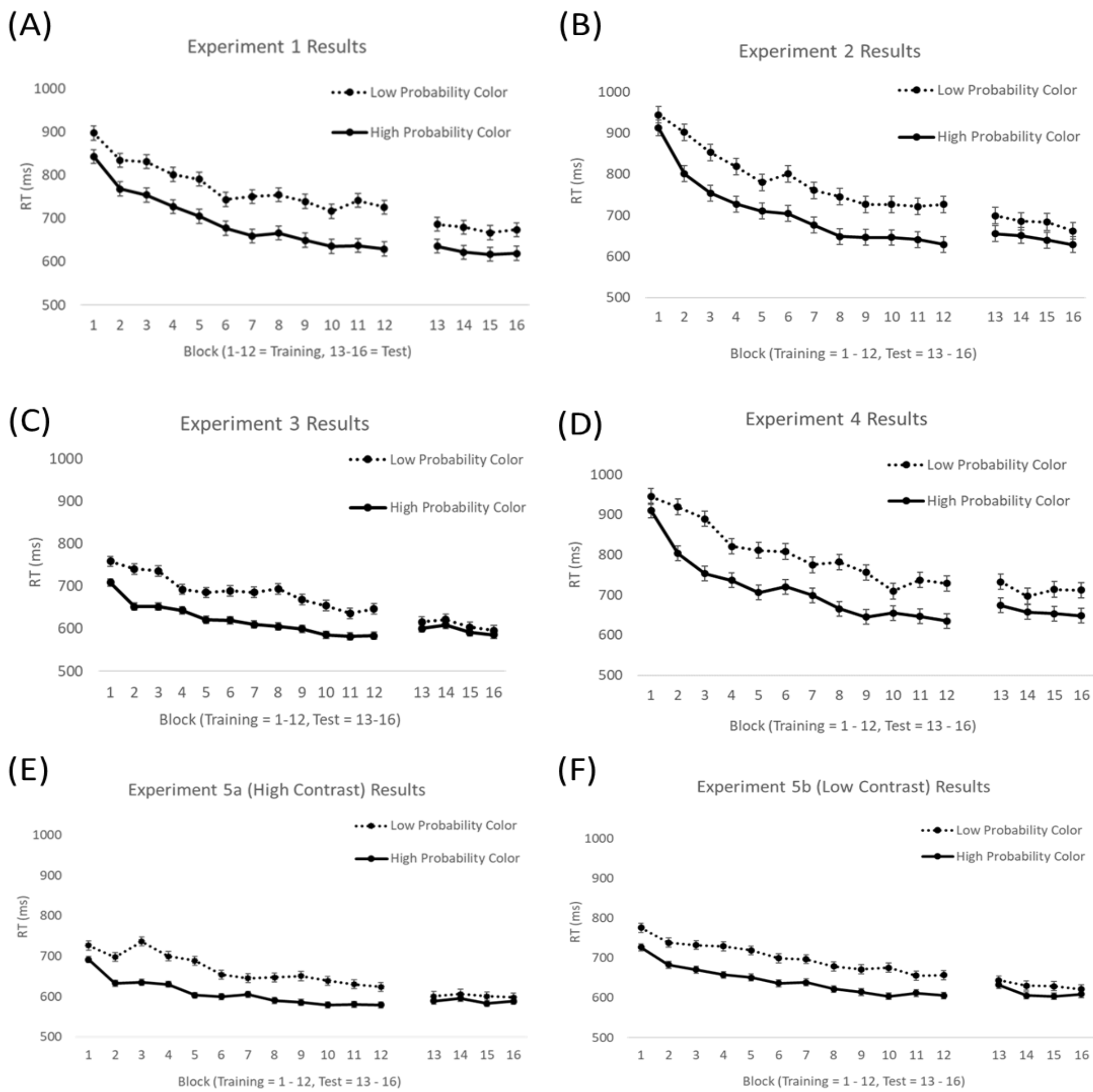

Figure 2. The results of Experiment 1 (A), Experiment 2 (B), Experiment 3 (C), Experiment 4 (D), and Experiment 5 (E and F).

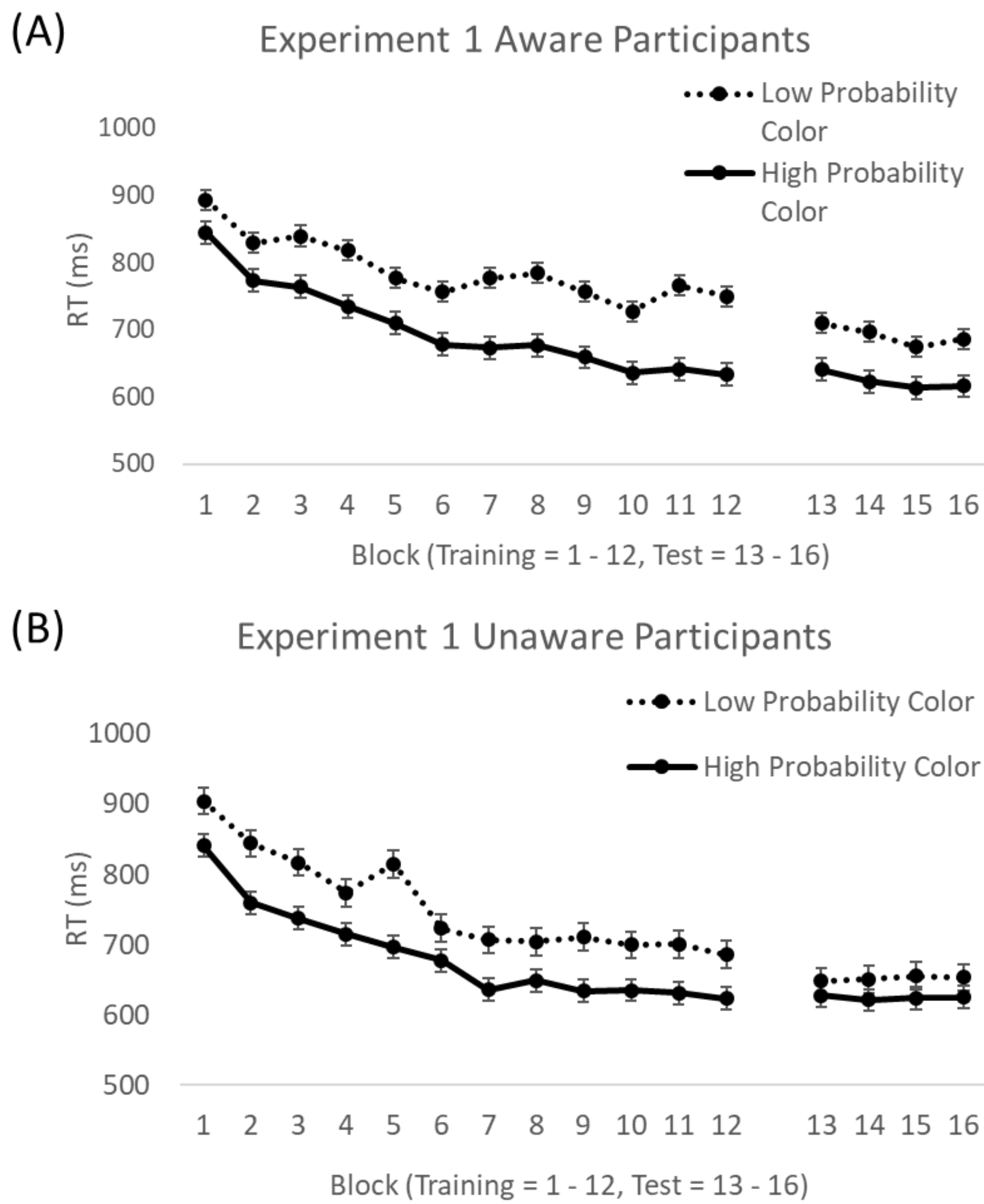

Figure 3. Results separated by explicit awareness. Participants still responded faster to the high probability color even when they were not explicitly aware of its predictive value.

Discussion

Experiment 1 was a direct replication of Sha and colleagues' (2017) second experiment. The purpose was to ensure that the statistical learning effect would replicate using a larger sample size and to further examine the possible confounding role of explicit awareness in this paradigm. We predicted that our results would be comparable to the original study; participants would respond faster to the high probability color in the training phase, and this effect would persist into the test phase. Furthermore, we predicted that although a substantial proportion of participants might become explicitly aware of the high probability color, there would not be a significant interaction between color and explicit awareness. Our results supported these hypotheses: participants did respond faster to the high probability color in both the training and test phases of the experiment, and although over half of participants were considered explicitly aware, the interaction between color and awareness was not significant. Thus, the effect of color did not depend on explicit awareness.

The results of this experiment support the prediction that implicit statistical learning can influence attention separate from volitional goal-driven control. Regardless of explicit awareness, participants continued to respond more quickly to targets presented in the high probability color in the test phase. This result is consistent with other studies of visual statistical learning, which have likewise suggested that statistical learning can occur outside of explicit awareness (Sha et al., 2017; Kruijne & Meeter, 2016; Jiang et al., 2015; Turk-Browne et al., 2009). Interestingly, however, over half of the participants in this experiment did become explicitly aware of the probability differences. This result is consistent with Sha and colleagues (2017), who found that approximately half of participants were aware of the high probability color in all of their experiments. However, it is possible that a number of the participants considered explicitly aware responded accurately to both questions by chance. Thus, in future experiments, we also asked participants to rate their level of confidence in their responses to the questions given to gauge whether participants truly recognized the high probability color or were unsure of their responses and therefore more likely guessing.

Explicit awareness may be inconsequential to statistical learning because it is a passive, automatic process. Experiment 1 provides support for this prediction. Both aware and unaware participants showed evidence of processing the stimulus colors in both the training and the test phase. Although there is likely a significant contribution of priming to this effect during the training phase due to more frequent repetitions of the high probability color, contributions of intertrial priming are unlikely to create differences during the test phase when targets occurred equally often in both colors. Sha and colleagues (2017) attributed this effect to the importance of diagnostic features to persistent learning. However, there are a number of other features of this task that might contribute to its effectiveness in eliciting implicit statistical learning. If statistical learning is truly a passive and automatic process that relies on the learning of diagnostic features, then participants should learn, regardless of explicit awareness, to prioritize targets in the high probability color in all of the remaining experiments.

CHAPTER 4

BINDING AND STATISTICAL LEARNING

Experiment 2

Experiment 1 replicated the task used by Sha and colleagues (2017) and provided evidence that selection history can bias attention separate from goal-driven influences. However, these effects should not be exclusive to this specific task, but should be present in other task conditions. Specifically, if the authors' conclusions regarding the importance of diagnostic features to the development of persistent attentional biases are supported, then we should see evidence of implicit statistical learning in other tasks as long as diagnostic features are included regardless of other changes to the task. Alternatively, diagnostic features alone might be insufficient to elicit implicit statistical learning, but there might be other features of the task used by Sha and colleagues and in Experiment 1 that contribute to its effectiveness. The remaining experiments were designed to test different conditions that might affect whether implicit statistical learning occurs while holding diagnostic features constant.

One aspect of this task that may contribute to its effectiveness is the inherent relationship between the target and color. Previous studies have demonstrated that binding modulates attention such that when competing features are separated, participants are more able to inhibit distraction and perform more accurately on tasks (Risko et al., 2005; Besner & Stolz, 1999). In Experiment 1, although the target was defined by its orientation, the presentation of colored targets creates a binding of color with other features of the stimulus that might have helped participants learn to associate color with probability of finding a target. If color is separated from the target, it is possible that participants will be more able to ignore color and thus fail to learn to prioritize the high probability color targets even when the colors maintain diagnostic value.

Thus, the purpose of Experiment 2 was to test whether the development of selection history biases is related to the inseparable nature of color and orientation in the colored lines used in Experiment 1. To accomplish this, we changed the task layout from Experiment 1 to separate the color from the target by presenting the line stimuli in white and surrounded by colored boxes. The target was defined as a horizontal or vertical line, and similar to Experiment 1, the targets were presented in red and green boxes. Diagnostic features were included in this task, such that both red and green boxes appeared in each trial, but targets appeared more frequently in one color (high probability color) during the training phase. We examined whether participants would continue to show a bias to the high probability color in the test phase, when targets were presented equally often in both colors, that is unrelated to explicit awareness even when color was separated from other defining features of the target.

Method

Participants

We collected data from 51 participants for Experiment 2. Participants were students at Michigan State University (ages 18-30). The task was completed in a single, 1-hour session. Participants were recruited using MSU's Human Subjects Pool (SONA) and received one hour of course credit for their participation in this experiment. Participation was voluntary. All procedures were approved by the Human Research Protection Program at Michigan State University, and written informed consent was obtained from all participants before beginning the experiment. One participant was excluded from the analysis for chance-level accuracy (~50% correct responses). This left 50 participants for the final analysis.

Stimuli

Stimuli for this experiment included a set of white lines surrounded by colored boxes (red, yellow, cyan, purple, blue, and lime). The lines were oriented horizontally, vertically, or diagonally (45° clockwise and counter clockwise). There were long (2° visual angle) and short (1° visual angle) versions of each line stimulus. Participants responded to the stimuli using a standard keyboard and all responses were collected using E-Prime software.

Procedure

The procedure for Experiment 2 was identical to Experiment 1 (see Figure 1), but rather than the stimulus consisting of an array of colored lines, the lines were white and surrounded by colored boxes. A target horizontal or vertical line was presented in either a red or a green box, and participants reported whether the target was a long or short line. The remaining five colored boxes contained distractors, which were long and short diagonal lines. Participants received feedback following their response indicating whether they responded correctly, incorrectly, or should respond faster (RT slower than 1000ms). Participants were explicitly informed at the start of the experiment that they should strive to respond both quickly and accurately. The experiment was broken down into a training phase and a test phase. During the training phase (first 12 blocks), the target was presented in one color in 75% of trials, and in the other color in only 25% of trials. In the test phase (final four blocks), the target appeared with equal probability in both colors. Both possible target colors were presented in each trial (Sha et al., 2017).

At the end of the task, participants were tested for explicit awareness of the high probability color. To accomplish this, participants were asked the same questions presented in Experiment 1 to determine whether they noticed that one color was presented more frequently than the other and whether they could identify the high probability color. Following each of these questions, participants were asked to rate their confidence in their answer using a Likert scale from 1 to 5 (1 = guessing and 5 = certain). A third question and subsequent confidence judgement were included to assess whether participants noticed a change in probability, or if they believed that the target probabilities were consistent throughout the experiment.

Results

Average accuracy for this task was high (M = .89, SD = .08). Participants were significantly more accurate for targets in the high probability color (M = .90, SD = .08) than for targets in the low probability color (M = .87, SD = .11), $t(49) = 2.76$, $p = .008$. For the RT data, we excluded trials where participants responded faster than 150 ms or slower than 3 standard deviations above their mean RT. This resulted in the removal of less than 2% of trials (M = .98, SD = .008). Only correct trials that fell within this range were included in the final analysis.

For the training phase, we conducted a Block (1 – 12) by Color (high probability color and low probability color) repeated-measures ANOVA. The results of this analysis revealed a main effect of both Block, $F(11,539) = 42.11$, $p < .001$, $\eta_p^2 = .46$, and Color, $F(1, 49) = 45.38$, $p < .001$, $\eta_p^2 = .48$. The interaction term was not significant, $F(11,539) = 1.57$, $p = .10$, $\eta_p^2 = .03$. Thus, participants became faster over time and were overall faster for the high probability color during the training phase (see Figure 2B). For the test phase, we conducted a second Block (13 – 16) by Color (high probability color and low probability color) ANOVA. Similar to the training phase, there were main effects of both Block, $F(3,147) = 3.91$, $p = .01$, $\eta_p^2 = .07$, and Color, $F(1, 49) = 18.93$, $p < .001$, $\eta_p^2 = .28$, and the interaction term was not significant, $F(3,147) = .61$, $p = .61$, $\eta_p^2 = .01$. Thus, participants continued to show a bias for the high probability color during the test phase, even though targets were presented in both possible colors equally often. Participants also continued to respond faster over time in the test phase of this experiment.

Awareness Data

In Experiment 1, Awareness was calculated based on participants' responses to two post-test questions: the first question probed whether the participant realized that the colors were not presented equally, and the second question asked the participant to identify the high probability color. In this experiment, 29 out of the 50 participants (58%) were considered explicitly aware by this standard. The aware participants were also significantly more confident in their responses, both about the probability difference (Aware: M = 3.45, SD = .91, Unaware: M = 2.24, SD = 1.09), $t(48) = 4.27$, $p < .001$, and in selecting the high probability color (Aware: M = 4.24, SD = .83, Unaware: M = 2.67, SD = 1.15), $t(48) = 5.62$, $p < .001$. Thus, this measure of awareness captures both correct responses and confidence.

In addition to these questions, participants were also asked whether they believed the probabilities changed during the experiment or remained consistent. Interestingly, exactly half of the participants chose each response (25 participants chose response 1, indicating no change, and 25 participants chose response 2, indicating a change partway through the experiment). Participants who responded correctly to this question were more confident (M = 3.04, SD = 1.14) than those who responded incorrectly (M = 2.36, SD = .95), $t(48) = 2.29$, $p = .03$. There was no difference in response to this question regardless of whether participants were considered explicitly aware based on their answers to the first two questions, $X^2(1) = .08$, $p = .77$. However, despite being no more accurate in discerning the change in probability, aware participants were more confident in their responses to this question (aware: M = 3.00, SD = 1.07, unaware: M = 2.29, SD = 1.01), $t(48) = 2.39$, $p = .02$. Thus, despite a high proportion of participants identifying the high probability color, many were unaware that the probability changed during the experiment.

Based on these results, we chose to use the standard of explicit awareness from Experiment 1, wherein participants were considered explicitly aware if they knew that one color was presented more often and were able to correctly identify the high probability color. To test the role of explicit awareness in whether participants developed a sustained bias for the high probability color during the test phase, we repeated our training and test phase analyses including awareness as a between-subjects factor. For the training phase, we conducted Block (1 – 12) by Color (low probability color and high probability color) ANOVA with awareness as a between-subjects factor. There was no interaction between Color and Awareness during the training phase, $F(1,48) = 1.48$, $p = .23$, $\eta_p^2 = .03$. For the test phase, a Block (13 – 16) by Color (low probability color and high probability color) repeated-measures ANOVA including Awareness as a between-subjects factor was calculated. Awareness did not interact with Color, $F(1,48) = 2.26$, $p = .14$, $\eta_p^2 = .05$, or Block, $F(3,144) = .647$, $p = .59$, $\eta_p^2 = .01$. Thus, as in Experiment 1, participants responded faster to the high probability color whether or not they were explicitly aware that targets were more likely to appear in that color.

Experiment 1 and 2: Does Binding Matter?

As a final step in the analysis of Experiment 2, we compared the results of Experiment 1 and 2 to examine whether the results for these tasks were different depending upon the nature of the display. First, an independent-samples t-test was conducted to examine whether participants' average RT for locating targets (regardless of color) was different in these experiments. The results of this task indicated no difference in RT for targets in Experiment 1 ($M = 701.60$, $SD = 124.06$) relative to targets in Experiment 2 ($M = 707.64$, $SD = 116.29$), $t(97) = -.25$, $p = .80$.

Thus, on correct trials, participants located targets equally quickly regardless of whether targets were colored or white and surrounded by colored boxes. Interestingly, however, participants were significantly more accurate in Experiment 2 (M = .89, SD = .08) than in Experiment 1 (M = .83, SD = .12), $t(97) = -3.10$, $p = .003$.

To test whether the configuration of the stimuli affected whether participants developed a persistent bias to the high probability color, we repeated the analyses for the training and test phases for Experiment 1 and 2 including Experiment as a between subjects factor. For the training phase, this analysis revealed no significant interaction between color and experiment, $F(1,97) = .03$, $p = .86$, $\eta_p^2 < .001$. This was also true for the test phase, $F(1,97) = .95$, $p = .33$, $\eta_p^2 = .01$. Thus, the effect of color was not dependent on the stimulus configuration. Given that these analyses largely support that Experiment 1 and 2 worked similarly, we conducted one final exploratory analysis to examine whether participants who were considered unaware in these tasks showed a significant effect of color during the test phase. By collapsing across similar experiments, statistical power to detect such an effect was increased. There were 39 unware participants in both experiments. This final Block (13 – 16) by Color (low and high probability color) analysis revealed a significant main effect of color for the unaware participants, $F(1,38) = 7.68$, $p = .009$, $\eta_p^2 = .17$. Thus, we observed evidence for learning through repeated selection that can continue to bias attention outside of explicit awareness and goal-driven strategy.

Discussion

Experiment 2 tested whether implicit statistical learning depends on the binding of the predictive feature (color) to other features of the stimulus. The target and surrounding distractors were presented in white and surrounded by colored boxes, and thus the color was no longer an inherent feature of the stimuli. However, despite this separation, the results of Experiment 2 mirrored those of Experiment 1: participants developed a persistent bias to respond faster to targets presented in a box of the high probability color and continued to prioritize targets in this color even during the test phase when targets appeared with equal frequency in both possible colors. Furthermore, average RT to target stimuli was not different between Experiment 1 and Experiment 2, and the stimulus layout did not change the effect of color in either phase of the experiment. These results suggest that stimulus and color binding is not a requirement for attentional bias to develop when features are selected repeatedly, but that attention might spread to process color even when it is separated from other features of the target.

Again, although over half of participants in Experiment 2 were explicitly aware of these differences in probability, the interaction between Awareness and Color was not significant, thus indicating that participants responded faster to targets presented in the high probability color regardless of explicit awareness. Therefore, the results of Experiment 2 suggest that statistical learning occurs regardless of whether a frequently selected feature is inherently bound to the stimulus, and that this type of learning can occur implicitly. This notion is further corroborated by the combined analysis of unaware participants across Experiment 1 and 2: even participants who did not become explicitly aware that one color was tested more often showed a bias toward the high probability color when it would have been more beneficial to prioritize both colors equally. Taken together, the results of Experiment 1 and Experiment 2 support the assumption that statistical learning does not depend on explicit awareness, but can occur implicitly. Furthermore, the inclusion of diagnostic features in both tasks provides additional support for Sha and colleagues' (2017) conclusion that diagnostic value is important to persistent statistical learning.

CHAPTER 5

SELECTION DIFFICULTY IN STATISTICAL LEARNING

Experiment 3

The results of Experiments 1 and 2 suggest that binding does not affect whether participants can develop a bias to frequently selected features. However, whether statistical learning can persistently bias attention could be influence by task difficulty, which might modulate both task-related attention and the amount of attention allocated to color, a seemingly irrelevant feature. Because attention is a limited capacity system, a high load on attention imposed by a more perceptually difficult task might prevent the processing of irrelevant features, whereas a lower load might leave participants with more available attentional resources to passively process irrelevant information (Lavie et al., 2004; Lavie, 2005). However, this passive processing might not lead to learning of diagnostic features in easier tasks because the association between the diagnostic feature and the outcome might be weaker when less attention is devoted to the task. This might, in part, explain the consistent selection history effect seen in the task designed by Sha and colleagues (2017): the difficulty of this task might be at an optimal level for participants to both passively process color and still devote enough attention to the task to learn the diagnostic values of the possible target colors. The remaining experiments assessed different aspects of task difficulty that might contribute to statistical learning.

Because load theory suggests that cognitive and perceptual load might affect attention differently, the remaining experiments controlled for cognitive load by reducing the response difficulty of the task. Rather than reporting the length of the line, participants reported its orientation. Experiment 3 tested whether statistical learning would be reduced under this easier response condition. Selection difficulty was also minimized by displaying colored lines that were homogenous in length, such that targets and distractors no longer shared any features. It was hypothesized that participants in this easier search task would passively process color, but that this would not result in a consistent bias for targets presented in the high probability color unless participants became explicitly aware. In other words, participants were expected to process the color cues under the low perceptual load, which did not exhaust attention and prevent the processing of color, but not implicitly learn the diagnostic values because task-related attention was less engaged in finding the target. Thus, it was hypothesized that both aware and unaware participants would show an effect of color during the training phase from priming, but that this effect would only be present during the test phase for participants who were explicitly aware.

Method

Participants

Data were collected from 50 participants for Experiment 3. Participants were students at Michigan State University (ages 18-30). The task was completed in a single, 1-hour session. Participants were recruited using MSU's Human Subjects Pool (SONA) and received one hour of course credit for their participation in this experiment. Participation was voluntary. All procedures were approved by the Human Research Protection Program at Michigan State University, and written informed consent was obtained from each participant before beginning the experiment.

Stimuli

Stimuli for this experiment were a set of colored lines (red, yellow, cyan, purple, blue, and lime) that were oriented horizontally, vertically, or diagonally (45° clockwise and counter clockwise). Participants responded to the stimuli using a standard keyboard and all responses were collected using E-Prime software.

Procedure

The procedure for Experiment 3 was similar to Experiments 1 and 2 (Figure 1). Participants located a target horizontal or vertical line and reported its orientation. During the training phase (first 12 blocks), targets appeared in one color in 75% of trials, and in the other color in only 25% of trials. In the remaining four blocks (test phase), the target appeared with equal probability in both colors. Both possible target colors (lime and red) were presented in each trial. At the end of the task, participants were asked three questions to assess their awareness and confidence in these judgements, as described in the procedure for Experiment 2.

Results

Total accuracy for this task was high (M = .92, SD = .05). Participants were significantly more accurate for targets presented in the high probability color (M = .93, SD = .04) relative to the low probability color (M = .91, SD = .08), $t(49) = 3.22$, $p = .002$. For the RT data, trials where participants responded faster than 150ms or slower than 3 standard deviations above their mean RT were excluded. Over 98% of trials were retained (M = .98, SD = .006), and from these remaining trials, only correct trials were included in the RT analyses.

A Block (1 – 12) by Color (low probability color and high probability color) repeated-measures ANOVA was conducted to examine participants' responses during the training phase of this experiment. The results revealed a main effect of Block, $F(11,539) = 25.70$, $p > .001$, $\eta_p^2 = .34$, and a main effect of Color, $F(1,49) = 62.68$, $p > .001$, $\eta_p^2 = .56$. Thus, during the training phase, participants responded faster over time and were faster overall for the high probability color trials (Figure 2C). The interaction term was also significant in this analysis, F(11,539) =

2.07, p = .02, η_p^2 = .04. For the test phase, we conducted a second Block (13 – 16) by Color repeated-measures ANOVA. Similar to the training phase, this analysis revealed main effects of both Block, F(3,147) = 4.67, p = .004, η_p^2 = .09, and Color, F(1,49) = 9.19, p = .004, η_p^2 = .16. Participants' overall RT continued to increase throughout the final blocks, and faster for the high probability color. The interaction term was not significant, F(3,147) = .15, p = .93, η_p^2 = .003.

Awareness Data

Similar to the previous experiments, participants who reported that more targets appeared in one color over the other and correctly identified the high probability color were considered explicitly aware. Out of the 50 participants, 27 were considered aware by this measure (54%). In this experiment, aware participants were only marginally more confident than unaware participants in their reports that one color was more frequent than the other, $t(48) = 1.88$, p = .066, but aware participants were significantly more confident in their choice of the high probability color after being told that one color was more frequent, $t(48) = 3.01$, $p = .004$.

As in Experiment 2, exactly half of participants were aware of the change in probability that occurred partway through the experiment. Again, 25 out of the 50 participants selected each possible response (1 = probabilities stayed the same during the experiment, 2 = probabilities changed partway through). This distribution was unchanged regardless of whether participants were considered explicitly aware based on the first two questions, $X^2(1) = .08$, $p = .78$. Likewise, participants were no more confident in their answers to this question whether they were considered aware ($M = 3.00$, $SD = .88$) or unaware ($M = 2.78$, $SD = 1.04$), $t(48) = .80$, $p = .43$. Interestingly, participants who answered this question correctly ($M = 3.16$, $SD = .85$) were marginally more confident in their responses compared to those who answered incorrectly (M = 2.64, $SD = .99$), $t(48) = 1.99$, $p = .053$.

To test whether the bias to attend the high probability color was dependent upon explicit awareness, we repeated our training and test phase analyses including Awareness. First, we conducted a Block (1 – 12) by Color (low probability color and high probability color) ANOVA with Awareness as a between-subjects factor. This analysis revealed a significant Color X Awareness interaction, F(1,48) = 7.32, p = .009, η_p^2 = .13. To follow up on this interaction, we conducted separate Block (1 – 12) by Color (low probability color and high probability color) ANOVAs for the aware and unaware participants. Both aware ($F(1,26) = 49.57$, $p < .0001$, η_p^2 = .66) and unware ($F(1,22) = 21.27$, $p < .0001$, η_p^2 = .49) participants showed a main effect of Color in the training phase.

To test for awareness effects in the test phase, we conducted a Block (13 – 16) by Color (low probability color and high probability color) including Awareness as a between-subjects factor. There was a significant Color X Awareness interaction, $F(1,48) = 4.43$, $p = .041$, η_p^2 = .09, suggesting that aware and unaware participants behaved differently. To follow up on this interaction, we conducted separate Block (13 – 16) by Color (low probability color and high probability color) ANOVAs for aware and unware participants. For the aware participants, there was a significant main effect of Color, $F(1,26) = 9.79$, $p = .004$, η_p^2 = .27. Conversely, this effect was not present in the unware participants, $F(1,22) = .67$, $p = .42$, η_p^2 = .03. Thus, although all participants responded faster to the high probability color during the training phase, only participants who were explicitly aware of the difference in probability showed a sustained bias for the high probability color during the test phase (Figure 4).

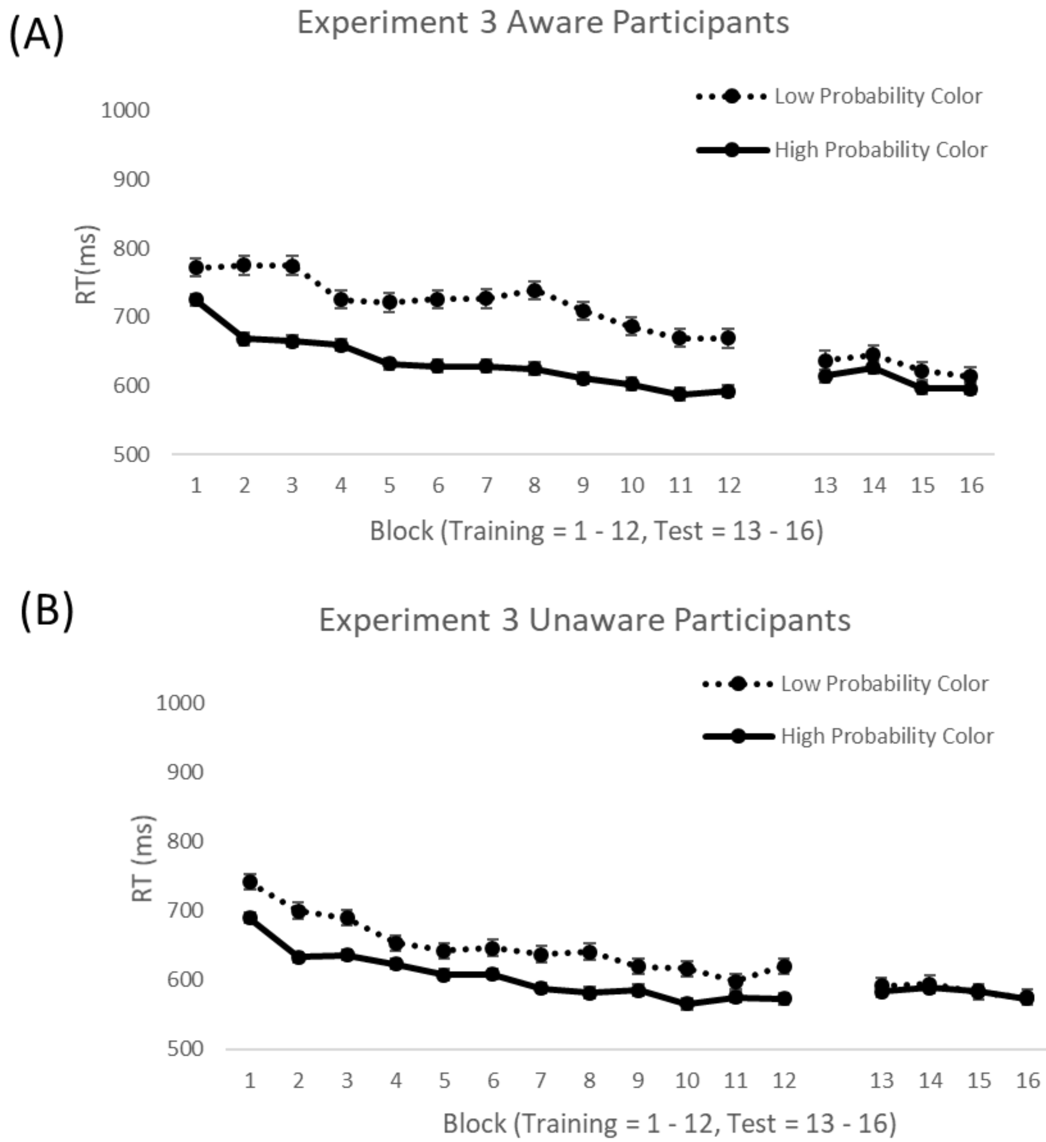

Figure 4. Experiment 3 results separated by awareness. Aware participants (A) show a substantial difference between the high probability color and low probability color targets that sustains through the test phase, whereas unaware participants (B) show a smaller difference in the training phase that does not persist into the test phase.

Discussion

The purpose of Experiment 3 was to demonstrate that implicit statistical learning does not occur automatically when frequently selected features have diagnostic value, but is modulated by task difficulty. Experiment 3 reduced task difficulty by presenting highly distinct targets and distractors and asking participants to report the orientation of the target. We predicted that under these conditions, participants would not develop a persistent and automatic bias to attend items presented in the high probability color because task-related attention would be reduced with the simpler task, but that participants would show a passive priming effect during the training phase because the low perceptual load allowed processing of color information. Participants who became aware were expected to prioritize the high probability color in the test phase, whereas those who remained unaware were expected to show no difference in RT for high and low probability color targets in the test phase. The results supported this prediction: overall, participants responded faster to targets presented in the high probability color, but this effect was overshadowed by a significant Color by Awareness interaction indicating that the effect of color depended on awareness. Only participants who were explicitly aware that targets were presented more frequently in one color and could identify this high probability color showed a persistent bias to attend the high probability color in the test phase.

The finding of significant Color by Awareness interactions in both the training and the test phases demonstrated that aware participants showed a stronger effect of color throughout the experiment (see Figure 4). Unaware participants still responded faster to targets presented in the high probability color during the training phase, but this effect is likely attributable to a short-term repetition priming (Sha et al., 2017). This suggests that participants passively processed color, but there was no evidence that the unaware participants learned the diagnostic value of the high probability color. These results challenge the conclusions of Sha and colleagues (2017) that implicit statistical learning depends primarily on diagnostic features. Reducing task difficulty allowed participants to passively process the color regardless of explicit awareness, but passive processing and the presence of diagnostic features were insufficient to produce lasting changes in attentional priority attributable to statistical learning in an easier task. Thus, Experiment 3 supports the prediction that both passive processing and task-related attention are necessary for statistical learning to occur.

Conversely, aware participants showed a bias for the high probability color that persisted into the test phase and thus cannot be attributed to repetition priming alone. However, because these participants were able to recognize the uneven probabilities of the two possible target colors and identify the high probability color, it is likely that these effects are attributable to the use of goal-driven attention to volitionally prioritize searching for targets in the high probability rather than an automatic learning via selection history. In support of this idea, participants were largely unaware that the probabilities changed during the experiment and were not any more confident in their answers regardless of their awareness of the high probability color or their accuracy in answering this question. Thus, it is likely that participants who were considered explicitly aware did not notice the decreased frequency of targets in the high probability during the final blocks and continued to prioritize it voluntarily. These results support the idea that diagnostic value alone may be insufficient to trigger persistent implicit learning, but that task difficulty might also influence whether selection history can enact changes to attention that can be distinguished from goal-driven attention.

Experiment 4

Experiment 3 demonstrated that statistical learning might require more than passive processing and the presence of diagnostic features to persistently change attention. Specifically, when task difficulty was reduced, participants passively processed color cues, but failed to learn diagnostic features outside of explicit awareness. Experiment 4 was designed to follow up on this finding and further assess whether task difficultly is a factor that determines whether or not implicit statistical learning will persistently bias attention. Experiment 4 manipulated selection difficulty to test whether participants would be more or less likely to implicitly learn to prioritize a more frequently selected color when a target is more difficult to find because it is more similar to distractors. In this task, participants again searched for a target horizontal or vertical line among diagonal distractors and reported its orientation. However, rather than using distractors rotated 45°, the distractor lines were rotated only slightly from the horizontal or vertical targets (5°), thus making the target more difficult to distinguish from the distractors and increasing the perceptual load of the task.

Based on the results of Experiment 3, which suggested a role for both task-related attention and the passive allocation of attention to irrelevant information as modulated by perceptual load, we predicted that optimal task difficulty would be required for statistical learning to occur. Increasing selection difficulty in Experiment 4 was expected to reduce the availability of attentional resources to passively process information about color, which was seemingly irrelevant to task goals, because locating the target amongst the challenging distractors was expected to exhaust attentional resources. Although task-related attention was expected to be engaged in this difficult selection condition, without enough attention available to process color, it was predicted that implicit learning would not occur in this experiment.

Method

Participants

Data for this experiment were collected from 50 participants. The participants were students at Michigan State University (ages 18-30). The task was completed in a single, 1-hour session. Participants were recruited using MSU's Human Subjects Pool (SONA) and received one hour of course credit for their participation in this experiment. Participation was voluntary. All procedures were approved by the Human Research Protection Program at Michigan State University, and written informed consent was obtained from all participants before beginning the experiment.

Stimuli

The stimuli for this experiment included a set of two possible target lines and four possible distractor lines. The two target lines were oriented canonically (i.e. one horizontal and one vertical). The distractor lines were horizontal and vertical lines rotated 5° clockwise or counter clockwise, making them more difficult to distinguish from the target than the 45° distractors used previously. Similar to Experiment 1 and 3, target and distractor lines were presented in different colors (red, yellow, lime, cyan, blue, and purple) against a black background.

Procedure

The procedure for this experiment was identical to Experiment 3 (see Figure 1), with the only differences in the orientation of the distractor lines. Participants reported the orientation of the target horizontal or vertical line, which was always presented in either red or green font. Participants completed 16 blocks with 48 trials each, including 12 training blocks during which targets occurred more frequently in one color (75% and 25%), and four test blocks where the targets appeared equally in both colors. Both possible target colors appeared in every trial. Participants were tested for awareness in the manner previously outlined following the completion of the task.

Results

Overall accuracy for this task was notably lower than accuracy in previous experiments (M = .74, SD = .12). Participants were significantly more accurate for high probability color targets (M = .79, SD = .14) relative to low probability color targets (M = .64, SD = .13), $t(49)$ = 7.68, p > .0001. For the RT analyses, trials during which participants responded faster than 150ms or slower than 3 standard deviations above mean RT were excluded (~3% of trials were excluded). This left approximately 97% of trials for the analysis (M = .97, SD = .05).

For the training phase, we conducted a Block (1 – 12) by Color (low probability color and high probability color) ANOVA. This analysis revealed a main effect of Block, $F(11,539)$ = 13.65, p < .0001, η_p^2 = .22, and a main effect of Color, $F(1,49)$ = 31.29, p < .0001, η_p^2 = .39. The interaction term was not significant, $F(11,539)$ = 1.08, p = .37, η_p^2 = .02. These results suggested that participants became faster over time and were overall faster for targets presented in the high probability color. For the test phase, we conducted a second Block (13 – 16) by Color (low probability color and high probability color) ANOVA. There was a significant main effect of Color in the test phase, $F(1,49)$ = 14.78, p < .0001, η_p^2 = .23, suggesting that participants continued to respond faster to targets presented in the high probability color in the test phase. There was no main effect of Block, $F(3,147)$ = 1.10, p = .35, η_p^2 = .02, and no interaction, $F(3,147)$ = .61, p = .61, η_p^2 = .01 (Figure 2D).

Awareness Data

As in the previous experiments, explicit awareness was determined by participants' answers to the first two questions asked during the post-test. These questions assessed whether participants recognized that targets were presented more often in one color and could identify the high probability color. By this measure, 31 participants were considered aware, and 19 were considered unaware. As in previous experiments, the participants who were considered aware by this measure were significantly more confident in their indication that probabilities were unequal (aware: $M = 3.97$, $SD = .95$, unaware: $M = 2.58$, $SD = 1.01$), $t(48) = 4.89$, $p < .0001$, and in their choice of the high probability color (aware: $M = 4.26$, $SD = .96$, unaware: $M = 2.74$, $SD = 1.28$), $t(48) = 4.77$, $p < .0001$. For the final question, which assessed whether participants noticed a change in the probabilities throughout the experiment (an answer of 1 indicating no change, and an answer of 2 indicating a change), 30 of the 50 participants correctly reported the change. Again, this was unrelated to whether the participants were considered explicitly aware, $X^2(1) = .91$, $p = .34$, although the aware participants were generally more confident in their responses (aware: $M = 3.13$, $SD = 1.09$, unaware: $M = 2.37$, $SD = 1.01$), $t(48) = 2.46$, $p = .02$. Participants' mean confidence was also equal despite whether they answered this question correctly (correct: $M = 2.80$, $SD = 1.10$, incorrect: $M = 2.90$, $SD = 1.17$), $t(48) = -.31$, $p = .76$. Thus, although a substantial proportion of participants were explicitly aware that targets were presented more often in one color than the other, participants largely indicated that they were guessing whether the probabilities changed throughout the experiment.

To assess the role of explicit awareness, we repeated the RT analyses using Awareness as a between subjects factor to assess whether it interacted with Color. For the training phase, a Block (1-12) by Color (low probability color and high probability color) ANOVA including

Awareness as a between-subjects factor was conducted. The results of this analysis revealed a significant Color X Awareness interaction, $F(1,48) = 5.82$, $p = .02$, $\eta_p^2 = .11$. For the test phase, we conducted a Block (13-16) by Color (low probability color and high probability color) ANOVA including Awareness as a between-subjects factor. The Color X Awareness interaction term was also significant in the test phase, $F(1,48) = 9.56$, $p = .003$, $\eta_p^2 = .17$.

To follow up on these significant interactions, we conducted separate analyses for aware and unaware participants. During the training phase, there was a main effect of Block for both unaware, $F(11,198) = 4.47$, $p < .0001$, $\eta_p^2 = .20$, and aware participants, $F(11,330) = 12.17$, $p < .0001$, $\eta_p^2 = .29$. The main effect of Color, however, was only present in the aware participants, $F(1,30) = 38.34$, $p < .001$, $\eta_p^2 = .56$. Thus, even during the training phase, where participants would be expected to show a bias toward the high probability color because of priming, only participants who were explicitly aware that targets were presented more often in one color than the other showed a bias toward the high probability color. Unaware participants did not learn to prioritize the high probability color despite its frequent presentation and diagnostic value. The follow-up analysis of the test phase yielded similar findings, indicating that only aware participants showed a main effect of Color, $F(1,30) = 35.12$, $p < .0001$, $\eta_p^2 = .46$. Interestingly, aware participants also showed a main effect of Block in the test phase, $F(3,90) = 3.38$, $p = .02$, $\eta_p^2 = .10$ (Figure 5).

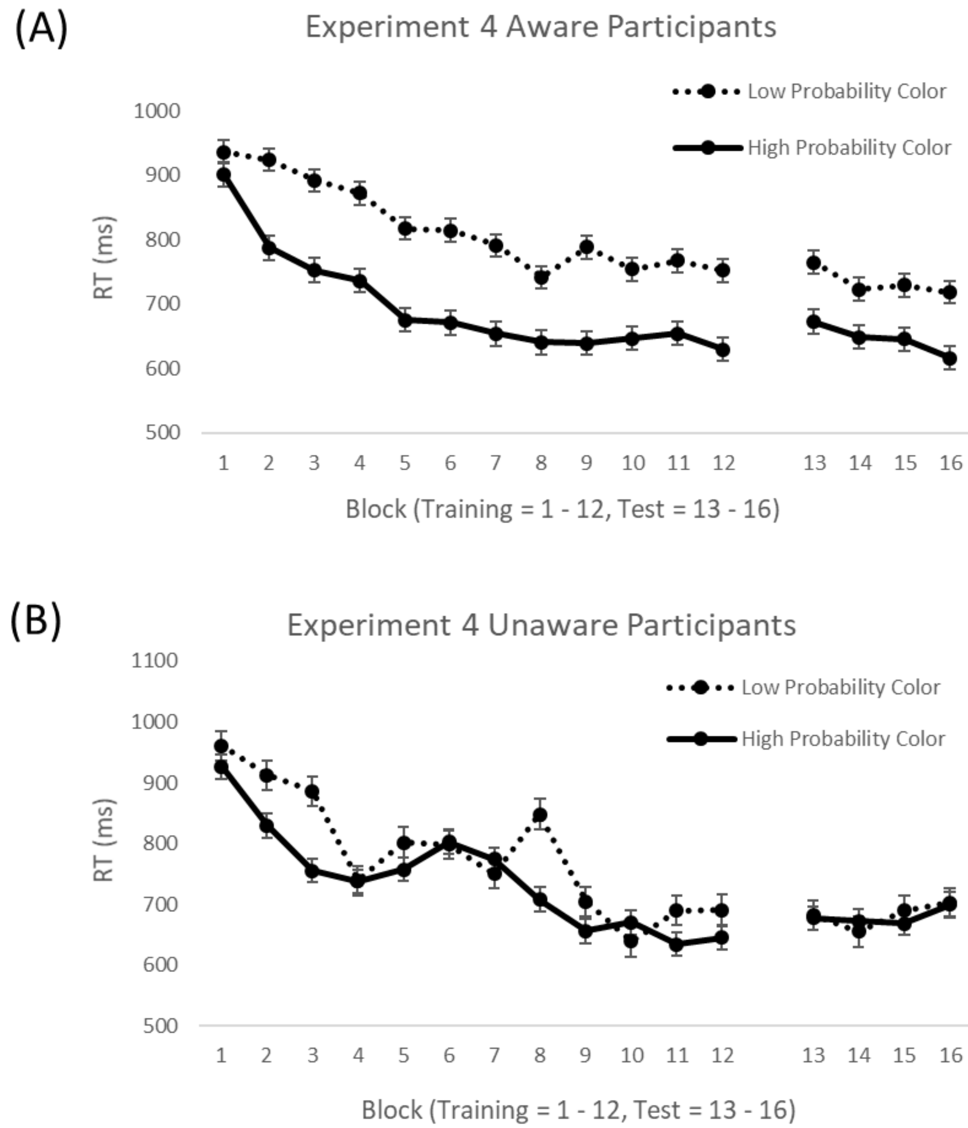

Figure 5. Results of Experiment 4 split by explicit awareness. Only participants who were aware that targets were more likely to appear in one color over the other (A) showed a bias for the high probability color in both the training and test phases. Unaware participants (B) did not show main effects of Color in either phase.

Discussion

The purpose of Experiment 4 was to test whether increasing selection difficulty by increasing the similarity between the target and distractors would modulate implicit statistical learning. It was hypothesized that increasing selection difficulty would increase task-related attention, but the increased perceptual load would tax attentional resources to reduce passive processing of color and thus result in a lack of attention to color altogether. The results supported the latter prediction: although participants responded faster to the high probability color during both the training and test phases overall, this effect was explained by a significant Color by Awareness interaction. Only aware participants responded faster to the high probability color in both the training and the test phases, whereas unaware participants failed to show any effect of color in either phase of the experiment.

Participants in Experiment 4 who were not considered explicitly aware failed to prioritize the high probability color even during the training phase. This indicates that participants generally either became explicitly aware of the high probability color and prioritized it accordingly, or largely failed to process color cues under the increased perceptual load imposed by high selection difficulty. These results further corroborate the conclusion from Experiment 3 that statistical learning does not bias attention automatically when features are selected frequently even when they are diagnostic of targets, but might also depend on an optimal level of task difficulty. In Experiment 3, which presented a simple task with a lower perceptual load, participants passively processed color cues, but this passive processing was insufficient to produce persistent learning without sufficient engagement of task-related attention. In Experiment 4, when the target was extremely difficult to distinguish from distractors, participants failed to passively process color cues and again showed no evidence of implicit learning. In both the easier and more difficult selection difficulty conditions, however, participants who became explicitly aware prioritized the high probability color.

Together, Experiments 3 and 4 challenge the conclusion of Sha and colleagues (2017) that persistent changes to attention from statistical learning rely on diagnostic features. Although the presence of diagnostic features might contribute to such changes in attention, simply presenting both possible target colors in each trial when one is more predicative of a target did not automatically result in such learning. Instead, there might be other processes involved in statistical learning. These experiments suggest a role for passive processing through which attention is allocated to seemingly irrelevant diagnostic features. The results of Experiments 3 and 4 suggest that this passive process is modulated by perceptual load induced by selection difficulty: passive processing for color was eliminated when increased search difficulty increased perceptual load and left no available resources to process color. This passive process might be an important first step in statistical learning, because learning cannot occur if the diagnostic feature is largely ignored, but passive processing without sufficient engagement of task-related attention did produce persistent learning. Similarly, engagement of task-related attention without passive processing allotted to the diagnostic feature did not produce persistent learning. The optimal engagement of both processes, in addition to strong diagnostic value, are proposed components of statistical learning.

CHAPTER 6

PERCEPTUAL DIFFICULTY IN STATISTICAL LEARNING

Experiment 5

The results from the previous experiments suggest that statistical learning is not an automatic process that occurs passively when features are repeatedly encountered and diagnostic of outcomes. Both decreasing and increasing selection difficulty by manipulating the similarity between targets and distractors resulted in substantial confounds of explicit awareness and goal-driven prioritization. Experiments 3 and 4 demonstrated that passive processing of color can be modulated by selection difficulty because perceptual load affects how much attention can be devoted to color, but devoting attentional resources through passive processing alone did not lead to statistical learning even in the presence of diagnostic features. Furthermore, these experiments also established potential boundary conditions of statistical learning, supporting the prediction that an optimal level of task difficulty is important for statistical learning.

The purpose of Experiment 5 was to present an alternative manipulation of task difficulty and examine its effects on statistical learning. In addition to selection difficulty, visual search tasks are made less efficient when the contrast of stimuli against the background is decreased and stimuli are thus harder to detect (Lupp, Hauske, & Wolf, 1976; Näsänen, Ojanpää, & Kojo, 2001). Increasing perceptual difficulty was expected to slow down overall task performance because low contrast stimuli are more difficult to evaluate, but was not expected increase perceptual load enough to eliminate passive processing of color. Thus, this manipulation was expected to be challenging enough to engage task-related attention, but to still leave attentional resources available to be allocated to color. We manipulated perceptual difficulty by including a high contrast condition (Experiment 5a), during which stimuli were presented in white font surrounded by colored boxes against the black background (as in Experiment 2) and a low contrast condition (Experiment 5b), during which stimuli were presented in a dark gray font surrounded by colored boxes against the black background (see Figure 1). In this experiment, participants again searched for a target horizontal or vertical line amongst distinct 45° diagonal distractors and made a judgment about its orientation.

Given that the results of Experiment 2 suggested that binding was unrelated to statistical learning and the results of Experiment 3 suggested that the orientation judgment task with easy distractors resulted in passive processing without persistent learning, we expected the results of Experiment 5a (high contrast condition), which used the task and stimuli from Experiment 3 with the unbound layout from Experiment 2 (see Figure 1), to mirror those of Experiment 3. Specifically, we expected a significant interaction between Color and Awareness, such that aware participants would respond more quickly to targets in the high probability color in both the training and test phases, but unaware participants would only respond more quickly to targets presented in the high probability color during the training phase. This result would again support the prediction that an easier task allows participants to passively process irrelevant color information, but that passive processing does not automatically lead to persistent changes to attention.

Conversely, we predicted one of three possible outcomes for Experiment 5b (low contrast condition). First, if selection and perceptual difficulty influence attention similarly and increase perceptual load enough to prevent any passive processing of color, then these results should mirror Experiment 4. If this prediction is supported, then participants in this task should show no evidence of processing color – whether from passive processing leading to priming effects, or from longer statistical learning. Second, increasing perceptual difficulty, unlike selection difficulty, might not increase perceptual load enough to prevent passive processing of color and might also fail to engage task-related attention because of the simplicity of the feature judgment. This would produce a result similar to Experiment 3 where both unaware and aware participants showed a priming effect during the training phase, but only aware participants continued to prioritize the high probability color during the test phase. Finally, increasing perceptual difficulty might be sufficient to engage task-related attention, but not load perceptual processing enough to completely prevent attention from "spilling over" to process color. Thus, persistent statistical learning would be expected if this prediction is supported. Participants should respond more quickly to targets presented in the high probability color in both the training and the test phase and regardless of explicit awareness.

Method

Participants

This experiment included two conditions: high contrast (Experiment 5a) and low contrast (Experiment 5b). We collected data from 101 participants: 51 participants for Experiment 5a and 50 participants for Experiment 5b. For Experiment 5a, one participant was excluded for chance level behavioral task performance, leaving 50 participants for the final analysis. For Experiment 5b, one participant was excluded from analyses because their average RT was extremely slow (more than 3 standard deviations larger than the mean RT). This left 49 participants for the final analysis for Experiment 5b, and 99 participants for the overall analysis. Participants were students at Michigan State University (ages 18-30). The task was completed in a single, 1-hour session. Participants were recruited using MSU's Human Subjects Pool (SONA) and received one hour of course credit for their participation in this experiment. Participation was voluntary. All procedures were approved by the Human Research Protection Program at

Michigan State University, and written informed consent was obtained from all participants before beginning the experiment.

Stimuli

Stimuli for this experiment were a set of lines presented in colored boxes (red, yellow, cyan, purple, lime, and blue) against a black background. In Experiment 5a, the lines were presented in white font for maximum contrast, and in Experiment 5b, the lines were presented in a low-contrast dark gray font (see Figure 1). The target line stimuli were horizontal and vertically oriented and the distractors were diagonal lines (45° clockwise and 45° counter clockwise). Participants responded to the stimuli using the number pad on a standard keyboard and all responses were collected using E-Prime software.

Procedure

The procedure for these experiments was identical to the procedures for the previous experiments (see Figure 1). Participants searched for a target vertical or horizontal line, presented in a red or green box among diagonal distractors and reported the orientation of the line. In the high contrast condition (Experiment 5a), the line stimuli were presented in white font against the black background. In the low contrast condition (Experiment 5b), the line stimuli were presented in dark gray font against the black background. During the training phase, the high probability color box contained the target in 75% of trials and the low probability color box contained the target in the remaining 25% of trials. The high and low probability colors (red and lime) were counterbalanced between participants. In the test phase, targets appeared equally often in both colors. Participants completed 12 training blocks and 4 test blocks, which were followed by a posttest including the three questions described in the procedure for Experiment 2 and confidence judgements for these responses.

Results

Experiment 5a

In the high-contrast condition, participants were highly accurate in their task performance (M = .91, SD = .07). Participants responded more accurately to targets presented in the high probability color (M = .93, SD = .05) than in the low-probability color (M = .88, SD = .14), $t(49)$ = 2.62, p = .012. For the RT analysis, trials in which participants responded too quickly (< 150 ms) or too slowly (more than 3 standard deviations above the individual's mean RT) were removed. The number of trials retained was high – less than 2% of trials were removed (M = .98, SD = .01).

For the training phase of this experiment, we conducted a Block (1 – 12) by Color (low probability color and high probability color) ANOVA. As in previous experiments, there was a main effect of Block, $F(11,539) = 18.77$, $p < .001$, $\eta_p^2 = .27$, indicating that participants became faster over time, and a main effect of Color, $F(1,49) = 83.71$, $p < .001$, $\eta_p^2 = .63$, indicating that participants responded faster overall to targets presented in the high probability color. The interaction term was also significant, $F(11,539) = 2.71$, $p = .02$, $\eta_p^2 = .05$. To test whether this bias toward the high probability color persisted into the test phase, we conducted a second Block (13 – 16) by Color (low probability color and high probability color) ANOVA. This analysis revealed a main effect of Color, $F(1,49) = 8.76$, $p = .005$, $\eta_p^2 = .15$, suggesting that participants did continue to respond faster to targets presented in the high probability color in the test phase (Figure 2E). There was no main effect of Block, and the interaction term was not significant.

Experiment 5a Awareness Results

Interestingly, unlike in the previous experiments, fewer than half of participants were considered explicitly aware using the previously described measure. Of the 50 participants, 20 reported that targets were presented more frequently in one color and correctly identified the high probability color (40%). Also unlike in previous experiments, these aware participants were not significantly more confident in their responses indicating that targets were more likely to be presented in one color than the other (aware: *M* = 3.40, *SD* = 1.13, unaware: *M* = 3.23, *SD* = 1.10), *t*(48) = .52, *p* = .61, nor in their selection of the high probability color (aware: *M* = 3.7, *SD* = 1.08, unware: *M* = 3.33, *SD* = 1.18), *t*(48) = 1.11, *p* = .27. Again, participants were no more likely to indicate that the probabilities changed regardless of explicit awareness, $X^2(1) = .25$, $p = .64$. Consistent with the previous experiments, approximately half of participants thought that the probabilities remained consistent throughout the task (27 out of 50) and half thought that the probabilities changed (23 out of 50).

To examine whether the results were driven by explicit awareness, we re-ran the previous analyses including awareness as a between-subjects factor. For the training phase, this Block (1-12) by Color (low probability and high probability) ANOVA revealed no significant interaction between Color and Awareness, $F(1,48) = 1.56$, $p = .22$, $\eta_p^2 = .03$, indicating that participants responded more quickly to targets presented in the high probability color during the training phase regardless of explicit awareness. To test whether this was also true for the test phase, we conducted a second Block (13 – 16) by Color (low probability and high probability) ANOVA with Awareness as a between-subjects factor. The results of this test likewise indicated no interaction between Color and Awareness, $F(1,48) = .34$, $p = .57$, $\eta_p^2 = .007$. Thus, participants continued to show a bias for targets presented in the High Probability Color in the test phase of this experiment regardless of explicit awareness.

Experiment 5b

Average accuracy for this task was high (M = .92, SD = .05). Similar to the previous experiments, participants were significantly more accurate for targets presented in the high probability color (M = .93, SD = .04) than targets presented in the low probability color (M = .91, SD = .08), $t(48) = 2.03$, $p = .05$. For the RT analyses, trials in which participants responded too quickly (< 150 ms) or slower than 3 standard deviations above the individual's average RT were excluded. This resulted in the removal of less than 2% of trials (trials retained: M = .98, SD = .008).

To investigate whether participants responded faster to targets presented in the high probability color during the training phase, we conducted a Block (1 – 12) by Color (low probability color and high probability color) repeated-measures ANOVA. This analysis revealed main effects of both Block, $F(11,528) = 20.29$, $p < .001$, $\eta_p^2 = .30$, and Color, $F(1,48) = 51.07$, $p < .001$, $\eta_p^2 = .52$. Thus, during the training phase, participants responded faster in the later blocks than the earlier blocks, and were overall faster for targets in the high probability color. The interaction term was not significant, $F(11,528) = .70$, $p = .74$, $\eta_p^2 = .01$. To examine whether this effect persisted into the test phase, we conducted a Block (13 – 16) by Color (low probability color and high probability color) repeated-measures ANOVA. Again, we found main effects of both Block, $F(3,144) = 3.84$, $p = .01$, $\eta_p^2 = .07$, and Color, $F(1,48) = 11.71$, $p = .001$, $\eta_p^2 = .20$, suggesting that participants continued to become faster as the training blocks progressed and, critically, continued to detect targets presented in the high probability color faster than targets in the low probability color. Thus, participants showed evidence of selection history biases in the low contrast condition (Figure 2F).

Experiment 5b Awareness Results

As in previous experiments, over half of the participants (28 out of 49, or approximately 57%) realized that the probabilities of the two target colors were unequal and could accurately identify the high probability color. Again, these participants were considered explicitly aware and the remaining 21 participants were considered unaware. Interestingly, unlike in previous experiments, aware participants were not significantly more confident in their judgement of whether one color was more frequent (Aware: M = 3.43, SD = 1.20, Unaware: M = 3.00, SD = .95), $t(47)$ = 1.35, p = .18, or in their choice of the high probability color (Aware: M = 3.46, SD = 1.23, Unaware: M = 3.05, SD = 1.28), $t(47)$ = 1.15, p = .26.

Again, approximately half of participants reported a probability change (25 out of 49), and half said that the probabilities remained consistent throughout the task (24 out of 49). This distribution was the same regardless of whether participants were considered aware, $X^2(1)$ = .55, p = .46. Aware (M = 2.89, SD = 1.07) and unaware (M = 2.67, SD = 1.02) participants were also equally confident in their answers to this question, $t(47)$ = .75, p = .18. Participants' confidence was also similar regardless of whether they responded correctly (M = 2.64, SD = 1.15) or incorrectly (M = 2.95, SD = .91) to this question, $t(47)$ = -1.07, p = .29.

To test whether selection history effects in this task were dependent on explicit awareness, we repeated the original analyses including awareness as a between-subjects factor in the ANOVA for both the training and the test blocks. The Color X Awareness interaction term was not significant in the training phase, $F(1,47)$ = 1.64, p = .21, η_p^2 = .03, or the test phase, $F(1,47)$ = 2.18, p = .15, η_p^2 = .04. Thus, the results of this task are not dependent upon explicit awareness; participants responded faster to targets presented in the high probability color even when it was no longer beneficial to prioritize one color over the other regardless of whether they realized that targets were presented more frequently in the high probability color.

Experiment 5a and 5b Results

Experiment 5a and 5b, taken together, tested whether increasing perceptual difficulty by manipulating the contrast of targets against the dark background would influence the likelihood that participants would develop a persistent bias to attend the high probability color. To check this manipulation, an independent samples t-test was calculated on average RT for the two conditions. As expected, the results of this test suggested that participants in the high contrast condition (5a) responded more quickly overall (M = 615.47, SD = 77.82) compared to participants in the low contrast condition (5b) (M = 647.86, SD = 79.41), t(97) = -2.05, p = .043. However, accuracy was not significantly different between contrast conditions (high: M = .91, SD = .07, low: M = .92, SD = .05), t(97) = -.98, p = .33. Finally, a chi-square test for independence was calculated to determine whether there was a significant difference in the proportion of participants considered explicitly aware between the two conditions. The association between condition and awareness did not reach significance, $X^2(1) = 2.91$, $p = .088$, indicating that participants were equally likely to become explicitly aware in both conditions.

To compare whether the results of these experiments were different between the two contrast conditions, a Block (1 – 12) by Color (low probability and high probability) repeated-measures ANOVA with Contrast Condition as a between-subjects factor was calculated for the training phase. The main effect of Condition was marginal, $F(1,97) = 3.56$, $p = .062$, $\eta_p^2 = .035$, and the Color by Condition interaction term was not significant, $F(1,97) = .02$, $p = .89$, $\eta_p^2 > .001$. For the test phase, a Block (13 – 16) by Color (low probability and high probability) repeated-measures ANOVA including Contrast Condition (5a/high contrast and 5b/low contrast) likewise revealed no interaction between Color and Condition, $F(1,97) = .70$, $p = .40$, $\eta_p^2 = .007$, and the main effect of Condition failed to reach statistical significance, $F(1,97) = 2.80$, $p = .097$, $\eta_p^2 = .03$. Thus, although the overall difference in RT and the marginal main effect of experiment in training phase RT between conditions suggests that participants found low contrast targets more slowly, there is no evidence that participants were otherwise performing differently in these conditions. Participants in both the high and low contrast conditions were equally accurate, equally likely to become explicitly aware, and showed similar biases toward the high probability color in both the training and the test phases.

Because participants performed relatively similarly despite the difference in perceptual difficulty, a final exploratory analysis was conducted to examine whether unaware participants in this type of task show an overall effect of color in the test phase. Data from Experiment 5a and 5b were combined and the aware participants were removed. This left data from 51 participants for analysis. The same Block (13 – 16) by Color (low probability and high probability) ANOVA was repeated for the test phase using only the unaware participants collapsed across condition. For the test phase, unaware participants did show a main effect of color, $F(1,50) = 7.27$, $p = .01$, $\eta_p^2 = .13$, providing evidence for attentional bias through statistical learning outside of explicit awareness and thus distinguishable from volitional, goal-driven control.

Discussion

Experiment 5 provided further insight into the question of whether task difficulty modulates implicit statistical learning. Although participants in the low contrast condition (5b) responded slower overall, indicating that this manipulation affected task difficulty, the combined results of these experiments indicated no differences in statistical learning based on stimulus contrast. Experiment 5a (high contrast condition) was expected to mirror the results of

Experiment 3, during which participants passively processed color enough to respond more quickly to high probability color targets during the training phase, but failed to implicitly learn diagnostic value enough to develop a bias that persisted into the test phase. However, participants in the high contrast condition responded faster to high probability color targets in both the training and the test phases, and these results were not dependent on explicit awareness. Similarly, participants in Experiment 5b (low contrast condition) also developed a persistent bias to attend the high probability color that was separate from explicit awareness. Overall, these results fail to support the prediction that perceptual difficulty modulates statistical learning, but instead demonstrated that implicit learning can occur in both high and low contrast conditions even under easier response and selection difficulties.

When considered with the results of the previous experiments, Experiment 5 provides further insight into their conclusions. First, based on the results of Experiment 1 and 2, which indicated that statistical learning biased attention regardless of whether color was an inherent feature of the target or was separate, Experiment 5a should have resulted in a similar pattern of behavior to Experiment 3. However, participants in Experiment 5a did learn to prioritize the high probability color regardless of explicit awareness, unlike in the bound version of the same task in Experiment 3. This challenges the conclusion that binding is irrelevant to statistical learning, but instead suggests a more complex relationship. It is possible that binding interacts with task difficulty such that the relationship between the stimulus and associated color modulates statistical learning when other task conditions are simplified. Second, these experiments demonstrated that statistical learning can occur even under simpler response and selection difficulties and is thus not exclusive to the orientation judgment task developed by Sha and colleagues (2017) and replicated in Experiments 1 and 2.

Taken together, the results of Experiments 5a and 5b again provide evidence that selection history can bias attention outside of explicit awareness. When data from the unaware participants in both conditions were analyzed together to increase statistical power, there was a significant effect of color in the unaware participants alone. This result provides support for a selection history mechanism that is separable from goal-driven attention, as participants who did not explicitly recognize the higher frequency of targets in the high probability color were unlikely to prioritize it volitionally. Because these effects were seen in the test phase, during which targets were equally likely to appear in both possible colors, the effect of color is also unlikely to have occurred because of repetition priming. However, the combined effects of repetition priming and statistical learning provide a reasonable explanation for the larger differences in RT to targets presented in the high and low probability colors during the training phase, where more frequent repetitions of the high probability color occurred, which were present in this task regardless of explicit awareness.

CHAPTER 7

GENERAL DISCUSSION

Modern cognitive psychologists have begun to acknowledge the failure of the top-down and bottom-up attention dichotomy to account for all aspects of attentional selection. Thus, the idea that attention can be biased toward features or items with which the observer has had previous experience, known as selection history, has begun to gain acceptance in the field as a third source of attentional bias. Whether items are associated with reward, statistical regularity, or repetition priming, repeated selection can result in an increase in the ability for these specific features and items to compete more readily for limited attentional resources regardless of goal-relevance or physical salience. However, as this area of research remains in its infancy, there are many unanswered questions regarding the conditions under which selection history can affect attention. The current work sought to provide insight into these conditions, specifically through studies of implicit statistical learning for predictive features. Table 1 provides a brief summary of the research questions and results from each of these experiments.

The experiments presented in the present work were based on Sha and colleagues' (2017) experiments, which demonstrated that when targets were presented in one of two possible colors with unequal probabilities, participants could implicitly learn to prioritize the color that was more predictive. Importantly, the authors argued that the key task component for implicit statistical learning was not simply presenting one color as a target more frequently, but manipulating the diagnostic value of color to ensure that the high probability color was more predictive of a target and the low probability color was more predictive of a distractor. The present work followed up on these conclusions by testing other task components in addition to the inclusion of diagnostic features, which were held constant across experiments, that were expected to modulate implicit statistical learning. First, we replicated Sha and colleagues' original experiment using a larger sample size to test whether statistical learning was confounded by explicit awareness. Second, we tested the potential effects of binding between the predictive feature and other defining features of the target on statistical learning. Third, we tested whether statistical learning would be modulated by task difficulty by manipulating both selection and perceptual difficulty. Table 2 summarizes the effect of color (low probability color RT – high probability color RT), separated by explicit awareness, in all of the experiments. In this table, a larger number indicates a greater bias toward the predictive high probability color. In general, participants responded significantly faster to targets presented in the high probability in both the training and the test phases. The following sections will address the individual research questions and discuss the results of the corresponding experiments.

Table 1.

Summary of the experiments and results.

	Task	Research Question	Results
1	Report target length Colored lines	Does awareness matter?	Main effect of color in both phases No effect of awareness
2	Report target length White lines in colored boxes	Does binding of color and stimulus matter?	Main effect of color in both phases No effect of awareness
3	Judge target orientation Colored lines/easy distractors	Does selection difficulty modulate statistical learning?	Test effect of color only in aware Training effect of color for unaware
4	Report target orientation Colored lines/hard distractors	Does selection difficulty modulate statistical learning?	Test color effect only in aware No effect of color in unaware
5a	Report target orientation White lines in colored boxes	Does perceptual difficulty modulate statistical learning?	Main effect of color in both phases No effect of awareness
5b	Report target orientation Gray lines in colored boxes	Does perceptual difficulty modulate statistical learning?	Main effect of color in both phases No effect of awareness

Table 2.

Means and standard deviations of RT for low – high probability RT. A larger value reflects a greater difference between RT for the two possible colors, which can be interpreted as the effect of the high probability color.

Exp.	Aware Training	Unaware Training	Total Training	Aware Test	Unaware Test	Total Test
1	M = 87.27	M = 70.79	M = 81.22	M = 68.41	M = 27.34	M = 53.33
	SD = 83.19	SD = 80.38	SD = 81.72	SD = 89.82	SD = 58.62	SD = 81.60
2	M = 97.15	M = 66.49	M = 84.27	M = 50.40	M = 23.40	M = 39.06
	SD = 96.77	SD = 74.08	SD = 88.46	SD = 66.28	SD = 56.68	SD = 63.48
3	M = 89.24	M = 44.83	M = 68.82	M = 20.82	M = 3.51	M = 12.86
	SD = 65.86	SD = 46.62	SD = 61.46	SD = 34.58	SD = 20.52	SD = 30.00
4	M = 121.91	M = 43.75	M = 92.21	M = 88.15	M = 2.92	M = 55.77
	SD = 109.62	SD = 113.86	SD = 116.57	SD = 97.93	SD = 88.85	SD = 102.55
5a	M = 70.62	M = 53.88	M = 60.58	M = 15.69	M = 10.59	M = 12.63
	SD = 52.83	SD = 41.93	SD = 46.82	SD = 28.20	SD = 31.73	SD = 30.18
5b	M = 68.19	M = 46.92	M = 59.08	M = 25.13	M = 9.32	M = 18.35
	SD = 69.53	SD = 35.18	SD = 57.86	SD = 46.47	SD = 17.84	SD = 37.55

Does Explicit Awareness Matter?

The first question addressed in the present work is whether selection history can be separated from goal-driven attention. More specifically, this work addressed whether statistical learning can occur implicitly or is more likely confounded with goal-driven attention due to a large proportion of participants that were explicitly aware of the high probability color. Consistent with Sha and colleagues, approximately half of our participants were able to recognize the unequal probability distributions of the two target colors and correctly identify the high probability color. Experiment 1 specifically examined whether statistical learning effects were driven by these aware participants, but explicit awareness was also measured in each of the subsequent experiments and analyses were conducted to control for this factor. As shown in Table 2, aware participants consistently showed a larger difference in RT for the high and low probability colors than the unaware participants. The results of these analyses indicated that, despite the consistently greater bias toward the high probability color for aware participants across experiments, explicit awareness did not interact with condition in a majority of the tasks (with the exception of Experiments 3 and 4, which will be discussed in a later section). Thus, consistent with previous work, persistent statistical learning was largely independent of explicit awareness (Sha et al., 2017; Kruijne & Meeter, 2016). This provides further evidence supporting the notion that statistical learning is an implicit and automatic guidance of attention that is not directly related to explicit awareness.

The results of these experiments indicated that diagnostic features can change attentional priority outside of explicit awareness. One possible reason for this change is that frequent selection can alter attentional priority in the early stages of perception by invoking local changes in activation within primary visual cortex (Schwartz, Maquet, & Frith, 2002; Furmanski, Schluppeck, & Engel, 2004). In this way, frequently selected features gain a subjective salience, which would increase their competitiveness for limited attentional resources on the attentional priority map automatically without explicit awareness. Implicit learning effects have also been hypothesized to stem from automatic retrieval of long-term associative memories formed between stimuli, responses, and other task elements in "event-files" when the associated stimulus is encountered (Hommel, 2004). According to this theory, participants in the present experiments learned to associate the high probability color with successful detection of the target and automatically retrieved this task set in subsequent trials regardless of whether they recognized this association.

Although statistical learning can bias attention without explicit awareness, it should be acknowledged that participants who became explicitly aware of the high probability color consistently showed a stronger and more robust effect of color than their unaware counterparts. Thus, although much of this learning can occur implicitly, the clear behavioral differences between the aware and unaware participants that indicate a role for subjective experience in modulating attentional priority given to each possible target color. Although both aware and unaware participants might have developed event-files that implicitly associated color with the likelihood of finding a target, aware participants likely used their subjective experience to guide attention beyond this automatic process. Unaware participants incidentally associated color with other aspects of the stimulus, but aware participants likely viewed the color as a relevant feature and incorporated it into their attentional template to improve target detection on a majority of trials. In this way, goal-driven attention might still be confounded with selection history, but the larger sample sizes used in the present work afforded enough statistical power to detect the smaller effect in unaware participants, which can be attributed to implicit learning rather than explicit guidance of attention.

In characterizing the role of explicit awareness in statistical learning, however, it is important to consider the boundaries between goal-driven attention and selection history. Although many investigators argue that goal-driven control is the strongest driver of attention (Jiang et al., 2015), others have suggested that there are greater limitations on the amount of goal-driven control that one can exert over attention and thus learning, whether explicit or implicit, should still be considered an instance of selection history. For example, Theeuwes (2018) argued that knowing the target does not necessarily mean that participants can use it to volitionally guide attention. Specifically, in studies where a target has remained consistent throughout a block, the effects previously attributed to top-down guidance of attention are confounded by intertrial priming. In true top-down guidance, participants should be able to use previous knowledge of a target to guide attention even when the target changes from trial to trial. However, investigators have found that top-down knowledge fails to increase participants' ability to locate a validly-cued target when it changes throughout a block (Mortier, Theeuwes, & Starreveld. 2005; Theeuwes et al., 2006). Similarly, Belopolsky and colleagues (2000) demonstrated this principle with contingent capture: when targets changed throughout a block such that participants had to adapt their top-down sets, distracting singletons captured attention regardless of whether they shared features with the target.

These arguments suggest that rather than guiding attention in a top-down manner, holding a single target or feature template in working memory might instead influence priming by reducing the threshold of activation for the template feature. This would also explain why all participants consistently prioritized the high probability color, but the effects were stronger in aware participants. Both aware and unaware participants were primed to prioritize the high probability color, but recognition of the high probability color allowed these participants to incorporate it into their search template, which could have strengthened priming of the high probability color. This account is similar to the automatic long-term memory activation accounts of implicit learning, but instead assumes that explicit knowledge automatically enhances priming above implicit learning and guides attention to the frequently-selected feature automatically outside of goal-driven control. The distinction between these accounts is unclear from the present work. However, the priming account is consistent with Kruijne & Meeter (2016), who found that explicitly instructing participants to prioritize the low probability color did not alter their bias toward the high probability color. Future studies should incorporate such counter-instruction conditions to test whether explicit knowledge can overcome statistical learning, and whether this is related to explicit awareness.

It is difficult to measure an observer's internal states in behavioral studies of attention. Exploring issues of explicit awareness and consciousness of learning through self-report measures are not without limitations. However, despite the interest in the question of whether explicit awareness of learning confounds biases from selection history with goal-driven control in laboratory studies, this point may be largely unimportant in understanding how items in the real world compete for attention in the context of the priority map hypothesis. The priority map hypothesis does not require a given stimulus to be selected based solely on any of the three sources of bias. Instead, any given item can be simultaneously associated with a level of goal-relevance, physical salience, and prior selection, and the values in each of these categories may change subjectively based on the observer's states, experiences, and current goals. Prior selection in a given context, when explicitly recognized by the observer, may affect both automatic lingering biases from selection history and volitional selection based on goal-relevance to increase the priority of a given stimulus.

Does Binding Matter?

A second question addressed in the present work is whether binding between an irrelevant but predictive feature and other defining characteristics of a stimulus is relevant to implicit statistical learning. One unique aspect of the task used by Sha and colleagues (2017) is the use of colored stimuli, creating an inherit binding between color and other defining features of the stimuli such as length and orientation. We predicted that this binding could influence learning by modulating participants' ability to selectively ignore color as an irrelevant feature. This prediction was based on other studies of binding and attention, which have demonstrated that reducing binding can also reduce interference between relevant and irrelevant features in the Stroop effect (Risko et al., 2005; Besner & Stolz, 1999).

The results of the current experiments do not provide a clear answer to the question of whether binding influences implicit statistical learning. In the length judgement task (Experiments 1 and 2), participants implicitly learned to prioritize the high probability color regardless of whether stimuli were presented in colored font or white font surrounded by colored boxes. Conversely, in the orientation judgement task (Experiments 3 and 5), participants showed this effect only when color was not bound to the line stimuli. Interestingly, the overall effect of color was strikingly similar for Experiments 3 and 5 (see Table 2). At a glance, this result is consistent with Experiments 1 and 2 (bound vs. unbound length judgment task), but the effect of color was null in Experiment 3 for unaware participants and thus completely driven by aware participants. These results suggest that the relationship between binding and statistical learning might be more complex. For example, the relationship between binding and explicit awareness might be modulated by task difficulty. Under easier task conditions, binding might drive whether participants become explicitly aware because color might attract more attention automatically if it is bound to the stimulus. Thus, participants should be more likely to consciously associate color with the probability of finding a target in the bound condition and thus be more likely to become explicitly aware, whereas they might ignore color more effectively in the unbound and easier task conditions. However, participants in Experiments 5 and 3 were not significantly more or less likely to become explicitly aware of the high probability color's predictive value, although fewer than half of the participants in the high contrast condition of Experiment 5 were considered explicitly aware.

Alternatively, binding might neither modulate awareness, nor bear any relationship to statistical learning if participants view the unbound stimuli as coherent objects. This perceptual grouping would likely allow attention to spread to color regardless of whether it is bound to the stimulus or surrounding it. Previous studies of selection history using reward learning such as Anderson and colleagues' (2011a) paradigm find persistent attentional bias to a high reward color using an unbound layout. The current results likewise hint at a null relationship between binding and propensity for implicit statistical learning, but the results of Experiment 3 remain anomalistic to this conclusion. Future work should first seek to replicate the current studies to ensure that the discrepancies in these results are a reliable effect of the experimental manipulations, or whether they occurred due chance or systematic error.

Is Selection History Automatic?

With the recent surge of acceptance for selection history as a category of attentional bias, there is little doubt that, unlike goal-driven selection, the lingering biases from selection history can influence attention outside of voluntary control. This is particularly evident in tasks during which participants often struggle to ignore a location or feature that was previously highly selected or rewarded (Preciado & Theeuwes, 2018; Anderson et al., 2011a). However, a central question in the previous work is whether learning that leads to a persistent bias to attention occurs automatically. Although Sha and colleagues (2017) demonstrated that diagnostic features were important to inducing persistent statistical learning, we predicted that diagnostic features alone would be insufficient to produce learning. In addition to diagnostic features, we predicted that altering task difficulty would also influence the development of statistical learning by modulating the amount of attention allocated to the task and to the processing of features outside of the defining and reported target features.

Experiments 3 and 4 examined the role of selection difficulty in statistical learning by manipulating the distinctiveness between targets and distractors. The main condition of interest to this question was in Experiment 4, where targets and distractors were highly similar and thus difficult to distinguish from one another. Increasing selection difficulty in this manner was expected to reduce attention devoted to color, particularly in unaware participants, because color should have been considered an irrelevant feature for finding a target defined by orientation. According to load theory (Lavie et al., 2004; Lavie, 2005), increasing perceptual difficulty should prevent processing of irrelevant information by exhausting attentional resources to attend relevant information. The results of Experiment 4 supported this prediction: only aware participants responded more quickly to high probability color targets in both the training and the test phases. Unaware participants showed no evidence of attentional bias toward the high probability color in either phase of the experiments. This suggests that because the distractors were highly similar to the target, participants devoted more attention to locating the target, and without sufficient attention remaining to process color, implicit statistical learning did not occur under conditions of increased selection difficulty.

Implicit learning is modulated by selective attention to predictive features and contexts. Using a contextual cueing paradigm, Jiang and Chun (2001) demonstrated that visual search was only facilitated by contextual learning if predictive configurations were selectively attended. When predictive configurations were presented in a non-target color and thus ignored during visual search, participants did not learn to use these predictive configurations to locate targets more efficiently. This finding suggests that implicit learning cannot occur without attention devoted to predictive information. The results of Experiment 4 corroborate this finding: without sufficient attentional resources available to process color, participants did not learn to prioritize the high probability color unless they were explicitly aware of its predictive value.

Experiments 3 and 4 indicated that selection difficulty can alter the amount of attention that is available to process irrelevant information. The effect of color for unaware participants in the training phase in Experiment 3 but not in Experiment 4 supports load theory because it suggests that participants under the easier load condition had enough remaining attentional resources after locating the target to passively process color enough to prioritize the high probability on the short term. Sha and colleagues (2017) attributed such a result to intertrial priming, which was expected during the training phase because the greater proportion of high probability targets would automatically lead to a greater number of repetitions that would automatically lower the activation needed to process high probability targets. However, without such an effect during the test phase occurring outside of explicit awareness, the results of Experiment 3 suggest that load theory alone does not adequately explain the conditions necessary for statistical learning. Although a lower perceptual load leaves attention available to process color, this passive level of processing is insufficient to produce learning beyond transient repetition priming effects. This result, particularly when considered with Experiment 4, does support the prediction that attention to predictive features is necessary for implicit statistical learning, but this passive attention alone – even in the presence of diagnostic features – is insufficient to produce persistent learning.

In addition to the availability of attentional resources to process irrelevant color information, we also predicted that task difficulty would modulate the amount of attention devoted to the task. Under more difficult task conditions, participants were expected to devote more attention to the task, whereas an easier task could be performed more automatically and thus allow attention to wander to off-task activities. The results of Experiment 3 suggest that such a mechanism is important to persistent learning. However, the results of Experiment 4 indicated that without attention available to process color, even devoting more attention to the task will not produce persistent statistical learning. Thus, we propose that implicit statistical learning requires an optimal level of task difficulty, wherein perceptual load is not too high as to exhaust attention and prevent the processing of the predictive feature, but the task is challenging enough to engage task-related attention.

A limitation of the present work is that cognitive load was not explicitly manipulated in the present studies. Both selection and perceptual difficulty manipulations altered perceptual load, but this produces an incomplete picture of the role of load theory in implicit statistical learning because perceptual and cognitive load are thought to have opposite effects on the processing of irrelevant information (Lavie et al., 2004; Lavie, 2005). It is possible that the line length judgment task provides a better avenue for implicit statistical learning because it increases cognitive load and thus allows attention to process irrelevant color cues. Finding a target based on its orientation and then reporting some other feature of the target such as length might load on frontal control processes, whereas the manipulations of task difficulty tested in the current work were loaded perceptual search processes. This would also explain why the effect of color in Experiments 1 and 2, which used the length judgment task, was much larger than in the orientation judgment tasks. Future work should test this prediction by manipulating cognitive load in statistical learning tasks.

Although task difficulty might modulate the amount of attention devoted to color and the task in general, not all aspects of task difficulty influenced learning in the same way. Despite the potential role of cognitive load induced by the length judgment task and its substantially stronger ability to induce statistical learning, the current work demonstrated that implicit learning can occur during the simpler orientation judgment task. In Experiment 5, participants developed a persistent bias to prioritize the high probability color in both the low and high contrast conditions using the orientation judgment task. Thus, changes in perceptual difficulty, unlike changes in selection difficulty in Experiment 4, did not change the likelihood that participants would learn to automatically prioritize the high probability color. However, participants did respond more slowly in the low contrast condition, indicating that the difficulty manipulation was successful. It is possible that perceptual difficulty did not influence statistical learning because unlike in selection difficulty, the competition between distractors and targets was not influenced by the manipulation. When targets and distractors were made more similar, distractors competed more strongly with targets to draw attention and thus required greater attention to the relevant orientation feature to reject distractors and correctly select the target. In the low contrast condition, however, all stimuli were made more difficult to see and thus did not compete more or less with one another than in the high contrast condition.

Conclusions

Attention is strongly influenced by prior knowledge and experience. When items are selected frequently or associated with reward, attention can be automatically biased to continue selecting them in future encounters. The present work examined this type of attentional bias, called selection history, for feature-based statistical learning. The results generally demonstrated that participants could learn to prioritize a color that was frequently selected as a target. The current work, however, did not investigate the potential mechanistic differences between statistical learning and reward learning, which are both considered instances of selection history (Awh et al., 2012). It is likely that these types of learning rely on distinct underlying mechanisms (Kim & Anderson, 2019), but it is also possible that they share a common mechanism. For example, performance feedback (Ravizza et al., 2012; Ravizza & Delgado, 2014) has been shown to improve task performance similarly to reward. Thus, it is possible that selecting the high probability color was associated with a reinforcing experience because it was more likely to be a correct selection and thus result in positive feedback. Like monetary reward, receiving positive feedback for selecting a correct target might have reinforced the behavior of selecting the high probability color in the current experiments. This prediction is consistent Levy and Glimcher (2012), who suggested that neurons represent various types of value in a domain general value, which is a potential mechanism through which selection history can change attention. Future studies should continue to examine the cognitive and neural mechanisms underlying the different types of learning associated with selection history.

Unlike the top-down and bottom-up dichotomy, the priority map hypothesis includes selection history as a category to account for these factors and provides a clearer approach for understanding how the most relevant information in the environment competes for limited attentional resources. The goal of this doctoral dissertation was to further examine this priority map approach and, specifically, to investigate the conditions under which selection history via implicit statistical learning can alter attentional priority. The present experiments demonstrated that human observers developed a lingering bias to prioritize a previously high probability color even when it was no longer beneficial to task performance. This overall effect was apparent regardless of the required target judgement (length versus orientation), the relationship between color and other defining features of the stimuli (colored lines versus colored boxes surrounding white/gray lines), and the relative ease of finding the target (high versus low contrast, distinct versus similar distractors).

In a majority of these experiments, learning biased attention toward the high probability color regardless of whether participants were explicitly aware of the probability differences. Thus, learning from selection history can occur implicitly and be distinguished from top-down influences. However, this implicit learning did not occur automatically in the presence of frequently selected diagnostic features. In two of the present experiments, participants did not maintain a lingering bias for the high probability color into the test phase without explicit recognition. This effect was most pronounced in the least efficient search task, during which the distracting stimuli were most similar to the targets. Thus, participants may fail to process features that they believe are irrelevant if perceptual load is too high, and this lack of attention results in a failure to implicitly learn diagnostic values. Although explicitly aware participants did show these effects in all of the experiments, this poses a potential confound between selection history and goal-driven attention. However, it is possible that selection history still guides attention even when targets are explicitly known, and the priority map hypothesis makes allowances for such cases. Future work should continue to parse out the contributions of goal-driven and history-driven biases in attentional selection and investigate the mechanisms through which statistical learning occurs and exerts persistent control over attention. However, it is clear from current literature and the present work that prior experience exerts a powerful influence on how information in the vast visual environment can compete effectively to gain access to limited attentional resources.

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