Visual statistical learning and its impact on spatial attention

A DISSERTATION SUBMITTED TO THE FACULTY OF THE
UNIVERSITY OF MINNESOTA BY

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IN PARTIAL FULFILLMENT OF THE REQUIERMENTS

FOR THE DEGREE OF DOCTOR OF PHILOSOPHY

Advisor: Prof. Yuhong Jiang

April 2014

Acknowledgements

I would never have been able to finish my dissertation without the guidance of my advisor and committee members.

Especially, I would like to express my deepest gratitude to my advisor, Dr. Yuhong Jiang, for her excellent guidance, caring, patience, and providing me with an outstanding atmosphere for doing research. She also patiently corrected my writing and financially supported my research.

Also, I would like to thank Dr. Khena Swallow and Dr. Tal Makovski, for supporting and helping me to develop my research for the past several years. I would also like to thank Dr. Wilma Koutstaal, Dr. Sheng He, Dr. Sashank Varma, Dr. Shmuel Lissek, and Dr. Jeanette Gundel for being my committee members and providing helpful advice.

I also thank my former advisor Dr. Min-Shik Kim and former committee members, Dr. Do-Joon Yi and Dr. Sang Chul Chong in the master's program at Yonsei University.

Last, but by no means least, I would thank my friends in Korea, the USA, and elsewhere for their support and encouragement throughout.

Dedication

This thesis is dedicated to my family for their love, endless support and encouragement.

Abstract

Visual statistical learning (VSL) refers to our ability to extract and use environmental regularities to guide visual perception and behavior. Previous research on VSL has emphasized its role in shaping the perception of repeated visual statistics, such as the consistent association between pairs of novel shapes. However, much less is known about the nature of such learning and its utility in guiding spatial attention and visuomotor action. This dissertation examines visual statistical learning in two major domains: perception and attention/visuomotor action. Part I focuses on how people learn a consistent association between multiple novel shapes. I show that such learning depends critically on having conscious awareness of the visual statistics. Part II provides evidence that when people perform tasks such as visual search, they are able to extract consistent visual statistics (e.g., the frequent locations of the search target) without explicit awareness of those statistics. This dissertation demonstrates that multiple forms of VSL may depend on different cognitive mechanisms.

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Introduction

We are constantly surrounded by an overwhelming amount of sensory information. About 10^{10} bits of visual information is deposited on the retina every second (Raichle, 2010). That is 1.25GB of data per second. Furthermore, the information is not static but is constantly changing. Yet, despite this continual and massive influx of data, we do not often have difficulty perceiving the visual environment, and we rarely notice the abundance of information surrounding us. How is this possible with limited cognitive resources?

One answer is provided by the important fact that the visual environment contains a high degree of statistical regularities. Some objects frequently co-occur within particular environments. Such spatial and temporal regularities provide rich statistical associations among objects and their context. For instance, a laptop is more often found on a desk than on the floor; rain, thunder, and lightening often follow dark clouds. Extracting statistical regularities of the visual environment is a natural and efficient way to perceive and represent the world (Oliva & Torralba, 2007). Some researchers argue that the human visual system possesses mechanisms that adapt to the statistics of the natural world (Turk-Browne, 2012).

Statistical learning refers to the cognitive process by which repeated patterns, or regularities, are extracted from the sensory environment (Turk-Browne, 2012). Such learning often happens without an intention to learn and without an awareness of what was learned. A classic example of statistical learning is the acquisition of new sound structure in the auditory modality. Saffran and colleagues showed that 8-month old infants are sensitive to auditory statistical regularities. They exposed infants to a stream of syllables, constructed from 12 syllables (e.g., *tu, pi, ro, bi, da, ku, go, la, bu, pa, do, ti*) that formed four tri-syllabic "words" (e.g., *tupiro, bidaku, golabu, padoti*). After a 2-minute exposure to streams such as "*bidakupadotibidakugolabutupiro …"*, infants were tested in a habituation procedure with two tri-syllables. One was a "word" (e.g., "*bidaku*") heard during the 2 min-exposure phase, and the other was a foil (e.g., "*tudabu*"). The foils were composed of three syllables that were never paired together. Saffran and colleagues found that infants showed more interest in the foil than in the word, as indexed by increased listening time (i.e., the duration of showing interest in each tri-syllable). That is, infants are capable of statistical learning after just two minutes of exposure to sound sequences (Saffran, Aslin, & Newport, 1996).

Subsequent research examined statistical learning in several sensory modalities including vision, audition, and tactile senses (Conway & Christiansen, 2005; for a review see Krogh, Vlach, & Johnson, 2012). Studies have tested various types of statistical regularities, including semantic (Otsuka, Nishiyama, Nakahara, & Kawaguchi, 2012), spatial, and featural regularities, and sequences of faces and scenes (Turk-Browne, Scholl, Johnson, & Chun, 2010; Zhao, Al-Aidroos, & Turk-Browne, 2013). Statistical learning has been shown in young infants, young and older adults, and in nonhuman primates (Frost, Siegelman, Narkiss, & Afek; 2013; Hauser, Newport, & Aslin, 2001; for a review see Turk-Browne, 2012).

This dissertation focuses on statistical learning in the visual modality. Researchers have proposed that visual statistical learning (VSL) facilitates and structures the perception of the natural visual environment (Turk-Browne, 2012). In two early studies modeled after Saffran et al.'s (1996) study, Fiser and Aslin (2001, 2002) asked participants to view displays of novel shapes presented at various spatial locations. Although participants engaged in no tasks, they demonstrated sensitivity to co-occurrence between pairs or triplets of shapes as well as their relative spatial locations (Fiser & Aslin, 2001) and temporal structure (Fiser & Aslin, 2002; Olson & Chun, 2001). Learning occurred in an "unsupervised" manner, in the absence of an overt task or explicit instruction. Other studies showed that consistent statistical information, such as the location of a visual search target in a scene, can readily guide spatial attention to important locations (Brockmole, Hambrick, Windisch, & Henderson, 2008; Chun & Jiang, 1998).

This dissertation will be divided into two parts that explore two traditions of visual statistical learning. The first tradition shows that people are sensitive to spatial and temporal co-occurrence of novel shapes even in the absence of any tasks. This form of "standard VSL" has been hypothesized to facilitate object perception in the real world (Oliva & Torralba, 2007). The second tradition examines the role of visual statistical learning in controlling visual attention. These studies measure VSL in the context of specific tasks. Before delving into the two parts of the dissertation, I would like to briefly elaborate on the definition of visual statistical learning and the potential role of explicit awareness in visual statistical learning.

Fiser and Aslin (2001, p. 1) defined visual statistical learning as "the ability of human observers to extract the joint and conditional probabilities of shape co-occurrences during passive viewing of complex visual scenes". This definition emphasizes the perceptual function of VSL and the fact that it emerges even without the observer engaging in any overt tasks. More broadly, Turk-Browne, Jungé, & Scholl (2005) defined visual statistical learning as “a subtle statistical relationship among visual objects in both space and time”. Although neither of these definitions specifically mentions the viewer’s explicit knowledge about the statistical regularities, many researchers refer to visual statistical learning as “implicit” or “unconscious” learning (Perruchet & Pacton, 2006; Turk-Browne et al., 2005, 2010; Turk-Browne & Scholl, 2009). In fact, what started out as “incidental learning” and “unsupervised learning” (Baker, Olson, & Behrmann, 2004; Fiser & Aslin, 2001, 2002) gradually migrated into “implicit learning” in more recent studies (Fiser & Aslin, 2005; Kim, Seitz, Feenstra, and Shams, 2009; Perruchet & Pacton, 2006; Turk-Browne et al., 2005, 2009, 2010). The terms “incidental learning” and “unsupervised learning” are neutral with regard to the participants’ experience. These terms highlight the fact that the participants have no intention to learn (e.g., no specific encoding tasks are required). But the terms “implicit” and “unconscious” learning imply that learning occurs even though participants are unaware of the visual regularities. Despite of the widespread usage of such terms (for a review, see Perruchet & Pacton, 2006; Turk-Browne, 2012), few studies have directly examined the degree to which explicit awareness contributes to VSL.

In other cognitive domains, explicit goals and intention contribute significantly to the organization of sensory input. For example, people intentionally create regularities by grouping semantically related words together to form “chunks” (groupings of items) in working memory and long-term memory (for a review, see Gobet, Lane, Croker, Cheng, Jones, Oliver, & Pine, 2001). Chunking in long-term memory relies on a variety of explicit strategies (Miller, 1956). For example, a string of 8 letters, G/F/B/I/L/C/I/S, is hard to remember. However, if these letters form acronyms (e.g., G/FBI/L/CIS), they become easier to remember. Such explicit strategies may be at play in VSL as well. In fact, several studies have shown that chunking is part of VSL. Frequently co-occurring items become chunked into a larger unit (Fiser & Aslin, 2005), providing a powerful mechanism for forming hierarchical structures of the complex visual world. Consistent with this notion, Orbán, Fiser, Aslin, & Lengyel (2008) showed that transitional and conditional probabilities among novel shapes support the formation of larger chunks that combine several novel objects together. Brady, Konkle, & Alvarez (2009) showed that statistical regularities compress the working memory representation of visual input. For instance, when some color pairs (e.g., red and green) were more likely to co-occur on a visual display than expected by chance, observers could remember more colors from the frequently paired colors than from unrelated colors.

If VSL is a form of chunking and if chunking often relies on explicit strategies, then it is likely that explicit knowledge contributes to VSL. This idea seems to run counter to the prevailing theory about VSL: that it occurs without an intention to learn and without explicit knowledge about what was learned (Perruchet & Pacton, 2006; Turk-Browne, 2012). This contradiction raises questions about whether VSL depends on explicit awareness, and whether different forms of VSL have different reliance on explicit awareness.

A major goal of Part 1 of this dissertation is to evaluate the role of explicit awareness in standard forms of VSL. In this part of the dissertation learning serves primarily the function of perceiving, rather than acting on, the visual world. Part 2 will also include an assessment of explicit awareness, but the main focus will be on forms of VSL that modulate visual action, such as the allocation of spatial attention and the direction of overt eye movements. Together, this dissertation delineates the nature of visual statistical learning, its dependence on explicit awareness, and its utility in modulating visual perception and action.

1. Part I: Explicit awareness in standard forms of visual statistical learning

1.1. Standard VSL paradigm

To examine how visual regularities are acquired, researchers have developed the "standard" VSL paradigm in which participants learn the spatial and temporal co-occurrence of novel shapes (Fiser & Aslin, 2001; Turk-Browne et al., 2005; Turk-Browne, 2012). In one paradigm, twelve novel shapes are presented sequentially in a continuous temporal stream (Figure 1A), or simultaneously in various locations of a spatial array (Figure 1B). These novel shapes are pre-assigned into six pairs (or four triplets), and the shapes in a pair (or a triplet) are always presented one after the other in the temporal stream, or at fixed locations in the spatial array. Suppose that shape A and shape B compose a pair. Whenever shape A appears, the next shape in the sequence is always B (or the shape at a specific location relative to A is always B). The pairs (or triplets) are repeated many times in the training phase of the experiment. To examine whether participants have acquired VSL for the repeatedly associated shapes, researchers typically administer a familiarity judgment task in a subsequent test phase (Figure 1C). In this task, participants are shown an old pair (or triplet) that they have seen earlier, along with a foil. The foil is a random recombination of a subset of the same 12 shapes. This learning and testing procedure is surprisingly powerful. Participants can often choose the old pairs (or triplets) at above chance levels, suggesting that they have acquired VSL (Fiser & Aslin, 2001, 2002, 2005).

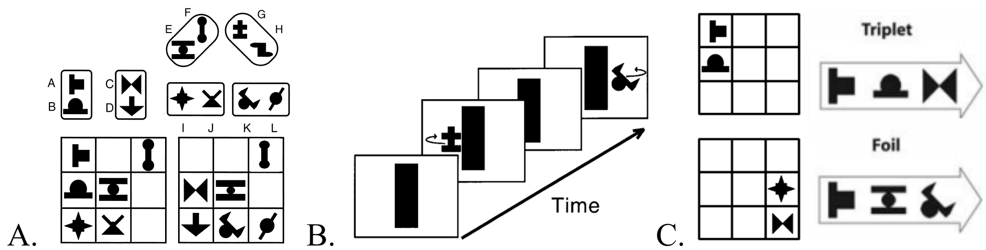


Figure 1. Standard visual statistical learning paradigms. A. Spatial visual statistical learning paradigm. Arrays are composed of three pairs (randomly and repeatedly chosen out of six pairs). B. Temporal visual statistical learning paradigm. A stream of shapes is composed of four triplets (for more detail, see the method in Experiment 1). C. The familiarity task. Spatial visual statistical learning paradigm (left) or temporal visual statistical learning paradigm (right). Figure A, B and C (left) are from Fiser & Aslin (2001, 2002) and Figure C (right) from Turk-Browne & Scholl (2009).

1.2. Is visual statistical learning implicit?

Early studies on visual statistical learning described it as unsupervised or incidental learning because no instruction about the regularity of shape pairings was given to participants (Fiser & Aslin, 2001; 2002). Recently, however, researchers have used a mixture of the terms “incidental” and “implicit” learning to characterize VSL (Perruchet & Pacton, 2006; Turk-Browne et al., 2005). The intermixed use of “incidental” and “implicit” learning implies that VSL is perhaps both incidental and implicit. However, whereas VSL is often incidental (because no instructions about the regularities are given; Eysenck, 1982), whether it is also implicit requires an assessment of participants' explicit knowledge. Yet few studies on VSL have provided such an assessment.

The experimental paradigm that is used to assess VSL has also received misleading terminologies. Several researchers have referred to procedures that assess VSL *indirectly* as an *implicit* measure of VSL. For example, Turk-Browne et al. (2005) assessed VSL using two measures. In one measure, participants made a familiarity judgment on old triplets and foil triplets. In another measure, participants were first shown a shape and then asked to press the spacebar whenever they detected this shape in a sequence of shapes. If people had learned the temporal sequence of a given triplet, then they should be faster in responding to the third item (which was predicted by the first and second items) compared with the first item (which could not be predicted). Although the familiarity test and the response time (RT) tests may be considered as "direct" and "indirect" tests of the triplet association, Turk-Browne et al. (2005) referred to these tests as "explicit" and "implicit", respectively. Similarly, Baker et al. (2004) used familiarity rating as an explicit measure, and RT measures as an implicit measure of novel shape associations. Both studies found evidence for VSL in both the RT measure and the familiarity judgment. Despite the similarity in procedure and results, the two studies reached opposite conclusions with regard to the role of explicit awareness in VSL. Turk-Browne et al. (2005, p. 552) concluded that, "VSL is nevertheless an implicit process because it operates during a cover task and without awareness of the underlying statistical patterns". Baker et al. (2004, p. 465), on the other hand, concluded that, "statistical learning was evident in both measures of performance (implicit) and familiarity ratings (explicit), suggesting that representations of shape combinations are explicit."

In a recent review, Turk-Browne summarized five reasons why visual statistical learning is a form of implicit learning (Turk-Browne, 2012). Here I quote:

*"*While statistical learning of object relationships occurred only when the objects were task-relevant, this learning happened without conscious awareness. Indeed, statistical learning was robust despite the fact: that (1) subjects were not informed about the presence of regularities, that (2) they performed a distracting cover task (one-back) during familiarization, that (3) the shapes were presented quickly, that (4) regularities from the two streams were interleaved, adding noise to the transitional probabilities, and that (5) learning was evident in an implicit RT measure. Moreover, during careful debriefing in the RT experiment, no subjects expressed awareness of the structure in the displays. These findings suggest that statistical learning is and is not automatic: selective attention to objects is required for their relationships to be learned, but once this input has been selected, learning takes place without conscious intent or effort." (Turk-Browne, 2012, p. 128).

These five points were made on the basis of one specific study (Turk-Browne et al., 2005), as such their validity to VSL more broadly is questionable. First, the characterization that "*statistical learning was robust"* is ambiguous. In most studies, the average performance for choosing the old pair/triplet is between 60-70%. Although for a two alternative forced-choice task this is higher than chance (50%), it is also far from perfect. Publication bias may have put many studies that fail to show VSL into a file drawer (Pashler & Harris, 2012; Pashler & Wagenmakers, 2012). Second, although "*(1) subjects were not informed about the presence of regularities,*" this does not mean that visual statistical learning is implicit. The most one can conclude from this paradigm is that VSL is incidental. Furthermore, although "*(2) they performed a distracting cover task (one-back) during familiarization,*" it is unlikely that participants were completely occupied to the point that they could not (intentionally or consciously) notice any regularity. Most of the cover tasks used in visual statistical learning are easy, such as pressing a button when the current shape is the same as the immediately preceding shape (the "one-back" task). This task is fairly effortless and may leave free sufficient (cognitive or attentional) resources to (deliberately, intentionally, or explicitly) process the repeated patterns. In addition, although *(3) the shapes were presented quickly,* the presentation rate was usually slow enough for shape perception. Most VSL studies adopted a slow presentation rate[1] (e.g., 1s/shape). To my knowledge, the shortest presentation time was 200 ms per shape (Turk-Browne et al., 2005). However, humans can recognize objects and scenes in as little as 65 ms (Grill-Spector & Kanwisher, 2005) or 13 ms (Potter, Wyble, Hagmann, & McCourt, 2013). The shortest presentation rate used in VSL studies - 200 ms - may be long enough for participants to explicitly construct the visual regularities. In fact, Turk-Browne and colleagues showed that VSL was better when shapes were presented more slowly (e.g., 800 ms/item rather than 200 ms/item). Because most VSL studies presented items at a rate of about 1s/item, substantial time was available to encode the shape associations explicitly. Also, Turk-

[1] The presentation durations of some studies: 2 sec per array in Fiser & Aslin (2001, 2005); 1 sec per shape in Fiser & Aslin (2002) and Turk-Browne & Scholl (2009); 3 sec per array in Roser, Fiser, Aslin & Gazzaniga (2011); 200 ms per shape in Turk-Browne & Scholl (2005) and Bertels, Franco, & Destrebecqz (2012); 800 ms per shape in Turk-Browne, Scholl, Chun, & Johnson (2009).

Browne (2012) suggested "*(4) regularities from the two streams were interleaved, adding noise to the transitional probabilities.*" Although the interleaved sequence of attended and unattended objects made it difficult to extract the regularities among attended objects only, the attended stream in Turk-Browne et al. (2005)'s study had only four triplets that were repeated many times (24 times). Furthermore, participants were asked to attend to the four triplets. The small number of triplets and the large number of repetitions would make explicit learning relatively easy. Finally, although it is true that "*(5) learning was evident in an implicit RT measure,*" learning was also evident in an explicit familiarity judgment task. We cannot conclude that learning is implicit just because one of the tasks measures VSL *indirectly*. Memory researchers have long warned that indirect memory tasks may tap into both explicit and implicit memory, and direct memory tasks may partially rely on implicit memory (Toth, Reingold, & Jacoby, 1994). For all these reasons, it seems that explicit knowledge could contribute greatly to VSL (at least in standard VSL experimental paradigms similar to those that are here under consideration).

Few studies have carefully assessed explicit awareness in VSL. Turk-Browne (2012) noted that, "*during careful debriefing in the RT experiment, no subjects expressed awareness of the structure in the displays.*" Yet the debriefing process was relatively crude. Most studies did not probe explicit awareness, and those that did, relied almost exclusively on informal oral debriefing (Fiser & Aslin, 2005). Published studies rarely presented the outcomes of such debriefing carefully. For example, a study reported that "these observations (post questionnaires) were reported during an informal debriefing chat and they were not quantified rigorously" (Fiser & Aslin, 2005). Yet it is entirely possible that those who noticed the pattern were the ones who most contributed to the evidence for VSL -- or may even drive the entire effect. This is because most studies use a small number of pairs or triplets (typically only 6 pairs or 4 triplets). If a participant becomes explicitly aware of the pairs/triplets, their accuracy in familiarity judgment should approach 100%. Just a few high performers (90-100%) can bring familiarity judgment performance to a moderately high level (60-70%), even if participants who reported no explicit awareness failed to show VSL. To more rigorously examine the role of explicit awareness in VSL, it is necessary to examine whether those who noticed the statistical regularity showed greater VSL than those who had no explicit awareness.

Indirect evidence for the idea that VSL may depend on explicit learning comes from contrasting the characteristics of participant groups who have been found to demonstrate implicit learning in other types of paradigms, versus the findings for VSL. A long-standing tradition of implicit learning using tasks such as artificial grammar learning, serial response time, and perceptual learning has shown that implicit learning is preserved in the presence of aging (Howard & Howard, 1992), neurological disorders (e.g., Parkinson disease, Smith, Siegert, McDowall, & Abernethy, 2001), low IQ (Reber, Walkenfeld, & Hernstadt, 1991), and increased cognitive load (Nissen & Bullemer, 1987; Rossetti & Revonsuo, 2000). Contrary to these findings, visual statistical learning is sensitive to aging (Arciuli & Simpson, 2011), cultural differences (Frost et al., 2013), perceptual grouping (Baker et al., 2004; Glicksohn, & Cohen, 2011), and selective attention (Turk-Browne et al., 2005). These findings imply that VSL is not likely to be exclusively, or predominantly, implicit learning. Because explicit awareness is limited to a very small amount of information (Cowan, 2001; Huang, Pashler, & Treisman, 2007), and is subjected to the participant's current goals, the reliance of VSL on explicit awareness would mean that VSL is similarly limited.

1.3. Paradigm issues

The standard paradigm of visual statistical learning is conducive to conscious learning. First, most studies employ no cover task in the training phase. Participants are asked to just look at the visual stimuli on the display (Fiser & Alsin, 2001, 2002, 2005; Glicksohn, & Cohen, 2011; Turk-Browne & Scholl, 2009; Turk-Browne et al., 2010). Under these unstructured conditions participants are likely to form their own hypothesis about the experimenter's intent. Second, many studies inform participants that although they can look at the stimuli without a specific task, they will be tested on these stimuli in a later phase of the experiment (Fiser & Aslin, 2001, 2002). This instruction strongly motivates participants to actively learn and remember the shapes and any patterns that they may discover.

Third, as noted by Turk-Browne and Scholl, the *"*familiarity task can also be readily influenced by explicit strategies and conscious guesswork (Turk-Browne & Scholl, 2009, p. 200)." Because the novel shapes were equally unfamiliar *prior to* the experiment, participants are left to infer that the familiarity judgment must be based on the training phase. To choose the more familiar pair/triplet they may actively retrieve what they have learned from the training phase. Their attempt to explicitly retrieve information from the training phase is likely to be successful for at least two reasons. First, the testing phase often immediately follows the training phase. With such a short retention interval, explicit memory is very good (Jacoby & Dallas, 1981). Second, the old pair/triplet used in the testing phase is almost always *identical* to a pair/triplet shown in the training phase. This simplifies the comparison process. This latter feature of VSL stands in contrast to more established implicit learning paradigms such as the artificial grammar learning (Reber, 1967; Figure 2). In artificial grammar learning, a finite-state “language” is constructed by applying a set of complex rules on several letters. The underlying rules (grammar) are difficult to identify owing to their complexity. In addition, these rules can generate grammatical strings that have never been shown before. So a familiarity judgment task in artificial grammar learning taps into the underlying rules rather than memory for the exemplars (Knowlton & Squire, 1996). Explicit memory for specific letter strings does not contribute to recognition success in artificial grammar learning, but explicit memory for specific shape pairs/triplets in standard VSL is adequate for distinguishing old pairs/triplets from foils.

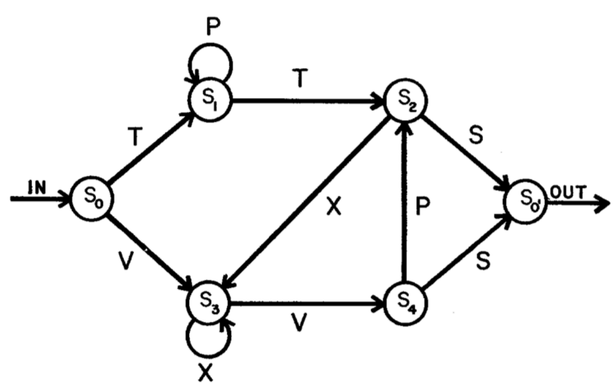


Figure 2. An example of grammars in artificial grammar learning (Reber, 1967)

Because the familiarity task is vulnerable to influence from explicit knowledge, several researchers have designed a response time task as an indirect measure of VSL (Bertels, Franco, & Destrebecqz, 2013; Kim et al., 2009; Turk-Browne et al., 2005; Turk-Browne & Scholl, 2009; Zhao et al., 2013). In this procedure, participants are shown a rapid stream of previously encountered pairs (or triplets), and asked to detect a pre-specified target shape in each test trial. The target shape in each test trial could be the first, second (or third shape) from the pair (or triplet). If people had learned the temporal sequence of the shapes, they should be faster in responding to later shapes in a pair/triplet than earlier shapes because the later shapes are predicted by earlier ones. Because the RT task does not directly ask people to think about the shapes they saw before, it is an indirect assessment of learning.

However, just like the familiarity task, the RT task can also be influenced by explicit knowledge. If participants possess explicit knowledge about triplets, they can actively anticipate the following shapes and respond as soon as they see the first shape. In addition, a recent study has questioned the logic of the RT task in assessing VSL. Most existing RT tasks have included only trained pairs/triplets. They have not scrambled the pairing among the shapes. Barakat, Seitz, & Shams (2013) showed that the later shapes in a triplet were responded to faster even when they were preceded by shapes from other unrelated triplets. This implies that, in other studies using the RT task, the enhanced RT to later shapes within a pair/triplet cannot necessarily be attributed to associative learning between repeatedly paired shapes. Finally, the robustness of the RT paradigm is questionable. In a preliminary study that I conducted, I was unable to replicate statistical learning in the RT paradigm. I adopted a very similar task to the one in Turk-Browne & Scholl (2009). After being exposed to six pairs repeatedly in the training phase, participants were presented with 1 of the 12 shapes from the training phase as the target to be detected for that trial. Then a stream of 14 shapes appeared one at a time in the center of the screen for 400ms each, followed by a 400ms pause. The stream included 12 novel shapes and a critical pair—a sequence of 2 shapes, the second of which was the target. The first shape in the critical pair was either the shape with which the target had been paired during learning (i.e., paired shape) or a shape from the other pair (i.e., non-paired shape). Participants made a quick key press whenever they detected the target shape. Whereas Turk-Browne & Scholl (2009) found that participants made a faster RT to the target shape following the paired shape than non-paired shape, I showed no difference between these two conditions. The difference between paired and non-paired shapes was not significantly different (RT: paired shape: 369 ms vs. non-paired shape: 372 ms, $p > .70$, N = 13). Consistent with Barakat et al. (2013), my preliminary study showed that the RT task was not sensitive to associative learning. This leaves us with just the familiarity judgment task as evidence for standard VSL.

1.4. Two recent contradictory studies

Recently two studies have directly assessed whether VSL was implicit but the findings were contradictory. The two studies employed highly similar paradigms, but arrived at opposite conclusions. Kim et al. (2005) exposed participants to four triplets (a total of 12 shapes) presented for 100 times during the training phase. To measure implicit learning, the researchers adopted the RT task. Specifically, participants were asked to detect a pre-specified target shape in rapid serial visual presentation (RSVP). They found that the participants made a faster response to the second and third shapes than to the first shape in a triplet, and this result was observed even after a one-week delay. To assess explicit awareness, Kim et al. (2005) performed a 12-alternative-forced-choice task (12-AFC) to assess explicit memory. Participants were shown the first shape from the old triplet and asked to select, from all 12 possible shapes, the two additional shapes in the associated triplet. Participants were unable to correctly identify those shapes at above-chance levels. Their chance performance on the 12-AFC task and their ability to demonstrate VSL after a one-week delay (as measured by the RT task) led Kim et al. (2005) to conclude that VSL reflected implicit learning. This conclusion was questioned by Bertels et al. (2012), who pointed out that the 12-AFC recognition task was too complicated to be sensitive to the underlying explicit knowledge. Instead, Bertels et al. (2012) showed participants two shapes from a triplet and asked them to choose the third shape from four possible alternatives. After each response, participants were asked whether they had remembered that shape or were just guessing. Bertels et al. (2012) found that participants were able to choose the correct shape at above-chance levels. In addition, correct recognition was often accompanied by a "remember" response rather than a guess. Therefore, Bertels et al. (2012) concluded that implicit learning cannot fully account for VSL.

The outcomes of the Bertels et al. (2012) study clearly give rise to doubts about the implicit nature of VSL. However, the results of that study were somewhat ambiguous. Although participants who were successful in the 4-AFC task tended to report that they had remembered the shapes rather than merely guessed, participants who performed at chance levels on the 4-AFC task did not benefit from reportedly having "remembered" the shape. Also, participants who learned the regularities (that is, performed above chance in the 4-AFC task) also correctly selected the shape 46% of the time although they were merely guessing. The study of Bertels et al. is therefore relatively weak in revealing an effect of explicit knowledge on VSL. One possible reason is that, unlike standard VSL studies, Bertels et al. may have used a training paradigm that yielded less explicit knowledge. Participants in their study had to detect letters embedded in a rapid stream of shapes presented at a high rate of 230 ms/item. This procedure may have reduced attention and awareness to the shapes. To understand the degree to which explicit awareness contributes to standard VSL paradigms, it is important to use standard paradigms that are representative of existing VSL studies. To this end, I will employ a paradigm in which participants passively view slowly presented shapes (using parameters taken from Fiser & Aslin, 2002; see Figure 3A).

1.5. Why is the question important?

Why is it important to test whether VSL is implicit or explicit? After all, the nature of learning does not change the fact that people have managed to acquire knowledge of the statistical regularities that are present in their visual environment. One reason is to correct a possibly mistaken conception in the literature. If VSL is predominantly explicit, then it is misleading to state that it is a form of implicit learning, and therefore it may exhibit other characteristics of implicit learning. One characteristic of implicit learning is that it does not depend on conscious awareness and has high capacity. For example, people are capable of acquiring implicit learning even when their attentional resources are occupied with a secondary task (Cohen, Ivry, & Keele, 1990; Schvaneveldt & Gomez, 1998; Vickery, Sussman, & Jiang, 2010). In addition, implicit learning exhibits high capacity (e.g., in one study, people could learn to distinguish 60 repeated random spatial layouts from 3,600 other spatial layouts, Jiang, Song, & Rigas, 2005). Implicit learning also shows no obvious proactive or retroactive interference (Jiang et al., 2005). If we ascribe high capacity and independence from limited cognitive resources to VSL, then it is tempting to think that it could serve very important functions in vision. In fact, several researchers have considered VSL as a critical mechanism for structuring the complex visual environment. The logic is that if people can rapidly learn the arbitrary association between novel shapes in the laboratory, they surely can learn the much more complex structure about how individual shapes are associated to form a progressively more complex visual world (Fiser & Aslin, 2005; Turk-Browne, 2012). On the other hand, if VSL is, instead, an "artificial" example of how people are able to explicitly learn the association between 4 triplets, each repeated 30 to 100 times, then it would be associated with the important functional constraints of explicit learning, namely dependence on cognitive resources and limited capacity. It is unclear how a limited-capacity system could shoulder the taxing demand of structuring the visual world.

Reber (1967, 1989) coined the term *implicit learning* to refer to *"an unconscious process that (b) yields abstract knowledge."* Since then several learning paradigms have satisfied these two criteria (Frensch & Stadler, 1998). VSL has not been subjected to the same kind of rigorous tests. Without such tests, it is risky to expand the theoretical and empirical enterprise of VSL by assuming that it reflects implicit learning.

The following two experiments examined the role of explicit awareness of visual regularities in visual statistical learning. The first study takes an individual differences approach and compares the learning performance between participants who had different levels of awareness of the experimental manipulation. The second study uses an experimental approach to compare the amount of learning for different levels of awareness within the same participants.

1.6. Experiment 1

Experiment 1 used the standard visual statistical learning paradigm: passive viewing during the training phase and familiarity judgment during the testing phase. The parameters of Experiment 1 were adapted from Fiser & Aslin's (2002) study. Using the standard paradigm made it easy to compare the current results with other research. In addition to assessing explicit awareness, I also examined the flexibility of learning. There are two main goals in Experiment 1.

First, I examined whether visual statistical learning is faithful to the exact visual statistics presented during training, or if it supports abstract inferences from the trained statistics. Specifically, transitive inference has been studied in human reasoning and in animal learning (Greene, Spellman, Dusek, Eichenbaum, & Levy, 2001; von Fersen, Wynne, Delius, & Staddon, 1991). For example, after learning that A is preferable to B, and B is preferable to C, humans and animals show preference for A over C even though A and C have not been directly contrasted during training (DeVito, Lykken, Kanter, & Eichenbaum, 2010). Existing VSL studies have focused primarily on the statistical association between shapes based on the frequency of co-occurrence. Whether transitive inference occurs in VSL is unclear. I adopted a similar paradigm to that used in transitive learning studies. Experiment 1 examined whether, after being exposed to shape pairs A and B, and B and C, but not A and C, participants could flexibly acquire the transitive association between A and C.

Second, I tested the role of explicit knowledge in VSL, including transitive learning. I added two post-experiment questionnaires to gauge participants' awareness level of the statistical regularities present in the stimuli. Based on the answers to the questionnaires, participants were divided into three groups: aware group, who noticed the regularities and also tried to remember the association; partially aware group, who either noticed the regularities or tried to remember the shapes; and unaware group, who neither noticed the regularities nor tried to remember the shapes. Then, I examined 1) whether these three groups differed in their performance on the familiarity judgment task, and 2) whether VSL had occurred for participants in the unaware group. If explicit knowledge of regularities influences VSL, then participants with greater awareness should show more evidence of visual statistical learning. Indeed, participants who remain completely unaware of the experimental manipulation may not show any evidence of visual statistical learning. Conversely, if the acquisition of visual statistical learning does not depend on conscious awareness (Kim et al., 2005; Turk-Browne et al., 2005), then explicit awareness should not influence the degree of visual statistical learning among the three groups.

Method

Participants

All 27 participants were naïve to the purpose of the study, and participated only one experiment. They were students from the University of Minnesota between 18 and 35 years old. There were 18 females and 9 males with a mean age of 20.1 years. All participants reported normal or corrected-to-normal visual acuity and no history of psychiatric or neurological disorders. Participants provided written informed consent prior to the study and were compensated for their time with course credits.

Equipment

Participants were tested individually in a room with normal interior lighting. They sat unrestrained about 40cm away from a 17" CRT screen (resolution 1024 x 768 pixels; refresh rate: 75 Hz). The experimental program was created in Psychtoolbox (Brainard, 1997; Pelli, 1997) implemented in MATLAB (www.mathworks.com).

Materials

Four triplets were made from twelve black novel shapes (5.65° x 5.65°), and then two pairs were made from each triplet. For example, if shape A, shape B, and shape C compose a triplet (triplet A-B-C), shape A and shape B could compose the first pair (pair A-B), and shape B and shape C could compose the second pair (pair B-C). Therefore, a total of eight pairs were composed from 12 shapes. This design allowed us to examine whether transitive inference learning could be acquired from lower-order statistical learning. We tested whether the association between shape A and shape C (the *transitive pair*) could be inferred by learning two separate pairs: A-B and B-C (the *premise pairs*). These eight pairs were repeated 64 times in a stream of shapes presented in a random order. In the testing phase, another eight pseudo-pairs were made from 12 shapes, called "foils." All shapes in the foils have been shown in the training phase, but had not been paired together.

A black vertical bar (5.7°-wide x 15.4°-long), an occluder, was displayed in the center of the white screen during both phases (see Figure 3).

Procedure

Training phase

In the training phase, a single shape emerged from behind the black vertical bar and moved smoothly at a constant speed, toward one side of screen and then returned to the bar along a straight path. As the moving shape came into contact with the vertical bar (i.e., occluder), it was gradually occluded by the bar. When the shape was completely occluded, it emerged from the other side as a different shape. The changed shape continued on the same trajectory with no interruption, gradually emerging from behind the bar on the other side of the screen. It took exactly 1 s for a single shape starting from the center (covered completely by the vertical bar) to move to the side of the screen and return to the initial position behind the bar. Participants were asked to “watch this movie carefully” for about 15 min. Participants took a break after every 64 shapes. Figure 3A illustrates the procedure in the training phase.

Testing phase

After the 15-min movie, a two-alternative forced-choice (2AFC) test was given to the participants, with 96 test sets (1 set = one old pair and one foil). Each of these test sets consisted of one of the 12 base pairs and one of the 12 foils. The base pairs included eight of the pairs exposed during training (premise pairs) and four transitive pairs. In each test set, one old pair and one foil were shown in an identical way as in the training phase, first emerging from behind the occluder into view and then moving back behind the occluding bar, with a 1 s pause between the base pair and the foil. The order of presentation was random. Participants were instructed to judge which pair was more familiar on the basis of the training phase. They were allowed unlimited time to make their decision. To increase statistical power, each set was tested eight times, for a total of 96 test trials. Figure 3B shows the procedure used in the testing phase.

Post-experiment questionnaires

As soon as the familiarity task was finished, participants were asked two questions on the screen sequentially. The first question was: “Did you try to remember which shapes changed into which other shapes in the first session (1: yes, 2: no)?” The second question was: “Did you notice some shapes consistently changed into certain other shapes in the first session (1: yes, 2: no)?” The questions remained on the screen until participants responded. No feedback was given.

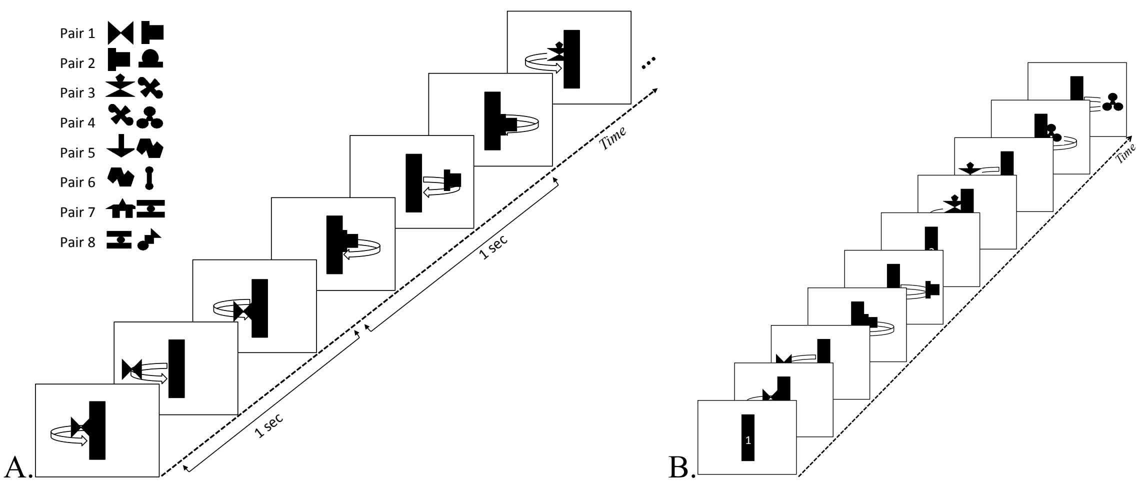


Figure 3. A schematic illustration of the stimuli and trial sequence used in Experiment 1. A. The passive viewing task in the training phase. Eight pairs were randomly made for each participant. B. The familiarity task in the testing phase. Items are not drawn to scale.

Results

Because participants were just passively watching the movie without making any responses, they did not generate any data during the training phase.

In the familiarity task, I separately analyzed premise pairs and transitive pairs. First, with the premise pairs, participants chose the old pair over the foil as the more familiar one 75.3% of the time, which was significantly higher than chance (50%), $t(26) = 6.13$, $p < .001$. To examine the role of conscious awareness in visual statistical learning, I divided participants into three groups based on their answers to the post-experiment questionnaires. Thirteen participants, who both tried to remember the shapes *and* noticed the regularities, were classified as the "*aware*" group. Eight participants, who either tried to remember the shapes or noticed the regularities, were classified as the "*partially aware*" group. The final group, the "*unaware*" group, had six participants, who neither tried to remember the shapes nor noticed any regularities. The aware group chose the old pair over the foil 91.1% of the time, significantly higher than chance, $t(12) = 12.11$, $p < .001$. Recognition rate lowered to 66.4% in the partially aware group, which was marginally higher than chance, $t(7) = 2.26$, $p = .058$. However, the unaware group chose the old pair 52.9% of the time, which did not differ from chance, $t(5) = .91$, $p > .40$ [2]. In addition, an ANOVA on the three groups revealed that the groups showed different performance in the familiarity task, $F(2, 24) = 16.40$, $p < .001$, $\eta p^2 = .58$. Specifically, the aware group performed better than the partially aware group, $t(19) = 3.48$, $p < .005$, and better than the unaware group, $t(17) = 6.97$, $p < .001$. The partially aware group also performed better than the unaware group, $t(17) = 7.00$, $p < .001$. All the p-values survived Bonferroni correction for multiple comparisons (critical $p = .017$). These results show

[2] Due to the small sample size of the unaware group (N=6), a bootstrapping analysis was applied.

that greater explicit knowledge corresponded to greater visual statistical learning, as assessed by participant's correct recognition of the premise pairs.

Similar results were observed for the transitive pairs. When averaged across all participants, transitive learning was significantly weaker (58.2%) than standard statistical learning (i.e., recognition of the premise pairs, 75.3%), $t(26) = 4.73$, $p < .001$. Nonetheless, transitive learning was significantly better than chance, $t(26) = 2.27$, $p = .032$. However, only the aware group showed above-chance transitive learning (68.0%), $t(12) = 3.02$, $p = .011$. Performance in the partially aware group (51.2%) and the unaware group (46.4%) was at chance, $t(7) = .75$ $p > .40$; $t(5) = .62$, $p > .50$[3], respectively. An ANOVA on the three groups found a significant main effect of group, $F(2, 24) = 4.43$, $p = .023$, $\eta p^2 = .27$. The aware group showed better performance than the partially aware group, $t(19) = 2.17$, $p = .043$, and the unaware group, $t(17) = 2.23$, $p = .04$. Performance of the partially aware group and the unaware group did not differ, $t(5.7) = .79$, $p > .40$. Figure 4 shows the 2AFC recognition results for visual statistical learning (i.e., the premise pairs, Figure 4A) and transitive inference learning (Figure 4B).

[3] I performed bootstrapping due to the small sample size (N=6) of the unaware group.

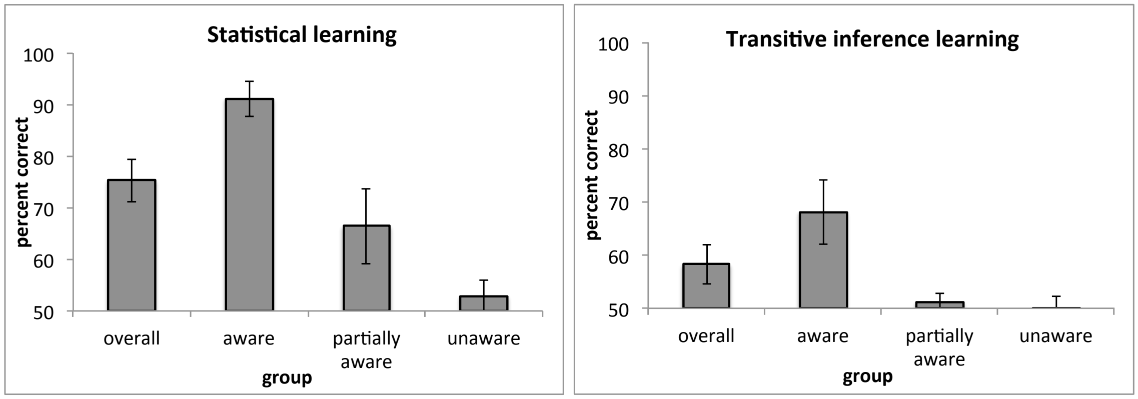


Figure 4. Results from the familiarity task of Experiment 1. A. Statistical learning with premise pairs, B. Transitive inference learning with transitive pairs. Error bars show ±1 S.E. of the mean.

Finally, I performed a full-factorial ANOVA that included type of learning (standard VSL or transitive inference learning) as a within-subject factor, and awareness level (aware, partially aware, and unaware) as a between-subject factor. This analysis revealed a significant main effect of the type of learning, suggesting that transitive learning was weaker than standard VSL, $F(1, 24) = 16.40$, $p < .001$, $np^2 = .41$. The main effect of awareness level was also significant, suggesting that both the standard VSL and transitive VSL was governed by explicit knowledge, $F(2, 24) = 13.54$, $p < .001$, $np^2 = .53$. The two factors did not show a significant interaction, $F(2, 24) = 1.75$, $p = .195$.

Discussion

Experiment 1 revealed significant visual statistical learning and transitive inference learning. However, explicit knowledge played a critical role in both types of learning. One criterion for implicit learning is that learners should not be aware of what they are learning. In Experiment 1, however, 21 out of 27 participants were either aware (or partially aware) of the statistical regularities, or had tried to remember the statistics. In addition, participants who had no explicit knowledge of the regularities did not show any statistical learning. The lack of learning in the unaware group shows that explicit knowledge of regularities is critical for above-chance levels of performance on the familiarity test. The results of Experiment 1 revealed no evidence that visual statistical learning is implicit learning. In transitive inference learning, although the overall level of learning was above chance, only the aware group showed transitive inference learning. Thus, both an intention to learn and an explicit awareness of what was learned are necessary to allow transitive inference in our paradigm. Therefore, the flexibility of VSL depends on explicit awareness.

Experiment 1 demonstrates that explicit awareness of regularities largely influences visual statistical learning and transitive inference learning. But might participants have acquired implicit learning that was not revealed by our testing procedure? Turk-Browne, Scholl, Chun, & Johnson (2009) found that some brain areas (e.g., caudate, hippocampus, LOC) were more activated by a structured stream with four repeated triplets than a random stream, even though participants showed no evidence of VSL in the familiarity task. These brain-imaging results indicate that people may be sensitive to statistical regularities in the absence of behavioral manifestations. However, the imaging data could be attributed to other differences between the regular and random streams, such as the implicit perceptual grouping of shapes. Indeed, the lateral occipital cortex (LOC), which showed high activity in Turk-Browne et al. (2009)'s study, is known for processing objects (Malach, Reppas, Benson, Kwong, Jiang, Kennedy, Ledden, Brady, Rosen, & Tootell, 1995). Thus, previous studies have not revealed compelling evidence for the existence of VSL in the absence of a corresponding familiarity effect. As reviewed earlier, the RT paradigm primarily reflects a general effect of temporal sequence, rather than associative learning (Barakat et al., 2013). Existing evidence, along with data from Experiment 1, shows that VSL is very weak or absent when people lack explicit awareness of regularities. Having explicit knowledge is critical to produce VSL. While future studies may reveal yet another, more sensitive measure of implicit VSL, the current study suggests that above-chance performance on the familiarity task is determined primarily by explicit awareness.

Because we assessed transitive learning, the current experimental design differed from standard VSL studies in one respect. The connecting shape (e.g., shape B) was presented twice as often as the other two shapes (e.g., A and C). How this factor changes explicit awareness is unclear. I think it is unlikely that participants in our study were specifically primed to become aware of the experimental manipulation. The current design involved eight base pairs during the training phase, and this is more than the six base pairs used in studies that did not test transitive inference (Fiser & Aslin, 2001, 2005). If anything, this factor may have reduced the likelihood that participants could explicitly learn all the pairs.

Because Experiment 1 used an individual-differences approach, the results are correlational in nature. Specifically, we have shown that explicit knowledge is highly (and positively) correlated with performance on the familiarity test. But did explicit knowledge *directly cause* visual statistical learning? Or perhaps the causal relationship is reversed; perhaps successful VSL had led participants to become aware of the statistical regularities. A third possibility is that the aware group was the only group who followed the instructions and paid attention to the movie. To resolve these ambiguities it is important to use an experimental approach that manipulates, rather than only measures, explicit awareness. To provide converging evidence for the idea that explicit knowledge contributes to standard visual statistical learning, Experiment 2 manipulated participants' awareness level in a within-subject design.

1.7. Experiment 2

Experiment 1 suggests that greater explicit knowledge of visual regularities yields stronger visual statistical learning. Experiment 2 further explores the relationship between awareness and VSL by experimentally manipulating awareness within an individual, rather than by relying on participants' subjective reports. Several paradigms have been developed to modulate awareness, such as the attentional blink (Chun & Potter, 1995; Dux & Marois, 2009; Raymond, Shapiro, & Arnell, 1992), object substitution masking (Enns & Di Lollo, 2000), binocular rivalry (Alais, 2012), and visual crowding (He, Cavanagh, & Intriligator, 1996). Here I used two of the paradigms to modulate awareness level: attentional blink and visual crowding. However, visual crowding turned out to not be highly effective in reducing awareness level. The experiment that examined VSL under different crowding conditions produced ambiguous data. I will describe this experiment briefly in the discussion, here focusing on the study using an attentional blink paradigm.

When two visual targets (T1 and T2) to be reported are presented within 200-500 ms of each other in a rapid visual stream, identification of the second target (T2) is greatly impaired (Raymond et al., 1992). This phenomenon is called the *attentional blink*

(Chun & Potter, 1995; Dux & Marois, 2009; Raymond et al., 1992; Shapiro, Arnell, & Raymod, 1997), or the AB. Several models have been proposed to explain the AB. Most of them focus on the concept of resource depletion. When attention dwells on the first target, it may be unavailable for the second (*the attentional dwell time hypothesis*: Duncan, Ward, & Shapiro, 1994). Or the first target and the intermediate distractors may interfere with the representation of the second target in working memory (*the interference model:* Shapiro, Raymond, & Arnell, 1994). Or the need to select the first target and to inhibit the intermediate distractors impairs participants' ability to select the second target (the *temporal loss of control account*, Di Lollo, Kawahara, Ghorashi, & Enns, 2005). Regardless of exactly what is thought to interfere with T2 processing, most models make a distinction between two stages of visual processing. In Chun and Potter's *two-stage* model, for example, all stimuli proceed through a first stage of perceptual processing without competition. However, to reach the level of explicit report the stimuli must also go through a second stage of consolidation. This stage is resource limited. When it is occupied by T1, it is unavailable for T2 (see also the *PRP model*, Jolicoeur & Dell'Acqua, 1998).

Empirical evidence provides strong support for the idea that the attentional blink affects T2 processing relatively late. That is, the attentional blink does not interfere with the early stage of T2 processing, resulting in unconscious perceptual and semantic processing of T2. However, the attentional blink renders it difficult for the representation of T2 to reach conscious awareness. In one study, Luck and colleagues recorded event related potentials (ERPs) while participants performed an attentional blink task. Participants first viewed a context word that created a semantic context. They then saw a stream of letters and numbers. Participants were asked to identify the parity of the single number (T1) and to report whether a subsequent word (T2) was related to the context word. The interval between T1 and T2 varied between 100-700 ms. Behavioral measures showed that participants were impaired at identifying the T2 word when the T1-T2 lag was short, demonstrating the attentional blink. Critically, however, the N400 component of the ERP, an index of semantic processing, was equally strong across all lags. These data indicated that T2 was processed deeply to the semantic level, and that the attentional blink interfered with conscious awareness rather than with perceptual and semantic processing (Luck, Vogel, & Shapiro, 1996). Other studies showed that although people often failed to identify T2 during short T1-T2 lags, the amount of semantic priming was equally strong at short and long lags (Maki, Frigen, & Paulson, 1997). Furthermore, stimuli that are chronically primed and hence can more easily gain access to awareness show reduced AB. These include one's own name (Shapiro, Caldwell, & Sorensen, 1997) and emotionally intense words (Anderson & Phelps, 2001).

I adopted the attentional blink to modulate awareness because this paradigm affects primarily awareness rather than perceptual and conceptual processing. When novel objects are presented as T2 in the AB paradigm, they should be perceived even when the T1-T2 lag is short, yet people are less likely to become aware of T2. If visual statistical learning can proceed in a truly unconscious manner, then shape pairs presented inside the attentional blink should yield just as much learning as shape pairs presented outside of the attentional blink. But if VSL depends on explicit awareness of the pairs, then shapes presented inside the blink should produce little to no learning.

In Experiment 2, I inserted two targets in a rapid stream of letters. The first target (T1) was a pair of identical digits (e.g., *3 3*). The second target (T2) was a pair of novel shapes. The two targets were separated by a varying number of letter displays, producing an interval of 200 ms (lag 2), 400 ms (lag 4), or 800 ms (lag 8). Shapes presented as T2 were selected from 12 possible shapes. These shapes formed 6 pairs. Two of the pairs were presented at each of the three T1-T2 lags. Some trials included shapes that were identical. The participant's were asked to detect if the shapes presented at T2 were identical or not. To index the AB, we measured T2 accuracy (indicating if the two shapes were identical or not) at different lags. We predicted that people should be less accurate in reporting T2 when the T1-T2 lag was shorter. To index VSL, we administered a familiarity judgment task that contrasted the old pairs with foils (similar to Experiment 1). Of interest is whether shape pairs shown at the shorter T1-T2 lags would yield less VSL.

Method

Participants

Twenty-seven new participants completed Experiment 2. There were 19 females and 8 males with a mean age of 21.6 years.

Materials and Procedure

<u>Training phase.</u> Participants pressed the spacebar to initiate each trial. On each trial participants were presented with a rapid serial visual stream (RSVP) of stimuli presented at a rate of 100 ms/item. The stream included T1, T2 and twenty distractor

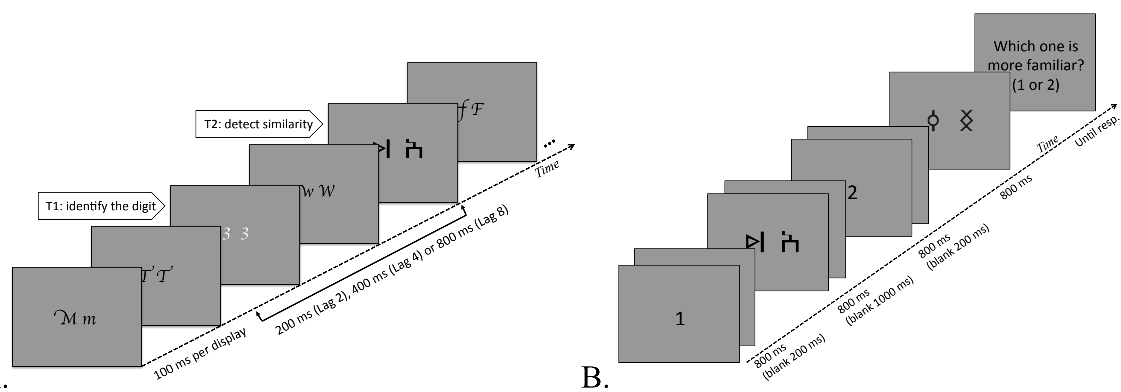
displays. The T1 display contained two identical white digits (e.g., 3 3), chosen randomly from 1 to 9 (font: Mistral) on each trial. The T2 display contained two black shapes. These shapes were chosen from six possible pairs of shapes produced from a set of 12 shapes known as glyphs (Turk-Browne et al., 2005, 2009). Two pairs were consistently assigned to each of the three temporal lags between T1 and T2. The distractor displays each contained two black alphabetic letters chosen randomly from 22 possible letters (excluding I, O, Q and Z to avoid confusion with digits; uppercase alphabet font: Mistral, lowercase alphabet font: Brush Script Std) [4]. The two letters in each display were always semantically identical (e.g., AA, aa, Aa, or aA). Different letters were used for different displays. All stimuli (alphabet letters, digits, and shapes) subtended 5° x 5°. Two stimuli were displayed side by side without a gap in the center of the screen.

The RSVP stream started with a 500ms fixation period. The T1 display could occur in serial positions 2-12. The T1 display was followed by one, three, or seven distractor displays before the presentation of the T2 display. Therefore the temporal lag between T1 and T2 was two, four, or eight, chosen at random. T2 was then followed by several distractor displays for a total of 22 displays per stream. At the end of the stream participants typed in the white digit that had been shown on the T1 display and pressed a button to report whether shapes on the T2 display were identical or different. On one third of the trials the T2 display contained identical shapes (these could be any of the 12 shapes). On the other trials the T2 display contained different shapes (drawn from the six base pairs). Visual feedback was given to indicate whether responses were correct or not.

[4] We chose the fonts based on their physical similarity to glyphs to maximize the attentional blink effect.

The training phase consisted of 432 trials (144 trials: same shapes for T2; 288 trials: different shapes for T2) and took about an hour to complete. Figure 5A illustrates the overall procedure of the attentional blink in Experiment 2.

Familiarity task. Following the training phase we tested visual statistical learning for the base pairs shown on the T2 displays. We created six foil pairs by recombining the 12 shapes from the 12 shapes. In each trial, participants were shown one pair and one foil in a random order (800 ms for each) separated by a 1 s blank display. Following the sequence, participants were asked to choose the more familiar one based on their experience in the encoding phase. Each base pair was tested against each foil in two different temporal orders. The order of the 72 trials (6 pairs x 6 foils x 2 orders) was randomized. Participants received no feedback. Figure 5B illustrates the procedure of the testing phase in Experiment 2.



A. B.

Figure 5. A schematic illustration of stimuli and trial sequence used in Experiment 2. A. The attentional blink task used in the training phase. B. The familiarity task used in the testing phase. Items are not drawn to scale.

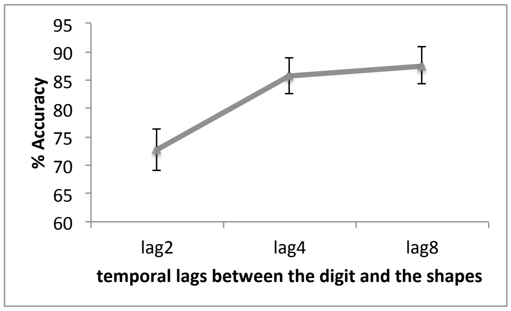
Results

AB performance

In the training phase participants correctly identified the white digit (T1) at 95.3%. Their overall accuracy for T2 was 74.5 %. Follow standard procedures adopted in previous studies on the AB, we excluded trials in which the T1 response was incorrect (Raymond et al., 1992).

Because the base pairs appeared only when the two shapes shown on the T2 display differed from each other, in this analysis I included only trials in which the two T2 shapes differed[5]. When T2 was presented in lag 2 (200 ms SOA), in lag 4 (400 ms SOA), and in lag 8 (800 ms SOA), accuracy was 72.7%, 85.7%, and 87.6%, respectively. An ANOVA showed that lag significantly influenced T2 accuracy, $F(2, 52) = 17.11$, $p < .001$, $np^2 = .40$. Planned contrasts showed that T2 accuracy was lower in lag 2 than lags 4 and 8, smallest $t(26) = 4.29$, largest $p < .001$. T2 accuracy was comparable between lag 4 and lag 8, $t(26) = 1.31$, $p = .20$. In the trend analysis, we observed a significant linear and quadratic trend of lag, $F(1, 26) = 18.70$, $p < .001$, $np^2 = .42$; $F(1, 26) = 11.79$, $p = .002$, $np^2 = .31$. These results showed that participants were less aware of the shapes when the lags between T1 and T2 were shorter. Figure 6A shows the attentional blink results.

[5] When all trials were included, the pattern of results was identical.

A. 

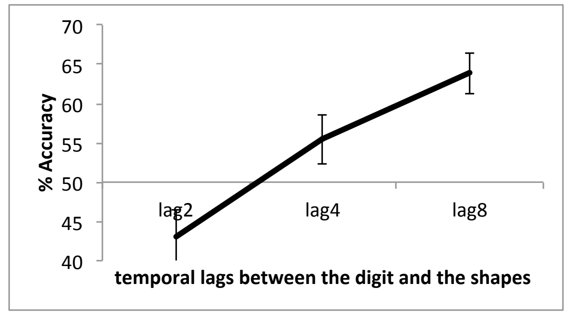
B. 

Figure 6. Results from Experiment 2. A. T2 accuracy in the attentional blink task. B. Accuracy in the familiarity task. Error bars show ±1 S.E. of the mean.

Figure 6B shows results from the familiarity task. Participants chose the base pair over the foil 43.1%, 55.4%, and 63.9% of the time in the lag 2, lag 4, and lag 8 conditions, respectively. An ANOVA on the three levels of lag showed a significant main effect of lag, $F(2, 52) = 10.59$, $p < .001$, $np^2 = .29$. Familiarity recognition was significantly above chance for pairs shown at Lag 8, $t(26) = 5.30$, $p < .001$, but was at chance for Lag 4, $t(26) = 1.75$, $p = .09$, or Lag 2, $t(26) = -2.07$, $p = .05$ (note this was numerically below chance). Only Lag 8 performance significantly deviated from chance when corrected for multiple comparisons (critical $p = 0.017$). Planned contrasts showed that recognition was significantly lower in Lag 2 compared with Lag 4 and Lag 8, smallest $t(26) = 2.84$, largest $p < .01$. Recognition performance differed marginally between Lags 4 and 8, although this difference did not survive corrections for multiple comparisons, $t(26) = 2.04$, $p = .051$. In the trend analysis, we found a significant linear trend of lag, $F(1, 26) = 16.68$, $p <.001$, $np^2 = .39$, but no quadratic trend, $F < 1$. These results show that VSL was significantly impaired for shape pairs presented at short T1-T2 intervals. That is, VSL did not survive the reduction in awareness experimentally induced through the attentional blink paradigm.

Discussion

Experiment 2 showed that shapes presented during the attentional blink window were learned less well than were shapes presented outside of the attentional blink. Because the attentional blink affects primarily conscious awareness of T2 rather than its perceptual processing (Anderson & Phelps, 2001; Luck et al, 1996; Maki et al., 1997), it is likely that the shapes had been processed but did not reach awareness. The dependence of visual statistical learning on the T1-T2 lag provides strong evidence for the idea that conscious awareness is a critical factor for visual statistical learning.

The findings in Experiment 2 have important implications. First, because perceptual processing of T2 is preserved in the attentional blink (Luck et al., 1996; Maki et al., 1997), the absence of statistical learning for base pairs presented at lag 2 suggests that unconscious perceptual processing is insufficient for visual statistical learning. Explicit awareness is critical for acquiring standard VSL.

As noted earlier, in an attempt to provide converging evidence I conducted a follow-up study that used visual crowding to reduce awareness of the statistical regularities. Crowding refers to the finding that a peripheral stimulus is harder to identify in the presence of adjacent flanking stimuli than when presented in isolation (see Pelli, Palomares, & Majaj, 2004 for a review). Stimuli in visual crowding are detectable but not identifiable. That is, participants are aware of whether the stimuli exist but unaware of what the stimuli are. For example, a participant verbally reported, "*I know that there are three letters. But for some reason, I can't identify the middle one which looks like it's being stretched and distorted by the outer flankers*" (Pelli et al., 2004, p. 1139).

In the current study, four triplets of glyphs were repeated 48 times in a stream of shapes in a random order. The stream of glyphs was presented above fixation (around 8.5°) on a gray display. To induce crowding, four fixed (and task-irrelevant) distractors simultaneously flanked the stream of glyphs either closely, 0.35° away from the glyphs (crowding condition) or farther away, 0.75° apart (no-crowding condition). Participants were asked to perform a one-back working memory task on the shapes while maintaining fixation below the shape stream (Figure 7). The near condition impaired one-back performance (d' = 2.31) relative to the far condition (d' = 3.58), suggesting that crowding had occurred. However, performance in the near condition was also quite high, allowing substantial processing of the crowded stimuli. In the subsequent familiarity test of the base pairs and foils, I found that participants were able to recognize the presented base pairs at above-chance levels both in the near condition (mean = 58%), $t(26) = 2.46$, $p = .021$, and in the far condition (mean = 59%), $t(26) = 3.39$, $p = .002$. This difference was not significant, $t(26) = .26$, $p > .70$.

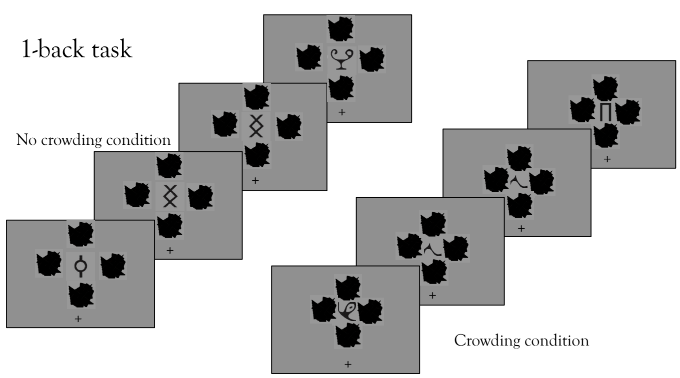


Figure 7. A schematic illustration of the visual crowding paradigm. Participants were instructed to maintain fixation, and to detect the repeated shape above the cross. In the

crowding condition, the distance between shape and distractors was closer than in the no crowding condition.

However, because participants were able to perceive the shapes at high accuracy even in the near condition, our experimental manipulation of crowding may have been too weak to influence VSL. Such high levels of accuracy suggest that participants might have moved their eyes to the stimuli on some proportion of trials. In addition, because the overall level of VSL was low in both the crowding and no-crowding conditions, we may have been limited by a floor effect to find an effect of crowding on VSL. Future studies that improve the effectiveness of visual crowding and increase the baseline rate of VSL are needed to resolve this ambiguity.

Although the main points we made from Experiment 2 are clear, two findings need further research. First, the lag effects differed slightly between the training and the testing phases. In the training phase, the pattern of T2 performance was Lag 2 < Lag 4 = Lag 8, resulting in both a linear and a quadratic trend of lag. However, in the testing phase, the pattern of T2 performance was Lag 2 <= Lag 4 <= Lag 8, resulting in just a linear trend of lag. This difference could be due to statistical noise in the recognition testing outcomes, or it may indicate that VSL depends on very high degrees of awareness that was present only at Lag 8. This question should be addressed in future studies that examine the lag effect more finely (e.g., by using more lags). A larger sample size would also be desirable.

Second, Experiment 2 leaves open the question of *why* VSL was sensitive to the attentional blink. So far we have proposed that it was due to reduced awareness. However, the myriad of models proposed to account for the AB have made various, sometimes contradictory, assumptions about what the AB reflects. Many associate the AB with a reduction in attentional resources (see Dux & Marois, 2009, for a review), but some have proposed that the AB reflects changes in cognitive control (Olivers & Nieuwenhuis, 2005, 2006; Taatgena, Juvina, Schipper, Borst, & Martens, 2009). In addition, one might wonder whether it was *attention* or *awareness* that was reduced under the AB. Some researchers believe that these are two different systems (Koch & Tsuchiya, 2007; Lamme, 2003), with visual awareness regarded as what is in the focus of attention (Lamme, 2003). However, others propose that attention and awareness are intricately related (Cohen, Cavanagh, Chun, & Nakayama, 2012). In the attentional blink, attention is often considered as a prerequisite for awareness (Tallon-Baudry, 2004). It is unclear whether it is attention or awareness that is more critical for VSL. This question might be a matter of semantics, but it clearly needs further investigation.

1.8. Summary of Part 1

Part I tested the role of explicit awareness of statistical (regularity) information in standard visual statistical learning. We employed two paradigms, a passive viewing task with post-test questionnaires (Experiment 1) and an attentional blink paradigm (Experiment 2). The results of Experiment 1 showed that a group of individuals, who were fully aware of the regularities, acquired better visual statistical learning (higher recognition of premise pairs) and also greater transitive inference learning (higher recognition of inference pairs) than did the other two groups (partial awareness group and unaware group). Another group of individuals, who reported partial knowledge of the statistical regularities, also acquired statistical learning, but not transitive inference learning. However their VSL was weaker than that of the aware group. The last group of individuals, who were unaware of the regularities, did not show any kind of learning. Experiment 1 suggests that transitive inference learning occurs only under explicit awareness of statistical regularity. In addition, explicit awareness positively correlates with the size of VSL.

To investigate whether awareness directly contributes to visual statistical learning, Experiment 2 manipulated the awareness level using the attentional blink paradigm. The conscious awareness of regularity was manipulated by using three temporal intervals between T1 (digits) and T2 (pairs of shapes) in a rapid visual stream. At longer intervals the shape pairs of T2 yielded greater explicit awareness. Correspondingly VSL was stronger for stimuli presented at longer T1-T2 intervals. Stimuli presented at the shortest interval yielded no VSL.

1.9. Part I Conclusion

To recap, there were three main sections in Part I. First, I introduced methods used to investigate standard visual statistical learning, raised several issues about the paradigm and reasons why VSL might involve explicit learning. Second, I performed two experiments to explore the role of explicit awareness in VSL. My results showed that explicit awareness of visual regularities is critical for VSL. Because explicit and implicit learning differ in their reliance on capacity-limited mechanisms (such as attention and working memory), clarifying the nature of VSL has implications for its function in visual perception. For example, if visual statistical learning is explicit learning, it should rely on selective attention. This has indeed been found to be the case (Baker et al., 2004; Turk-Browne et al., 2005). Given the severe limits in attention and working memory, an explicit learning system is unlikely to be very powerful in structuring the complex visual world. Although it is possible that future studies would reveal a more sensitive measure of implicit VSL, so far I have not encountered a reliable means to extract VSL in the absence of awareness.

Finally, I emphasize that it is important to re-examine assumptions made previously about VSL (e.g., that it reflects implicit learning and hence may have very high capacity). Future studies that employ the standard paradigm of VSL should include objective and sophisticated assessments of awareness. It is no longer adequate to assume that just because participants passively viewed visual stimuli, they have not acquired explicit knowledge about them.

2. Part II: How do statistical regularities influence behavior?

2.1. Part I vs. Part II

Part I examined how visual statistical information is acquired, and whether explicit awareness is necessary in one form of VSL: learning the co-occurrence of novel objects in space and time. Results showed that the strength of visual statistical learning depends on explicit awareness of the statistical regularities. No evidence of implicit learning emerged even though pairs of shapes were repeated many times.

However, there are many additional forms of visual statistical learning beyond just the acquisition of object co-occurrence. The standard VSL paradigm examined in Part 1 is geared toward discovering environmental regularities, yet such learning is not oriented toward enhancing performance. In fact, in most standard VSL studies participants are not required to perform any tasks during the initial exposure or encoding phase. Other forms of statistical learning, however, are oriented toward performance. The acquisition of environmental regularities directly results in more efficient attentional allocation or visuomotor action. It is toward this second form of statistical learning that I now turn in Part II. A unique aspect of performance-oriented statistical learning is that learning is assessed not through perceptual familiarity, but through enhanced performance on visuospatial tasks. The main goal of Part II is to investigate how visual statistical learning affects behavior. Specifically, Part II will examine how VSL modulates covert attention (as indexed by RT in Part II-1) and overt attention (as indexed by saccadic eye movements in Part II-2).

2.2. Multiple sources of spatial attention

Decades of research have shown that visual attention is driven by multiple sources (Awh, Belopolsky, & Theeuwes, 2012; Egeth & Yantis, 1997; Pashler, 1999; Wolfe, 2007). For example, Awh et al. (2012) proposed that attentional guidance has three sources. The first is the *current behavioral goal* that directs spatial attention voluntarily toward task-relevant items. For example, when searching for a specific food in the refrigerator people would prioritize features of the food item they have in mind (Jonides, 1981; Posner, 1980). Second, *perceptual saliency* also guides spatial attention, biasing attention toward perceptually salient stimuli. For instance, a black swan among a group of white swans is easy to spot (Egeth & Yantis, 1997; Itti & Koch, 2000; Theewues, 2013). Finally, Awh and colleagues also suggested that attention may be guided by *selection history*, an often neglected topic in attention research. Past experience including associative learning (Anderson, Laurent, & Yantis, 2011; Awh et al., 2012; Chun & Jiang, 1998), working memory (Soto, Hodsoll, Rotshtein, & Humphreys, 2008), and episodic and semantic memory (Moores, Laiti, & Chelazzi, 2003; Stokes, Atherton, Patai, & Nobre, 2012) can guide spatial attention (Hutchinson & Turk-Browne, 2012).

Several studies have shown a close relationship between implicit statistical learning and spatial attention. In one implicit learning paradigm, the serial reaction time task (SRT; Nissen & Bullemer, 1987), participants are shown one visual stimulus on a display, and are asked to press a key corresponding to the location of the stimulus. The location of a sequence of stimuli may be entirely random, or may follow a pre-determined sequence. Response time is faster when the sequence of locations repeats than when it is random, even though participants are unaware of the repetition (for a review, see Stadler & Frensch, 1998). These findings show that implicit learning may speed up responses in a serial reaction task. However, because the SRT task involves just a single stimulus on the display, it is unclear whether implicit learning affects attentional allocation among multiple objects.

Another set of studies has used visual search to examine the impact of implicit learning on the deployment of spatial attention. For example, in the contextual cueing paradigm, participants search for a target object among several distractors on a visual display. Unbeknownst to participants, some displays are occasionally repeated whereas other displays are new (except for the target's location). Although participants are unaware of the display repetition, they are faster finding the target on repeated displays than on new ones (Chun & Jiang, 1998). For several years contextual cueing has been considered as a prime example of how implicit learning affects spatial attention (Chun, 2000, Chun & Jiang, 1998, 2003). However, some recent studies have raised the possibility that the RT facilitation reflects increased readiness to respond on repeated displays, rather than more efficient allocation of spatial attention (Kunar, Flusberg, Horowitz, & Wolfe, 2007).

Perhaps the best demonstration of how implicit learning affects spatial attention is the paradigm of probability cueing (Druker & Anderson, 2010; Geng & Behrmann, 2002; Jiang, Swallow, Rosenbaum, & Herzig, 2013; Miller, 1988; Umemoto, Scolari, Vogel, & Awh, 2010). In this paradigm, participants search for a target among distractors. There is one and only one target on each trial. However, across multiple trials, the target is more often presented in some locations (the high frequency, "rich" locations) than others ("sparse" locations). Although participants usually cannot explicitly identify the target-rich locations, they are faster at finding the target when it appears in the rich locations than in the sparse locations. Thus, the probability of the target's location cues spatial attention toward high-probable locations (Geng & Behrmann, 2002, 2005; Jiang, Swallow, & Rosenbaum, 2013; Jiang, Swallow, Rosenbaum et al., 2013; Miller, 1988).

2.3. Priority maps

When viewing a natural scene, spatial attention may be influenced by multiple sources, such as perceptual saliency, current goals, and previous experience. How do these sources interact and eventually guide spatial attention to the most important location? Several researchers have proposed the concept of an attentional "priority map" (Bisley & Goldberg, 2010; Fecteau & Munoz, 2006; Itti & Koch, 2000). Bottom-up input (e.g., physical saliency) and top-down signals (e.g., goals/plans) converge to produce a "priority" weight for each location. The higher the priority weight, the more likely the location will be attended. Neurophysiologists have localized the priority map to the lateral inferior-parietal cortex (LIP; Bisley, 2011), although the exact anatomical location need not concern us here.

The attentional priority map not only affects how we deploy spatial attention, but also contributes to spatial working memory, in which attention is allocated based on one's recent memory of the visual space (Soto et al., 2008). Using fMRI, Ikkai & Curtis (2011) found that the priority map involves the maintenance of a working memory representation. They proposed that spatial attention and spatial working memory share common resources and mechanisms. Indeed, behavioral studies have revealed an interaction between spatial attention and spatial working memory. Awh and colleagues argued that spatial attention is an integral component of spatial working memory: rehearsal of remembered locations depends on attending to those locations (Awh & Jonides, 2001; Awh, Jonides, & Reuter-Lorenz, 1998). Other research has shown that the content of visual working memory influences attentional allocation in subsequent visual search tasks (for recent reviews, see Franconeri, Alvarez, & Cavanagh, 2013; Olivers, Peters, Houtkamp, & Roelfsema, 2011; Stokes, 2011; Woodman, Carlisle, & Reinhart, 2013). Prominent new theories of attention consider visual working memory as attention directed to an internal representation (Chun, 2011; Kiyonaga & Egner, 2013).

However, the reliance on the priority map and the interaction with working memory are specifically about goal-driven attention. It is unclear whether the third source of spatial attention, implicit learning, relies on the priority map and whether it interacts with working memory. Indeed, researchers disagree about whether implicitly learned attention is affected by a secondary working memory task. When a visual working memory load was added, some studies found that contextual cueing was reduced (Travis, Mattingley, & Dux, 2013), others showed no reduction (Vickery et al., 2010), and still others found mixed results (Annac, Manginelli, Pollmann, Shi, Müller, & Geyer, 2013; Manginelli, Langer, Klose, & Pollmann, 2013). These inconsistencies may partly be attributed to the complexity of the contextual cueing paradigm itself. As noted earlier, contextual cueing may reflect a combination of effects, including enhanced decision responding and more efficient spatial attention. To understand how implicit learning influences attention it is necessary to adopt a simpler paradigm. Fortunately, probability cueing provides just such a paradigm. Unlike contextual cueing, the probability cueing paradigm does not employ repeated configurations. Instead, it reflects changes of spatial attention following location probability learning (Geng & Behrmann, 2002, 2005; Jiang, Swallow, & Rosenbaum, 2013).

In Part II, I will use spatial probability cueing to examine implicitly learned attention.

2.4. Part II-1. VSL guides spatial attention

Using a spatial probability cueing paradigm, this section examines the interaction between spatial working memory and two sources of spatial attention: goal-driven attention and implicitly guided attention. Specifically, I test whether adding a visual working memory load interferes with endogenous cueing and probability cueing. In these experiments, participants first encode an array of visual stimuli into working memory.

During the retention interval they perform a visual search task. The visual search task is guided by two types of spatial cueing: endogenous (goal-driven) cueing and probability (implicitly learned) cueing. If endogenous cueing and probability cueing share common mechanisms with visual working memory, then adding a working memory load should interfere with participants' ability to use these spatial cues.

In Experiment 1, we used a central arrow to guide spatial attention to one of the four visual quadrants. The direction of the arrow changed from trial-to-trial, but for a given trial, the quadrant cued by the arrow had a higher probability than any of the uncued quadrants to contain the search target. Based on previous research by Posner, Jonides and colleagues (Jonides, 1980; Posner, 1980), we expected that visual search would be faster when the target was in the cued quadrant rather than in one of the uncued quadrants. If endogenous cueing draws on the same resource as spatial working memory, then adding a working memory load should reduce the cueing effect. Consequently, the difference in RT for a target in cued versus uncued quadrants (i.e., the validity effect) should be smaller when a working memory load is added.

In Experiment 2, we replaced the central arrow cue with an implicitly learned cue. Across multiple trials the target was more often found in one high-probability visual quadrant (i.e., the rich quadrant) than in any of the other (low-probability) quadrants (i.e., sparse quadrants). Previous studies showed that participants could use the target's statistical regularities to orient spatial attention without explicit awareness of the regularities (Chun & Jiang, 1998; Lambert, Naikar, McLachlan, & Aitken, 1999; Umemoto et al., 2010). Participants are faster and more efficient in finding the target in the high-probability region than the low-probability region (i.e., probability cueing;

Druker & Anderson, 2010; Geng & Behrmann, 2002, 2005; Jiang, Swallow, & Rosenbaum, 2013; Miller, 1988; Walthew & Gilchrist, 2006). Probability cues and endogenous cues convey the same amount information, but crucially, probability cueing does not depend on goal-driven attention because it is implicit. If implicitly learned spatial attention shares similar mechanisms to spatial working memory, then probability cueing should also decline when a working memory load is added. Conversely, a lack of interference from a spatial working memory load would suggest that implicitly learned attention is dissociated from spatial working memory. Testing the interaction between visual working memory and two types of spatial attention is important for understanding not only the relationship between spatial attention and spatial working memory but also how spatial attention may be subdivided.

Experiment 3 was conducted to replicate the results and to extend the findings of Experiment 2 to multiple different types of spatial working memory tasks.

2.4.1. Experiment 1: Endogenous cueing under color-array WM load

Experiment 1 examined the impact of a secondary spatial working memory load on endogenous spatial cueing. Previous studies have examined the effect of visual working memory load on visual search (Woodman et al., 2013 for a review). Most studies observed that imposing a visual working memory load impairs visual search (Oh & Kim, 2004; Woodman & Luck, 2004, but see Woodman, Vogel, & Luck, 2001). Experiment 1 went beyond these previous studies in its focus on spatial cueing rather than visual search. Whereas visual search measures the serial shift of spatial attention among multiple stimuli (Wolfe, 1998), spatial cueing measures the orienting of spatial attention to cued locations (Posner, 1980). It is therefore important to extend previous findings from visual search to spatial cueing.

In the spatial working memory task, participants performed change detection on two color arrays presented a few seconds apart. The two arrays were identical except for the change of one color. Participants were asked to report the location of the color change. This task required participants to remember the location of colors on the display, exerting demands on spatial working memory (Vickery et al., 2010). During the interval that separated the two color arrays, participants performed a cued visual search task. They searched for a T target among L distractors and reported the orientation of the T (left or right, see Figure 8).

For the visual search task, participants first saw an arrow presented at the fixation point. The arrow could be directed toward any one of the four visual quadrants, and its orientation changed randomly on each trial. However, for a given trial, the quadrant indicated by the arrow was more likely to contain the search target (50%) than any of the three uncued quadrants (16.7% probability). Participants were informed of the arrow's predictability. To measure spatial cueing, we compared search RT on valid trials, in which the target appeared in the cued quadrant, with that on invalid trials, in which the target appeared in one of the uncued quadrants. In the absence of a secondary working memory task, participants should make faster responses to valid trials than invalid trials (Jonides, 1980; Posner, 1980). If endogenous cueing relies on the same mechanism as spatial working memory, then imposing a working memory load should reduce the validity effect.

Method

Participants

Participants in this study were students at the University of Minnesota between the age of 18 and 35 years old (8 males and 10 females; mean age of 20.4). A pre-specified sample size of 18 was used. The sample size was chosen to be comparable to previous studies on similar topics (e.g., Vickery et al., 2010). All participants reported normal or corrected-to-normal visual acuity and normal color vision. Participants provided written informed consent before the experiment and were compensated for their time.

Equipment

The equipment was identical to that used in Part I. Participants were tested individually in a room with normal interior lighting.

Materials

In the visual working memory task, two color arrays were presented one after the other in the center of the screen. Each color array contained four colored squares (each square subtended 3.9º x 3.9º). The colors were arranged in the same spatial configuration as the arrow keys on standard US keyboards, with three colors aligned horizontally and a fourth color above the middle of the three (Figure 8). This alignment was used because participants used the arrow keys to report the location of the changed color. The gap between the colors was 0.50º. The two arrays differed in one color. The five colors for the two arrays were randomly drawn from six distinctive colors (red, green, blue, yellow, magenta, and cyan). The location of the color that changed was randomly chosen on each trial. The arrays were presented against either a black or a white background (15.8º x15.8º). The color of the background cued participants to different working memory conditions (white: high working memory load condition; black: no working memory load condition).

Visual search was presented during the retention interval of the working memory task. A spatial cue using a black arrow (size: 1.9º x 1.9º) was directed toward one of the four visual quadrants (the direction of the arrow was 45º, 135º, 225º, or 315º). The search display contained one target (a white T rotated to the left or right) and 7, 11, or 15 distractors (white Ls rotated 0º, 90º, 180º, or 270º) presented against a neutral gray background. Each search item subtended 1.9º x 1.9º. The locations of the items were chosen randomly from a 10 x 10 invisible matrix (29º x 29º), with the constraint that an equal number of items (two, three, or four) appeared in each visual quadrant. The orientation of the target was randomly chosen on each trial, so the target identity and motor response did not correlate with any experimental factors.

Procedure

Participants initiated each trial by clicking on a small white square (1.0º x 1.0º), which occupied a random location within the central 2.5º x 2.5º area. The mouse click enforced fixation before each trial because it required eye-hand coordination. After the click and a 300 ms delay, an array of 4 colors was displayed for 500 ms. Participants were asked to remember the colors and their locations if the array was presented against a white background, or to ignore the array if it was presented against a black background. Following a 500 ms neutral-gray blank interval, an arrow cue flashed for 100 ms at the center of the display, followed by a 100 ms blank screen and then the visual search display. The arrow was directed toward one of the four visual quadrants, randomly selected on each trial. Participants searched for a T among Ls, and pressed the left or right arrow key to indicate whether the T was rotated to the left or to the right. The search display remained until participants made a response. This was followed by audio feedback about response accuracy (three chirps lasting a total of 300 ms for a correct response, or a 200 ms buzz and a 2 sec timeout for an incorrect response[6]). The second color array appeared on the probe display after the sound feedback. The array was identical to the first color array except for the color of one square. On trials when the background was black (i.e., participants were instructed to ignore the color task), no response was required; the probe display disappeared after 1 sec. On trials when the background was white (participants were instructed to attend to the color task), the probe display remained until participants pressed one of the arrow keys to report the corresponding location of the color change. A smiley face icon followed each correct response and a sad face icon followed each incorrect response. Figure 8 illustrates the procedure.

[6] The total auditory feedback duration for incorrect trials was longer than that for correct trials to discourage incorrect visual search responses. However, this also made the retention interval longer for the working memory task when search was incorrect. The difference in retention interval was not considered as a significant factor because search accuracy was very high and because incorrect trials were removed from the data analysis.

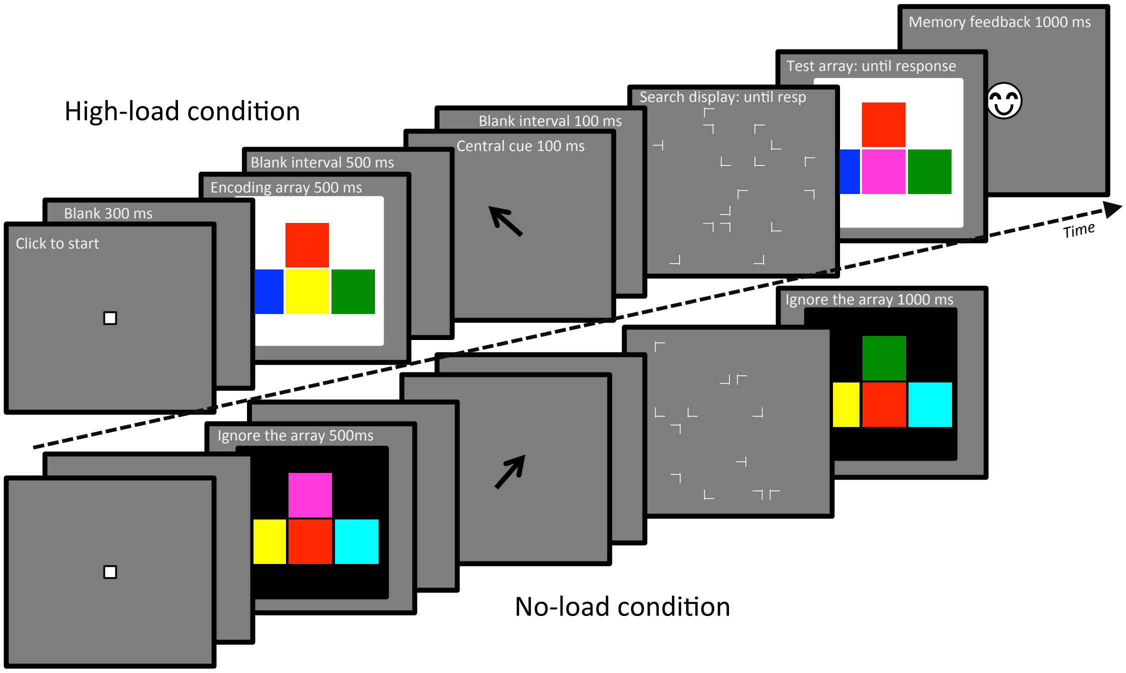


Figure 8. *A schematic illustration of the stimuli and trial sequence used in Experiment 1 of Part II-1. Items are not drawn to scale.*

After 10 practice trials (or more if participants had difficulty performing the two tasks), participants completed 432 experimental trials. They were asked to perform both tasks as accurately as they could. Speed was also emphasized for visual search but not for the working memory task. In addition, the experimenter encouraged participants to use the central arrow to guide search. Participants were informed that the target would be in the cued quadrant on one half of the trials (50%), which was higher than chance (25%), and in each uncued quadrant on 17% of the trials. Trials were self-paced and participants could take a break whenever they wanted.

Design

Working memory load (no-load or high-load), cue validity (valid or invalid), and set size (8, 12, or 16 items) were the three within-subject factors. On half of the trials (i.e., when the color array was displayed against a black background) participants ignored the working memory task, whereas on the other half of the trials (i.e., when the color array was displayed against a white background) they encoded the array in memory. These trials were randomly intermixed. Orthogonal to the working memory manipulation, we varied the validity of the central arrow cue. On 50% of the trials the cued quadrant contained the target (valid cue trials), whereas on the other trials the target appeared in one of the other three quadrants (invalid cue trials; 16.7% probability in each quadrant). Although there were an equal number of valid and invalid trials, owing to the presence of four quadrants the cue validity was higher than chance. Finally, the number of items on the search display could be 8, 12, or 16, allowing us to measure the efficiency of visual search RT as a function of set size. All trial types (memory type (2) x cue validity (2) x set size (3): 12 types of trials; 36 trials per each type) were presented in a random order.

Results

1. Visual working memory accuracy

The analysis of visual working memory focused on trials in which a correct search response was made because the memory delay was longer when search was incorrect (see footnote 8). This criterion excluded 1.7% of total trials.

The overall working memory accuracy was 85.5%. Working memory accuracy was higher in the valid condition, where the spatial cue predicted the target's quadrant (87.1%), than in the invalid condition (83.9%), $t(17) = 2.99$, $p = .008$. This reduction could be caused either by reorienting spatial attention from the cued quadrant to uncued quadrants or by greater memory decay because longer search RT on invalid trials increased the working memory retention interval.

2. Visual search accuracy

Visual search accuracy was high (98.3%). However, all three experimental factors influenced accuracy. Search accuracy was slightly but significantly higher in the high-load condition (98.6%) than the no-load condition (98.0%), $F(1, 17) = 4.71$, $p < .05$, $\eta p^2 = .22$, significantly lower when the central arrow was invalid rather than valid, $F(1, 17) = 5.91$, $p < .03$, $\eta p^2 = .26$, and significantly lower when more items were on the display, $F(2, 34) = 3.82$, $p < .04$, $\eta p^2 = .18$. These factors did not interact, all *p*s > .18.

3. Visual search RT

In this analysis we excluded trials with RTs longer than 10 sec (0.26% of the data) and trials with an incorrect search response. Figure 9 shows the mean RTs separately for the high working memory load and no load conditions.

We conducted an ANOVA using working memory load (no-load or high-load), cue validity (valid or invalid), and set size (8, 12, or 16) as within-subject factors. This analysis showed that search RT was significantly slower when participants remembered rather than ignored the color array, $F(1, 17) = 33.31$, $p < .001$, $\eta p^2 = .66$, which means the working memory manipulation was effective in slowing down visual search. The main effect of cue validity was also significant, suggesting that participants used the arrow cue to deploy spatial attention, $F(1, 17) = 81.73$, $p < .001$, $\eta p^2 = .83$. In addition, search was slower with larger set sizes, $F(2, 34) = 144.49$, $p < .001$, $\eta p^2 = .90$. The interaction between working memory load and set size was not significant, $F < 1$.

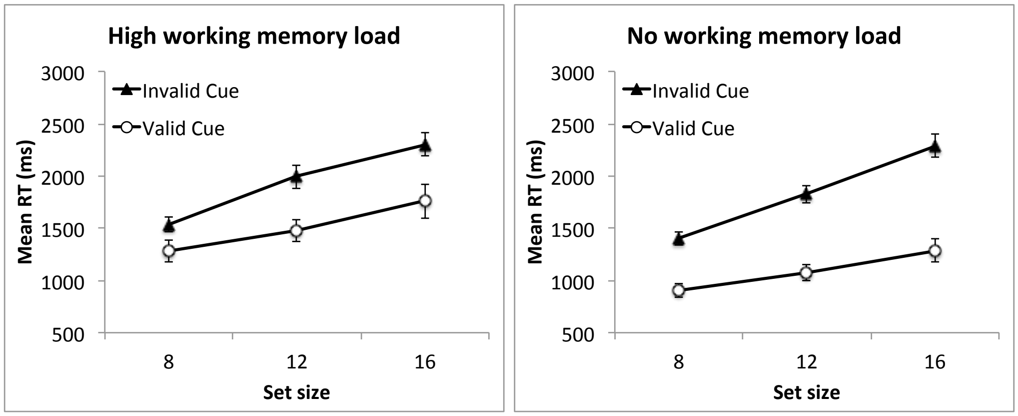


Figure 9. Visual search results from Part II-1 Experiment 1. Error bars show ±1 S.E. of the mean.

A significant interaction between cue validity and set size showed that the central arrow cue had improved search efficiency, $F(2, 34) = 19.34$, $p < .001$, $\eta p^2 = .53$. Importantly, the validity effect was reduced under working memory load, leading to a significant interaction between working memory load and cue validity, $F(1, 17) = 18.58$, $p < .001$, $\eta p^2 = .52$, and a marginally significant 3-way interaction, $F(2, 34) = 2.46$, $p = .10$, $\eta p^2 = .13$. A valid central arrow increased visual search speed and made the search slope shallower (i.e., more efficient search), in both the high-load and no-load conditions, all *p*s > .25. However, the cue effect was significantly reduced under high load.

The above analysis included trials in which participants made an incorrect response in the working memory task. Even when incorrect trials in working memory task (about 14.5%) were excluded from the analysis, the pattern of results was the same.

Because visual search was significantly *less* accurate, and also significantly faster, on high-load than no-load trials, one may be concerned about a speed-accuracy tradeoff. A common approach to address this concern is to combine RT and accuracy to create an "inverse efficiency index" (Townsend & Ashby, 1978, 1983). This index was calculated as RT divided by accuracy, increasing RT more in conditions associated with lower accuracy. Here we performed such an analysis using inverse efficiency as the main dependent measure. All statistical results replicated what we reported using RT alone. That is, the size of endogenous cueing was significantly smaller in the high-load than the no-load condition, $F(1, 17) = 18.92$, $p < .001$, $\eta p^2 = .53$. Thus, the slight difference in accuracy did not change our conclusions.

Discussion

Experiment 1 showed that the endogenous cueing effect was reduced when participants held the locations of four colors in their working memory. This finding replicated and extended previous research on the relationship between visual working memory and spatial attention (Oh & Kim, 2004; Woodman & Luck, 2004). Like previous findings, we showed that exerting a working memory load slowed down visual search. Furthermore, adding a working memory load interfered with attentional orienting to the cued location. This finding implies that spatial working memory and goal-driven attention share common mechanisms (Awh & Jonides, 2001; Chun, 2011; Franconeri et al., 2013; Gazzaley & Nobre, 2012; Kiyonaga & Egner, 2013).

2.4.2. Experiment 2: Probability cueing under color-array WM load

Experiment 2 used a similar experimental paradigm as Experiment 1, except that we replaced the endogenous spatial cue with an implicitly learned, probability cue. Specifically, I removed the central arrow cue but manipulated the location probability of the target T. The target was more often located in one visual quadrant than in any of the other three quadrants. Over time participants developed an attentional preference for the high-probability, rich quadrant. Importantly, location probability learning yielded the same amount of information as the endogenous cue used in Experiment 1. The implicitly cued quadrant contained the search target on 50% of the trials and each uncued quadrant contained the target on 16.7% of the trials. A previous study had found that endogenous cues and spatial probability cues were comparable in their effectiveness at guiding spatial attention. These two types of cues sped up RT and enhanced search efficiency to a similar degree (Jiang, Swallow, & Rosenbaum, 2013).

If probability cueing also shares common mechanisms with spatial working memory, then imposing a visual working memory load should interfere with probability cueing. Alternatively, if implicitly guided spatial attention relies on a separate processing resource than spatial working memory, then unlike endogenous cueing, probability cueing should be robust under a visual working memory load.

Method

Participants

Six males and 12 females participated in Experiment 2 (mean age 20.4 years).

Materials

Experiment 2 used the same working memory and visual search tasks as Experiment 1, but the central arrow cue was removed.

Procedure

The procedure was similar to Experiment 1 except that the display containing the central arrow cue was removed.

Design

We manipulated the target's location probability in the visual search task. Across multiple trials, the target appeared in one quadrant (the high-probability "rich" quadrant) on 50% of the trials, and appeared in any one of the other three quadrants (the low-probability "sparse" quadrants) on 16.7% of the trials. Which quadrant was rich was randomly selected for each participant but remained the same for a given participant. Importantly, participants were not given any instruction about the target's location probability, so any attentional bias toward the rich quadrant would reflect incidental learning.

The design, material and procedure of Experiment 2 were similar to those of Experiment 1 except for the type of spatial cueing. The total number of trials was 432. Similar to Experiment 1, we manipulated three factors within participants: working memory load (no-load or high-load), probability cue (rich condition vs. sparse condition), and search set size (8, 12, or 16). All trial types (memory type (2) x probability cue (2) x set size (3): 12 types of trials; 36 trials per each type) were randomly intermixed in presentation order.

Recognition

At the completion of the experiment we assessed participants' level of explicit awareness of the probability manipulation. Participants were first asked to report whether they thought the location of the search target was random or whether it was more often found in some parts of the screen than others. Regardless of their answer they were told that the target's location was not random and were asked to choose the quadrant where the search target was most often found.

Results

1. Visual working memory accuracy

Similar to Experiment 1, trials in which participants made an incorrect visual search response were excluded from the working memory analysis. This removed 1.2% of the trials. Overall working memory performance was 91.8%, which was marginally higher than that observed in Experiment 1, $t(34) = 2.02$, $p = .051$. It appears that the removal of the central arrow had reduced the interference of the search task on visual working memory. In addition, working memory accuracy was comparable whether the search target appeared in the rich quadrant (92.6%) or sparse quadrants (91.1%), $F(1, 17) = 2.70$, $p > .11$. Also, working memory accuracy did not differ across visual search set size, $F < 1$. Probability cue and set size did not interact, $F(2, 34) = 1.09$, $p > .30$.

2. Visual search accuracy

Visual search accuracy was comparably high across all conditions (mean 98.8%). None of the conditions or their interactions affected search accuracy, all *p*s > .23.

3. Visual search RT

Similar to Experiment 1, we excluded from the RT analysis incorrect trials as well as trials that took longer than 10 sec to respond (0.04% of the data). Figure 10 shows mean RTs across different conditions.

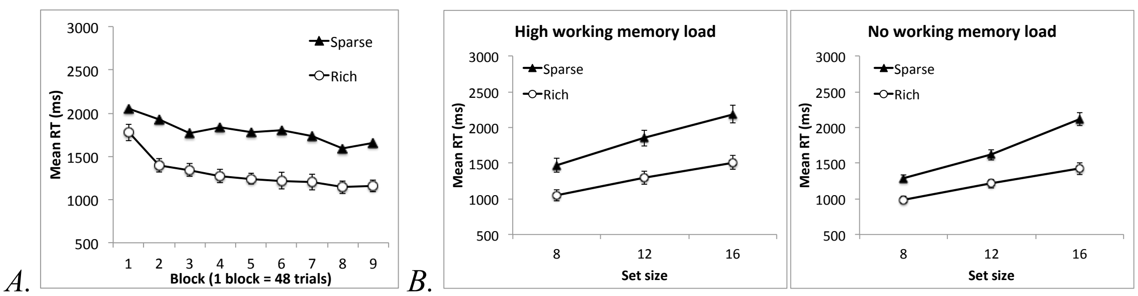


Figure 10. Results from Part II-1 Experiment 2. A. Search RT across the 9 blocks. Error bars show ±1 S.E. of the difference between the rich and sparse conditions. B. Search RT in Blocks 2-9, separately for the two working memory conditions and different set sizes. Error bars show ±1 S.E. of the mean. Some error bars may be too small to see.

To examine the acquisition of probability cueing, we first examined search RT over the course of the experiment, combining data from all set sizes and both working memory conditions (Figure 10A). The data were binned into 9 blocks to smooth the learning curve. An ANOVA on probability cue condition (rich or sparse) and block (1-9) revealed that the target was found more quickly when it was in the rich quadrant rather than a sparse quadrant, $F(1, 17) = 101.38$, $p < .001$, $\eta p^2 = .86$. RT also became faster as the experiment progressed, $F(8, 136) = 14.86$, $p < .001$, $\eta p^2 = .47$. Probability cue condition and experimental block showed a marginally significant interaction, $F(8, 136) = 1.83$, $p = .076$, $\eta p^2 = .10$. Trend analysis on the interaction term showed an insignificant linear trend, $F(1, 17) = 1.71$, $p = .20$, but a significant quadratic trend, $F(1, 17) = 6.63$, $p = .02$, $\eta p^2 = .28$. The significant quadratic trend was explained by the fact that probability cueing increased from the first to the second block and then stabilized. Relatively rapid probability learning had also been shown in previous studies (Jiang, Swallow, Rosenbaum et al., 2013; Umemoto et al., 2010). Because probability cueing appeared to have stabilized after the first block, we pooled data across Blocks 2-9 in the next analysis. The same was done in all subsequent experiments.

Figure 10B shows averaged search RT from Blocks 2-9, separately for the two working memory load conditions and three set sizes. An ANOVA including working memory load, probability cue condition, and set size revealed a significant main effect of working memory, $F(1, 17) = 4.87$, $p < .05$ $\eta p^2 = .22$. Search RT was slower when participants had to perform the working memory task (1.56 sec) than when they could ignore it (1.44 sec). In addition, we found a significant probability cueing effect: RT was faster when the target was presented in the rich quadrant than when it was in the sparse quadrants, $F(1, 17) = 108.69$, $p < .001$, $\eta p^2 = .87$. Finally, RT was longer with more items on the display, revealing a significant main effect of set size, $F(2, 34) = 159.67$, $p < .001$, $\eta p^2 = .90$.

A significant interaction between probability cue condition and set size showed that search was more efficient in the rich quadrant than in the sparse quadrants, $F(2, 34) =$

18.89, $p < .001$, $\eta p^2 = .53$. Unlike Experiment 1, however, working memory load did not interact with probability cueing. If anything, the data went in the opposite direction: the difference between rich and sparse conditions was slightly greater when participants performed the working memory task than when they did not, $F(1, 17) = 5.27$, $p < .04$, $\eta p^2 = .24$. The 3-way interaction was not significant, $F(2, 34) = 1.30$, $p > .25$, nor was the interaction between working memory load and set size, $F(2, 34) = 1.17$, $p > .30$.

The results were replicated when the 9.2% of trials in which participants made an incorrect working memory response were eliminated.

4. Recognition

When asked whether they thought the target appeared randomly or more often in some regions than others, 12 of the 18 participants said that the target's location was random. Among these 12 participants, only three participants correctly identified the rich quadrant out of the four quadrants in the forced-choice task that followed. This percentage (3 out of 12) was at chance (25%). Among the 6 participants who said that the target's location was not random, only 2 chose their rich quadrant correctly. Altogether only five of the 18 participants correctly identified the rich quadrant, which did not differ from chance, $\chi(1) = 0.074$, $p > .50$.

In Part 1 I had found that standard visual statistical learning of shape co-occurrence is sensitive to explicit awareness. Did explicit awareness also contribute to probability cueing? To address this question, I separated participants based on their recognition accuracy in the forced-choice task into two groups. The five participants who correctly identified the rich quadrant formed the "aware" group, whereas the other 13 formed the "unaware" group. This factor did not influence the pattern of probability cueing results. Awareness group did not interact with probability cueing condition (rich or sparse), or with any higher-order effects involving cue condition, all *p*s > .25. Thus, although the acquisition of statistical regularity information for shape co-occurrences is susceptible to explicit awareness, and dependent on such awareness, there is no evidence that explicit awareness had contributed to probability cueing (Geng & Behrmann, 2002; Jiang, Swallow, & Rosenbaum, 2013). These findings support the classification of probability cueing as a form of implicitly learned attention.

5. Experiments 1 vs. 2

To directly compare Experiment 1 (endogenous cueing) and Experiment 2 (probability cueing), we conducted an ANOVA using cue type (endogenous cue or probability cue) as a between-subject factor, and the other three manipulations (working memory load, cue validity, set size) as within-subject factors. Only data from blocks 2-9 in both experiments were used in this analysis. We found one significant interaction that involved cue type: the interaction between working memory load, cue validity, and cue type, $F(1, 34) = 19.58$, $p < .001$, $\eta p^2 = .37$. Specifically, whereas adding a visual working memory task impaired endogenous cueing, it slightly increased probability cueing.

Notably, cue type did not interact with any other factors – it did not interact with cue validity or set size, for instance, suggesting that endogenous cues and probability cues were very similar in terms of facilitating RT and in enhancing search efficiency. The two cues differed only in their sensitivity to spatial working memory load. A secondary working memory load impaired endogenous cueing but not probability cueing.

Discussion

Experiment 2 showed that probability cueing could guide spatial attention toward target rich locations. The size of probability cueing, as indexed by a reduction in RT and a reduction in search slope, was comparable to that of endogenous cueing used in Experiment 1. However, a secondary visual working memory load did not influence probability cueing. These results contrasted with findings from Experiment 1, in which endogenous cueing became less powerful under a visual working memory load. Because the same visual working memory task was used in both experiments, the findings of Experiment 2 cannot be attributed to weak experimental manipulations. In addition, the visual working memory load slowed down overall RT in the search task of Experiment 2, again suggesting that the working memory load was effective. Finally, a direct comparison between endogenous cueing and probability cueing showed a significant interaction effect: *whereas visual working memory load interfered with the efficiency of the central arrow cue, it did not reduce the efficiency of the probability cue.*

These findings have two implications. First, they show that whereas goal-driven attention shares common mechanisms with visual working memory, implicitly learned attention is dissociated from visual working memory. Second, spatial attention is not a unitary system. Only some forms of spatial attention depend on visual working memory. We will discuss the characteristics and implications of a multi-system view later.

2.4.3. Experiment 3: Load-transfer in probability cueing

The main goals of Experiment 3 are to replicate the findings of Experiment 2 with other types of visual working memory tasks and to confirm the findings in a new experimental design.

In Experiment 3, we adopted a new experimental design to evaluate the cross-load transfer of probability cueing. Specifically, participants were trained to develop an attentional preference for different locations under different working memory loads. On trials without working memory load (i.e., no working memory condition), the target was frequently found in one visual quadrant (the no-load rich quadrant). On trials under high-load working memory (i.e., high working memory condition), the target was frequently found in another visual quadrant (the high-load rich quadrant). In this design, we can evaluate whether people acquired probability cueing toward the high-load rich quadrant on high-load trials as robustly as they did on no-load trials. In addition, we can also evaluate the transfer of probability cueing across load. For example, on no-load trials, we could test whether participants preferred to search not only the no-load rich quadrant where the target was most often found, but also the high-load rich quadrant. The high-load rich quadrant contains the target on just 16.7% of trials, the same frequency as the sparse quadrants. If participants had acquired probability cueing under high load and such cueing was insensitive to working memory load, then probability cueing should be shown in the high-load rich quadrant on no-load trials. Thus, strong evidence for the dissociation between probability cueing and spatial working memory could come from two statistically significant effects: 1) the presence of probability cueing toward the high-load rich quadrant on high-load trials (learning under high-load), or 2) the presence of probability cueing toward the high-load rich quadrant on no-load trials (cross-load transfer). This dissociation would strengthen the conclusion that spatial probability cueing is immune to working memory load.

A second contribution of Experiment 3 is that we tested four different working memory tasks. Experiment 3A used color working memory; Experiment 3B used two kinds of spatial working memory, including 10-dot array and 4-dot sequence [7]; and Experiment 3C used object working memory. Several previous studies have shown that compared with color working memory, spatial working memory can more effectively interfere with spatial attention (Travis et al., 2013; Vickery et al., 2010; Woodman & Luck, 2004). Although the color-location memory task used in Experiments 1 and 2 was effective in slowing down visual search and interfering with endogenous cueing, its lack of an effect on probability cueing raised questions about whether other forms of spatial working memory load also had no effects on probability cueing.

Method

Participants

Seventy-eight new participants completed Experiment 3. Table 1 lists the characteristics of the participants.

[7] I tested 18 participants in another spatial working memory task: the 2 sequential dot working memory task. In the two-dot working memory task, a sequence of two dots was presented (Woodman & Luck, 2004). The procedures were identical to the 10-dot array working memory task except that two dots (instead of 10 dots) were sequentially (instead of simultaneously) presented. However, loading two sequential dots was not an effective manipulation as shown by the finding that the 2 sequential dot working memory task did not slow down visual search. Although probability cueing was robust under the 2-dot sequential working memory load, it is possible that the working memory load was too low. Therefore, I report here two other spatial working memory tasks that did significantly slow overall visual search RT.

Table 1. Participants in Experiment 3

Experiment	Mean age (yrs)	Female	Male	Total
Exp.3A. color-array WM	18.9	12	6	18
Exp.3B. spatial WM	20.7	26	10	36
Exp.3C. object WM	21.5	13	11	24

Materials

In all tasks except Experiment 3C, the visual search task used the same materials as the first two experiments. Experiment 3A used the same color array working memory task as that used in the first two experiments. The nature of the working memory task in Experiment 3B and Experiment 3C differed and will be described next.

Procedure

The procedure used in Experiments 3A and Experiment 3B was the same as that of Experiment 2, except for the change in the working memory tasks. Participants first saw a memory array. They encoded it to memory if the dots in the array were white (high-load), or ignored the presentation if the dots were black (no-load). Then they performed the visual search task. Following the search response and sound feedback, the memory test probe was presented. Participants ignored the probe on no-load trials, or judged whether the probe was the same as the encoding array on high-load trials. The procedure of Experiment 3C will be described separately.

Design

Similar to Experiment 2, we manipulated working memory load (high-load or no-load), probability cueing condition, and set size (8, 12, or 16). The probability cue condition differed from the simpler design used in Experiment 2. Specifically, two visual quadrants were randomly selected to be the high-load rich quadrant and the no-load rich quadrant. On trials when participants had to hold high working memory load, the visual search target was more often located in the high-load rich quadrant (50% of the time) than in either the no-load rich quadrant or the sparse quadrants (16.7% of the time in each quadrant). On trials when participants ignored the encoding display, the visual search target was more often located in a different, no-load rich quadrant (50% of the time) than in either the high-load rich quadrant or the sparse quadrants (16.7% of the time in each quadrant). Participants were not informed of the probability manipulation. Experiment 3A and Experiment 3B consisted of 432 trials, and Experiment 3C consisted of 720 trials. All conditions were presented in a randomly intermixed order.

2.4.3A Experiment 3A: color-array working memory

A color-array working memory experiment identical to the one in the previous two experiments was adopted in this newly designed visual search experiment. Using the same working memory task can make it easy to compare the results to Experiment 2 and to examine the load-specific transfer effect. The material, procedure and design were described above (see Figure 8).

Results

1. Visual working memory accuracy

Similar to Experiment 2, we excluded trials in which participants made an incorrect visual search response. This removed 3.4% of the trials. The mean accuracy was 86.3%, 84.5%, and 86.0%, separately for trials in which the visual search target fell in the sparse quadrants, the no-load rich quadrant, and the high-load rich quadrant, respectively. Working memory performance was unaffected by probability cueing conditions, $F < 1$.

2. Visual search accuracy

Table 2 shows visual search accuracy and RT for Experiments 3A-3C. In Experiment 3A, none of the experimental factors (working memory, probability cue, and set size) affected search accuracy, ps > .06. I will present search RT data next.

Table 2. Visual search accuracy (%) and RT (ms) from experiments in Experiment 3, separately by working-memory load (no-load and load) and quadrant type (sparse, no-load rich, and high-load rich quadrant). S.E. of the mean is shown in parentheses.

	Search accuracy (%)	Search RT (ms) (S.E.)					
		No-load condition (low-load in Exp. 3C)			High-load condition		
		Sparse	No-load rich (low-load in Exp. 3C)	High-load rich	Sparse	No-load rich (low-load in Exp. 3C)	High-load rich

Exp.3A. Color-array WM	96.7	1548.69 (66.89)	1326.72 (88.14)	1384.04 (62.14)	1963.21 (126.58)	1787.78 (122.34)	1697.41 (117.02)
Exp.3B. 10-dot locations WM	98.9	1607.60 (92.31)	1325.80 (42.75)	1374.46 (69.35)	1687.95 (92.81)	1413.01 (44.28)	1363.89 (77.95)
Exp.3B. 4-dot sequence WM	99.1	1589.75 (76.04)	1320.48 (49.52)	1332.21 (92.85)	1642.12 (78.02)	1396.70 (65.27)	1337.16 (78.14)
Exp.3C. Object WM	92.5	1175.61 (45.95)	995.05 (43.34)	1086.62 (47.98)	1742.06 (58.66)	1618.75 (62.16)	1570.97 (51.81)

3. Visual search RT

In the RT analysis, outliers (over 10 sec, 0.09% of the data) and trials with an incorrect search response were excluded. Similar to Experiment 2, probability cueing emerged rapidly and was relatively stable from Block 2 onward. This was also the case in the other experiments. Therefore, I combined data from Blocks 2-9. Figure 11 shows search RT in Experiment 3A as a function of working memory load, target quadrant, and set size.

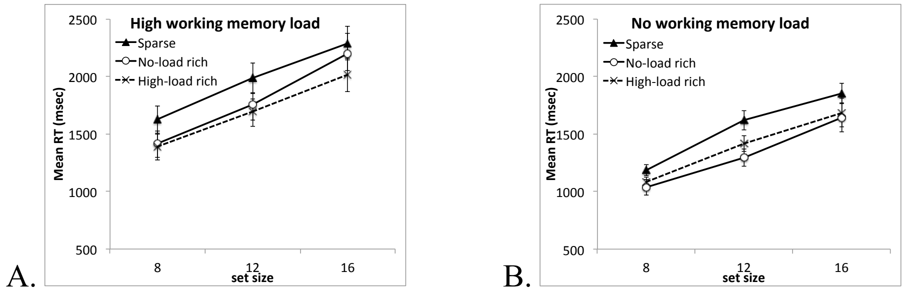


Figure 11. Results from the visual search task in Experiment 3A. Search RT was averaged across Blocks 2-9. A. High working memory load condition; B. No working memory condition. The different lines represent the different target-quadrant conditions. Error bars show ±1 S.E. of the mean.

An ANOVA on working memory load (no-load or high-load), probability cue condition (sparse, no-load rich, or high-load rich), and set size (8, 12, or 16) as factors revealed three main effects: slower RT under high working memory load than no load, ($F(1, 17) = 31.06$, $p <.001$, $\eta p^2 = .646$), slower RT at higher set sizes, ($F(2, 34) = 156.06$, $p < .001$, $\eta p^2 = .902$), and slower RT in the sparse quadrants than the rich quadrants ($F(2, 34) = 5.93$, $p = .006$, $\eta p^2 = .259$). None of the other effects were significant, all *p*s > .25. Although probability cue condition did not interact with set size, $F < 1$, it is important to note that search RT was slowed down by the addition of a spatial working memory task. However, working memory load did not affect probability cueing, yielding no interaction effects between load and probability cue condition, $F(2, 34) = 1.36$, $p = .27$. Follow-up analysis showed that RT was significantly slower when the target was in the sparse quadrant than when it was in the high-load rich quadrant, $F(1, 17) = 17.36$, $p = .001$, $\eta p^2 = .51$, or the no-load rich quadrant, $F(1, 17) = 6.57$, $p = .02$, $\eta p^2 =$ T.28. The latter two conditions did not differ significantly from each other, $F < 1$.

4. Cross-load transfer in visual search RT

Two predictions were made based on the view that probability cueing is dissociated from spatial working memory. First, on high-load trials, participants should be significantly faster in the high-load rich quadrant than the sparse quadrants. Restricting the analysis to high-load trials showed that participants were significantly faster when the target was in the high-load rich quadrant rather than the sparse quadrants, $F(1, 17) = 24.65$, $p < .001$, $\eta p^2 = .592$. Probability cue condition did not interact with set size, $F < 1$.The second prediction we made was about cross-load transfer. Specifically, on no-load trials, although the target was equally unlikely to appear in the high-load rich quadrant and the sparse quadrants, participants may nonetheless demonstrate faster RTs when the target was in the high-load rich quadrant. Such a finding would suggest that participants had acquired an attentional bias toward the high-load rich quadrant and that this bias showed cross-load transfer. To test this prediction, we restricted our analysis to no-load trials and compared RT when the target was in the high-load rich quadrant and the sparse quadrants. This analysis showed that RT was significantly faster in the high-load rich quadrant, $F(1, 17) = 5.44$, $p = .032$, $\eta p^2 = .242$, but search efficiency was comparable between sparse and high-load rich quadrants, $F < 1$.

5. Load-specificity in visual search RT

In a final analysis I examined whether probability cueing showed any evidence of load-specific learning. I focused on data from trials in which the target was in either the no-load rich or the high-load rich quadrants, and tested whether this factor interacted with working memory load. Any load-specific learning would manifest as faster RT in the no-load rich quadrant under no-load, and faster RT in the high-load rich quadrant under high-load. This, however, was not supported by the data. The interaction between working memory load and probability cue condition was not significant, $F(1, 17) = 1.66$, $p > .20$.

6. Experiment 2 vs. Experiment 3A

The magnitude of probability cueing was approximately 222 ms in Experiment 3A, which was considerably smaller than that in Experiment 2 (approximately 510 ms). This difference can be accounted for by differences in the overall target probability in the rich quadrants. In Experiment 3A, although the no-load rich quadrant had a 50% probability of containing the target on no-load trials, it only had a 16.7% probability of containing the target on high-load trials. So the overall probability of the target falling in each of the two rich quadrants was 33.3%. In contrast, in Experiment 2, the rich quadrant had a 50% probability of containing the target. The stronger probability cueing observed in Experiment 2 compared with Experiment 3A indicates that participants were sensitive to the exact probability discrepancy between the rich and sparse quadrants.

Discussion

Using the color array working memory task, Experiment 3A replicated and extended the findings from Experiment 2. Results showed that probability cueing was unaffected by working memory load. In addition, although the "rich" quadrants differed for high- and low- load trials, probability cueing showed full transfer across working memory load conditions.

2.4.3B Experiment 3B: Spatial working memory

Experiments 2 and 3A showed that probability cueing was unaffected by a secondary color working memory task. However, one may be concerned that the color working memory task was insufficient to exhaust spatial working memory capacity. Cowan (2001) proposed that the capacity of human working memory is approximately 4. People may be able to hold more than 4 items in memory if they can form chunks of the individual items. Because the memory load used in Experiments 3A was 4, this may have left some capacity remaining for the visual search task. It is, therefore, important to repeat these experiments using a spatial working memory task with a heavy load. To this end, we adopted the 10-dot location memory task in Experiment 3B. This task is very challenging. Even with strategies such as chunking, participants generally cannot remember more than 4-6 spatial locations (Jiang, Olson, & Chun, 2000; Simons, 1996). As we will see in the experimental results, performance on the 10-dot memory task was substantially lower than that found for the color working memory task.

In addition to the 10-dot location working memory task, Experiment 3B included another task, the 4-dot sequence working memory task. Travis et al. (2013) recently showed that implicit learning, as evidenced by contextual cueing, was sensitive to one specific type of spatial working memory load. Contextual cueing was diminished when participants held in working memory the spatiotemporal sequence of four locations. In the spatiotemporal memory task, participants saw a sequence of four locations and had to remember not only the spatial locations of the dots but also the temporal order in which the locations appeared. Later they saw another sequence of four dots. The second sequence occupied the same spatial locations as the first sequence, but the temporal order may have changed. This task interfered with contextual cueing (Travis et al., 2013), even though none of the other visual working memory tasks produced any interference (Vickery et al., 2010: color array working memory, 2 sequential dot working memory, or 10-dot location memory).

We deemed it important to adopt the spatiotemporal memory task of Travis et al. in Experiment 3B because this task may have the greatest potential to exhaust working memory capacity and to interfere with implicitly learned attention. These two tasks provide a strong test for the independence between spatial working memory and implicitly learned spatial attention.

Method

Materials and procedure

<u>10-dot location WM task</u>

The encoding and probe displays each contained an array of 10 dots presented in randomly selected locations within an invisible 10 x 10 matrix (matrix size: 29º x 29º; dot diameter: 1º). The array was presented for 500 ms and followed by a 500 ms blank display. On half of the trials the dots were black, in which case participants ignored them. On the other half of the trials the dots were white, and participants were asked to remember their locations and to report whether the two arrays were the same or different. Regardless of the color of the dots, on half of the trials the encoding and probe arrays occupied identical locations. On the other half of the trials the two arrays differed in the location of one dot (the parameters were adopted from Vickery et al., 2010). Figure 12A depicts the procedure. The design of the experiment was otherwise similar to that of Experiment 3A.

4-dot sequence WM task

The encoding and probe sequences were both composed of a sequence of four dots (dot diameter 1.4º). This sequence included four sequentially presented dots (100 ms presentation duration plus 400 ms blank). The locations of the four dots were chosen randomly from 16 possible locations (8 equidistant locations on an imaginary outer concentric circle with an eccentricity of 5º, 8 other equidistant locations on an imaginary inner concentric circle with an eccentricity of 10º; these parameters were adopted from Travis et al., 2013). The dots were either black (no-load condition; participants ignored the dots) or white (high-load condition; participants memorized the locations of the dots and their temporal sequence). On half of the trials the order of the dots was identical for the encoding and probe sequences. On the other half of the trials the temporal order of the dots was reshuffled. Although the same spatial locations were occupied, the temporal order differed between the encoding and the probe sequences (see Figure 12). Other aspects of the experimental design were the same as those of Experiment 3A.

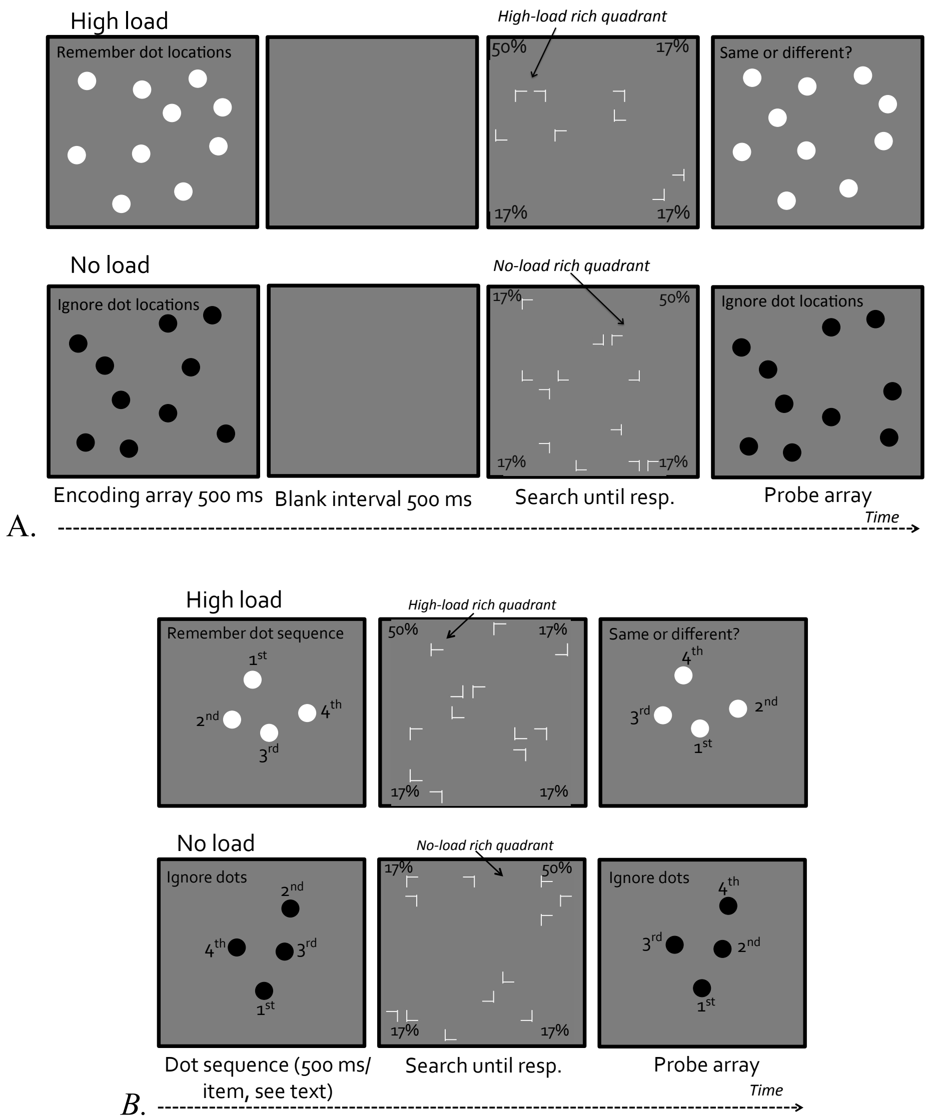


Figure 12. A schematic illustration of the stimuli and trial sequences used in Experiment 3B. A. 10-dot location working memory task. B. 4-dot sequence working memory task. Items are not drawn to scale.

Results

1. Visual working memory accuracy

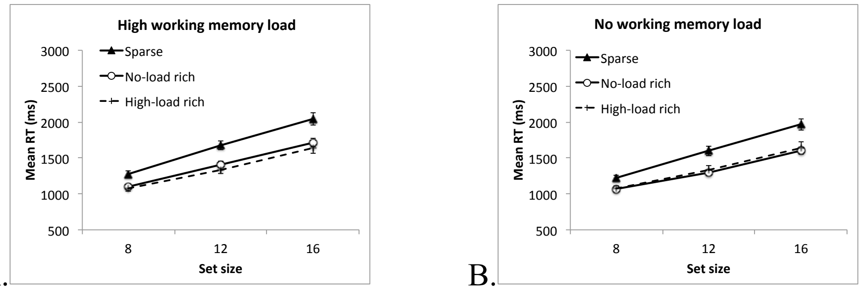
Incorrect search trials were excluded for working memory accuracy analysis (10-dot location working memory: 1.11%, 4-dot sequence working memory: 0.10%). Mean working memory accuracy for the 10-dot task was 65%, which was substantially lower than that of Experiment 3A (86%), $t(34) = 7.34$, $p < .001$. Mean memory accuracy for the 4-dot sequence task was 83%, which was comparable to that of Experiment 3A, $t(34) = .86$, $p > .30$. In both spatial working memory tasks, memory accuracy was unaffected by probability cue conditions (10-dot task: 64.2% in the sparse condition, 64.6% in the no-load rich condition, and 65.4% in the high-load rich condition, $F < 1$; 4-dot sequence task: 81.68%, 82.24%, and 83.17% on trials when the target was in the sparse quadrants, the no-load rich quadrant, and the high-load rich quadrant, respectively, $F < 1$).

2. Visual search accuracy

Visual search accuracy was high: 98.9% in the 10-dot location working memory task and 99.1% in the 4-dot sequence working memory task. It was unaffected by any experimental factors, all ps > .20.

3. Visual search RT

In the RT analysis, we excluded outliers (over 10 sec, 0.13% of the data) and trials with an incorrect search response. An analysis that included experiment (10-dot location or 4-dot sequence memory) as a between-subject factor revealed no interaction between experiment and other factors, smallest $p > .30$. Because there were no meaningful differences between the two spatial working memory tasks in the visual search results, data across all participants were pooled to increase statistical power.



A. B.

Figure 13. Results from the visual search task in Experiment 3B. Data were the average from Blocks 2-9. A. Data from the high working memory load condition. B. Data from the no working memory condition. Error bars show ±1 S.E. of the mean.

Similar to the other experiments, we averaged data across blocks 2-9 to examine effects of working memory load, probability cue condition, and set size (see Figure 13). An ANOVA showed that all three main effects were significant. Specifically, RT was faster in the no-load condition than the high-load condition, $F(1, 34) = 12.16$, $p = .001$, $\eta p^2 = .26$, faster when fewer items were on the display, $F(2, 68) = 346.84$, $p < .001$, $\eta p^2 = .91$, and faster when the target appeared in the rich quadrants rather than the sparse quadrants, $F(2, 68) = 26.43$, $p < .001$, $\eta p^2 = .44$. A significant interaction between probability cue condition and set size indicated that probability cueing enhanced visual search efficiency (i.e., the search slope was shallower), $F(4, 136) = 7.33$, $p < .001$, $\eta p^2 = .18$. None of the other interaction effects were significant, all *p*s > .14 (see Figure 13B). Planned contrasts showed that RT was significantly slower when the target was in the sparse quadrants rather than the high-load quadrant, $F(1, 34) = 47.96$, $p < .001$, $\eta p^2 = .59$, or the no-load quadrant, $F(1, 34) = 33.65$, $p < .001$, $\eta p^2 = .50$. The latter two conditions did not differ significantly from each other, $F < 1$. Thus, even though the spatial working memory load had slowed down search RT significantly, it did not weaken probability cueing.

3. Across-load transfer in visual search RT

When analyzing only high-load trials, participants found the target in the high-load rich condition more quickly than in the sparse condition, $F(1, 34) = 46.88$, $p < .001$, $\eta p2 = .58$. In addition, search efficiency was greater in the high-load rich quadrant than in sparse quadrants, $F(2, 68) = 10.18$, $p < .001$, $\eta p2 = .23$, for the interaction between condition and set size, demonstrating significant probability cueing.

When only no-load trials were analyzed, faster RT was observed in the high-load rich quadrant than in the sparse quadrants, $F(1, 34) = 32.80$, $p < .001$, $\eta p2 = .49$. Thus, participants had acquired an attentional bias toward the high-load rich quadrant. In addition, cueing exhibited cross-load transfer, allowing participants to search faster in the high-load rich quadrant even on trials without a working memory load.

4. Load-specificity cueing in visual search RT

We examined whether RT in the no-load rich quadrant is faster than that in the high-load rich quadrant under no-load condition, and vice versa. The interaction between the two types of rich quadrants and the working memory demand (ignore or remember the arrays) was tested. If there were load-specificity cueing, any load-specific learning would manifest as faster RT in the no-load rich quadrant under no-load condition, and faster RT in the high-load rich quadrant under high-load condition. However, the interaction between working memory load and quadrant type was not significant, $F(1, 35) = 2.72$, $p > .10$.

Discussion

Experiment 3B supported the findings from Experiment 2 and Experiment 3A using two new spatial working memory tasks. Probability cueing was robust against adding different types of spatial working memory (Jiang et al., 2000; Travis et al., 2013; Vickery et al., 2010). The 10-dot location working memory task required encoding a large number of locations in spatial working memory, which is a demanding task. In addition, the 4-dot memory task required precise memory of the temporal order of individual dot locations. Although the spatial working memory load was high enough to slow down overall search performance, it failed to weaken probability cueing. Probability cueing toward the high-load rich quadrant was significant under high working memory load. In addition, probability cueing toward the high-load rich quadrant was also shown under no-load trials (i.e., load-transfer), even though on those trials the target was rarely located in the high-load quadrant. Experiments 3A and 3B therefore provide strong evidence for the independence of probability cueing and spatial working memory.

2.4.3C Experiment 3C: task-relevant object working memory

Experiment 3A and Experiment 3B found robust probability cueing under various types of working memory. These findings indicate that implicitly guided spatial attention does not utilize visual working memory resources. However, the color arrays, 10-dot locations, and 4-dot sequences were all unrelated to the visual search task. Because the working memory load was unrelated to the visual search task, these experiments may not have provided the best opportunity to observe an interaction between working memory and probability cueing.

Experiment 3C tests whether working memory load that is relevant to the visual search task influences probability cueing. Unlike the other experiments, participants performed a single-task that had both a working memory component and a visual search component. The search items were novel objects and the search target changed from trial to trial. A cue at the beginning of the trial informed participant about the search target for that trial. In the low-load condition, the cue displayed one object. In the high-load condition, the cue displayed two objects, one of which would appear in the search display. Because participants did not know which of the cued objects would be in the search display, they had to hold two objects in visual working memory. Visual working memory has a low capacity for complex objects, with a capacity on the order of 1-2 objects (Eng, Chen, & Jiang, 2005). Previous studies have found that the two-target trials corresponded to much slower and less efficient visual search compared with the one-target trials (Menneer, Barrett, Phillips, Donnelly, & Cave, 2007; Menneer, Cave, & Donnelly, 2009; Vickery et al., 2010). In addition, visual working memory was actively involved in visual search if the search target changed from trial to trial (Woodman et al., 2013). Therefore, Experiment 3C allowed us to examine whether probability cueing was sensitive to working memory load when the load was an inherent aspect of the search task.

Method

Materials and procedure

Participants in Experiment 3C performed just one task – visual search. The search items were "glyphs," similar to those used in Experiment 2 of Part I. A novel aspect of this experiment is that the visual search target changed from trial to trial. Each trial started out with a cue display that showed participants either one or two glyphs. Participants were told to look for the glyphs in the following search display. The cue display lasted 500 ms, followed by a 500 ms blank interval. Then an array of 8, 12, or 16 glyphs was displayed until participants found the cued glyph. Regardless of whether one or two glyphs were cued, only one of them appeared on the search display. Participants were asked to press the spacebar as soon as they detected the cued glyph. This response erased the search display and initiated a response display with the digits "1" or "2" replacing the glyphs. Participants selected the digit that corresponded to the same location as the cued glyph. The spacebar response provided an RT measure whereas the digit response provided an accuracy measure. In this design, the number of cued glyphs corresponded to the working memory load: one (low-load) or two (high-load). Because participants had to search for the cued glyph, the working memory load was an intrinsic component of the visual search task. Figure 14 shows the design and procedure.

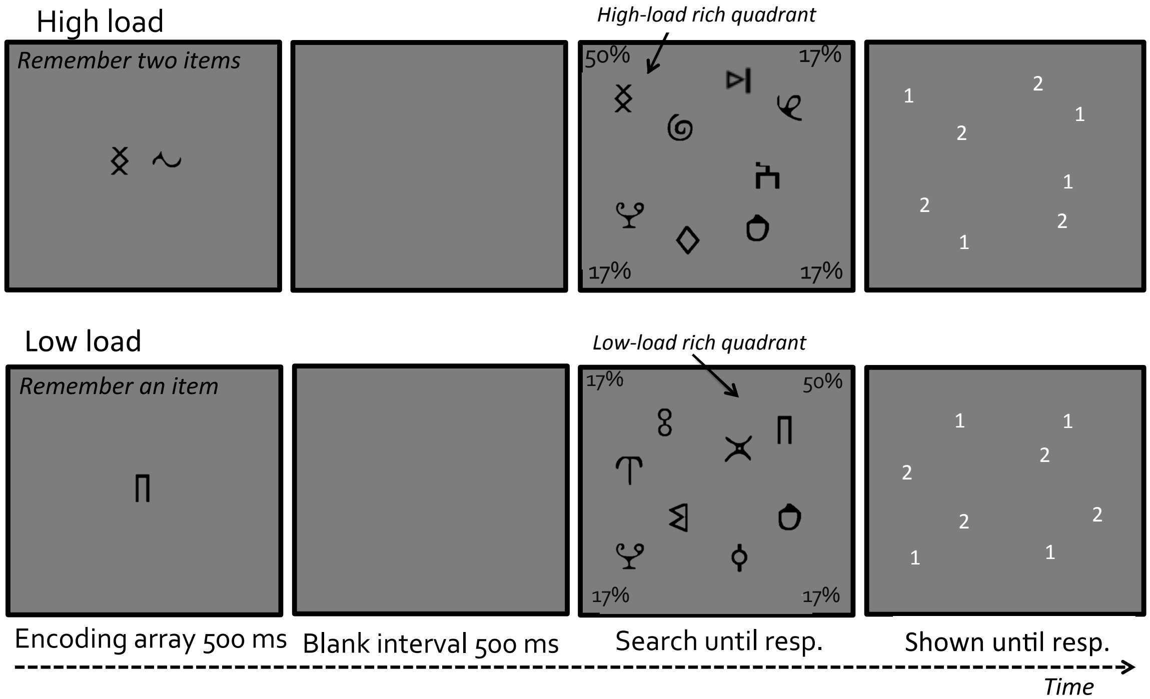


Figure 14. A schematic illustration of the stimuli and trial sequence used in Experiment 3C. Items are not drawn to scale.

Results

1. Visual search accuracy

Visual search accuracy was significantly higher in the low-load condition (one-target search task, mean 96.4%) than the high-load condition (two-target search task, mean 88.6%), $F(1, 23) = 71.65$, $p < .001$, $\eta p^2 = .76$. Thus the one versus two-target manipulation was effective in loading up working memory capacity. The main effect of probability cue condition was also significant, $F(2, 46) = 4.306$, $p = .019$, $\eta p^2 = .158$, but working memory load (the number of potential targets) and probability cue condition did not interact, $F(2, 46) = 2.14$, $p > .10$. Table 3 shows accuracy data separated by probability cue condition and working memory load.

Table 3. Accuracy from Experiment 3C. The parentheses show S.E. of the mean.

WM load	Sparse quadrant	One-target rich quadrant	Two-target rich quadrant
low-load (one target)	96.0% (1.1%)	96.8% (0.9%)	96.0% (1.0%)
high-load (two targets)	87.3% (1.4%)	90.1% (1.5%)	89.1% (1.5%)

2. Visual search RT

We excluded trials with an incorrect response and trials that took longer than 10 sec to complete. The latter eliminated 0.09% of all trials.

To examine the pace of location probability learning, I divided the 720 trials into 12 experimental blocks. Because the two-target search task showed significantly lower performance than the one-target search task, these two tasks were separately analyzed. In one-target search, an ANOVA including probability cue condition and block showed that people were faster when the target was in the rich quadrants rather than the sparse quadrants, $F(2, 44) = 18.25$, $p < .001$, $\eta p^2 = .45$, and faster in later blocks than earlier blocks of the experiment, $F(11, 242) = 5.44$, $p < .001$, $\eta p^2 = .20$. These two factors showed a significant interaction, $F(22, 484) = 1.74$, $p = .021$, $\eta p^2 = .07$. The linear trend in the interaction term was significant, $F(1, 22) = 4.70$, $p = .041$, $\eta p^2 = .18$, suggesting that probability cueing increased with training. Further analyses showed that RT was slower in the sparse condition than the low-load rich condition, $F(1, 22) = 58.92$, $p < .001$, $\eta p^2 = .72$, also slower than in the high-load rich quadrant, $F(1, 22) < 8.91$, $p = .007$, $\eta p^2 = .29$. Also, when the target was presented in the one-target quadrant, RT is faster than when the target was presented in the two-target quadrant, $F(1, 22) = 6.90$, $p = .015$, $\eta p^2 = .24$ (see Figure 15A, *right*).

In the two-target search task, an ANOVA including probability cue condition and block showed that people were faster when the target was in the rich quadrants rather than the sparse quadrants, $F(2, 42) = 6.65$, $p = .003$, $\eta p^2 = .24$, and faster in later blocks than earlier blocks of the experiment, $F(11, 231) = 4.93$, $p < .001$, $\eta p^2 = .19$. These two factors did not interact, $F < 1$. The linear trend in the interaction term was not significant, $F(1, 21) = 1.95$, $p = .177$. Further analyses showed that RT was slower in the sparse condition than the low-load rich condition, $F(1, 21) = 5.61$, $p = .028$, $\eta p^2 = .21$, and also slower than in the high-load rich quadrant, $F(1, 23) < 19.58$, $p < .001$, $\eta p^2 = .46$. However, the RT is not different between when the target was in the low-load rich quadrant and when it was in the high-load rich quadrant, $F < 1$ (Figure 15B, *left*).

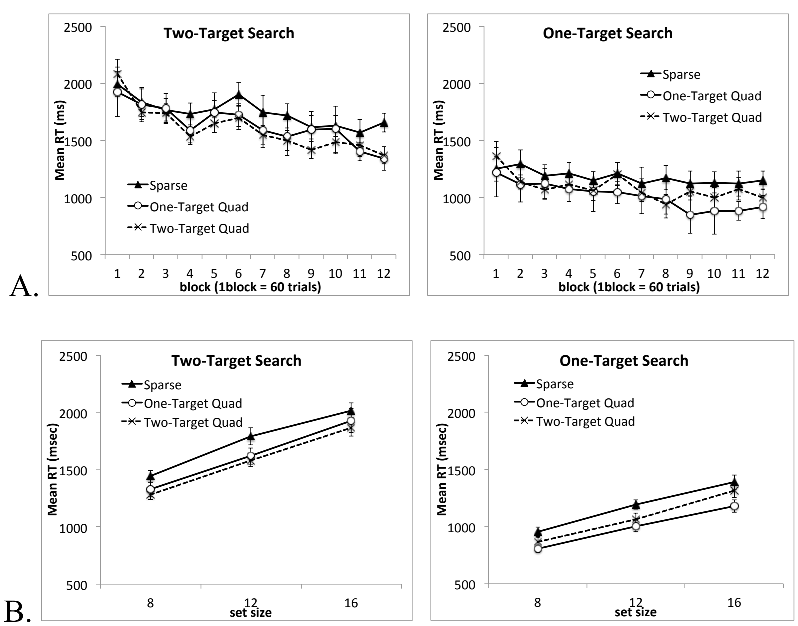


Figure 15. Results from the visual search task in Experiment 3C. A. Search RT across the 12 blocks. Error bars show ±1 S.E. of the difference between the sparse condition and

each of the two rich conditions. B. Search RT in Blocks 2-12, separately for the different working memory conditions and different set sizes. Error bars show ±1 S.E. of the mean.

In the second analysis we restricted our investigation to blocks 2 to 12. We conducted an ANOVA using working memory load, probability cue condition, and set size as factors (Figure 15A, 15B, right panel). All main effects were significant: RT was faster on one-target trials than two-target trials, $F(1, 23) = 361.32$, $p < .001$, $\eta p^2 = .94$, faster in the rich quadrants than sparse quadrants, $F(2, 46) = 15.14$, $p < .001$, $\eta p^2 = .40$, and faster when fewer items were on the display, $F(2, 46) = 201.62$, $p < .001$, $\eta p^2 = .90$. Probability cuing manifested as a large reduction in search RT, without a significant reduction in search slope, $F(2, 46) = 1.12$, $p > .25$. This may reflect low statistical power or noise (some conditions had only 20 trials per set size) (see Figure 15A, *right*). Search slope was steeper in the high-load condition (74 ms/item) than the low-load condition (54 ms/item), resulting in a significant interaction between working memory load and set size, $F(2, 46) = 12.45$, $p < .001$, $\eta p^2 = .35$. In addition, working memory load and probability cue showed a significant interaction, $F(2, 46) = 5.85$, $p < .005$, $\eta p^2 = .20$. This interaction suggests that probability cuing exhibits some load specificity. None of the other interactions were significant, Fs < 1.12, ps > .25 (Figure 15B).

4. Across-load transfer

To test whether probability cueing was robust under high working memory load, I analyzed only high-load trials. The analysis revealed faster RT when the target was in the high-load rich quadrant than in the sparse quadrants, $F(1, 23) = 27.88$, $p < .001$, $\eta p^2 = .55$.

Also, I restricted the analysis to low-load trials and compared conditions when the target was in a sparse quadrant (16.7%) and the target was in the high-rich quadrant (16.7%). The result revealed that participants were significantly faster in the high-load rich condition than the sparse condition, $F(1, 23) = 14.46$, $p = .001$, $\eta p^2 = .386$. Thus, this experiment revealed a significant cross-load transfer of probability cueing.

5. Load-specific probability cueing in visual search RT

We focused on data from trials in which the target was in either the low-load rich or high-load rich quadrant and tested whether this factor interacted with working memory load. Load-specific learning would be revealed if the target in the low-load rich quadrant was found more quickly on one-target search trials, whereas the target in the high-load rich quadrant was found more quickly on two-target search trials. This was indeed the case, $F(1, 23) = 12.98$, $p = .001$, $\eta p^2 = .36$, for the interaction between the type of rich quadrant and working memory load, demonstrating load specificity.

6. Recognition

Table 4 shows recognition responses from the 78 participants in Experiment 3.

Table 4. Recognition results from Experiment 3. Number of participants (out of 78) who chose the three types of quadrants where the target was most often found, separately for people who initially said the target's location was random (N =39) or not random (N=39).

	Participants who said the target's location was random (N=39)			Participants who said the target was more often in some places than others (N=39)		
Where was the glyph most often found	No-load rich quad	High-load rich quad	Sparse quadrants	No-load rich quad	High-load rich quad	Sparse quadrants
	21	8	10	18	6	15

The total number of participants who selected the no-load (or low-load) rich, high-load rich, or a sparse quadrant as where the target was most often found was 39, 14, and 25, respectively. If participants had guessed at random, the expected number of participants who chose these quadrants should have been 24, 24, and 48, respectively. The observed frequency deviates from chance, χ (2) = 26.08, $p < .001$. These data show that participants had some explicit awareness of the target's location probability. Whereas they chose the no-load (or low-load) rich quadrant at above-chance levels, χ (1) = 21.95, $p < .001$, their choice for the high-load rich quadrant did not differ from chance, χ (1) = .12, $p > .70$. Thus, participants had some explicit awareness that the target was more often located in the no-load rich quadrant. However, they had little insight that the target was just as frequently biased toward the high-load rich quadrant.

Discussion

Using four new working memory tasks, Experiment 3 extended the findings of Experiment 2 by showing that imposing a spatial working memory load did not reduce probability cueing. Probability cueing remained robust when participants held in working memory (1) the locations of four colors (Experiment 3A), (2) the locations of 10 simultaneously presented dots, (3) the temporal order of 4 sequentially presented locations (Experiment 3B), (4) and 1-2 visual search templates (Experiment 3C). These experiments differed from one another in the exact way in which spatial working memory was implemented, but together they cover nearly all types of spatial working memory tasks that have ever been designed. These data provided compelling evidence for the dissociation between spatial working memory and one form of spatial attention: implicitly learned attention.

In Experiment 3C we loaded working memory with task-relevant objects. Similar to the other experiments, we showed that probability cueing was observed under either low or high working memory load, and learning transferred across working memory load. However, Experiment 3C also demonstrated load-specific learning. Participants were fastest in finding the target in the one-target-rich quadrant on one-target search trials, but fastest in finding the target in the two-target-rich quadrant on two-target search trials. It is important to note that these data do not support the idea that high working memory load has *interfered* with probability cueing. If it had, probability cueing would have been weaker under high-load than low-load, but our data did not support that. What our data did show, however, is that participants could use the working memory load as a cue for visual search. This finding is perhaps not surprising because the load (one-target or two-target) is itself predictive of where the target was likely to be. Load-specific learning did not emerge in Experiments 3A and Experiment 3B, however, perhaps because the working memory task was unrelated to the visual search task.

In Experiment 3, the secondary working memory load appears to have influenced participants' explicit knowledge about where the target was likely to be. However, explicit awareness did not correspond to visual search performance. First, although participants had recoverable awareness of the no-load rich quadrant (or one-target quadrant in Experiment 3C) but not the high-load rich quadrant (or two-target quadrant in Experiment 3C), probability cueing was equal in strength toward these two quadrants. Second, we conducted a further analysis on search RT using participant group as an additional factor, separating participants based on the forced-choice recognition results. This factor did not interact with probability cue condition, working memory, or their interactions, all *p*s > .057[8]. Thus, explicit awareness did not correspond to the pattern of probability cueing and did not contribute to visual search.

2.4.4. Summary of three experiments

Experiment 1 found that imposing a working memory task weakens endogenous cueing. Adding a visual working memory reduced participants' ability to orient spatial attention to locations cued by a central arrow. On the other hand, implicitly guided attention is immune to working memory interference (Experiments 2-3). Probability cueing remains strong when visual working memory is loaded. In addition, probability cueing transferred across different levels of working memory load (Experiment 3). These data show that whereas goal-driven attention shares similar mechanisms with spatial working memory, implicitly guided attention is dissociated from spatial working memory.

[8] I analyzed all experiments in Experiment 3, including the two-dot experiment.

2.4.5. Part II-1 Conclusion

In sum, these experiments provide strong evidence for the idea that spatial working memory is more closely related to goal-driven attention than to implicitly guided attention. Whereas endogenous cueing is reduced under a secondary visual working memory load, implicitly learned probability cueing is robust to interference from various visual working memory tasks.

Unlike the type of visual statistical learning examined in Part I, the type of visual statistical learning examined in Part II does not depend on explicit knowledge about the target's likely locations. Participants in Experiment 2 could not identify the target-rich quadrant at above chance levels. With a much larger sample size and a modified design, Experiment 3 provided evidence that participants showed above-chance recognition rates for the no-load (or low-load) rich quadrant. However, the same participants had no inkling that the target was also frequently located in the high-load rich quadrant. Because probability cueing was comparable between no-load rich and high-load rich quadrants, explicit awareness could not account for the extent of learning. Furthermore, when participants who recognized either one of the rich quadrants were separated from participants who chose a sparse quadrant, these two groups did not show any difference in their performance. Thus, whereas learning the statistical co-occurrence of shapes depends on explicit knowledge (Part I), the acquisition of a spatial attentional bias toward high-probable locations was largely implicit.

Why does the standard form of VSL (Part 1) depend on explicit awareness, whereas probability cueing does not? There are several possibilities. First, the exposure or learning phase of standard VSL involves purely perception, but probability cueing is instantiated in the process of searching for a target. Brain regions involved in guiding spatial attention may be less dependent on explicit awareness than regions involved in visual perception. Second, it is possible that implicit learning had occurred in the standard VSL paradigm but it may not be expressed in tasks such as familiarity judgment. Also, probability cueing involves subtle but complex statistics, whereas the statistics used in standard VSL are relatively simple. Search targets in the probability cueing task could appear in 100 possible locations, making it difficult for participants to explicitly recognize the target-rich quadrant. In addition, the difficult visual search task may have left little attentional resources for participants to consciously code the target-rich locations. In contrast, the association between a pair/triplet of shapes in the standard VSL paradigm is less complicated. Finally, the visual statistics used in probability cueing are useful for behavior. Location probability cueing substantially speeds up visual search. In contrast, the object associations formed in the standard VSL paradigm are not useful in this way. In many cases participants had no task to perform, and learning the statistical association could not have benefited behavior. As a result any form of learning in the standard paradigm may have depended on the participants' volition.

2.5. Part II-2: Mechanisms of location probability learning: Attentional guidance or response facilitation?

Part II-1 demonstrated that visual search was accelerated in locations that frequently contained a search target, even though participants were unaware of the target's location probability. Although we had assumed that the target's location probability has improved spatial attention toward the rich locations, direct evidence for this assumption is weak. In most visual search experiments, location probability learning manifests as a large facilitation in overall RT. However, RT gain could reflect changes in spatial attention or changes in decision-related processes that happen after the target has been found. The goal of Part II-2 is to provide direct evidence that location probability learning actually modulates spatial attention. Specifically, we monitored saccadic eye movements during the experiment and focused on the direction of the first saccade. Because the first saccadic eye movement is often made long before the target is found (typical saccadic latency is around 200 ms), it is a relatively pure index of spatial attention (Eckstein, Drescher, & Shimozaki, 2006; Jones & Kaschak, 2012; Peterson & Kramer, 2001). Measuring eye movements also allowed us to examine the role of oculomotor learning in probability cueing.

The majority of the data reported in this section have been published in the following article: Jiang YV, Won BY, and Swallow KM (in press). First saccadic eye movement reveals persistent attentional guidance by implicit learning. *Journal of Experimental Psychology: Human Perception & Performance.* These data also form the basis for a conference report of the same title, on which I am the first author (Won, Swallow, & Jiang, 2014, *Vision Sciences Society*). A large portion of the writing in this section overlaps with the published article, although I have revised it to fit with the larger picture presented here, and to include new data not reported in that article.

The question of whether implicit learning affects spatial attention or decision-related responding was initially raised in studies of contextual cueing. The *attentional guidance view* suggests that the implicitly acquired (repeated) contexts ("context map" in Chun, 2000) drive spatial attention to the target location. In contrast, the *response-*

facilitation view proposes that contextual cueing enhances decisional processes that occur after the target has been found (Kunar et al., 2007). Most studies use the slope of the RT-set size function as an index of attention in visual search. Because decisional processes that occur after target detection should be similar regardless of the number of items on the display, the response-facilitation view predicts that contextual cueing changes the intercept of the RT-set size function (i.e., overall RT) without reducing the slope of that function. The attentional guidance account, in contrast, predicts that contextual cueing should make the slope of the RT-set size function shallower. Empirical data are mixed, with some but not all studies finding a reduction in search slope (Chun & Jiang, 1998; Kunar et al., 2007; Kunar, Flusberg, & Wolfe, 2008; Rausei, Makovski, & Jiang, 2007). The complexity of the contextual cueing paradigm (e.g., the potential contribution of configuration memory) has made this question difficult to resolve.

Studies using the probability cueing paradigm have found some evidence for the attentional guidance account. Two studies showed that the visual search slope was shallower when the target was in the rich rather than the sparse locations (Geng & Behrmann, 2005; Jiang, Swallow, & Rosenbaum, 2013), a pattern that was also observed in Part II-1 of this dissertation. However, a third study showed probability cueing even when the display contained just one item (Druker & Anderson, 2010). Because attentional guidance is presumably not needed to find a single item (Kunar et al., 2007), probability cueing under this condition may suggest that location probability has affected decision-related processes. Eye tracking data are similarly ambiguous. One study constrained the target's location such that it never repeated on consecutive trials. Under this condition participants were no more successful at orienting their first saccade toward the rich region than toward the sparse region (Walthew & Gilchrist, 2006). Yet another study using a similar design reached the opposite conclusion (Jones & Kaschak, 2012).

However, several methodological aspects of the two eye-tracking studies noted above may have weakened their conclusions. First, the studies used a small number of possible target locations (e.g., 8, rather than 100 locations as used in Part II-1). In addition there was a large difference in the likelihood that a target would appear on one side of the screen than the other (66% versus 33%). These parameters may produce explicit awareness of the probability manipulation, changing the nature of attentional guidance. This possibility cannot be ruled out because neither study assessed explicit awareness. In addition, both studies restricted the target's location such that it never repeated on consecutive trials. This manipulation introduced undesired nonrandom statistics that may have interfered with implicitly learning where the target was likely to appear (for an analysis, see Druker & Anderson, 2010).

In Part II-2, we selected parameters that are not likely to induce explicit awareness and a design that facilitates implicit learning (Jiang, Won, & Swallow, in press). First, the target could appear in any one of 100 locations rather than in only one of eight locations (Walthew & Gilchrist, 2006), and the rich quadrant had a target on 50% of the trials whereas each sparse quadrant had a target on 16.7% trials. This ratio (3:1:1:1) is subtler than what was used before and has produced chance-level explicit recognition in a previous study (Jiang, Swallow, Rosenbaum et al., 2013; see also Part II-1 Experiment 2). In addition, the current experiment eliminates the constraint that prohibits the repetition of target locations on consecutive trials. The large number of possible target locations (i.e., 100 locations) makes it unlikely that the target would appear in the same location on consecutive trials. We also introduce a new experimental phase to assess the persistence of probability cuing -- not only examining probability cueing in the training phase but assessing its persistence in a testing phase. In the testing phase the target was equally likely to appear in any quadrant (25% probability, Figure 16). Under this condition immediate repetition of the target's location happens equally often in the rich and sparse quadrants. If implicit learning of the target's location probability guides attention, then participants should more often direct their first saccades toward the rich quadrant in the training phase, and this preference should persist in the testing phase. But if implicit learning affects only post-search decisional processes, then an RT gain should not be accompanied by more frequent first saccades toward the rich quadrant.

In addition to examining the attentional guidance account using a modified spatial probability cueing paradigm (Experiment 1), I also explore the role of oculomotor response in implicitly guided attention. Past studies, including neurophysiology and behavioral experiments, have already shown compelling evidence for a close relationship between spatial attention and saccadic eye movements (Awh, Amstrong, & Moore, 2006; Moore, Amstrong & Fallah, 2003; Shepherd, Findlay, & Hockey, 1986; Sheliga, Riggio, & Rizzolatti, 1995; see Krauzlis, Lovejoy, & Zénon, 2013 for a recent review). Because the eyes are oriented toward the high-frequency location as often as the target is located there, it is possible that participants have developed an oculomotor routine toward the rich quadrant.

Experiment 2 directly examined the role of oculomotor responses in spatial probability cueing. Participants inhibited eye movements during the training phase, but were either free to move their eyes during the testing phase (Experiment 2A), or continued to maintain fixation in the testing phase (Experiment 2B). If oculomotor responding is critical to acquiring spatial probability cueing, then probability cueing should be eliminated when the eyes are not allowed to move. Alternatively, if probability cueing reflects primarily high-level attention learning, then the acquisition of probability cuing should remain robust even when eye movements are minimized. A final experiment examined if the learned probability cueing persists even when participants are asked to direct their eyes to sparse locations (Experiment 3).

Experiment 1-3. General Method

Participants

We aimed to test a final sample size of 12 participants in each of the eye tracking experiments. The sample size (N = 12) was selected because it provided an estimated power greater than 0.90 based on our previous behavioral work (Cohen's d = 1.6 in Jiang, Swallow, Rosenbaum, et al., 2013, Experiment 3). All participants were naïve to the purpose of the study and completed just one experiment. They were students from the University of Minnesota between 18 and 35 years old. Participants provided written informed consent prior to the study and were compensated for their time. Experiments 2A and 2B required participants to maintain fixation. Several participants had difficulty following this instruction (4 in Experiment 2A, and 10 in Experiment 2B); their data were excluded from the final analysis. Table 5 provides the participant characteristics for all four experiments.

Table 5. Participants in four experiments in Part II-2.

	Mean age (years)	Number of Female	Number of Male
Experiment 1	20.1	8	4
Experiment 2A	22.5	12	4
Experiment 2B	20.3	11	11
Experiment 3	19.4	7	5

Equipment

The visual search task used the same materials as those of Part II-1. Monocular eye tracking was obtained at 120 Hz using an ISCAN-ETL 300 that tracked the left eye position based on pupil and corneal reflectance.

Materials

In most experiments, on each trial 12 items (a target T and 11 distractors Ls) were presented in randomly selected locations in an invisible 10 x 10 grid (13.7º x 13.7º) (middle figure in Figure 1), with the constraint that there were 3 items in each visual quadrant. Two other experiments (Experiment 2A and 2B) required participants to maintain central fixation during visual search. In these experiments we adjusted the size of items such that farther items were larger. Search items were presented in randomly selected locations chosen from 32 possible locations. These locations were selected from four concentric rings with a radius of 1.14º, 2.74º, 4.57º, or 8.0º (each ring had 8 equidistant locations) (right figure in Figure 16). Item size was scaled according to a cortical magnification factor (Carrasco, Evert, Chang, & Katz, 1995; farther items were larger). The search items were white and the background was black (Figure 16).

Design

Following 10 trials of practice using randomly positioned items, participants completed 4 experimental blocks, with 96 trials in each block. In the first two blocks (the training phase), the T was presented in the rich quadrant on 50% of the trials, and in any one of the three sparse quadrants on 16.7% of the trials. The rich quadrant was counterbalanced across participants but remained the same for a given participant. In the last two blocks (the testing phase), the T was equally likely to appear in any quadrant (25%). Because the orientation of the T was randomly selected for each trial, the location probability manipulation did not correlate with the participant's manual response. Figure 16 shows the probabilities of the target's location in the training and testing phases.

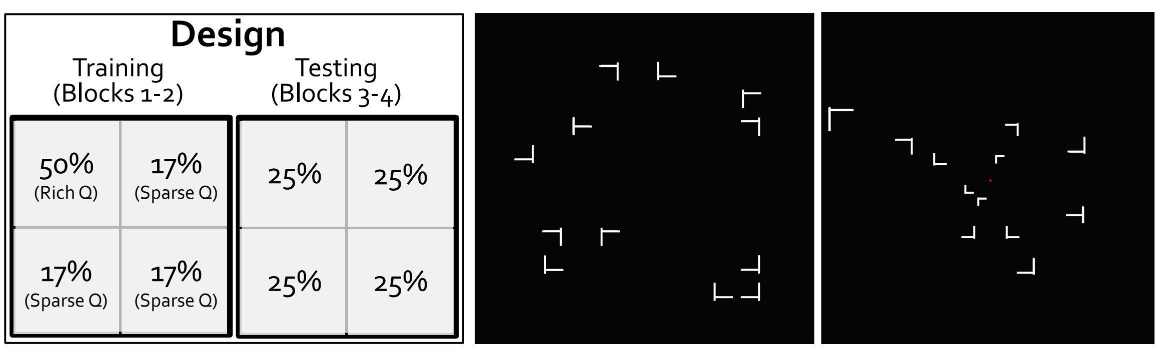


Figure 16. An illustration of the design and stimuli used in this study. Left: The target was more often presented in a high-probable, "rich" quadrant than in a sparse quadrant in the training phase but was equally probable in all quadrants in the testing phase. Middle: A sample visual search display used in Experiment 1, Experiment 3 and some sessions of Experiment 2A. Right: A sample visual search display used in Experiment 2B and some sessions of Experiment 2A.

Procedure

Eye position was calibrated using a five-point calibration procedure. Following calibration, participants performed a block of visual search. At the beginning of each trial they fixated on a central fixation square (0.23ºx0.23º). Upon stable fixation, the experimenter initiated the search trial with a mouse click, which immediately brought out the search display. The display remained until participants made a keyboard response (either the left or right arrow key) to indicate the T's orientation. The search display was erased after the response and participants received sound feedback about their response accuracy. Participants were asked to minimize eye blinks during search. Eye blinks were allowed between trials. After each block participants took a short break. Calibration of the eye position was repeated before every block.

At the end of the experiment, participants were asked whether they thought the target was equally likely to appear anywhere on the display. Regardless of their answer, they were told that the target was more often located in one quadrant than the others, and asked to choose the rich quadrant.

Data analysis

Search accuracy and RT comprised the behavioral data. For the eye movement data, we first flagged trials with bad data, defined as (1) the horizontal or vertical position had a value less than 0, or (2) the pupil diameter was less than 4 standard deviations below the mean pupil size. These time points corresponded to times when the eye tracker lost the eye data momentarily or when participants blinked. The percentage of trials in which the eye data were flagged as *bad data* was less than 2% in all three experiments. The bad samples were replaced using linear interpolation between the preceding good sample and the next good sample. The eye data were then smoothed using a moving window average between 3 adjacent samples. The time points during which the velocity of the eye position exceeded 30º per sec defined saccades. A graph plot of the eye position data verified that the velocity criterion accurately identified saccades. Trials on which a saccade could not be reliably detected were removed from the eye data analysis.

2.5.1. Experiment 1. Incidental probability learning with eye movements

In Experiment 1, participants were free to move their eyes during both the learning and the testing phases, and they were not informed of the target's location probability in either phase.

Results

1. Behavioral data

Visual search accuracy was 99.1% and was unaffected by any experimental factor, smallest $p > .10$. Behavioral analysis focused on correct trials. In addition, trials with an RT longer than 10 sec were excluded as outliers (0.26% of the trials).

Figure 19 shows mean RT as a function of probability cue condition and experimental block. An ANOVA including probability cue condition (rich or sparse), phase (training or testing), and block (the first or second block of each phase) revealed significant main effects of all three factors. RT was faster when the target was in the rich quadrant rather than the sparse quadrants, demonstrating probability cueing, $F(1, 11) = 18.22$, $p < .001$, $\eta p^2 = .62$. RT was faster in the testing phase than the training phase, F(1,

11) = 53.77, $p < .001$, $\eta p^2 = .83$, and faster in the second block than in the first block of each phase, $F(1, 11) = 33.64$, $p < .001$, $\eta p^2 = .75$.

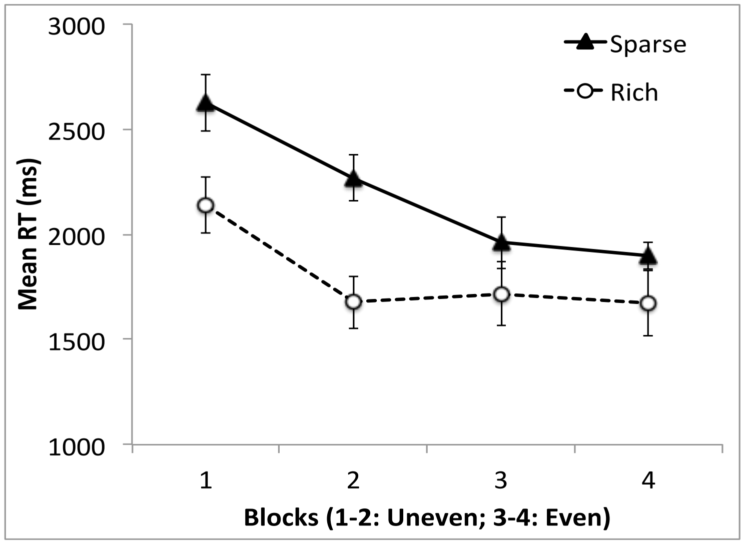


Figure 17. Visual search RT in Part II-2 Experiment 1 as a function of the target's quadrant (rich or sparse) and block. The target was more often presented in the rich quadrant than in any sparse quadrant in the first two blocks, but equally appeared in any quadrant in the last two blocks. Error bars show ±1 S.E. of the mean.

Although probability cueing appeared to have declined from the training phase to the testing phase, the interaction between phase and cue condition was not significant, $F(1, 11) = 3.28$, $p = .097$, $\eta p^2 = .23$. Follow-up analyses confirmed that probability cueing was significant both during the training phase, $F(1, 11) = 12.83$, $p < .01$, $\eta p^2 = .54$, and during the testing phase, $F(1, 11) = 6.78$, $p < .05$, $\eta p^2 = .38$. The only other significant effect was the interaction between phase and block: the RT reduction (i.e., performance improvement) from the first to the second block was more pronounced during the training phase than the testing phase, $F(1, 11) = 28.80$, $p < .001$, $\eta p^2 = .72$. Other effects were statistically insignificant, $F < 1$.

As found in several previous studies, large RT performance gains were observed after just the first experimental block, indicating that a substantial probability cueing effect occurred very early (Jiang, Swallow, Rosenbaum, et al., 2013; Jiang, Swallow, & Rosenbaum, 2013; Smith, Hood, & Gilchrist, 2010; Umemoto et al., 2010). This finding shows that the 96 trials in the first block were adequate to acquire stable probability cueing.

In the recognition test, 4 of the 12 participants correctly chose the rich quadrant, which did not differ from chance (25%), $\chi(1) = .44$, $p > .50$. In addition, the three participants who made the correct recognition choice initially reported that they thought the target was equally likely to appear anywhere on the display. It is possible that recognition rates may have been higher if we had probed awareness immediately after training. However, the chance-level recognition rate was inconsistent with the results from the testing phase, during which probability cueing remained strong. Participants therefore demonstrated probability cueing immediately before the recognition test on which they failed to correctly report the rich quadrant. Although they responded faster to the target when it appeared in the rich quadrant than in any sparse quadrant, participants could not explicitly choose the rich quadrant. This result again confirms that probability cueing reflects largely implicit learning. Table 6 provides the recognition results for all four experiments.

Table 6. Recognition results from Experiment 3.

	The number of participants who said the	The total percent of people who correctly

	target was not random	identified the rich quadrant
Experiment 1 (incidental learning; N = 12)	5	33%
Experiment 2A (fixating eyes in training phase; N = 16)	7	44%
Experiment 2B (fixating eyes in both sessions; N = 22)	14	32%
Experiment 3 (N = 12)	4	33%

2. Eye data

Trials with bad eye tracking data (e.g., due to blinking, see the *analysis* part of the method, 3.2% of the data) were excluded from further analyses. Participants made an average of 7.2 saccades per trial (S.E. = 0.4), which is consistent with the difficult nature of the visual search task. The T/L visual search task is highly inefficient and requires serial scanning of the display (Wolfe, 1998). On 37.6% of the trials, the first saccade was directed toward the rich quadrant, which was significantly higher than chance (25%), $t(11) = 2.77$, $p < .05$. In fact, participants were nearly 1.8 times more likely to direct the first saccade toward the rich quadrant than toward any one of the sparse quadrants.

How did the proportion of first saccades change over time, and was it affected by the target's actual location? First, the first saccade data were separately analyzed by experimental block and target location (Figure 18). An ANOVA including the target's actual location (rich or sparse quadrants), phase (training or testing), and block (first or second block of each phase) revealed just one marginally significant effect: phase, $F(1, 11) = 4.27$, $p = .063$, $\eta p^2 = .28$. The preference for directing the first saccade toward the rich quadrant declined somewhat from the training phase to the testing phase. Nonetheless, planned contrasts showed that the first saccade was more often directed toward the rich quadrant than sparse quadrants in both the training phase ($t(11) = 2.96$, $p < .05$) and the testing phase ($t(11) = 2.31$, $p < .05$). None of the other main effects or interaction effects reached significance, smallest $p = .09$. First saccade was not influenced by the target's actual location. That is, participants were equally likely to direct their first saccade toward the rich quadrant regardless of whether the target was in the rich or sparse quadrants. Because the first saccade was insensitive to the target's actual location, it appeared to have been made before participants had acquired any information about where the target was.

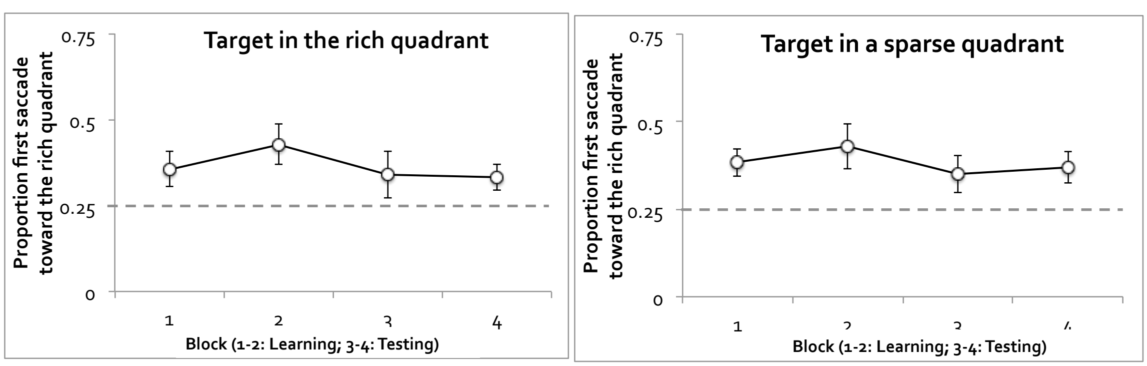


Figure 18. Eye movement data from Part II-2 Experiment 1: Proportion of first saccades toward the rich quadrant, shown separately for when the target was in the rich quadrant (left) and when the target was in a sparse quadrant (right). The dotted gray line shows chance level. Error bars show ±1 S.E. of the mean.

3. Relationship between RT and eye movement data

The tendency to direct first saccades toward the rich quadrant showed that participants had prioritized that quadrant. To establish a link between such attentional prioritization and visual search RT, we examined whether search RT was influenced by the direction of the first saccade. This analysis was conducted on data from the testing phase, which tested the persistence of probability cueing. When the target was in the rich quadrant, RT was faster if the first saccade was directed toward the rich quadrant (mean = 1543 ms) rather than a sparse quadrant (mean = 1851 ms), $t(11) = 2.74$, $p < .05$. These findings strengthen the idea that spatial attention, as indexed by the first saccades, contributed to visual search performance.

Discussion

Experiment 1 provided strong evidence that implicit learning guides spatial attention. After about 200 trials of training, both RT and eye-tracking data showed that participants developed a spatial bias toward the target-rich quadrant. This bias remained strong for as many as 200 trials in the testing phase, even though the target's location probability had become random. Importantly, probability cueing was reflected not only in search RT but also in first saccades. Because the first saccade was made soon after trial onset but long before the behavioral response, it reflects attentional guidance rather than post-search decisional processes. Recognition test responses showed no evidence of explicit awareness.

The methods adopted in the current experiment substantially improve on those used in previous eye-tracking studies on the same topic (Jones & Kaschak, 2012;

Walthew & Gilchrist, 2006). By using parameters that promoted implicit learning and by examining the long-term persistence of probability cueing, Experiment 1 provides clear evidence that implicit learning guides spatial attention. However, because Experiment 1 did not directly manipulate decisional factors, we cannot exclude the possibility that implicit learning might also affect response decisions. This is a separate but important question to examine in the future.

2.5.2. Experiment 2. Incidental probability learning without eye movements

Experiment 2 examines the impact of oculomotor responses on location probability learning. Because oculomotor response and spatial attention are closely related (Krauzlis et al., 2013 for a recent review), it is possible that the development of an oculomotor routine (based on frequent saccades toward the rich quadrant) is a key component to probability cueing. Participants in Experiment 2 were asked to maintain central fixation during the training phase. They were allowed to freely move their eyes in the testing phase (Experiment 2A) or were required to continue maintaining central fixation throughout both the training and testing phases (Experiment 2B). We examined whether the elimination of overt oculomotor responses also eliminates probability cueing.

A challenge of Experiment 2 is that it is difficult to maintain central fixation in the type of T/L visual search task that we have used here. This difficult type of search task requires participants to shift spatial attention serially. Owing to the close coupling between spatial attention and saccades, the requirement to maintain central fixation produces conflict between covert and overt attention. Significant cognitive control is needed to resolve this conflict. The inhibition of eye movements and the conflict between covert and overt systems of attention are likely to weaken learning.

2.5.2A. Experiment 2A. Training phase without eye movements and testing phase with eye movements.

In Experiment 2A, participants searched for the target while fixating their eyes on a central fixation point during the training phase. The experimenter sat next to them and verbally reminded them to maintain fixation when saccades were noticed. The size of the search items was scaled such that items farther away from fixation were larger (see Figure 16, right panel). In the testing phase, participants were allowed to move their eyes. The search items were uniform in size.

We excluded data from participants who made more two or more saccades on more than 30 trials of the training phase. This criterion removed data from 4 participants, leaving us with a final sample of 12 participants.

Results

We first examined the fixation data from the training phase to verify that participants had maintained fixation. The mean percentage of trials in which no saccades were made was 84% (S.E. = 3.5%), and the mean number of saccades across all trials was 0.57 (S.E. = 0.09). This was substantially less than that observed in Experiment 1 (mean 7.2 saccades per trial), $t(22) = 13.76$, $p < .001$. Thus, participants were successful at minimizing eye movements in the training phase.

1. Behavioral data

Search accuracy was moderately but significantly higher when the target was in the rich quadrant (98.7%) rather than a sparse quadrant (97.8%), $F(1, 11) = 10.77$, $p = .007$, $\eta p^2 = .495$. In addition, accuracy was marginally lower in the training phase (97.4%) than the testing phase (99.0%), $F(1, 11) = 4.66$, $p = .054$, $\eta p^2 = .298$. The interaction between quadrant types and phase did not reach significance, $F < 1$.

After excluding incorrect trials and outliers (0.13% of all trials had an RT greater than 10 sec), the RT data revealed a significant probability cueing effect (see Figure 19). An ANOVA including probability cue condition (rich or sparse), phase (training or testing), and block (the first or second block in each session) revealed a significant main effect of probability cue condition, $F(1, 11) = 22.07$, $p = .001$, $\eta p^2 = .67$, as participants were faster in the rich condition than the sparse condition. The main effect of block was also significant, as RT was faster in the second block than the first block of each phase, $F(1, 11) = 62.31$, $p < .001$, $\eta p^2 = .85$. None of the other effects were significant, all ps > .20. In addition, there was a significant main effect of phase, $F(1, 11) = 12.19$, $p = .005$, $\eta p^2 = .53$. The training phase used items whose size varied according to the item's eccentricity (farther items were larger). The testing phase used uniform-sized items. Because participants could more easily see the large items in the periphery, RT was faster in the training phase than the testing phase.

Notably, probability cueing did not interact with phase, $F(1, 11) < 1.75$, $p = .21$. Even though the stimuli had changed and the fixation requirements had also changed between the training and test phases, probability cueing did not decline.

Did probability cueing depend on eye movements? The answer is "no". Because participants in the training phase maintained steady fixation, the significant cueing effect observed in that phase could not be attributed to the development of an oculomotor routine, $F(1, 11) = 56.42$, $p < .001$, $\eta p^2 = .84$.

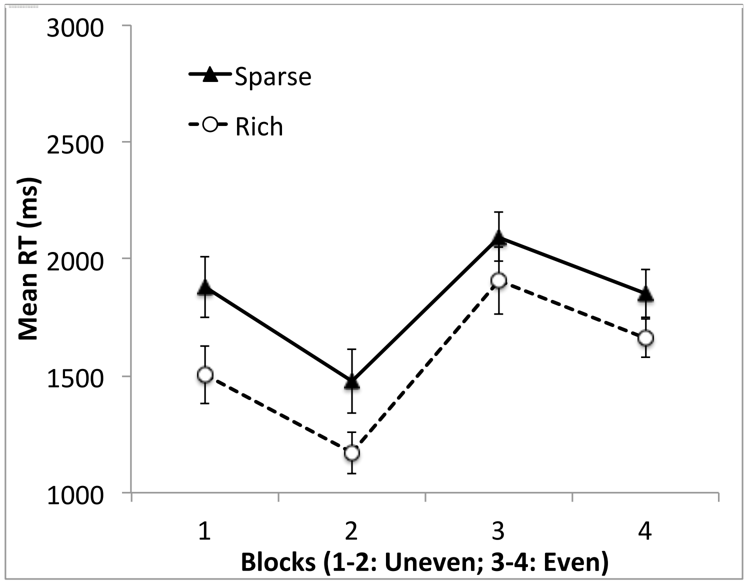


Figure 19. Visual search RT in Part II-2 Experiment 2A. Error bars show +/-1 S.E. of the mean.

2. Eye movement data

As reported earlier, and in accordance with the experimental requirements, participants made few saccades in the training phase of the experiment. Did learning influence first saccades? If so, in the testing phase when allowed to move their eyes, participants should be more likely to direct the first saccade toward the previously rich quadrant.

In the testing phase, participants made an average of 4.2 (S.E. = 0.2) saccades per trial when the target was in a sparse quadrant and 1.2 saccades (S.E. = 0.1) per trial when the target was in the rich quadrant. This difference was significant, $t(11) = 14.58$, $p < .001$. However, owing to the relatively few number of saccades, the first saccade data appeared to be less strong than those seen in Experiment 1. On average, 32.9% of the first saccades were directed toward the rich quadrant. Although this was numerically higher than chance, it did not reach statistical significance, $t(11) = 1.36$, $p > .10$. As seen in Figure 20, first saccade was unaffected by the target's actual location or experimental block (both *p*s > .20). The relatively weak data from the first saccade warrant further investigation.

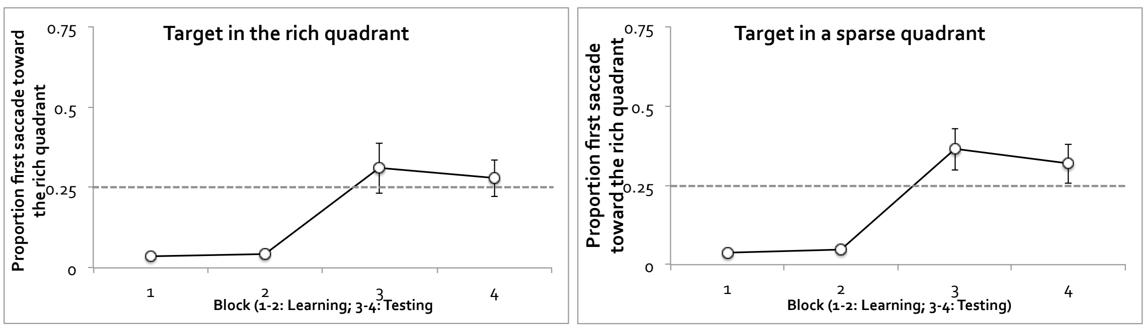


Figure 20. Eye movement data from Part II-2 Experiment 2A: Proportion of first saccades toward the rich quadrant (when participants were allowed to move their eyes only during testing phase blocks 3 and 4), shown separately for trials when the target was in the rich quadrant (left) and the sparse quadrants (right). The dotted gray line shows chance level. Error bars show ±1 S.E. of the mean.

3. Experiment 1 vs. Experiment 2A

To examine whether the necessity to maintain steady fixation had reduced learning, we compared the testing phase data between Experiments 1 and 2A. In both experiments probability cueing had persisted in the testing phase. This analysis showed a main effect of probability cue condition, $F(1, 22) = 9.64$, $p = .005$, $\eta p^2 = .31$, but no interaction between probability cue condition and experiment, $F < 1$. In the testing phase, probability cueing (the RT difference between the rich and sparse quadrants) was 233 ms in Experiment 1 and 312 ms in Experiment 2A. These data provide compelling evidence that probability cueing cannot be reduced to low-level oculomotor learning. First saccades in the testing phase also were comparable between the two experiments (Experiment 1: 35% vs. Experiment 2A: 32.9%), $t(22) = 0.34$, $p > .74$.

2.5.2B. Experiment 2B. No eye movement in both phases.

In Experiment 2A, probability cueing was observed even though participants were not moving their eyes during the training phase. These results show that frequently saccading toward a specific visual quadrant was not critical in establishing probability cueing. However, there was some evidence that perhaps probability cueing had been less persistent under this condition. In the testing phase only 32.9% of the first saccades were directed toward the previously rich quadrant. Although this was not statistically less than that observed in Experiment 1, it did not reach significance on its own. These data raise the possibility that overt oculomotor response may be important for producing a persistent attentional bias. Another possible explanation for the apparently reduced effect is the difference in task demands and stimuli between the training and the testing phases. Participants were required to maintain fixation in the training phase but not the testing phase, and the stimuli changed to accommodate for cortical magnification factors in the training phase but not in the testing phase. These changes may have weakened the transfer of probability cueing across the two phases. In fact, overall RT was slower in the testing phase of Experiment 2A than in the training phase.

To test whether the apparent reduction in probability cueing shown in the testing phase of Experiment 2A was due to a change in task demands and stimuli, in Experiment

2B we used the same task demands and stimuli in the training and testing phases. In both phases the size of the visual search items was adjusted according to the cortical magnification factor. In addition, participants were asked to minimize eye movements in both the training and the test phase. The data of ten participants were removed because they failed to maintain good fixation: on more than 15% of the trials they had made more than 2 saccades.

Results

1. Behavioral data

In Experiment 2B, we focused on the behavioral data because participants were required to not move their eyes. Eye movement data were only used to ensure compliance with the instructions.

Visual search accuracy was high (mean = 95.3%). Accuracy was marginally higher when the target was in the rich quadrant rather than the sparse quadrants, $F(1, 11) = 3.70$ $p = .081$, $\eta p^2 = .252$ and marginally higher in the testing phase than the training phase, $F(1, 11) = 3.77$ $p = .078$, $\eta p^2 = .255$. The second block showed higher accuracy than the first block, $F(1, 11) = 9.78$ $p = .01$, $\eta p^2 = .471$. A marginally significant interaction between phase and probability cue condition showed that cueing had declined somewhat in the testing phase, $F(1, 11) = 3.72$, $p = .08$, $\eta p^2 = .253$. The other effects were not significant, all *p*s > .29.

Incorrect trials and outliers (0.09% of all trials had an RT greater than 10 sec) were eliminated from further RT analysis. An ANOVA including probability cue condition (rich or sparse), phase (training or testing), and block (the first or second block in each session) showed three significant main effects: RT was faster when the target was in the rich quadrant rather than the sparse quadrants, $F(1, 11) = 8.25$, $p = .015$, $\eta p^2 = .429$, faster in the testing phase than the training phase, $F(1, 11) = 23.25$, $p = .001$, $\eta p^2 = .679$, and faster in the second block than the first block of each phase, $F(1, 11) = 36.43$, $p < .001$, $\eta p^2 = .768$.

A marginally significant interaction between probability cue condition and phase showed that probability cueing had declined marginally from the training to the testing phase, $F(1, 11) = 3.70$, $p = .081$, However, follow-up tests showed that both phases showed robust probability cueing: the training phase $F(1, 11) = 19.55$, $p = .001$, $\eta p^2 = .640$, the testing phase, $F(1, 11) = 14.64$, $p = .003$, $\eta p^2 = .571$.

The interaction between phase and block was significant, $F(1, 11) = 13.15$, $p = .004$, $\eta p^2 = 545$, as the reduction of RT from the first to the second block was more obvious in the training phase than the testing phase. A significant interaction between probability cue condition and block was also observed, $F(1, 11) = 5.87$, $p = .034$, $\eta p^2 = .35$. The reduction of cueing in the second block in both phases caused the significant interaction between probability cue condition and block. The 3-way interaction was not significant, $F(1, 11) = 1.52$, $p > .20$, $\eta p^2 = .122$.

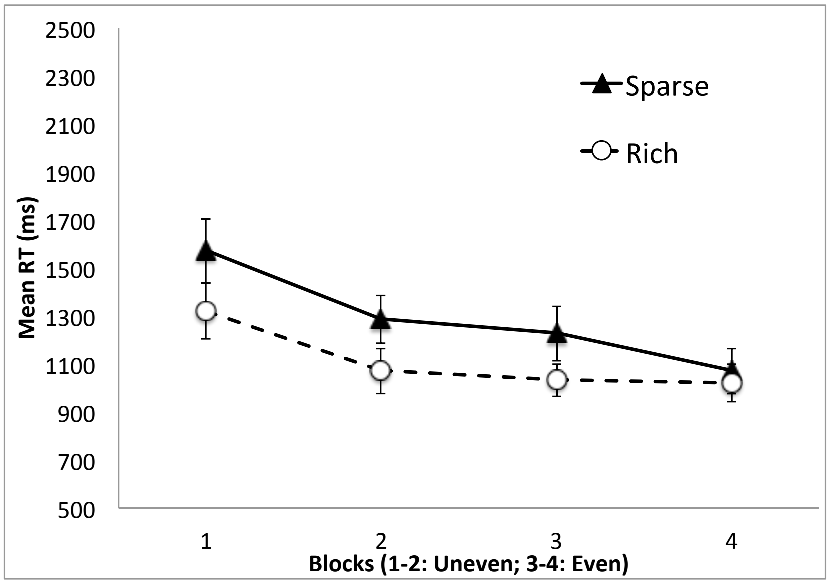


Figure 21. Visual search RT in Part II-2 Experiment 2B. Error bars show +/-1 S.E. of the mean.

Why did probability cueing seem to decline as the testing phase was prolonged? There are several possible reasons. First, oculomotor responses may contribute to the persistency of probability cueing. Alternatively, when people must suppress eye movements, the requirement for such sustained voluntary inhibition may interfere with probability cueing. Finally, we may have reached a celling effect because RT had approached 1 sec (see Figure 21).

Discussion

Experiment 2 provides evidence that probability cueing reflects primarily high-level attentional learning, rather than oculomotor learning. Although eye movements were minimized in the training phase, participants became faster at finding the target when it appeared in the rich quadrant rather than a sparse quadrant. In addition, this attentional bias showed some persistence in the testing phase, as manifested by faster RT and a greater tendency to direct the first saccade toward the rich quadrant. The magnitude of probability cueing in the testing phase was comparable between Experiments 1 and 2A. Because probability cueing was expressed in the training phase in which no eye movements were allowed, oculomotor learning was not necessary for either the acquisition or the expression of probability cueing.

In Experiment 2, participants were trained while they maintained fixation but tested while they freely moved their eyes (Experiment 2A) or trained and tested without any eye movements allowed (Experiment 2B). These experiments provide one of the strongest tests of the oculomotor learning account. Another complementary approach to test this account is to reverse the eye movement instructions between the learning and testing phases -- that is, allowing participants to freely move their eyes during learning (with an uneven target distribution) but then requiring them to maintain fixation during testing (with an even target distribution). If probability cueing modulates covert attention, then, under these conditions, it should be expressed in the testing phase even though participants are not allowed to move their eyes. This prediction was confirmed in a follow-up experiment ($N = 4$). In the testing phase when saccades were minimized (mean number of saccades was 0.60 per trial), participants were 182 ms faster at finding a target in the rich quadrant than in a sparse quadrant. Consistent with Experiment 2A, the expression of probability cueing did not depend on making saccades.

Experiment 2 has also revealed preliminary evidence that the need to maintain central fixation may have interfered with the persistence of probability cueing. Probability cueing, as measured by RT, was marginally smaller in the testing phase than the training phase in Experiment 2B. It was numerically smaller in the testing phase than the training phase in Experiment 2A. In addition, the first saccadic eye movement produced weak data in Experiment 2A's testing phase. These marginal effects, if confirmed with a larger sample, would suggest that oculomotor response is important in *sustaining* (even if not for inducing) location probability learning. Probability cueing appeared to be less persistent when attention was trained in the absence of eye movements. It is possible that oculomotor learning contributes to the persistence of an attentional bias. Alternatively, the need to maintain central fixation may have produced a conflict between overt and covert attention. This conflict may have weakened attention learning itself. These issues should be tested in future research.

2.5.3. Experiment 3. Intentional eye movement to a sparse quadrant

An important question about implicitly learned attention is its interaction with goal-driven attention. Experiments 1-2 and other studies from our lab have shown that implicitly learned attention is highly persistent. People continue to prioritize locations that frequently earlier had contained a target, even though the target is now randomly distributed. This long-term persistence distinguishes implicitly learned attention from goal-driven attention, which changes rapidly when the observer's goals change (Jiang, Swallow, Rosenbaum et al., 2013). However, a persisting attentional bias could be maladaptive if it does not adjust according to the observer's goal. Do people continue to prioritize the rich quadrant when they need to deploy attention elsewhere? That is, does a previously learned attentional bias interfere with the current behavioral goal?

Previous research on this question has observed somewhat mixed results. In one study, Jiang, Swallow, & Rosenbaum (2013) instructed participants to prioritize a specific visual quadrant indicated by a central arrow cue. The arrow changed its direction from trial-to-trial. Whichever quadrant it pointed at was more likely to contain the search target (similar to Experiment 1 of Part II-1). Jiang and colleagues found that the arrow cue was highly effective at re-directing attention. In fact, participants showed little evidence of prioritizing the previously rich quadrant. Thus, when goal-driven attention conflicts with implicitly learned attention, goal-driven attention appears to dictate the current behavior (see also Rosenbaum & Jiang, 2013, for similar results using the contextual cueing paradigm).

However, two other studies found limited impact of instructions on the persistence of probability cueing. In one study, following training, Jiang, Won et al. (in press) explicitly informed participants that the target's location would be random, and that they should try to distribute their attention equally to all regions of the space. Participants were unable to use this (more global) task instruction. In the testing phase they continued to prioritize the rich quadrant, even though the target was in fact equally likely to appear in all regions. In another study, participants searched for a target on a tabletop. They sat at one side of the tabletop during the training phase and developed probability cueing toward the rich quadrant. Participants then moved their seat to an adjacent side of the tabletop, producing a 90º change in viewpoint. Following viewpoint change, the spatial bias moved to new environmental locations on the tabletop. The viewer-centered persistence was shown even when participants were asked to search the environment-centered rich quadrant first (Jiang, Swallow, & Sun, 2014).

Together, these studies show that although goal-driven attention can override implicitly learned attention, this does not always happen. Overriding was successful when participants had to change their spatial attention on a trial-by-trial basis (e.g., with the arrow cue), but not when they received a single instruction at the beginning of an entire block of trials (e.g., search upper left first).

One reason why a single instruction failed to fully override probability cueing may be because participants sometimes forgot the instructions. Continually remembering the instructions and executing them requires substantial cognitive control (Duncan, Emslie, Williams, Johnson, & Freer, 1996). The trial-by-trial cue helped participants remember what they were supposed to do, but a single instruction at the beginning of the experiment may not. If this is the case, then enforcing the instructions with an eye tracker should strengthen the effectiveness of the instructions. We therefore took advantage of the eye tracking setup and examined whether, after acquiring an implicit attentional bias toward the rich quadrant, people would continue to prioritize that quadrant when they were instructed to attend elsewhere. Following the same training phase as that used in Experiment 1, we instructed participants to first look for the target in one specific quadrant. The instructed quadrant always differed from the rich quadrant that was used during training, although participants were not informed of the location probability manipulation. If goal-driven attention can override an implicitly learned bias, then participants should prioritize the instructed quadrant rather than the previously rich quadrant.

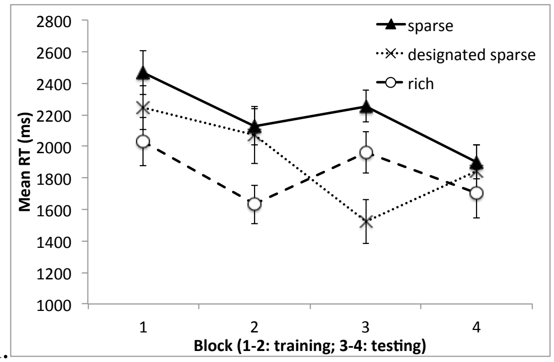
Method

This experiment was similar to Experiment 1, except for an instruction given at the beginning of the testing phase. In the training phase participants performed 2 blocks of trials in which they often found the target in the rich quadrant (50%), rather than in any of the sparse quadrants (17%). In the testing phase the target's location was random (25% in each quadrant; 2 blocks). At the beginning of the testing phase participants were asked to always direct their first saccade toward one specific quadrant. This quadrant was the same throughout the testing phase and differed from the previously rich quadrant. An experimenter sat next to the participant to monitor their eye movement patterns. Finally, to examine whether the instructions had simply masked probability cueing, at the beginning of the second testing block (Block #4 overall), participants were told to distribute their attention equally. They were not given any specific instructions about their eye movements in particular.

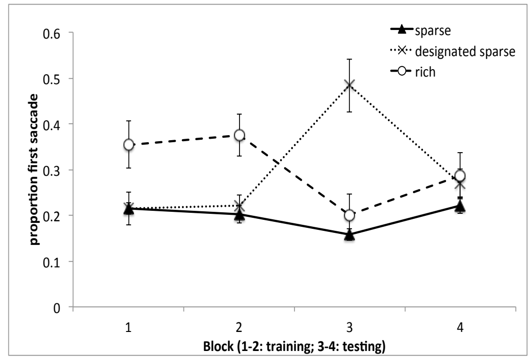
Results

1. Behavioral data

Participants were highly accurate in finding the target (mean accuracy = 99.2%). Accuracy was slightly higher in the second block than the first block of each phase, $F(1, 11) = 5.71$, $p = .036$, $\eta p^2 = .34$. Accuracy was unaffected by phase (training or testing), the target's quadrant, or their interactions, smallest $p > .50$.



A.



B.

Figure 22. Visual search RT in Part II-2 Experiment 3. A. Search RT. B. First saccadic eye movements. Error bars show +/-1 S.E. of the mean.

Incorrect trials and outliers (0.17% of all trials had an RT greater than 10 sec) were excluded for further RT analysis. Figure 22A shows mean RT in these three conditions, separately for the four experimental blocks. In the training phase, participants were significantly faster when the target was in the rich quadrant rather than the sparse quadrants, $F(1, 11) = 30.75$, $p < .001$, $\eta p^2 = .74$. This effect did not interact with block, $F < 1$. RT was also faster in the second than the first training block, $F(1, 11) = 16.95$, $p = .002$, $\eta p^2 = .61$. Replicating Experiment 1, participants had acquired probability cueing and this effect occurred as early as the first training block.

Because the instructions in the testing phase asked participants to saccade toward one specific quadrant, the target's location could fall in one of three types of quadrants: the rich quadrant where the target was most often found in the training phase (*rich*), the sparse quadrant designated as the first saccade quadrant in the testing phase (*designated sparse*), and the other sparse quadrants (*sparse*). In the first testing block (Block #3 overall) participants were asked to direct their first saccade toward the *designated sparse* quadrant. An ANOVA on RTs, evaluating the effect of the target's location showed a significant main effect, $F(2, 22) = 11.89$, $p < .001$, $\eta p^2 = .52$. Planned contrasts showed that participants were significantly faster when the target fell in the *designated sparse* quadrant than the other *sparse* quadrants, $t(11) = 5.69$, $p <.001$, suggesting that they were highly successful in following instructions. In fact, the *designated sparse* condition was significantly faster than the *rich* condition, $t(11) = 2.29$, $p = .043$, which also significantly differed from the other *sparse* condition, $t(11) = 2.39$, $p = .036$. Thus, spatial attention was determined primarily by explicit (externally specified) goals when these goals conflicted with implicitly learned attentional biases. However, implicit bias was not immediately eliminated.

In the second testing block participants were asked to abandon systematic spatial biases. They were immediately capable of following this instruction. RT did not differ across three target locations, $F(2, 22) = 1.20$, $p > .30$. Specifically, RT became equivalent between the *designated sparse* condition and the *sparse* condition, $t(11) = .42$, $p > .60$. The implicitly learned bias toward the rich quadrant remained to a small degree, but the difference between the *rich* (1.7 sec) and *sparse* (1.9 sec) conditions was not significant, $t(11) = 1.33$, $p > .20$.

Another way of understanding these results is to track two effects of task instructions over time. First, the instruction clearly influenced whether the *designated sparse* condition was prioritized. When people were told to prioritize the *designated sparse* quadrant in Block #3 (the first testing block), a large RT difference between this condition and the *sparse* condition emerged. When people did not receive this instruction (Blocks 1, 2, and 4), their RT was similar between the *designated-sparse* and *sparse* conditions. The interaction between condition (designed sparse or sparse) and Block (3 or

4) was significant, $F(1, 11) = 28.56$, $p < .001$, $\eta p^2 = .72$. Thus, participants were capable of adjusting their spatial attention volitionally based on their momentary behavioral goal.

In contrast, the instruction seemed to have some but weak effects on removing the attentional bias toward the previously *rich* quadrant. When comparing the *rich* and *sparse* conditions in Blocks 3 and 4, we observed a marginally significant main effect of condition, $F(1, 11) = 4.51$, $p = .057$, $\eta p^2 = .29$. This effect did not interact with block, $F < 1$. Thus, neither an instruction to prioritize a new quadrant before Block 3 nor the instruction to distribute attention evenly before Block 4 had completely eradicated probability cueing toward the rich quadrant.

2. Eye movement data

The eye movement data were consistent with the behavioral results (Figure 22B). Participants more often directed the first saccadic eye movement toward the rich quadrant than the sparse quadrants in the training phase, $t(11) = 2.59$, $p = .025$. In the testing phase, the first saccadic eye movement was determined primarily by the instructions. Most of the first saccades were directed toward the *designated-sparse* quadrant in Block #3, $t(11) = 4.04$, $p = .002$. By Block 4, first saccades were relatively evenly distributed across all quadrants, $F < 1$.

Discussion

Experiment 3 showed that explicit instructions affected, but did not fully eliminate, probability cueing. Participants were highly successful at following the task instructions. This was shown clearly in the eye movement data. When asked to look first toward the *designated-sparse* quadrant in Block 3, participants faithfully directed most of their first saccades there. When told to treat all quadrants equally in Block 4, participants showed no clear bias toward any quadrants in their first saccadic eye movements. Nonetheless, the instructions did not completely eradicate probability cueing. This was shown most clearly in RT. Probability cueing declined somewhat from training to testing, but remained strong in the first block of testing phase (Block 3 overall). The reduction in the testing phase could be due to several reasons: instructions, a change in the underlying target statistics, or new learning accumulated from directing first saccades toward the *designated-sparse* quadrant. The RT data showed more evidence than the eye movement data for the persistence of probability cueing. This was likely because the instructions were specifically about deploying the first eye movement toward the *designated-sparse* quadrant, whereas RT was sensitive to subsequent attentional movements. Together, these data show that although people can flexibly adjust their attentional priority based on explicit instructions, they were unable (within the current testing-time duration) to fully eradicate the long-lasting influence of an implicitly learned attentional bias.

2.5.4. Part II-2 conclusion

In Part II-2, I explored the mechanisms that are involved in location probability learning. Previous studies using the contextual cueing paradigm had provided mixed results. Some studies show that contextual cueing primarily enhances decisional process that occur after the target has been found (Kunar et al., 2007; Kunar et al., 2008), but other studies suggest that contextual cueing guides spatial attention to the target's location (Chun, 2000; Chun & Jiang, 1998). To examine the role of implicit VSL on attention, I adopted a simpler paradigm: probability cueing. Experiment 1 showed that probability cueing affected spatial attention, as reflected by first saccadic eye movements. Experiment 2 showed that probability cueing could be observed even when people maintained central fixation. Experiment 3 showed that an instruction to attend elsewhere did not fully eradicate probability cueing. These experiments provide strong evidence for the idea that implicit visual statistical learning is a powerful mechanism for spatial attention.

3. Grand Summary and General Discussion

3.1. Summary of all experiments

Part I demonstrated that the statistical regularities between co-occurring visual objects are acquired when participants are explicitly aware of the co-occurrence relationship. I presented two experiments. The first experiment compared familiarity judgment of object triplets among participants who were aware, partially aware, or unaware of the statistical regularities. The results showed that performance scaled with the level of explicit awareness – people who had intentionally encoded the regularities and had remembered them were more successful at selecting the base pairs, whereas people who had no reportable awareness performed at chance level. The second experiment used the attentional blink paradigm to systematically vary awareness level for shape pairs presented during different T1-T2 lags. The results showed that VSL was impaired when the base pair was presented at Lag 2, during a time when participants' awareness of the pairs was impaired. These results indicate that explicit awareness contributes to visual statistical learning.

Part II examined the impact of visual statistical learning on the deployment of spatial attention in a visual search task. Using the probability cueing paradigm, six experiments showed that visual statistical learning guides spatial attention. Many kinds of working memory load did not influence implicitly guided spatial attention. This implies that implicitly learned spatial attention is dissociated from visual working memory. Also, visual statistical learning guides first saccades toward locations that are more likely to contain the search target. Experiments using an eye-tracker revealed that low-level oculomotor responding is not critical for probability cueing. In addition, RT and saccadic eye movement driven by implicit probability learning are relatively insensitive to explicit instruction. In conclusion, whereas the statistics among co-occurring visual object stimuli are explicitly acquired, visual statistics about the location of visual search targets are learned implicitly.

3.2. Theoretical implications

3.2.1. Part I: The acquisition of statistical regularities from the external world

1. Criteria for "implicit" learning

Previous studies defined implicit learning as "the unconscious process by which subjects respond to the statistical nature of the stimulus array and lead them to their decision (Reber, 1967, p. 863; Reber & Allen, 1978)," or "nonepisodic learning of complex information in an incidental manner, without awareness of what has been learned (Seger, 1994, p. 163)," and "the adaptation to the regularities of the world that evolves without intention to learn, and without a clear awareness of what we know (Perruchet & Pacton, 2006, p. 233)." Thus, implicit learning is (i) an *unconscious* process that (ii) extracts complex information, (iii) yielding *no awareness* of what has been learned.

Standard visual statistical learning of the co-occurrence between novel objects does not meet these criteria. I have shown that the majority of participants were aware of what they had learned (#3). Some participants had an intention to learn and therefore were aware of the process of learning (#1). Compared to other forms of visual statistics such as those used in artificial grammar learning, the standard visual statistical learning paradigm involves relatively simple statistics (i.e., pairwise association) (#2). For these reasons, standard VSL predominantly taps into explicit learning.

2. Why did previous studies assume that VSL is implicit?

Much of contemporary research has assumed that standard VSL involves implicit learning. This assumption may have reflected the fact that standard VSL exhibits some common features with other implicit learning paradigms. For example, Reber (1967) emphasizes that implicit learning is an automatic process that occurs without effort. Because standard VSL was revealed even when participants were asked to simply look at the visual displays, it seems quite effortless. The fact that young infants are sensitive to statistical regularities in the auditory (Saffran et al., 1996) and visual (Kirkham, Slemmer, & Johnson, 2002) modality further bolsters the claim that learning may have been unconscious and automatic. Direct investigation of the automaticity of VSL, however, has not supported this claim. For example, the standard form of VSL increased in older children compared with young children (Arciuli & Simpson, 2011). It is also absent when people selectively attend to other shapes (Turk-Browne et al., 2005). Nonetheless, the confusion between incidental and implicit learning may have led to a mischaracterization of the nature of standard VSL. The attractive characteristics of implicit learning, such as its insensitivity to brain injuries, minimal attentional demands, and its high capacity, may also have led researchers to be more willing to consider VSL as implicit learning.

Ed Yong (2012, p. 298) remarked, "Positive results in psychology acts like rumors: easy to spread but hard to reject". Meanwhile, attempts to replicate those studies, especially when the findings are negative, go unpublished (Ed Yong, 2012). Fortunately, several recent studies including the current dissertation have begun to question the role of awareness in the standard VSL paradigm (see also Bertels et al. (2013) in visual statistical learning). Of course, one negative result does not invalidate the entire enterprise. If the original effect is not strong, negative replication will arise through chance alone (Ed Young, 2012). However, it is important to not take for granted the implicit nature of VSL.

3. Standard VSL is empirically weak

Two experiments in Part I found that in the absence of explicit knowledge participants did not acquire VSL. Then, does this result indicate that nothing had been acquired by passive exposure to the repeated spatial-temporal co-occurrence of the visual objects? It is difficult to reach this conclusion because it is akin to affirming the null hypothesis. Although participants did not show any learning in behavior, neuroscience measures may reveal differences between repeated object pairs/triplets and random ones (Turk-Browne et al., 2009). New, creative behavioral indices may also uncover hidden evidence of learning. Future studies should develop new experimental paradigms that are particularly sensitive to implicit learning. It is clear that the existing paradigm (exposure plus familiarity judgment tests) reveals primarily explicit learning.

The lack of VSL in the absence of awareness is consistent with one of two possibilities: repeated spatial-temporal coincidence of visual objects does not generally lead to strong learning, or that learning has happened but is not revealed by the familiarity judgment test (or the RT test). Although the current state of knowledge does not distinguish between these two possibilities, it is clear that the popular VSL paradigm currently used in many studies is not suited for examining implicit learning. First, passive viewing is vulnerable to participant boredom and experimental demand characteristics. Sometimes, researchers used a cover task, but most of these tasks are not challenging (e.g., the one-back task). Because the pairs or triplets are presented at a moderate speed without any interference, participants may have enough attentional resources remaining to notice the visual regularities. Also, because of the limited number of stimuli (usually six pairs or four triplets) and the high number of repetitions (e.g., 24-100), it is relatively easy to detect and explicitly learn these pairs. Finally, the testing phase usually tests the exact pairs or triplets from the training session, so the test taps into a relatively simple form of learning (e.g., learning of the exemplars rather than an abstract rule).

The most frequently used paradigms – passive viewing during exposure and the familiarity task at test – are susceptible to many confounding factors. It will be necessary to develop well-controlled paradigms to examine how, and if, people can non-intentionally and truly implicitly form associative learning of co-occurring visual objects.

3.2.2. Part II: The influence of VSL on spatial attention

1. Working memory and spatial attention

Both working memory and attention are capacity-limited processes. These two cognitive processes have been studied separately for many years, but recently, empirical and theoretical research has shown that these two processes are closely related. They may use similar cognitive and neural mechanisms (Cowan, 2001). The deployment of attention influences the rehearsal locations in spatial working memory (Awh & Jonides, 2001), and conversely, loading visual working memory interferes with orienting spatial attention in visual search (Olivers et al., 2011; Woodman et al., 2013). Indeed, recent theoretical accounts propose that working memory is regarded as *attention* deployed to an internal representation (Chun, 2011; Chun, Golomb, & Turk-Browne, 2011; Kiyonaga & Egner, 2013). The current study both supports and extends these theoretical considerations in new ways.

First, Experiment 1 using an endogenous cueing paradigm adopted from Posner (1980) to show that goal-driven attention was impaired under a secondary visual working memory task. That is, holding color-location associations in working memory interfered with orienting spatial attention toward a cued location in the visual search task. These results not only replicated previous findings from visual search (Oh & Kim, 2004; Woodman et al., 2013; Woodman & Luck, 2004), but also extended them to spatial cueing. Whereas visual search involves rapid shifts of attention among multiple search elements (Wolfe, 1998), spatial cueing reflects the orienting of spatial attention to a cued location (Posner, 1980). Therefore, the current experiments demonstrate that spatial orienting, a major component of spatial attention, is influenced by visual working memory.

Importantly, however, when guided by implicit learning, spatial attention is not influenced by concurrent visual working memory load. Participants could prioritize high-probability, target-rich locations even when holding in working memory several colors, dot locations, a spatiotemporal sequence of dots, or irregular shapes. Not only was there no evidence for a reduction in the size of probability cueing, but also was cueing fully transferred across memory load conditions (or partially transferred in the object working memory task). These results were not due to the use of ineffective (weak) working memory manipulations. The overall search RT slowed down under working memory load, suggesting that the working memory manipulation was effective. Our data therefore show that goal-driven attention and implicitly learned attention interact differently with visual working memory. These findings refine our understanding of the relationship between spatial attention and spatial working memory, and strongly support a recently proposed attention model: the *dual-system view of attention* (Jiang, Swallow, & Capistrano, 2013).

2. Dual system: procedural attention

Rehearsal of the locations of color patches or dots in working memory requires prioritizing the spatial locations occupied by these items. Because the encoding display was presented before the visual search display (or a cue display), rehearsing and attending to the working memory items potentially interferes with how spatial attention is prioritized (i.e., priority map). This hypothesis was supported in Experiment 1 in Part II-

1. In contrast, the lack of interference from spatial working memory on probability cueing strongly supports the idea that probability cueing relies on a different process than spatial working memory and goal-driven attention. In fact, the different dependencies on working memory for the two types of spatial cueing are difficult to explain if we assume that only a single mechanism handles both implicit learning and goal-driven attention. A recent study (Jiang, Swallow, & Capistrano, 2013) proposes that spatial attention is a dual-system. It has two components: a declarative component and a procedural component. Goal-driven attention depends on the declarative component of attention, which can be conceptualized as the priority map (Corbetta & Shulman, 2002; Fecteau & Munoz, 2006). The declarative component of attention can be modulated by behavioral goals such as those provided by the central arrow cue used in Experiment 1. The procedural component of attention, on the other hand, refers to the online shifting of spatial attention. Simply speaking, the procedural component is more involved with *how* spatial attention is being oriented than with *where* spatial attention is finally located. Any visual task such as visual search involves not only planning but also actual execution. Much like eye movement, which has a clear procedural component, spatial attention also has a strong procedural component. It is involved in the actual shift of attention in space.

More specifically, probability cueing is considered a form of procedural attention acquired through reinforcement learning (Jiang, Sigstad, & Swallow, 2013; Jiang, Swallow, & Capistrano, 2013). Successful responses to targets reinforce the attentional shifts that landed on the target, increasing the likelihood that they will reoccur. These attentional shifts may be conceptualized as a Euclidian vector. For example, in experiments where the target's location is random, each vector is equally likely to be reinforced over a period of time, and there are no prioritized directions (vectors). However, when the target is more often found in some regions over a period of time than in other regions, some vectors are more strongly reinforced than others, increasing the likelihood that attention will be oriented to the region again. Implicit learning seems to modulate the procedural component of spatial attention. Shifting spatial attention trial by trial toward one location more often than others during visual search modulates the direction and size of the vector and the next attentional shift. Empirical studies have provided evidence for this view. Contextual cueing does not occur before the actual search begins (Jiang, Sigstad et al., 2013), and spatial probability cueing is viewer-centered (Jiang & Swallow, 2013). This procedural component raises the important question of whether actual oculomotor responding is a critical component of probability cueing, a question that I tested in Part II-2.

3.2.3. Part II-2: Implicit probability learning and saccadic eye movements

1. Attentional guidance account

Part II-2 shows that implicit probability learning influences overt attention as well as covert attention. When allowed to move their eyes during visual search in the probability cueing paradigm, participants more often directed their first saccade toward the rich quadrant. The significant correlation between probability cueing in RT and eye movements supports the proposal that attention and eye movements are tightly coupled (Kowler, 2011).

In Part II-2, the first saccades were measured while participants were searching for a target in the probability cueing paradigm. The three experiments showed strong evidence for the attentional guidance account of implicit learning. Although participants were unaware of the fact that the target was more often in some locations than others, they were faster at finding the target in the rich quadrant than the sparse quadrants. In addition, they were almost twice as likely to direct the first saccadic eye movement toward the rich quadrant than to any of the sparse quadrants. Because first saccades occur long before the target is found, these data support the idea that implicit learning has affected attentional guidance during the search process, rather than post-detection decisional processes.

We also showed that probability cueing persisted for almost 200 trials after the target's location became random. In contrast, goal-driven attention is highly sensitive to the validity of the spatial cue (Jonides, 1980). In addition, Experiment 2 showed that the attentional bias persisted even though participants were asked to minimize their eye movements.

2. Implicitly acquired spatial attention involves procedural attention, not oculomotor learning.

Several theories, such as the premotor theory of attention (Rizzolatti, Riggio, Dascola, & Umiltá, 1987) and the attention-for-action theory (Allport, 1989), explain covert attention as an integral component of eye movements or other actions. However, although the shift of spatial attention often accompanies saccadic eye movement, the procedural component is not accounted for solely by oculomotor response. Previous research has also shown that implicitly acquired spatial attention is unlikely to be instantiated in low-level, oculomotor learning. First, probability cueing was shown when the display was presented very briefly (e.g., 150 ms, whereas eye movement takes about

200 ms on average) and when fixation was ensured with an eye tracker (Geng & Behrmann, 2005). Second, frequent saccades toward a rich quadrant did not produce probability cueing if the target's location was pre-cued by a central arrow (Jiang, Swallow, & Rosenbaum, 2013). Saccades toward the rich quadrant are therefore neither necessary nor sufficient to yield probability cueing. Instead, probability cueing is likely to reflect high-level, attentional learning. Nonetheless, by considering probability cueing as a form of procedural attention (discussed in Part II-1), implicitly learned attention is considered as a *precursor* to oculomotor learning. Therefore, this form of attention may be strongly related to the premotor aspect of attention (Rizzolatti et al., 1987) whereas goal-driven attention can be abstracted from online attentional shifting and is a prime candidate for configuring the priority map of spatial attention.

3. The impact of redirecting attention on implicitly driven attention

Although probability cueing was persistent beyond the initial training phase, explicit instructions are a stronger source of moment-to-moment attentional guidance. Experiment 3 showed that when participants were asked to direct their first eye movement to a sparse quadrant, they were successful in prioritizing that quadrant. However, instruction did not completely eradicate residual preference for the previously rich quadrant. Visual search continued to be moderately faster in that quadrant than in the non-designated sparse quadrants. Thus, goal-driven and implicitly learned attention are two major sources of attentional guidance. The former dominates in a given situation, though it does not completely override the latter.

3.3. Further questions

Part I. Standard Visual Statistical Learning

Due to the weak paradigms currently most often employed in standard visual statistical learning, many questions regarding that paradigm are still unresolved. For example, does standard VSL depend on visual working memory? Or might it remain strong when visual working memory is fully occupied? This question and other issues about standard VSL cannot be addressed without a significant improvement in the experimental paradigm.

The two experiments reported in Part 1 also leave many questions. First, in Experiment 1, two slightly different post-test questionnaires were given to participants. The first question *("Did you try to remember which shapes changed into which other shapes in the first session?*) is more related to *intention* whereas the second question ("*Did you notice some shapes consistently changed into certain other shapes?*") is more related to *explicit awareness*. The small sample size prevented us from separately analyzing data based on different responses to these two questions. It would be interesting in future studies to test whether intention and awareness have different effects on VSL.

The attentional blink experiment of Part 1 also raises an interesting question. The attentional blink paradigm was used to modulate participants' level of awareness for the visual regularity. Although we only focused on the explicit awareness perspective in the attentional blink paradigm, attentional blink also taps into changes in attentional resource. During short lags not only are people less aware of T2 they may also have less attention and working memory resources for processing T2. Future studies should examine whether the reduction in VSL in the short lags is due primarily to reduced awareness of the statistical regularities or to a lack of attentional resources. Although this could be a matter of semantics, at least some researchers have argued that attention and awareness are not one and the same (for a review, see Lamme, 2003).

Both experiments reported in Part 1 contained an intermediate awareness level condition (partial knowledge group in Experiment 1 and lag 4 condition in Experiment 2). Interestingly, participant performance in these conditions was also between the high awareness level condition and the no awareness level condition. Furthermore, both experiments showed statistical learning is a monotonic function of the level of awareness. It is possible that the distinction between explicit and implicit learning is not a matter of all or none. These two types of learning may be placed at two extremes on a continuum. For example, whereas artificial grammar learning and location probability learning are primarily implicit, standard VSL of object pairs/triplets lies closer to the other end of the continuum: it benefits from increased awareness of the statistical regularities. Although this idea requires further development, it raises the interesting possibility that VSL is not a process-pure mechanism. It likely reflects a combination of explicit and implicit learning. The involvement of both hippocampus and caudate in standard VSL is consistent with this proposal (Turk-Browne et al., 2009).

Part II. Spatial attention driven by visual statistical learning

Part II revealed that implicitly learned attention relies on a different mechanism than goal-driven attention. Although these findings are straightforward, they also raise several interesting questions for future research. First, the underlying neural mechanisms for the two forms of spatial attention have not been explored. Neurophysiological studies have shown that parietal cortex contains different neurons representing visual space differently (e.g., eye- and head- centered representation), and some neurons can modify their receptive fields in anticipation of an impending saccade (Colby & Goldberg, 1999). The heterogeneity of neurons in the parietal cortex may support the multiple subsystems of spatial attention. Neuroimaging studies have proposed that several other brain regions are related to spatial attention, including the frontal eye fields, posterior parietal cortex, basal ganglia and the thalamus, superior colliculus, and the cerebellum (Corbetta & Shulman, 2002). It is possible that whereas the fronto-parietal regions are more important for goal-driven attention (Corbetta & Shulman, 2002), subcortical regions (e.g., the basal ganglia and superior colliculus) may be more involved in implicitly learned attention (Krauzlis et al., 2013; Packard & Knowlton, 2002). This proposal should be tested in future neuroimaging and patient studies.

Second, how do the subsystems of spatial attention interact, especially when various sources of spatial attention (e.g., goal-driven attention and implicit learning) provide conflicting signals? Experiment 3 has begun to address this question. However, the data from Experiment 3 were not completely clear-cut. While it is clear that participants could use the experimentally provided instructions to deploy spatial attention, probability cueing toward the rich quadrant was weakened but not eliminated. The weakening may be attributed to the conflicting goal-driven cue, but it might also reflect the change in visual statistics (i.e., the target’s location was random in the testing phase). The degree to which implicitly learned attention is encapsulated from goal-driven attention requires further investigation.

Conclusion

This dissertation examined 1) whether the statistical association between novel visual objects can be acquired without explicit awareness and 2) how statistical learning implicitly guides spatial attention and saccadic eye movements. These studies show that there are multiple types of visual statistical learning. These types differ in their role (for perception versus for visuomotor action) and in their dependence on conscious awareness.

Why do these two types of learning - statistical association between objects and probability cueing – differ in their reliance on awareness? The two-stream view of vision (Goodale & Milner, 1992) may provide an explanation. Visual processing is divided into an occipito-temporal ventral stream and an occipito-parietal dorsal stream. According to Goodale and Milner, the ventral stream is involved primarily in object perception (i.e., vision for perception), but the dorsal stream is involved primarily for visually guided actions (i.e., vision for action) (Goodale & Milner, 1992; Milner & Goodale, 2008). Interestingly, the dorsal stream of processing depends less on conscious awareness than does the ventral stream (James, Culham, Humphrey, Milner & Goodale, 2003; Goodale, Milner, Jakobson, & Carey, 1991; Fang & He, 2005). Likewise, I have shown here that statistical learning of the spatiotemporal relationships between novel objects depends on awareness. Such learning is acquired in the absence of any tasks and therefore likely relies exclusively on the perceptual (ventral) stream of processing. In contrast, visual search involves covert and overt spatial attention and is largely a function of the dorsal stream of processing. Its independence from awareness bodes well with the two-stream view of vision.

Of course, conscious awareness is not required in all types of learning involving perception. Perceptual learning of low-level visual properties such as orientation and motion direction is largely implicit. In addition, complex artificial grammar learning can be acquired in the absence of any visuomotor or attention tasks. Nonetheless, relatively rapid acquisition of environmental regularities takes advantage of the multiple learning mechanisms that humans possess. Explicit, conscious learning allows us to extract arbitrary associations between novel objects quickly. Although this form of learning may be limited by attention and working memory capacity, it has the advantage of being flexible. Changes in behavioral goals can rapidly reconfigure what we intend to learn. At the same time, implicit learning supports the acquisition of new attentional priority. Such learning occurs in the context of a visual search task and is a powerful source of attentional guidance. Once acquired, implicitly learned attention persists over time and is relatively insensitive to working memory demands. This dissertation has delineated major characteristics of these two types of statistical learning. It has also begun to examine the interaction between explicit, goal-driven attention and implicit learning. The multiple forms and mechanisms of visual statistical learning are likely to help solve the different demands of the multitude of visual tasks confronting us.

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