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Characterization of Implicit Sequence Learning and the Influence of Individual Differences on Performance

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Characterization of Implicit Sequence Learning and the Influence of Individual Differences on Performance

A dissertation submitted in partial satisfaction of the

requirements for the degree Doctor of Philosophy

in Psychology

by

Lauren M Burakowski

2014

ABSTRACT OF THE DISSERTATION

Characterization of Implicit Sequence Learning and the Influence of Individual Differences on Performance

by

Lauren M Burakowski

Doctor of Philosophy in Psychology

University of California, Los Angeles, 2014

Professor Scott Johnson, Chair

This work aimed to understand the limits and capabilities of implicit sequence learning, or internalizing statistically-defined regularities in a stream of stimuli without awareness or intention to learn. Both spatial and nonspatial informational components were manipulated in presented streams of stimuli, and undergraduates learned regularities in both categories of information and applied this knowledge to test trials. Evidence for a unique contribution of a spatial component to visual implicit sequence learning was presented, and changes in performance across the quarter were examined. This work supported a model of implicit learning as a general principle of neural processing (Reber, 2013) and a model of unidimensional and multidimensional systems involved in implicit sequence learning (Keele et al., 2003).

The dissertation of Lauren M Burakowski is approved.

Adriana Galván

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Scott Johnson, Committee Chair

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2014

DEDICATION

To Grandma Mary, for her incredible love and support throughout my life.

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VITA

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Chapter 1

General Introduction

1.1 Introduction

Every day we are bombarded with regularities and patterns, some of which provide structure for our behavior and guide development as we extract and assimilate the essential information in our surroundings. Humans are sensitive to a variety of environmental regularities across modalities. These patterns inform many of our fundamental abilities implicitly, without an intention to learn on our part or even awareness that learning has taken place. Implicit sequence learning allows us to internalize some of those patterns so we can potentially use the knowledge in other cognitive processes (Reber, 1967; Destrebecqz & Cleeremans, 2001). For example, visual sequence learning is essential for understanding regularities in our visual environment and processing complex scenes (Chun & Jiang, 1998).

Through a process (or principle) labeled “implicit learning” by Reber (1967), it is thought that we unconsciously extract and adapt to information that facilitates the development of a vast array of abilities including language, motor skills, perception, music, and social behaviors (Rohrmeier & Rebuschat, 2012; Reber, 2013). Implicit learning has also been defined as a mechanism through which new information was acquired without the intention to learn, so that the resulting knowledge was difficult to express (Berry & Dienes, 1993), or as an unconscious learning process that resulted in abstract knowledge (Reber, 1989). Implicit learning has often resulted in the extraction of the underlying structure of the input, providing learners with the opportunity to generalize the pattern across stimuli sets.

Identifying tasks that elicit implicit learning can be a challenge. Seger (1994) proposed several criteria for identifying implicit learning, which may assist in task selection. According to Seger, the information learned must be complex, as opposed to simple association; the information must be learned incidentally, as opposed to through hypothesis testing; and the information must be unconscious and not verbalizable. These criteria were helpful in guiding the development of protocols to examine the mechanisms involved in learning. The goals of the current studies were to examine the nature and limits of implicit learning, explore individual differences in implicit learning, and understand learning observed in these studies in context of current theories of implicit learning. Exposure to a complex, rule-governed environment or stimuli set under conditions which allow for incidental learning could promote implicit learning in pursuit of these goals, while experimenters measured how well participants could express acquired knowledge and how conscious they were of that knowledge (Cleeremans & Dienes, 2008). The current studies did just that: exposed participants to a complex, rule-governed sequence of structured shape strings, and measured both knowledge acquired and consciousness of that knowledge.

1.2 Why use a finite state grammar paradigm?

Implicit learning has commonly been studied in three paradigms: artificial grammar learning (AGL), dynamic system control, and sequence learning (Cleeremans & Dienes, 2008). The current studies employed a modified AGL paradigm to examine the limits of implicit sequence learning of a probabilistic structure in adults; specifically, a finite state grammar (FSG). The finite state grammar determined how shapes could be combined to create sequences (Cleeremans, Destrebecqz, & Boyer, 1998) viewed by participants. The current studies employed an FSG because it allowed for the creation of a complex, rule-governed environment with an underlying structure that could be learned without awareness and manipulated to test the contribution of different components (dimensions) to learning. If participants show evidence of learning an underlying FSG and cannot explicitly report the probabilistic information that they learned, the learning was considered to be implicit.

Looming shapes were chosen as stimuli for the current studies to examine implicit sequence learning. Previous work with artificial grammars has used strings of letters as stimuli and asked participants to memorize the letter strings (Reber, 1967). Others have used letters (for example, upright and rotated Ts and Ls) in visual search tasks (e.g., Olson & Chun, 2002). Shapes were used in this protocol because the design allowed these studies to test the contribution of one or several components of information, as well as easily manipulate those components. Color and shape dimensions could be systematically changed, and the influence of a spatial component on learning could also easily tested by distributing the shapes in space or presenting them in the same location. Manipulating all of these dimensions in the same paradigm allowed for valid comparisons of learning across studies.

Shapes loomed and only appeared one at a time on the screen. This design choice was made so that participants only saw the sequences in the order in which they were presented; no visual scanning back across the pattern could occur. Additionally, participants may have found it less challenging to explicitly identify patterns if all of the shapes had remained on the screen. Finally, to allow for the exclusion of a spatial component, shapes must be presented with no spatial relationship to each other, or in the same place on the screen. To keep the design consistent across studies, stimuli did not remain on the screen during the studies manipulating spatial information.

1.3 Models of learning

Implicit learning seems to contrast strongly with explicit learning, which is typically conscious, effortful, and hypothesis-driven. Implicit and explicit learning were at least partially neurally (Yang & Li, 2012) and behaviorally (Berry & Broadbent, 1984; 1988) dissociable. While explicit learning was accessible by multiple neural networks in adults, implicit learning was not, contributing to the difficulty in measuring implicit learning (Cleeremans & Dienes, 2008).

However, a recent review (Reber, 2013) suggested that implicit learning is less clearly defined than a specific neural region or network; instead, it operated as a general principle that governed processing of information in the brain. This conceptualization reconciled neuropsychological findings showing that complex implicit learning was impaired in patients with medial temporal lobe damage, a structure once solely associated with explicit learning (Chun & Phelps, 1999). Implicit learning was a constant, ever-present process in this conceptualization, underlying all behavior regularity and adjustment (Reber, 2013).

A slightly different model of sequence learning proposed by Keele, Ivry, Mayr, Hazeltine, and Heuer (2003) posited that two distinct learning systems represented sequential regularities in the brain and have different computational capabilities. These systems, referred to as unidimensional and multidimensional, were thought to represent different, but often overlapping, types of learning. Unidimensional learning was implicit and automatic, and only learned one dimension at a time. Multidimensional learning could be implicit or explicit, and more than one dimension could be learned and integrated. This system was not necessarily automatic and could be controlled explicitly. Dimensions could be thought of in two ways: as multiple variables within a modality, or variables across modalities. To integrate across two dimensions, such as shape and location information, for example, the learner created associations within the multidimensional system.

The unidimensional and multidimensional systems were predicted to have different attentional requirements. Since the unidimensional system automatically formed associations along a single dimension, the learning was not disrupted by task-relevant information from other dimensions. The multidimensional system also formed associations automatically; however, attention constrained what information was processed. If uncorrelated or random information in a different dimension was unattended, it would not have impacted learning of the attended information in the current task. If the random information was task-relevant and attended, it would have disrupted learning. Therefore it was attentional constraints, rather than capacity limitations, that determined the impact on learning of uncorrelated dimensions (Keele et al., 2003).

Much of the support for this model stemmed from the serial reaction time (SRT; Nissen & Bullemer, 1987) task. Participants were asked to respond to various signals, such as tones or stimuli appearing in locations on a screen, as quickly as possible. The primary measurement was reaction time, which could be compared across conditions, or blocks of trials, which have random sequences and sequences ordered according to an underlying structure. If participants were able to respond differentially to the structured compared to the random sequences, this suggested that learning had occurred and provided a quantifiable way to compare learning across manipulations (Keele et al., 2003).

Although Reber's (2013) reconceptualization of implicit learning as a general principle underlying all information acquisition may encompass this theory, this model seems to capture the variability in results of neuroimaging and behavioral studies more cleanly than the strict, traditional implicit/explicit distinction. However, additional data supporting this theory using tasks other than the SRT are essential to further understand the value of this framework for studying and understanding learning. The SRT, while versatile, required responses after each stimulus and was not optimized to examine passive sequence learning. The SRT also required a large number of practice trials before reaction time differences were reliable. A task that supports learning on a shorter time scale allows for the adaptation of the protocol to studies with diverse population, such as infants, children, and animals.

1.4 Summary of studies

A thorough understanding of the type and extent of abstract knowledge created in implicit learning, or the extent to which implicit learning produces unconscious knowledge (Cleeremans, Destrebecqz & Boyer, 1998), is essential for understanding the interactions of implicit learning networks with other mechanisms. Previous work has shown that participants could learn the structure of a complex, rule-governed stimuli set without awareness, and they reported that they performed less accurately than they actually did (Reber, 1967, 1989; Seger, 1994). However, since some work has suggested that successful performance in an artificial grammar learning task did not necessarily require implicit learning of the rules of the underlying grammar (Perruchet & Pacteau, 1990), the knowledge that resulted from implicit learning lacks specification. The acquired knowledge was examined in the following work.

The first set of studies (1-4) examined undergraduates' ability to succeed in this protocol and learn an underlying probabilistic structure, as well as the transfer of knowledge and priority of processing surface compared to underlying relationships. Study 1 tested the feasibility of this paradigm by exposing undergraduates to structured sequences and comparing the structured sequences to random sequences. Study 2 began to test the information that participants were learning by comparing sequences formed by two underlying FSGs (one familiar, one novel). If participants were able to differentiate between the two structures without expressing explicit knowledge of the structure, then they learned enough of the initial structure to compare and contrast sequences implicitly. Learning one dimension was enough to succeed in these tasks. This study afforded further exploration into the abstractness of the information learned.

Study 3 focused on the abstractness of knowledge acquired. The design duplicated Study 2, with the exception of the shapes in the test phase. All of the familiar shapes from the learning phase were replaced with novel shapes in the test phase. For participants to be able to succeed in differentiating between the structures, transfer of the knowledge acquired during the learning phase must have occurred. If participants could transfer that knowledge, they must have abstracted the underlying FSG to some extent. Participants had to process along two dimensions to succeed.

The abstractness of knowledge acquired was examined more closely in Study 4. Participants were asked to differentiate between four types of trials, two of which matched the original structure. Structure and shape set (familiar/novel) were crossed so that half of the trials for each structure were presented with novel shapes. This manipulation aimed to elucidate participants' relative distribution of attention or learning to surface relationships between individual shapes or to the underlying probabilistic structure. Transitional probability is a statistical measure that describes the predictability of adjacent items in an array or sequence (Miller & Selfridge, 1950). It is possible that extracting the transitional probabilities would have allowed adults to learn the underlying relationships between elements in the shape strings and succeed in this task. Learning two dimensions was necessary to succeed in this task.

The second set of studies (5-8) sought to understand the addition of spatial information into this protocol. Did spatial information provide a unique advantage in visual processing? How did it influence learnability? Spatial information conveyed by the arrangement of elements in a sequence may have been an important cue for implicit sequence learning. Evidence suggested that parallel, independent mechanisms were involved in processing implicit learning in different modalities, a result of the complex interaction of neural networks involved in both domain specific and domain general processing (Conway & Pisnoi, 2008). Because location information is specific to visual processing, the addition of spatial location in the proposed work investigated a domain specific component of the processing networks. Shin and Ivry (2002) demonstrated that spatial information was an important part of implicit sequence learning by manipulating the timing and sequential information in an SRT task. Participants were asked to press a button when an X appeared in specific locations on a screen, and the presence of both temporal and spatial information resulted in improved performance. However, spatial information may not play a consistent role in learning sequences. Cleeremans and McClelland (1991) suggested that subjects could learn about complex spatial sequential relationships, but that they were unable to fully transfer this knowledge to separate tasks. Subsequent studies have supported this finding (Cleeremans & Dienes, 2008; Kirkham, Slemmer, Richardson, & Johnson, 2007).

The contribution of an uninformative spatial component was the focus of Study 5. Shapes were presented in the same location throughout the study, so that location information was present but did not indicate which probabilistic structure was currently being displayed.

With two dimensions, both location and order information, learning should have been easier for participants. Study 6 also manipulated spatial information; however, locations weren't consistent, but conflicting, throughout the study. Location (consistent/random) and underlying structure (familiar/novel) were crossed to produce four test trials, and examined the contribution of a conflicting spatial component. Was spatial information that is not consistent (but still semi-structured) still processed and involved in generating responses? These studies involved processing two dimensions.

The final two studies are complementary. Study 7 examined learning in the presence of only spatial information by showing random shapes in locations following a consistent path of movement to different areas around the screen. Study 8 presented shapes following an underlying FSG in random locations; spatial information was not consistent (random). These two studies provided one component of information that participants could have learned. Comparisons across the studies would allow assessment of ability to learn each type of component, in addition to how having learned one component differs from having learned two components.

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Chapter 2

Finding structure in noise:

Implicit sequence learning and performance across the term

2.1 Introduction

Humans are sensitive to a variety of patterns in the environment, which inform many fundamental abilities including language, motor skills, perception, music, and social behaviors (Clegg, DiGirolamo, & Keele, 1998; Rohrmeier & Rebuschat, 2012). These processes generally occur implicitly, without an intention to learn on our part or even awareness that learning has taken place. Implicit sequence learning, or internalizing a sequence without conscious effort, allows us to learn patterns or structures in the environment so we can apply the knowledge in other cognitive processes (Reber, 1967; Destrebecqz & Cleeremans, 2001).

Considerable controversy has surrounded the examination and definition of implicit learning. Can humans really learn without awareness? If so, what can be learned implicitly? While recent evidence from behavioral and neuroimaging studies suggests that implicit learning processes are distinct from explicit learning (Reber, 2013), there remain important unanswered questions about the nature of implicit learning. This paper aims to address two of these questions. To what extent does implicit learning produce abstract knowledge, and if so, what is the nature of this knowledge? To what extent are there individual differences in the learning process? A third goal of this work is to examine recent theories of implicit learning in light of the results of these studies.

Implicit learning seems to contrast strongly with explicit learning, which is typically conscious, effortful, and hypothesis-driven (Reber, 1967). While explicit learning is accessible by conscious effort in adults, implicit learning is characterized by a lack of conscious access to knowledge, contributing to the difficulty in measuring implicit learning (Cleeremans & Dienes, 2008). Identifying tasks that elicit implicit learning can be a challenge. Seger (1994) proposed several criteria for identifying implicit learning. According to Seger, the information learned must be complex, as opposed to simple association; the information must be learned incidentally, as opposed to through hypothesis testing; the information must be unconscious and not verbalizable; and the neural bases must not exclusively correspond with explicit (i.e., hippocampal) learning structures. These criteria are helpful in guiding the development of protocols to examine the mechanisms engaged during learning.

To promote implicit learning, participants can be exposed to a complex, rule-governed environment or stimuli set under conditions which allow for incidental learning, while measuring how well subjects could express acquired knowledge and how conscious they were of that knowledge (Cleeremans & Dienes, 2008). Artificial grammar learning paradigms (e.g., Reber, 1967) were used to examine the limits of implicit learning through sequence learning in adults; specifically, using a finite state grammar (FSG). An FSG is a structure or set of rules that determines how shapes can be combined into sequences (Cleeremans, Destrebecqz, & Boyer, 1998). The present studies exposed participants to complex, rule-governed sequences of shape strings conforming to an FSG and tested both implicit knowledge acquired and consciousness of that knowledge.

2.1.2 Examination of acquired knowledge

Our understanding of the type and extent of abstract knowledge created during implicit learning, or the extent to which implicit learning produces unconscious knowledge (Cleeremans, Destrebecqz & Boyer, 1998) is evolving. Previous work shows that participants can learn the structure of a complex, rule-governed stimuli set without awareness, while they report that they performed less accurately than they actually did (Reber, 1967, 1989; Seger, 1994). However, since some work suggests that successful performance in an artificial grammar learning task does not necessarily require implicit learning of the rules of the underlying grammar (Perruchet & Pacteau, 1990), the knowledge resulting from implicit learning lacks specification. The following studies begin to address this question of specifying what is learned by asking participants to identify the target sequence when compared against another (nontarget) sequence. Participants cannot respond solely based on the absence or presence of structure; they must separate the previously learned structure from the novel structure. Conscious awareness need not be a requirement for this separation. This is an important point; we are examining implicit learning, which requires participants to be unaware of their acquired knowledge. Previous work shows that valid tests of awareness include forced-choice tests such as recognition (Cleeremans, Destrebecqz, & Boyer, 1998). Since the current studies target implicit learning, participants who explicitly remembered the sequences, based on self-report, will be excluded from analyses (Mayr, 1996).

Many studies have demonstrated that at least some knowledge gained during an implicit learning task can be abstract. Work using sequences of letters (Knowlton & Squire, 1996) show that participants can learn abstract, grammatical relationships in bigrams and trigrams of letters implicitly (without awareness) and transfer this knowledge to a new set of letters. Both amnesic and control participants were tested in a transfer task with novel letters (after training with the familiar letter set) and showed evidence of transfer of the underlying relationships (Knowlton & Squire, 1996). Reber (1969) found that participants learned the abstract structure underlying an artificial language following exposure to exemplar sentences. Participants memorized strings of letters corresponding to an underlying FSG, and then were asked to learn more strings of letters. If these new strings were composed of the same letters but a different underlying structure, learning was disrupted. However, if participants were shown new letters with the same underlying FSG, learning was not disrupted. These studies suggested that participants learned the abstract relationship between the elements in the structure, not the surface relationships between stimuli.

Another study of implicit learning using FSGs found that participants instructed to find the underlying structure and those learning incidentally had acquired the same knowledge, and concluded that the knowledge was represented abstractly in the participants learning implicitly through the use of a transfer task (Mathews et al., 1989). A comprehensive review of sequence learning suggests that representations of sequences might be complex, with multiple levels of information in a hierarchy involving neural networks (Clegg, DiGirolamo, & Keele, 1998).

2.1.3 Individual differences

A few papers have suggested that individual differences in implicit learning in typically-developing adults exist and can be measured (e.g., Howard & Howard, 1997; Rauch et al., 1997). Reber, Walkenfeld, and Hernstadt (1991) found relatively greater variability in explicit than implicit learning, with a significant correlation between an explicit learning task and IQ but a nonsignificant correlation between artificial grammar (implicit) learning and IQ. In addition, age differences in the complexity of information learned implicitly have been identified (Howard & Howard, 1997), as well as variability in the location and strength of recruitment of brain areas involved in implicit learning in individual participants (Rauch et al., 1997). Current standardized protocols and tests may not capture individual differences in implicit learning, and thus a greater understanding of the nature of variability in these processes and neural substrates depends on thorough examination through targeted experiments.

There are often more potential influences on variability in performance than the targeted psychological construct. Previous studies have shown that motivation, academic performance, and personality factors such as level of extraversion and conscientiousness varied based on the time of the semester undergraduates chose to sign up for studies (Bender, 2007; Witt, Donnellan, & Orlando, 2011). Since the personality factors implicated in influencing time of participation may be more strongly predictive of burnout than actual workload is (Jacobs & Dodd, 2003), participants who signed up later in the quarter may have been feeling more stress than participants who signed up earlier in the quarter, regardless of their workload. Additionally, performance deficiencies on repetitive, aversive tasks have been observed in participants signing up later in the term (Navarick & Bellone, 2010), and the current tasks are certainly repetitive (although not aversive, in this author's opinion). These previous findings suggest that a thorough examination of the impact of the time of participation on performance may be necessary to rule out the impact of sign up time on the current studies, especially when comparing results across experiments.

2.1.4 Theories of learning

A recent review by Reber (2013) suggested that implicit learning operates as a general principle governing processing of information in the brain, as opposed to a clearly defined specific neural region or network. Implicit learning was a constant, ever-present process in this conceptualization, underlying all behavior regularity and adjustment (Reber, 2013).

A slightly different model of sequence learning proposed by Keele, Ivry, Mayr, Hazeltine, and Heuer (2003) posited that two distinct learning systems represented sequential regularities in the brain and have different computational capabilities. These systems, referred to as unidimensional and multidimensional, were thought to represent different, but often overlapping, types of learning. Unidimensional learning was implicit and automatic. This system learned one dimension at a time. Multidimensional learning could be implicit or explicit, and more than one dimension could be learned and integrated. This system was not necessarily automatic and could be controlled explicitly. Dimensions could be thought of in two ways: as multiple variables within a modality, or variables across modalities. To integrate across two dimensions, such as shape and location information, for example, the learner created associations within the multidimensional system.

Much of the support for this model stemmed from the serial reaction time (SRT; Nissen & Bullemer, 1987) task. Participants were asked to respond to various signals, such as tones or stimuli appearing in locations on a screen, as quickly as possible. The primary measurement was reaction time, which could be compared across conditions, or blocks of trials, which have random sequences and sequences ordered according to an underlying structure. If participants were able to respond differentially to the structured compared to the random sequences, this suggested that learning had occurred and provided a quantifiable way to compare learning across manipulations (Keele et al., 2003).

2.1.5 Summary

The present studies examined the extent and level of abstractness of the knowledge acquired during sequence learning. Study 1 assessed participants' ability to identify structured versus random strings. Study 2 pitted strings formed using the previously learned structure against strings formed using a novel structure at test. Study 3 constructed the test strings from novel shapes (using the same two familiar and novel structures), requiring transfer of the underlying structure to succeed. Study 4 examined the priority of processing surface relationships between shapes versus the underlying structural regularities crossing shape novelty (familiar versus novel) with structure novelty (familiar versus novel). We predicted that participants would be able to identify a learned structure compared to a random or a new structured sequence at above chance levels.

2.2 Method and Results

2.2.1 Participants

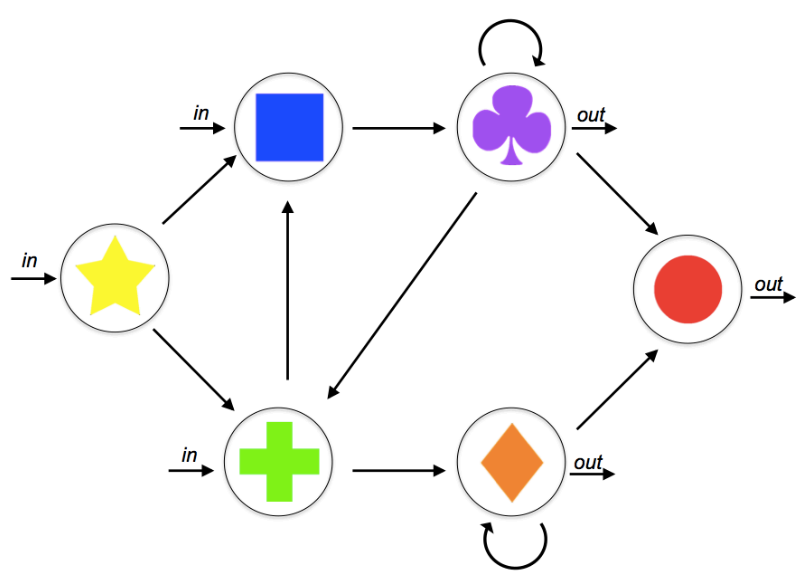
We recruited and tested 250 UCLA undergraduates (189 female) for the four studies. We excluded 42 participants: 21 for expressing explicit knowledge of the patterns (8 in Study 1, 9 in Study 2, 0 in Study 3, 4 in Study 4), 12 as statistical outliers (4 in Study 1, 3 in Study 2, 2 in Study 3, 3 in Study 4) using Cook's distance of less than 4/n as a criterion (Bollen & Jackman, 1990), 2 due to experimenter error, 1 due to participant error, 5 due to failure to track or calibrate, and 1 due to some type of colorblindness. Participants were recruited through the Psychology Department SONA Systems Subject Pool; all received course credit or extra credit for participation.

2.2.2 Materials and Design

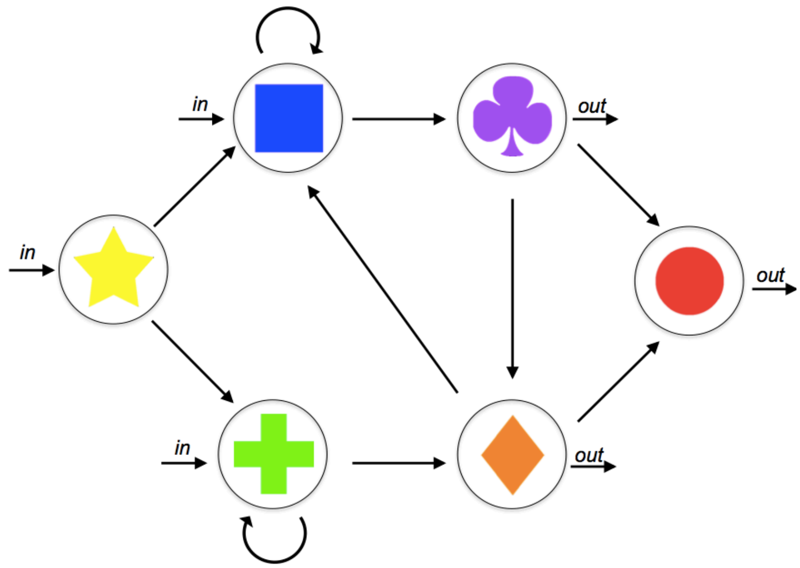
We displayed stimuli on a 1680x1050 pixel screen with a refresh rate of 60hz, presented through SR Experiment Builder. Six colored shapes were randomly selected from a set of eight shapes (shape set A) at the beginning of each session to populate the grammatical structures, and loomed at a rate of 60 frames per second (from 160x160 to 280x280 pixels). Shapes were presented one at a time on a black background at the center of the screen. There were three possible underlying structures: the target structure (always the same; see Figure 2.1a), the nontarget structure (see Figure 2.1b), and random (no structure/not matching other structures). All structures were constrained to start and end with the same elements within each subject.

Figure 2.1. a) The statistical structure underlying the target FSG A. This structure determines the order of the shapes in the learning phase and half of the trials in the test phase in all of the studies. b) The statistical structure underlying the non-target FSG B. This structure determines the order of the shapes in half of the trials in the test phase in Studies 2, 3, and 4.

a)



b)



There were 18 strings in the learning phase and 36 strings (18 target, 18 other) in the test phase. The strings were randomly selected without replacement from a set of strings so that no individual string was repeated in the learning or test trials (to provide participants with as many unique examples of the grammar as possible). During the learning phase, participants viewed 18 strings of consecutive looming shapes, structured according to the grammar (specific instantiation of the structure chosen at random from 36 choices), concatenated into a sequence and separated by a brief (0.5-1.5 second) attention-getter (colorful image that moved in conjunction with a sound). Each string was composed of 6-8 looming shapes (shapes could be repeated, according to the rules of the grammar).

Participants were excluded from analyses if they expressed explicit knowledge of the underlying finite state grammar in the post-experiment questions. The design was between subjects. Time slots for participants to sign up for the studies were posted no more than a week in advance of the date of participation. Participants were excluded as outliers if Cook's distance was above the criteria set for each study by 4/n, where n was the sample size (Bollen & Jackman, 1990). An alpha level of 0.05 was used for all statistical tests.

2.2.3 General Procedures

Participants were consented and told that they would be watching shapes on a monitor and would receive instructions during the study, which they could click through with a mouse. Participants were asked for their age, SAT scores (if applicable), level of arousal (tiredness), and colorblind status after the consent process. Each study was presented as a task comparing learning across development with no reference to attending to a pattern to reduce the incidence of explicit, effortful learning. Since subjects were not informed that this is a task in which they need to attend to the structure, they were generally surprised by the task in the test phase.

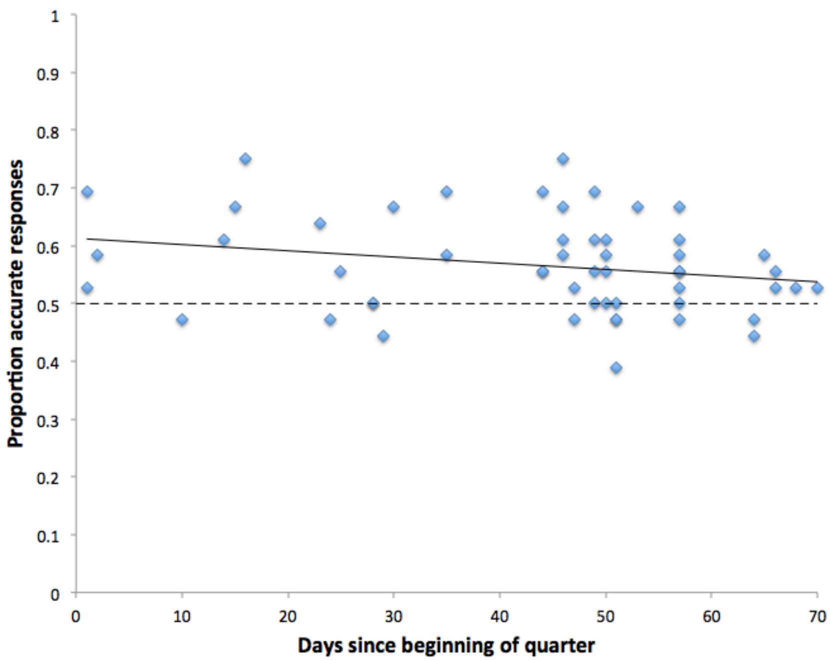
The experiment was separated into two phases. The learning phase was created using the same FSG for all four studies (described above); only the test phase structures could be different. In the test phase, adults were presented with a sequence of 36 shape strings one at a time and instructed to press the right mouse button if the displayed string matched the pattern in the learning phase and the left mouse button if it did not. Strings were presented once. Feedback (Correct/Incorrect) was provided after each trial.

Participants were asked about their subjective experience of the study after they have completed it, including if they noticed a pattern and how frustrated they became with the study. These questions were included after the study to check for awareness of learning and engagement with the task.

2.2.4 Study 1

We presented 53 participants with two sequences of shapes one at a time at test, one random and one following the structure from the learning phase. Participants viewed 18 structured strings formed using FSG A (figure 2.1a) and 18 random strings. We found that participants were able to identify the structure from the learning phase when compared against a random sequence; accuracy was significantly higher than chance (M = 0.57, SD = 0.083, $t(52)$ = 5.78, $p < 0.001$, d = 0.79). There was no change in accuracy across trials (b = 0.002, $t(34)$ = 1.76, p = 0.087). Performance across the quarter did not significantly depend on the day of participation (see Figure 2.2; regression: *b* = -.001, *t*(51) = -1.71, *p* = 0.093). A regression to probe the contribution of academic performance (college grade point average; GPA) found that GPA does not predict performance (*b* = -.015, *t*(48) = -.54, *p* = 0.59).

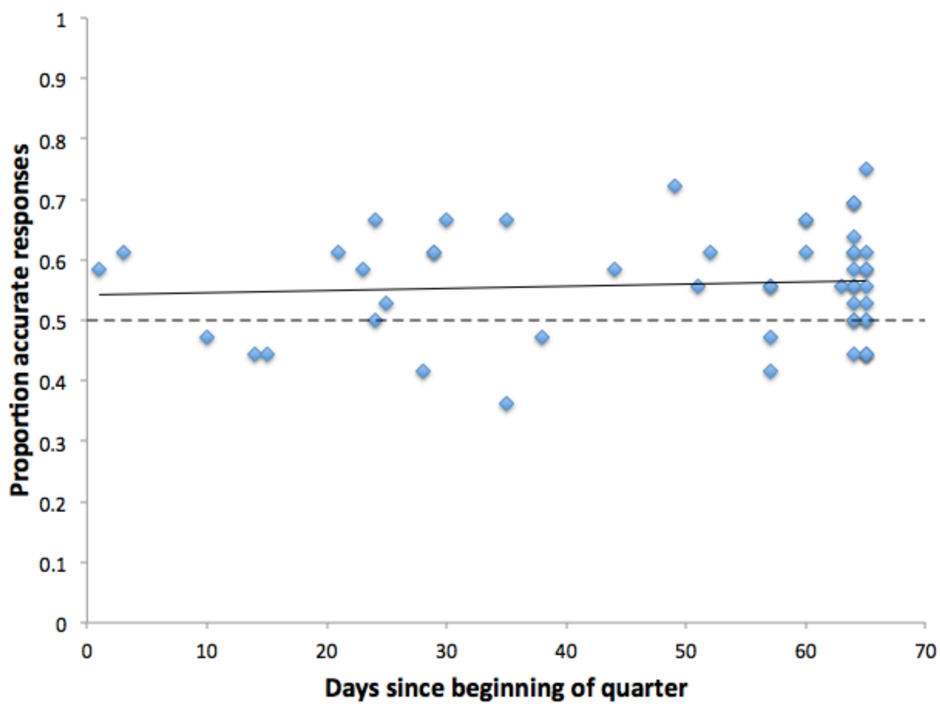
Figure 2.2. Study 1- Accuracy of performance on the task (as a proportion out of 1) is plotted against the day in the quarter that each subject participated. Accuracy is significantly above chance. The solid line is the line of best fit to the data, and the dotted line is chance (.50).



2.2.5 Study 2

We presented 52 participants with two sequences of shapes one at a time at test, one following the structure from the learning phase and the other following a new structure of comparable difficulty. Participants viewed 18 structured strings formed using FSG A and 18 structured strings formed using FSG B (Figure 2.1b). We found that participants had learned how to differentiate the structure from the learning phase against the new structure; accuracy was significantly higher than chance (*M* = 0.56, *SD* = 0.088, *t*(51) = 4.87, *p* < 0.001, *d* = 0.67). Performance across the quarter did not significantly depend on the day of participation (see Figure 2.3; regression: *b* < 0.001, *t*(50) = 0.57, *p* = 0.57). Again, there was no change in accuracy across trials (*b* = 0.001, *t*(34) = 1.19, *p* = 0.24). A regression to probe the contribution of academic performance found that GPA does not predict performance (*b* = 0.007, *t*(49) = 0.17, *p* = 0.87).

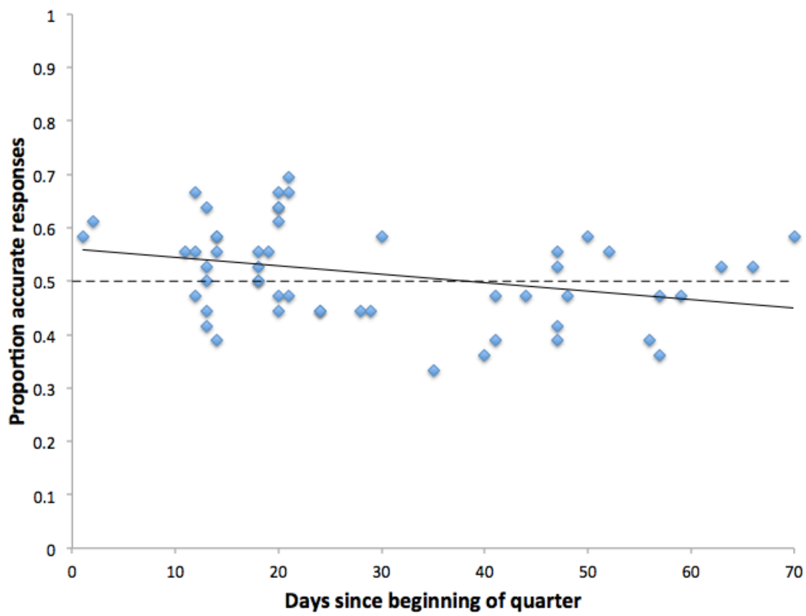
Figure 2.3. Study 2- Accuracy of performance on the task (as a proportion out of 1) is plotted against the day in the quarter that each subject participated. Accuracy is significantly above chance. The solid line is the line of best fit to the data, and the dotted line is chance (.50).



2.2.6 Study 3

At test, we presented strings formed using two structures (familiar and novel) in novel shapes to assess transfer of learning. Participants (n = 53) viewed 18 structured strings formed using FSG A and 18 structured strings formed using FSG B, presented with shape set B (novel shapes). Overall, we found that participants were not significantly different than chance (*M* = 0.51, *SD* = 0.089, *t*(52) = 1.15, *p* = 0.13, *d* = 0.16), which suggested that transfer of learning did not occur across stimuli sets. Performance across the quarter significantly depended on the day of participation (see Figure 2.4; regression: *b* = -.002, *t*(51) = -2.42, *p* = 0.019), such that participants who signed up in the beginning of the quarter were more successful than participants who signed up later in the quarter. There was no change in accuracy across trials ($b < 0.001$, $t(34) = 0.33$, $p = 0.75$). A regression to probe the contribution of academic performance found that GPA does not predict performance ($b < -0.001$, $t(37) = -.012$, $p = 0.99$).

Figure 2.4. Study 3- Accuracy of performance on the task (as a proportion out of 1) is plotted against the day in the quarter that each subject participated. Accuracy is not significantly above chance, suggesting that participants could not transfer knowledge across stimuli sets. The solid line is the line of best fit to the data, and the dotted line is chance (.50).

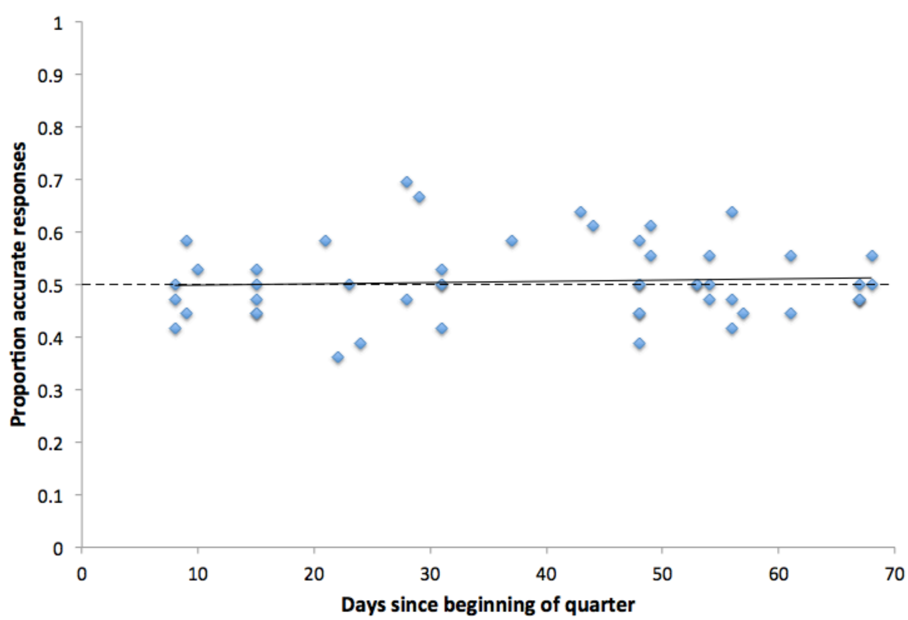


2.2.7 Study 4

In the test phase of Study 4, 50 participants were presented with 18 structured strings formed using FSG A and 18 structured strings formed using FSG B, half of each structure presented with shape set A (familiar shapes) and half presented with shape set B (novel shapes) to form four types of test trials. This design allows us to examine the priority of processing of surface and underlying features of the input. We found that participants were not able to differentiate between the underlying structures (accuracy is not different from chance: $M = 0.51$, $SD = 0.074$, $t(49) = 1.19$, $p = 0.54$, $d = 0.16$).

Additional analyses suggest that they were not able to ignore the shapes as cues: participants were significantly above chance in correctly identifying the previously learned structure when the shapes matched the novelty status of the FSG (i.e., familiar structure and shapes: $M = 0.61$, $SD = 0.23$, $t(49) = 3.44$, $p = 0.001$; novel structure and shapes: $M = 0.64$, $SD = 0.20$, $t(49) = 5.03$, $p < 0.001$) and significantly below chance when the shapes did not match the novelty status of the FSG (i.e., familiar structure and novel shapes: $M = 0.36$, $SD = 0.21$, $t(49) = -4.55$, $p < 0.001$; novel structure and familiar shapes: $M = 0.40$, $SD = 0.23$, $t(49) = -2.98$, $p = 0.004$). Performance across the quarter did not significantly depend on the day of participation (see Figure 2.5; regression: $b < 0.001$, $t(48) = 0.44$, $p = 0.66$). There was no change in accuracy across trials ($b = 0.001$, $t(34) = 1.40$, $p = 0.17$). A regression to probe the contribution of academic performance found that GPA does not predict performance ($b = -0.001$, $t(38) = -.037$, $p = 0.97$).

Figure 2.5. Study 4- Accuracy of performance on the task (as a proportion out of 1) is plotted against the day in the quarter that each subject participated. Accuracy is not significantly above chance, suggesting that participants processed the relationships between shapes in this task. The solid line is the line of best fit to the data, and the dotted line is chance (.50).



2.3 Discussion

The primary purposes of these studies were to examine implicit learning of a structure underlying strings of shapes, understand how different manipulations of the test phase impact application of that learning, and probe the potential influence of time of sign up in the quarter on performance. Study 1 established that adult participants were able to differentiate between a previously learned structure and random series of shapes in this paradigm, and Study 2 showed that participants were significantly more accurate than chance in differentiating between a previously learned structure and a second novel structure. Two manipulations of the sequences presented in the test phases of Studies 3 and 4 examined participants' abilities to transfer implicitly learned knowledge across stimuli sets and the priority of processing surface versus underlying structural relationships, respectively. Comparisons of accuracy scores across the quarter in Study 3 suggested that time of participation has the potential to influence results, especially in cross-study comparisons.

Implicit learning has been commonly studied in three paradigms: artificial grammar learning (AGL), dynamic system control, and sequence learning (Cleeremans & Dienes, 2008). The current studies use an AGL paradigm to examine the limits of implicit learning through sequence learning in adults- specifically, a finite state grammar (FSG). Using a finite state grammar, we created a complex, rule-governed environment with an underlying structure that can be learned without awareness. The underlying grammar was designed to be similar in structure to the grammar used by Reber (1967). Implicit learning often results in the extraction of the underlying structure of the input, potentially allowing learners to generalize the pattern across stimuli sets.

Implicit learning is acquired without conscious knowledge or effort on the part of the participant. Although a departure from the typical methods of studying implicit learning, this protocol was successful in eliciting implicit learning in adults, as evidenced by Study 2. The knowledge appears to have been acquired quickly in this protocol (18 exemplars in the learning phase). Previous work suggested that sequential knowledge did not appear to be reorganized during the test phase (Clegg, DiGirolamo, & Keele, 1998). There was no change in accuracy over trials across each study, suggesting that the underlying structure was rapidly learned during the first part of the experiment and that feedback after each trial did not influence performance.

In a test of the efficacy of this protocol in eliciting responses and engagement, the participants of Study 1 did not have to learn the underlying structure presented in the learning phase to succeed at test. They merely had to recognize the difference between structured and randomly generated sequences, which they were able to do. They may have been learning the underlying FSG, but that was not required for successful performance on the task. However, Study 2 requires that participants had learned the underlying statistical structure of FSG A to succeed as they are also shown sequences constructed using another structure at test. The sequences produced by FSGs A and B do not overlap for strings of shapes 6-8 units long, so the only way to successfully differentiate between the two FSGs during test phase is to (implicitly) compare each test sequence to the structure learned in the first phase of the study. Participants succeeded in this task, suggesting that they were able to compare each test sequence to the implicit knowledge of the previously presented structure and responded accordingly. They were unaware of this process, with many reporting that judgments were made because it “felt right” or they had “a hunch”. These results fit well with the existing literature on implicit sequence learning.

Study 3 found that, overall, participants could not transfer implicitly learned knowledge to a new set of stimuli. This result contrasted with Reber’s findings that transfer occurred across stimulus sets (Reber, 1969). However, the day in the quarter of the sign up significantly predicted participants’ accuracy scores. Participants were more successful in the task earlier in the quarter. A third variable, potentially personality characteristics, may have been responsible for this discrepancy, which echoes previous literature suggesting that voluntary sign-up procedures can allow personality differences to systematically bias results (Aviv et al., 2002; Zelenski, Rusting, & Larsen, 2003). Personality characteristics were a better candidate than intelligence, as GPA did not predict performance. Although the current work cannot definitively identify the reason for the change across the quarter, the time in the quarter that undergraduate participants sign up for studies can be predicted by personality differences, as well as higher levels of motivation and academic achievement. An interaction between participant engagement and task difficulty and/or complexity may result in a systematic change in performance across the quarter. Engagement may be mediated by personality characteristics, arousal, stress, and/or tiredness of the participants. Study 3 may have been just difficult enough to overtax the participants in the second half of the quarter, resulting in chance performance, while participants in the first half of the quarter found the level of difficulty just challenging enough. This interaction between arousal and performance is reminiscent of the Yerkes-Dodson law (Yerkes & Dodson, 1908).

The impact of the time of participation in the quarter should be taken into consideration when planning data collection. Possible remediation to control for this “quarter effect” include collecting data uniformly throughout the term, collecting data concurrently across studies that will be compared to each other (with each participant randomly assigned to a study), and matching data collection times across studies. Alternatively, as a systemic change, participants can be randomly assigned a window of time in which to sign up for studies. Students can be assigned a one or two week period to sign up for studies during the term. Using this last method, potential effects of personality characteristics and workload should balance out across the quarter without any additional steps during data collection.

Participants were unable to successfully identify the FSG from the learning phase (FSG A) in Study 4, suggesting that processing of surface relationships between the displayed shapes has priority over the underlying structural relationships. However, participants were significantly more accurate than chance on trials with FSG A and the original shapes, as well as trials with the nontarget grammar (FSG B) and novel shapes. Participants were less accurate than chance on trials using the target grammar with novel shapes and trials presenting the non-target grammar in the original shapes, suggesting that the highly salient change in the shapes presented was the factor that pulled their judgment of the underlying structure, not the surface relationship between the shapes. Future studies should equate the salience of the change in stimuli and structure to fully address the question of priority of processing.

Alternatively, the lack of learning in Study 4 could provide evidence for the operation of the multidimensional system. The unidimensional and multidimensional systems were predicted to have different attentional requirements. In the unidimensional system, learning was not disrupted by task-relevant information from other dimensions (Keele et al., 2003). However, attention constrained what information was processed in the multidimensional system. Since the complex information is task relevant, it may have disrupted learning.

Participants were successful in tasks with one dimension, but not two dimensions (shape identity and structure). Although Reber's (2013) reconceptualization of implicit learning as a general principle underlying all information acquisition may explain these findings, the dimensional model seems to capture much of findings in the current studies. However, additional data supporting the dimensional model using tasks other than the SRT, upon which most of the current support for the model is based, are essential to further understand the value of this framework for studying and understanding learning. The SRT, while versatile, required responses after each stimulus and was not optimized to examine passive sequence learning. The SRT also required a large number of practice trials before reaction time differences are reliable. A task that supports learning on a shorter time scale allows for the adaptation of the protocol to studies with diverse population, such as infants, children, and animals. The current studies make use of a task that fits these criteria, and merits further investigation.

The lack of spatial information in the structures is a limitation of these studies. When included in future work, manipulating the relationship between the structures generating the order of shapes and the location in which those shapes appear will allow for assessment of anticipatory eye movements through eye tracking. Spatial information may be uniquely useful additional component of information to visual learning mechanisms (Luck & Vogel, 1997), and thus facilitate visual learning. Much of the previous implicit learning work has been done with sequences of letters, and looming shapes might engage a different neural subsystem or present different challenges during learning than letters. Presenting sequences of shapes in lieu of letters allows for a shorter learning phase (as participants do not memorize the learning sequences), and facilitate the transfer of the protocol to studies with younger age groups. In future studies, testing additional manipulations of the underlying structures and shapes will allow examination of how these manipulations impact performance or ability to learn and differentiate patterns implicitly, in addition to adding to our understanding of transfer of implicitly learned knowledge across stimuli.

Sequence learning is a productive way to study complex forms of implicit learning. These studies provide evidence for implicit sequence learning, suggesting that awareness is not necessary for sequence learning to occur. The limits of this learning merit further study as work in this area continues. Examining implicit sequence learning is essential to furthering our understanding of how we process our complex, daily environment, as well as provide insight into mechanisms underlying language, social, and perceptual development. In conclusion, the current studies demonstrate that adults successfully discriminated an implicitly learned structure from both a random sequences and unique structure when presented through looming shapes on a computer screen. There are limits on implicit sequence learning of looming shapes and the timing of participation in the quarter should be taken into consideration when planning data collection.

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Chapter 3

Influence of a spatial component on implicit learning across the quarter

3.1 Introduction

Regularities in our environment provide important clues to support our behavior and learning. We are sensitive to a variety of patterns in the environment, guiding our acquisition of language, motor skills, perception, music, and social behaviors (Clegg, DiGirolamo, & Keele, 1998; Rohrmeier & Rebuschat, 2012). Much of this learning happens without awareness of what has been learned or even an intention to learn. This type of learning is referred to as implicit learning. Internalizing a sequence without conscious effort, or implicit sequence learning, allows for learning of environmental structures or patterns for possible application of the knowledge in other cognitive processes (e.g., Reber, 1967; Destrebecqz & Cleeremans, 2001). Spatial sequence learning is essential for motion perception and production of action sequences in daily life; for example, in developing the routines we use to prepare for our day each morning, for typing, and for perceiving complex visual scenes (Chun & Jiang, 1998).

The current studies contributed to understanding of the factors impacting and limits of implicit learning of a statistically defined structure. The focus was on the influence of a spatial component on learning. Spatial orienting has been shown to contribute to implicit learning (e.g., Mayr, 1996; Olson & Chun, 2002); however, the extent and form of this contribution is still a matter of debate. The purpose of this work was three-fold: 1) To examine the contribution of a spatial component (or spatial orienting) to implicit sequence learning; 2) probe individual differences in implicit sequence learning in a typical population; and 3) aid in critically examining recent theories of implicit learning.

Implicit learning can be promoted using a complex, rule-governed stimuli set under conditions which allowed for incidental learning, while measuring participant awareness of and ability to express acquired knowledge (Cleeremans & Dienes, 2008). Past studies have used artificial grammar learning paradigms (e.g., Reber, 1967; Burakowski & Johnson, in preparation) to probe the limits of implicit sequence learning in adults through a finite state grammar (FSG). Finite state grammars are structures or sets of rules that specify how shapes may be concatenated into sequences (Cleeremans, Destrebecqz, & Boyer, 1998). In the current studies, participants were shown complex, rule-governed sequences of shape strings conforming to an underlying FSG and tested on both implicit knowledge acquired and consciousness of that knowledge.

3.1.1 Spatial Learning

A significant portion of implicit learning research has been conducted with letters. Previous work with artificial grammars has used strings of letters as stimuli and asked participants to memorize the letter strings (Reber, 1967). Others have used letters (for example, upright and rotated Ts and Ls) in visual search tasks (e.g., Olson & Chun, 2002). However, shapes were used in this protocol because the design allowed these studies to test the contribution of one or several components of information, as well as easily manipulate those components. Spatial and shape dimensions could be systematically changed, and the influence of a spatial component on learning could easily tested by distributing the shapes in space. The manipulation of these dimensions in the same paradigm allowed for valid comparisons of learning across studies.

Spatial components of implicit sequence learning have been studied in several different paradigms. Mayr (1996) presented participants with independent sequences of shapes and locations to explore simultaneous learning of spatial and order structures. He observed implicit learning of spatial sequences and that participants were able to learn spatial and non-spatial (object-response) sequences simultaneously, suggesting that these factors were processed independently (Mayr, 1996). These findings provided evidence of our ability to learn a spatial component implicitly, pointed to the adaptability of implicit learning, and demonstrated that multiple informational components were processed and learned simultaneously. The current studies manipulated how many components of information participants were presented with and the impact on learning.

The context cueing paradigm had also been employed to assess participants' visual learning of spatially organized stimuli and could aid in developing an understanding of the capabilities of implicit sequence learning. Chun and Jiang (1998) used a contextual cueing paradigm to show that consistencies in the spatial layout of stimuli were learned as cues to facilitate performance without awareness of the regularities. This paradigm was employed to further investigate how spatial relationships are learned (Olson & Chun, 2002). Rotated letter "T"s and "L"s were presented to participants in spatial arrangements. Participants had to identify a target in the arrays, some of which were repeated. Although unaware of the consistency in the patterns across time, the participants were sensitive to information from the presented context, as evidenced by a decrease in reaction time. The implicit memory of invariant spatial contexts facilitated target identification by cueing the location of the target and guiding attention. Consistencies in the spatial organization of the visual context facilitate implicit learning, even in the presence of a certain amount of random, uninformative noise in the visual environment (Olson & Chun, 2002). One of the current studies (Study 3) aimed to replicate this finding in the present paradigm.

Another demonstration of spatial implicit learning that was helpful in understanding the current studies comes from the serial reaction time (SRT) task. Shin and Ivry (2002) manipulated the timing and sequential information in this SRT task. Participants were asked to press a button when an X appeared in specific locations on a screen and the presence of both temporal and spatial information resulted in improved performance. Reframed, the presence of two informational components supported learning of regularities in the input. The current studies will address this same question in passive sequence learning. From the existing literature, spatial information appeared to play an important role in implicit sequence learning. However, the limits of learning and impact of changes in a spatial component on learning were still unclear.

3.1.2 Individual differences

Studies of implicit sequence learning have been conducted with typical and atypical populations. Adults of a variety of ages learn statistical dependencies implicitly, but some differences were observed (Howard & Howard, 1997). Young adults learned more complex higher-order information than older adults (Howard & Howard, 1997), which may be related to changes in fluid intelligence with age (Danner et al., 2011- check). Dyslexics were found have unimpaired spatial context learning, but they did show some impairments in higher-order implicit sequence learning (Howard, Howard, Japikse, & Eden, 2005). Many of these studies have relied on comparisons across tasks to examine variability. Currently, widely used protocols may not have captured individual differences in implicit sequence learning. A thorough examination through targeted experiments is necessary to attain a greater understanding of the variability in learning.

Personality characteristics were another possible source of variability in implicit learning tasks. Motivation, academic performance, and personality factors such as level of extraversion and conscientiousness have been show to vary based on the time of the term in which undergraduates volunteer for studies (Bender, 2007; Witt, Donnellan, & Orlando, 2011). Additionally, the previously mentioned personality factors may have been more strongly predictive of burnout than actual workload (Jacobs & Dodd, 2003), which may introduce further variability into performance. When comparing results across experiments, non-uniformly distributed variability can pose problems for analyses. The current studies examined of the impact of the time of participation on performance to weigh in on the necessity of ruling out the impact of sign up time on these studies.

3.1.3 Theories of learning

Models of learning are useful in guiding task formation and testing of hypotheses. A recent model of sequence learning posited that two distinct learning systems represent sequential regularities in the brain and have different computational capabilities (Keele, Ivry, Mayr, Hazeltine, & Heuer, 2003). The unidimensional and multidimensional systems represented different, but often overlapping, types of learning. Unidimensional learning was implicit and automatic and learned one dimension at a time, while the multidimensional system could be implicit or explicit while learning and integrating more than one dimension simultaneously.

The majority of support for this model was derived from the SRT task (Nissen & Bullemer, 1987) task. In this task, participants responded to signals such as tones or stimuli on a screen as quickly as possible. Reaction time, the measure of interest, was compared across conditions, or blocks of trials. These conditions had both random sequences and sequences ordered according to an underlying structure. Differences in reaction times across conditions suggested that learning had occurred and provided a quantifiable way to compare learning across manipulations (Keele et al., 2003).

Another conceptualization of implicit learning was that it operated as a general principle governing processing of information in the brain, as opposed to a clearly defined specific neural region or network (Reber, 2013). Implicit learning was a constant, ever-present process in this conceptualization, underlying all behavior regularity and adjustment (Reber, 2013).

3.1.4 Summary

These studies examined the binding of the color/shape and spatial location of the stimuli, as well as possible unique advantages to processing statistical information visually. Study 1 examined participants' abilities to discriminate between two FSGs when spatial information was present but noninformative. Study 2 probed participant discrimination of an implicitly learned FSG in the presence of conflicting spatial information. Shapes in Study 3 were completely randomized, so that they were noninformative, and were presented in two distinct spatial structures (as opposed to structures controlling the order of the shapes). Study 4 was the complement of Study 3, presenting two FSGs ordering shapes with random (lack of) spatial information. We predicted that participants would be able to discriminate between the two structures (FSG or spatial) unless the information removed in the manipulation was crucial to support implicit sequence learning.

3.2 Method and Results

3.2.1 Participants

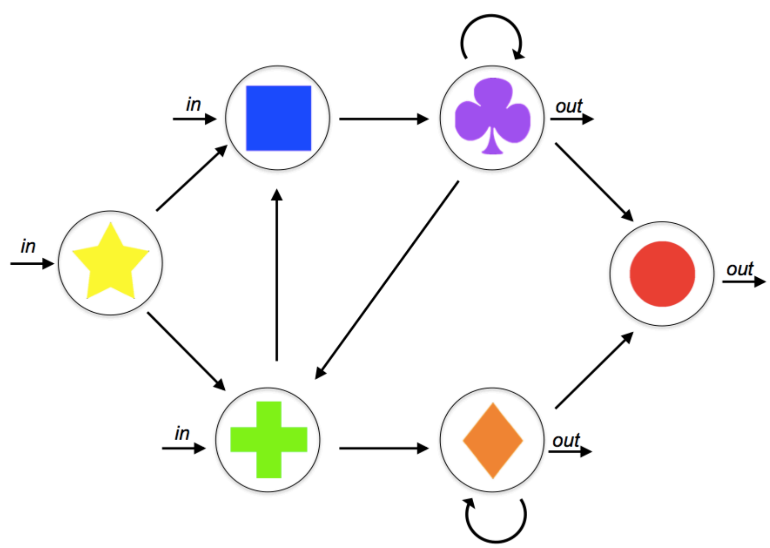
We recruited and tested 204 UCLA undergraduates (162 female) in the four studies. We excluded 70 participants: 47 for expressing explicit knowledge of the patterns (19 in Study 1, 13 in Study 2, 13 in Study 3, 2 in Study 4), 9 as statistical outliers (2 in Study 1, 4 in Study 2, 2 in Study 3, 1 in Study 4), 1 due to experimenter error, 2 due to participant error, 10 due to failure to track or calibrate, and 1 due to some type of colorblindness. Participants were recruited through the Psychology Department SONA Systems Subject Pool; all received course credit or extra credit for participation.

3.2.2 Materials and Design

The materials and procedure were essentially identical to those used by Burakowski and Johnson (in preparation). Stimuli were presented on a 1680x1050 pixel screen with a refresh rate of 60hz using SR Experiment Builder. Eye movement data were collected using an EyeLink 1000 eye tracker with a sampling rate of 500hz (SR Research). The program randomly selected six differently colored shapes from a set of eight shapes at the beginning of each session to populate the grammatical structures, which loomed at a rate of 60 frames per second (from 160x160 to 280x280 pixels) one at a time on a black background. There were three possible underlying structures governing the order of the shapes presented: the target structure, FSG A (see Figure 3.1a), the nontarget structure, FSG B (see Figure 3.1b), and random (no structure/not matching other structures). All structures were constrained to start and end with the same elements within each subject. There were also two structures constraining the order of the locations in which shapes appeared in Study 3 (Figure 3.2). All studies are between-subjects.

Figure 3.1. a) The statistical structure underlying FSG A. This structure determined the order of the shapes in the learning phase and half of the trials in the test phase in Studies 1, 2, and 4. b) The statistical structure underlying FSG B. This structure determined the order of the shapes in half of the trials in the test phase in Studies 1, 2, and 4.

a)



b)

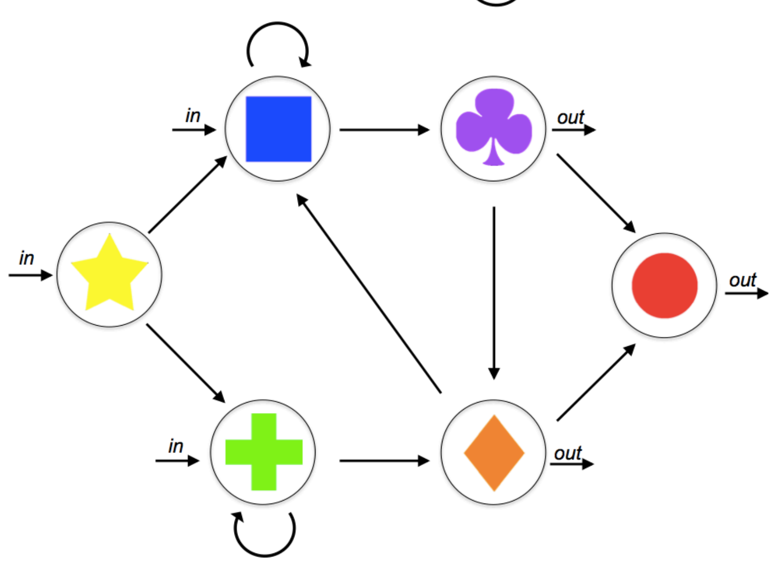
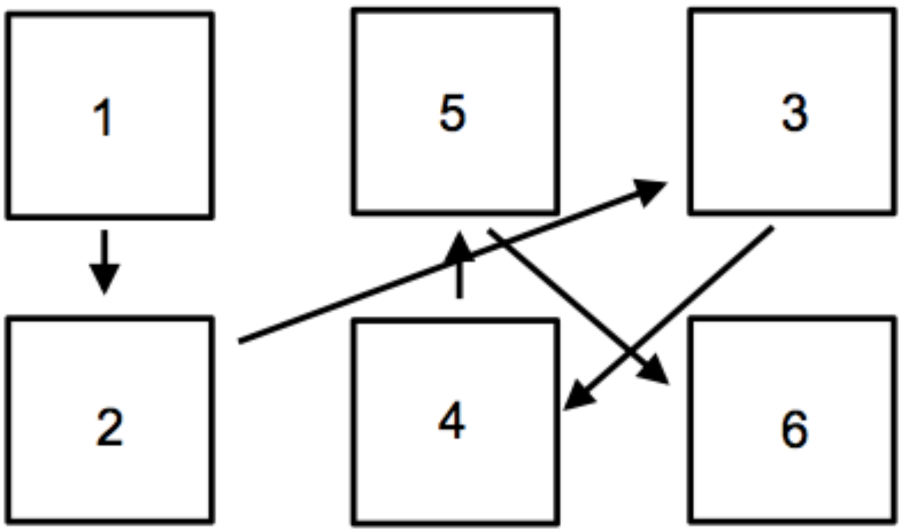


Figure 3.2. An example of the spatial structure used to create strings in Study 3.



In the learning phase, 18 strings were shown, and 36 strings (18 target, 18 other) are presented in the test phase. To provide maximum exposure to unique examples of the FSG, a set of strings was created and during each session strings were randomly selected without replacement so that no individual string was repeated in the learning or test trials. During the learning phase, participants viewed 18 strings (chosen from the prepared set) of consecutive looming shapes, following the regularities of the FSG. These strings were displayed as a sequence and separated by a brief (0.5-1.5 second) centrally presented attention-getter (colorful image moving with sound).

Participants were excluded from primary analyses if they expressed explicit knowledge of the underlying FSG. Time slots for signing up to participate were posted no more than a week in advance of the test date. Scan patterns (collected via eye tracking) may provide clues to the mechanisms used to process the shape sequences, as participants may change their looking pattern or duration as the information needed to process each test string changes with learning. Additional analyses will examine the change in eye movement latencies across trials to further probe implicit sequence learning of the statistically defined structure. A reduction in latency may be observed as participants learn the underlying structure of the strings.

Participants were excluded as outliers if Cook's distance was above the criteria set for each study by 4/n, where n was the sample size (Bollen & Jackman, 1990). An alpha level of 0.05 was used for all statistical tests.

3.2.3 General Procedures

The general procedures are, again, essentially identical to those used by Burakowski and Johnson (in preparation). During the consent process, participants were told that they would be reading instructions and watching shapes on a monitor, and would click through instructions with a mouse. Participant age, SAT scores (if applicable), level of arousal (tiredness), and colorblind status were recorded. Each study was introduced as an examination of learning across development without reference to a pattern to reduce explicit learning.

The studies were separated into a learning and test phase. Strings in the learning phase were formed with FSGA (Figure 3.1a) for Studies 1, 2, and 4; only the test phase structures could be different. Study 3 presented structures controlling the order in which locations were occupied on the screen. In the test phase, 36 shape strings were presented one at a time. Participants were instructed to press the right mouse button if the string fit the pattern in the learning phase and the left mouse button if it did not. Feedback (Correct/Incorrect) was provided after each trial.

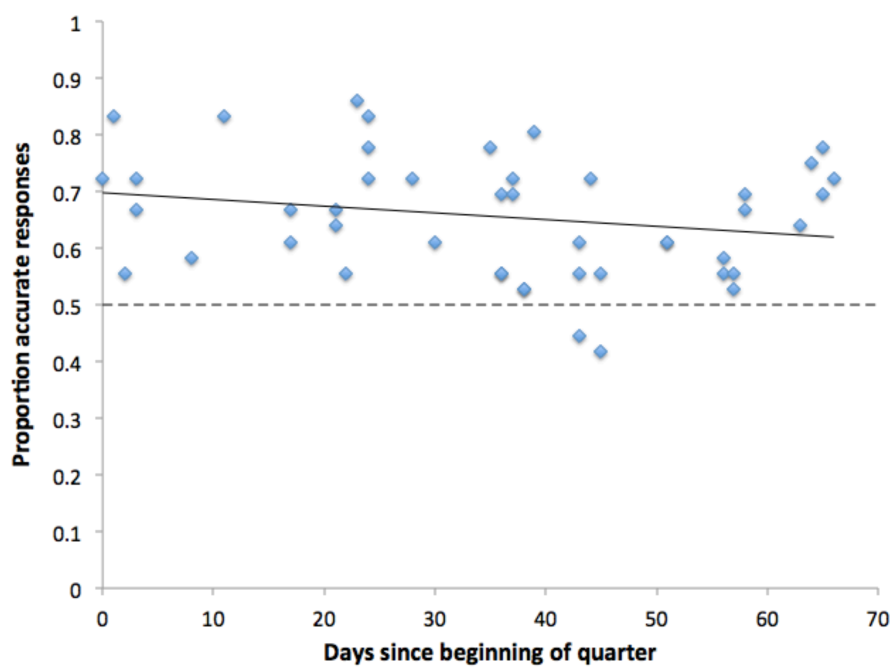
Questions regarding participants' subjective experience were included after the study to check awareness of learning and engagement with the task (i.e., if they noticed a pattern and how frustrated they felt). Participants were generally surprised and often slightly frustrated by the task in the second phase of the study.

3.2.4 Study 1

The first study held location information constant so that it was not uniquely informative. In the learning phase, each shape was assigned a spatial location on the screen. This assignment was held constant across both phases of the study. Strings formed using FSG A were presented in the learning phase, and strings created with both FSG A and FSG B (Figure 3.1a and 3.1b) were presented in the test phase. Participants (n = 46) successfully discriminated between a previously learned and novel structure (one sample t-test: $M = 0.66$, $SD = 0.11$, $t(45) = 9.96$, $p < 0.001$, $d = 1.47$), which suggested that participants could differentiate between FSGs in the absence of uniquely informative spatial information.

Performance across the quarter did not significantly depend on the day of participation (see Figure 3.3; regression: $b = -.001$, $t(44) = -1.48$, $p = 0.15$). A regression to probe the contribution of academic performance (college grade point average; GPA) found that GPA did not predict performance ($b = -.023$, $t(43) = -.52$, $p = 0.61$). There was no change in accuracy across trials ($b = 0.001$, $t(34) = 0.77$, $p = 0.45$).

Figure 3.3. Study 1- Accuracy of performance on the task (as a proportion out of 1) is plotted against the day in the quarter that each subject participated. Accuracy is significantly above chance. The solid line is the line of best fit to the data, and the dotted line is chance (.50).



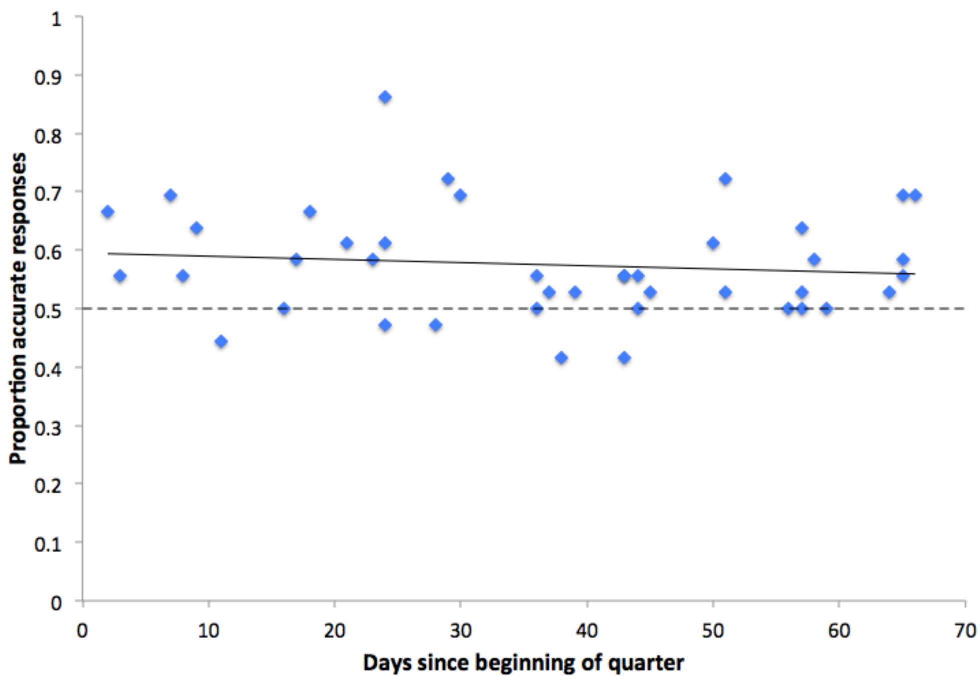
3.2.5 Study 2

The goal of this study was to examine discrimination of an implicitly learned FSG in the presence of conflicting spatial information. Does spatial information (either not uniquely informative, or random) influence learnability of the underlying structure? The learning phase is the same as Study 1: Strings were created using FSG A, and each shape was assigned a spatial location on the screen (referred to as spatial location association (SLA) 1). The test phase had four different types of test trials (9 of each type): FSG A with SLA 1, FSG A with random spatial location associations for each shape, FSG B with SLA 1, and FSG B with random SLAs. Participants (n = 42) again successfully discriminated between a previously learned and novel structure ($M = 0.57$, $SD = 0.092$, $t(41) = 5.25$, $p < 0.001$, $d = 0.81$).

Additional analyses showed that participants responded differently to one type of test trial. For the nontarget FSG (FSG B) with SLA 1, participants were not able to successfully choose "no" and were at chance ($M = 0.55$, $SD = 0.22$, $t(41) = 1.40$, $p = .17$). Responding was below chance for FSG A with random SLAs ($M = 0.37$, $SD = 0.18$, $t(41) = -4.61$, $p < 0.001$), indicating that participants were incorrectly choosing "no". Participant responding was above chance for the other two trials types: Participants correctly choose "yes" for FSG A with SLA 1 ($M = 0.68$, $SD = 0.19$, $t(41) = 6.25$ $p < 0.001$), and correctly choose "no" for FSG B with random SLAs ($M = 0.72$, $SD = 0.20$, $t(41) = 7.32$, $p < 0.001$).

Performance across the quarter did not significantly depend on the day of participation (see Figure 3.4; regression: $b = -.001$, $t(40) = -.72$, $p = 0.47$). A regression to probe the contribution of academic performance found that GPA did not predict performance ($b = 0.093$, $t(37) = 1.81$, $p = 0.079$). There was no change in accuracy across trials ($b < 0.001$, $t(34) = 0.48$, $p = 0.64$).

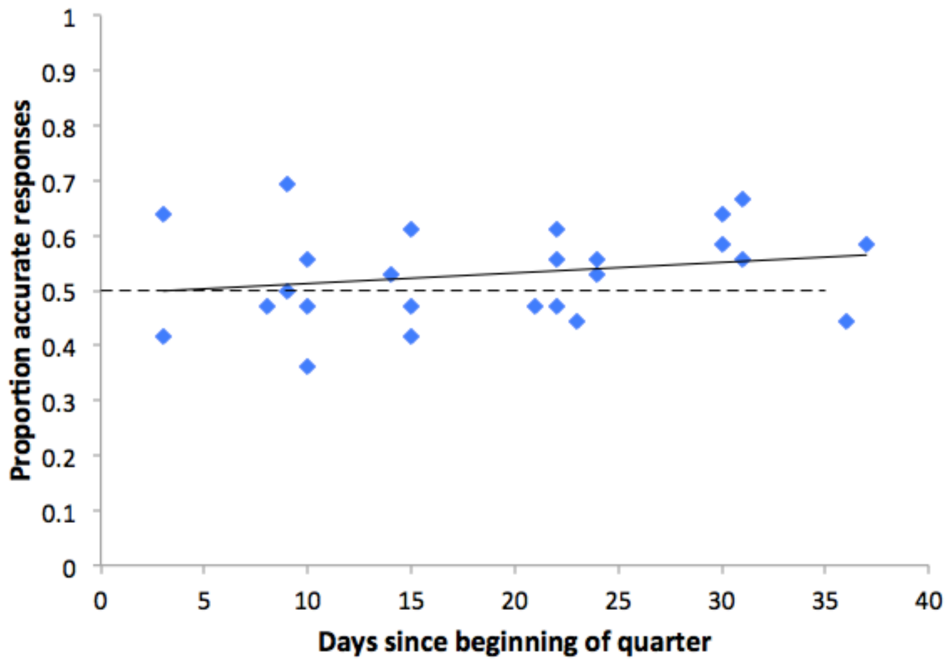
Figure 3.4. Study 2- Accuracy of performance on the task (as a proportion out of 1) is plotted against the day in the quarter that each subject participated. Accuracy is significantly above chance. The solid line is the line of best fit to the data, and the dotted line is chance (.50).



3.2.6 Study 3

The third study presented two distinct spatial structures with random shapes (Figure 3.2), examining learning when only spatial regularities were present. Participants (n = 25) successfully discriminated between previously learned and novel spatial structures (*M* = 0.53, *SD* = 0.086, *t*(24) = 1.75, *p* = 0.047, *d* = 0.35), which suggested that spatial information was sufficient for implicit sequence learning without information detailing the ordering of the shapes. Regressions to probe the contribution of time of participation (day) and academic performance to task performance found that day did not predict performance (see Figure 3.5; *b* = .002, *t*(23) = 1.10, *p* = 0.28), and GPA did not predict performance (*b* = -.006, *t*(21) = -.12 *p* = 0.91). There was no change in accuracy across trials (*b* = 0.002, *t*(34)= 1.33, *p* = 0.19).

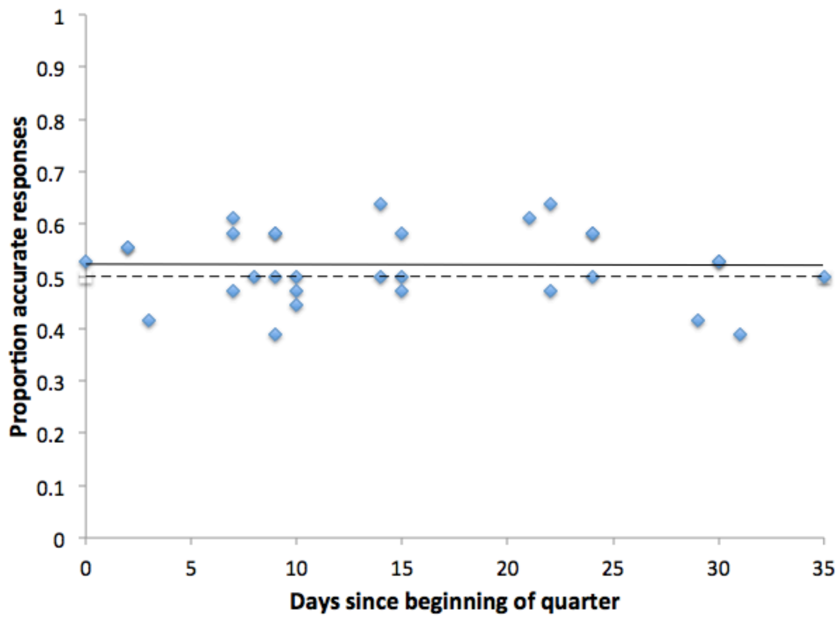
Figure 3.5. Study 3- Accuracy of performance on the task (as a proportion out of 1) is plotted against the day in the quarter that each subject participated. Accuracy is significantly above chance. The solid line is the line of best fit to the data, and the dotted line is chance (.50).



3.2.7 Study 4

The fourth study presented a structure ordering the appearance of the shapes (like the first two studies) but with random spatial assignments (for each string, shape locations were chosen randomly). Participants (n = 35) successfully discriminated between the previously learned and novel structures (*M* = 0.52, *SD* = 0.066, $t(34) = 1.99$, $p = 0.027$, $d = 0.34$), which suggested that order information in the presence of inconsistent spatial information was sufficient for implicit sequence learning. Regressions to probe the contribution of time of participation (day) and academic performance to task performance found that day did not predict performance (see Figure 3.6; $b < -.001$, $t(33) = -.072$, $p = 0.94$), and GPA did not predict performance ($b = 0.007$, $t(33) = 0.40$, $p = 0.69$). There was no change in accuracy across trials ($b = -.002$, $t(34) = -1.02$, $p = 0.32$).

Figure 3.6. Study 4- Accuracy of performance on the task (as a proportion out of 1) is plotted against the day in the quarter that each subject participated. Accuracy is significantly above chance. The solid line is the line of best fit to the data, and the dotted line is chance (.50).



3.2.8 Comparison across studies

Comparing performance across studies may help answer the question of the relative difficulty of each task. Study 1 presented consistent (not uniquely informative) spatial information with the structured order information, while Study 4 presented the same order information with random spatial information. Participants were significantly more accurate in Study 1 (M = 0.66, SD = 0.11) than Study 4 (M = 0.52, SD = 0.066, $t(79)$ = 6.53, p < 0.001).

Studies 3 and 4 both presented one type of predictive and one type of random information: random shapes in study 3 and random locations in study 4. There was no difference in accuracy scores between Study 3 (M = 0.53, SD = 0.086) and Study 4 (M = 0.52, SD = 0.066, $t(58)$ = 0.40, p = 0.69), which suggested that the type of random information might not have mattered in determining whether it will impact learning.

3.3 Discussion

These studies examined the factors impacting the limits of implicitly learning of a statistically defined structure using strings of shapes presented sequentially as stimuli. The focus was on the influence of a spatial component on learning. Participants were able to differentiate between the target and nontarget sequences in all of the above studies, showing evidence of implicit sequence learning of both spatial and nonspatial information. Implicit learning could take place when learning is observational, unlike some previous work that had suggested otherwise (Kelly & Burton, 2001). Additionally, the time of participation in the quarter did not predict performance.

Study 1 manipulated the amount of information contained in the spatial component of the sequence. Each shape was presented in the same (its own) location during each trial, regardless of the type of trial (target structure or nontarget structure). Spatial information was consistent across the study and did not directly help participants identify the target structure. Participants learned the target structure; only the order information was necessary when spatial information was consistent. Participants were most accurate in this study; learning two types of information may result in better performance than relying solely on one type. This finding is consistent with previous work by Shin and Ivry (2002), and showed that components of information could be integrated to aid performance. Two dimensions were present (order and spatial information), and performance was facilitated. The results suggested that participants were attending to both of the components, so attention was not a limiting factor.

Study 2 was designed to probe further into the role that the type of spatial information played in learnability of a sequence. Shapes were presented in consistent locations in the learning phase of the study, and for half of the trials for each type of structure (target/nontarget) in the test phase. The other half of the test trials did not have consistent spatial information (i.e., the locations for each shape were chosen randomly for each trial), resulting in four types of trials. Overall, participants were able to successfully identify the target structure. However, the change in spatial structure strongly influenced judgments of the structures. Participants indicated that the target strings did not match the target structure when the location information was random, and could not decide if the nontarget strings matched the target structure when the location information was consistent with the learning phase (they were at chance). A possible explanation for this behavior is that the location associations were a salient cue for participants, and judgments were partially conditional upon that type of information. Participants responded accurately on trials with the target strings and consistent location information, and the nontarget strings and random spatial location information. Despite receiving feedback after decisions, behavior did not change across the study, which suggested that implicit learning was responsible for performance on this task. Location information seems to have been an important cue for participants; when spatial information was present, participants attempted to use it to guide their responses. Two dimensions were present (order and spatial information), and participants performed well.

In the third study, participants viewed a sequence of strings that were organized by location; the order of the locations appearing on the screen contained the structure. Shapes are chosen at random to fill the locations in the structure. Participants were able to discriminate between the target and nontarget spatial structures. These results showed that one dimension, spatial information, was sufficient for learning regularities implicitly.

Study 4 was the complement of Study 3. Participants were exposed to a structure determining the order of the shapes while location information was random. Learning was again observed, despite the absence of spatial regularities. These results showed that spatial information was not necessary for visual sequence learning. Participants were able to filter out the randomness in the location information to make accurate judgments during the task.

As seen from the above results, the presence of informative spatial information is not necessary for learning. The mere presence of spatial information in the input, with the shapes spread out on the screen randomly, might have supported learning. Participants were more accurate in their judgments when the locations of the shapes were consistent than when locations were random. This pattern suggested that participants were still processing the spatial information, despite the uninformative nature of the input. A possible explanation for this result was that the location information did not impose an additional load on memory. Individual features of units, like color and location, were integrated in visual working memory, as opposed to being stored independently (Luck & Vogel, 1997). Luck and Vogel (1997) found that the capacity of visual working (explicit) memory was about four units. In comparison, the strings in this study were six to eight units long. To succeed in the tasks, participants could not solely compare strings using working memory; they needed to have learned the underlying structure to be successful. The addition of a nonrandom spatial component may have tapped into advantages unique to visual learning and provided additional information, which was used to bind to each unit in memory and increase the ease of differentiating between units. In this way, spatial information may have reduced the difficulty of learning a statistical structure visually.

The results of these studies could be explained by both the dimensional theory and the conceptualization of implicit learning as a general principle of processing. Participants were able to learn and use information presented with two components, regardless of which manipulation was applied. The dimensional theory predicts that participants would have engaged both the unidimensional and multidimensional systems to have integrated across both components and used the information to respond to the task. Engagement of this system would have resulted in the same type of result as engagement of the general principle governing processing of information in the brain (Reber, 2013), and thus did not differentiate between theories.

The time of participation in the quarter did not influence performance. Some tasks of particular difficulty or requiring certain levels of engagement may have been impacted by variability in participant pools across the term (Bender, 2007; Burakowski & Johnson, in preparation). Even though performance was not predicted by day of participation in any of the current studies, checking for or controlling for contamination due to participant effects remained important, especially for researchers who wish to compare results statistically across studies.

The knowledge (or lack thereof) applied in the test phase appears to have been acquired quickly in this protocol, with only 18 exemplars in the learning phase. Previous work suggested that sequential knowledge did not appear to be reorganized during the test phase (Clegg, DiGirolamo, & Keele, 1998). There was no change in accuracy over trials across each study, suggesting that the underlying structure was rapidly learned during the first part of the experiment and that feedback after each trial does not influence performance.

Academic performance, indexed by GPA in the current studies, did not predict performance on the tasks. Academic performance was positively correlated with widely used measures of cognitive ability (Brody, 1997), which could be conceptualized as the ability to learn explicitly and report what has been learned. These studies seemed to be tapping into an ability that was not measured cleanly by academic performance, and may vary independently. This particular result lent support for a theory of two mechanisms for explicit and implicit learning operating independently, in agreement with a recent review by Reber (2013).

In conclusion, adults could implicitly learn one FSG well enough to differentiate it from another FSG when exposed to strings of shapes, and a spatial component facilitated that process. When taken together with the results from other studies using the same paradigm (Burakowski & Johnson, in preparation), these studies provided more evidence for implicit visual sequence learning in a passive paradigm, as well as supported the construct of an independent mechanism responsible for implicit learning.

3.4 References

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Chapter 4

Comparisons Across Studies

4.1 Comparison of means

All of the current studies were presented with the same paradigm with the same stimuli, and all but Study 7 used the same underlying structure in the learning phase (FSG A). In this chapter, the introduction chapter, and the conclusion chapter, the studies in Paper 2 are referred to as Studies 5-8 instead of Studies 1-4, respectively.

Performance was expected to differ across studies, or manipulation of information that may have been learned and used to succeed in the test phase. A one way analysis of variance was conducted with study number as group and accuracy (performance) as the dependent variable. There is a significant difference in performance across studies, $F(7, 348) = 14.29$, $p < 0.001$ (see Figure 4.1). Planned posthoc analyses were conducted using t-Tests with Bonferroni corrections. Participants were significantly more accurate in Study 5 than all other studies (see Table 4.1). When presented with two non-random components, like in Study 5, participants are more successful than when presented with one component or with random information.

Figure 4.1. Comparison of means (in proportion of correct responses) across studies.

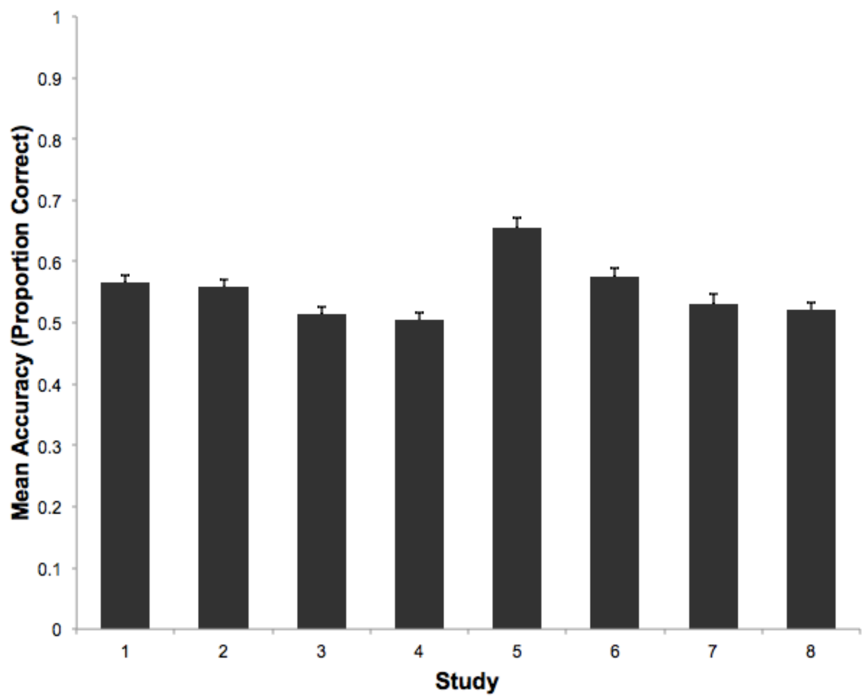

Table 4.1. Comparisons against Study 5. Bonferroni corrected independent sample t-Tests with Study 5 and all other studies. Accuracy in Study 5 is higher than all other studies. Standard Deviations appear in parentheses below means.

Study	Mean (*SD*)	Mean Difference	*p*
Study 1	0.57 (0.083)	0.089	<0.001
Study 2	0.56 (0.088)	0.096	<0.001
Study 3	0.51 (0.089)	0.14	<0.001
Study 4	0.51 (0.073)	0.15	<0.001
Study 5	0.66 (0.11)	-	-
Study 6	0.57 (0.092)	0.081	<0.001
Study 7	0.53 (0.086)	0.13	<0.001
Study 8	0.52 (0.066)	0.13	<0.001

Participants were significantly more accurate in Study 1 than Study 4 (mean difference = 0.069, p = 0.004). Participants are able to succeed in Study 1 because they were using one component, structure, to make responses. Whether participants learned the underlying structure or just recognized the presence of it did not matter for this argument; however, performance on the following studies suggests that participants did learn the underlying structure. Participants in Study 4 were not able to use the informative component (structure/order of the shapes) to successfully make judgments, and seem to be using the shape identities (familiar or novel) instead, and were unable to both transfer knowledge across stimuli sets and differentiate between two structures organizing the stimuli.

Additionally, participants were significantly more accurate in Study 6 than Study 3 (mean difference = 0.061, p = 0.022), and more accurate in Study 6 than Study 4 (mean difference = 0.069, p = 0.004). Learning was not observed in Studies 3 and 4. Participants were not able to transfer knowledge of an underlying structure across a change in stimuli (shape set), but they were able to transfer this knowledge across a spatial dimension (Study 6). This difference in performance points to a possible unique advantage of spatial information in visual processing. Processing information in the visual dimension, at least in this paradigm, seems to be easier than processing information about the underlying structure of stimuli or the specific stimuli characteristics.

4.2 Exclusions

This series of experiments focused on implicit learning. As implicit learning has generally been defined to occur below awareness and result in unverbalizable knowledge, participants were excluded if they expressed explicit knowledge of the underlying structure; specifically, sufficient knowledge to differentiate the structure from the learning phase from the comparison in the test phase. Participants were expected to perform better if they explicitly noticed the pattern or structure, as they would be making judgments based on an explicit criterion (or criteria, depending on how much of the pattern they noticed) instead of responding based on a vague “feeling” that the pattern matched what was presented in the learning phase or not.

Explicit knowledge seemed to help participants perform better in most, but not all, of the studies. Participants excluded in Study 1 (n = 8, $M = 0.74$, $SD = 0.12$) scored significantly better than non-excluded participants (n = 53, $M = 0.57$, $SD = 0.083$, $t(59) = 5.16$, $p < 0.001$). Participants excluded in Study 2 (n = 9, $M = 0.69$, $SD = 0.12$) again scored significantly better than non-excluded participants (n = 52, $M = 0.56$, $SD = 0.088$, $t(59) = 3.73$, $p < 0.001$). Participants excluded in Study 5 (n = 18, $M = 0.75$, $SD = 0.12$) scored significantly better than non-excluded participants (n = 46, $M = 0.66$, $SD = 0.11$, $t(62) = 3.03$, $p = 0.004$). Finally, participants excluded in Study 7 (n = 13, $M = 0.72$, $SD = 0.21$) scored significantly better than non-excluded participants (n = 25, $M = 0.53$, $SD = 0.086$, $t(24) = 4.09$, $p < 0.001$). However, participants excluded in Study 6 (n = 13, $M = 0.61$, $SD = 0.15$) did not score significantly better than non-excluded participants (n = 42, $M = 0.57$, $SD = 0.092$, $t(53) = 0.93$, $p = 0.36$). Not enough participants were excluded in Studies 3, 4, and 8 to run analyses (zero, four, and two respectively).

A potential explanation for the lack of difference between excluded and included participants in Study 6 was that Study 6 was more complex than the other studies in which participants were successful. Participants had to learn the same amount of information in the learning phase as in the other spatial studies. During the test phase, however, participants had to keep track of two FSGs and two types of spatial information (trials in which shapes were randomly located and trials that matched the spatial location associations from the learning phase). This may have added an additional processing load, as two different representations needed to be formed regarding the same component to succeed on the task. This additional complexity may have reduced the influence of explicit knowledge on performance.

Chapter 5

General Conclusions

5.1 General Conclusions

This body of work sought to examine the nature and limits of implicit learning, explore individual differences in implicit learning, and understand learning observed in these studies in context of current theories of implicit learning. Overall, adults can learn implicitly using the protocol employed by the current studies, so it was useful for examining limits of implicit sequence learning. Different manipulations of the information presented to participants in the learning and test phases had differential effects on learning. These manipulations provided support for both the Keele et al. (2003) and Reber (2013) theories of implicit learning.

Chapter 2 demonstrated that the paradigm employed in the current studies was successful in eliciting implicit visual sequence learning using looming shapes and underlying statistical structures (FSGs). Participants were able to learn a structure and differentiate from both randomly ordered shapes (no structure) and a novel structure. However, participants were not able to transfer knowledge across stimuli sets. A potential explanation for this observation is that participants were not processing the underlying structure abstractly, but instead processed the surface relationships between the shapes. Alternatively, surface features such as shape identity could have strongly influenced participants' judgments. Participants were not able to use the informative component (structure/order of the shapes) to successfully make judgments, but seemed to be using the shape identities (familiar or novel) instead. This study (Study 4) may have been difficult because participants were asked to both transfer knowledge across stimuli sets and differentiate between two structures organizing the stimuli. In addition, it appeared that the attentional constraints on the multidimensional system may have played a role in performance by allocating attention away from the underlying structure of the shapes.

Chapter 3 addressed the contribution of two (spatial and order) components of information to sequence learning. Participants succeeded in sequence learning with two (spatial and order) components of information, and also when those two components were crossed to produce four combinations to track. This result suggested a potentially unique advantage of visual processing when combined with order. Participants performed best in Study 5. In this study participants were exposed to two components of information, both of which were structured. Shape was organized using a probabilistic structure, and location was organized using a deterministic structure (shapes always appeared in the same location across the study). Two types of structured information resulted in improved learning.

A processing advantage for spatial information was also supported by participants' failure in Study 4 but success in Study 6. Those studies both presented two components of information, either shape identities or shape location associations, respectively, in addition to the order of the shapes. Participants were successful when the dimension with additional (potentially confusing) information was spatial. Visual implicit learning may be optimized to process spatial information, as fine-grained spatial information is uniquely a visual system feature.

Overall, these analyses demonstrate that different manipulations of the information participants are presented with in the learning and test phases have differential effects on learning. The finding that performance did not change across trials in any of the studies supported the conception of this task as accessing implicit learning. Mechanisms generating performance were not accessible to explicit thought, and thus performance could not be altered intentionally. Additionally, participants reported that they did not have explicit knowledge of the underlying structures.

One dimension, the underlying structure of the order of the shapes, was manipulated in Studies 1 and 2. Studies 7 and 8 also involved manipulating one dimension; spatial location and order of shapes, respectively. The manipulations in Study 3 and 4 involved two dimensions, the shape set and underlying structure of the order of the shapes. Studies 5 and 6 also manipulated two dimensions, underlying structure and spatial location information. These studies provided support for both the dimensional model (Keele et al., 2003) and the general principle conceptualization (Reber, 2013), as previously discussed.

The number of dimensions of information manipulated in each study did not seem to predict success on the task. In both Studies 3 and 4, and 5 and 6, participants were exposed to two dimensions that changed. However, participants did not display the same pattern of performance across the pairs of studies- they only succeed in Studies 5 and 6. The distribution of attention during the task might have played a role in the successful performance in studies with a spatial component. Participants could have modulated their attention based on the type of information they were receiving. Alternatively, spatial information might have been easier for participants to process and integrate with information provided by the underlying FSG. This interpretation builds off of previously discussed observations in this document, providing a multi-faceted argument of the unique advantage spatial information provided to visual sequence learning.

5.2 Future directions

This paradigm allows for the manipulation of various components of information to further explore the capabilities of human implicit sequence learning. An important direction of investigation that remains to be examined is the influence of a new set of shapes (stimulus set) during the test phase presented with a spatial component. Transfer should be observed, further supporting a unique advantage of spatial information in visual processing (as participants did not transfer knowledge of the structure without spatial information). Variations on this theme include manipulating the amount of information in the spatial component (consistent as in Study

5, conflicting as in Study 6, and deterministic as in Study 7). Changing the amount of information contained in the spatial component would impose a differential processing load and perhaps result in a reduced ability to transfer knowledge, if attention was directed to processing the more complex spatial information.

In addition to manipulating other components of information in this paradigm to further explore the limits and capabilities of implicit sequence learning, eye tracking technology could be used successfully to demonstrate a measurable relationship between participant learning and eye movements. In an effort to understand infant learning, the same protocol can be tested with infants using habituation. Adults and infants are predicted to perform similarly on these tasks. Using this method with infants may provide a measurement of implicit learning in infants, allowing researchers to gain traction in understanding the underlying mechanisms of both implicit and statistical learning.

5.3 References

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