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Assessing the Implicitness of Visual Statistical Learning at the Individual Level

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DEDICATION

This thesis is dedicated to my father, Dana, and my mother, Teresa. I never could have gotten this far without their guidance and support.

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ABSTRACT

Previous research has examined visual-statistical learning at the individual level but used measurements which are not sensitive enough to detect differences at the individual level. This study investigated temporal visual-statistical learning but used a recently modified task designed to be more sensitive to individual performance. This study also incorporated an indirect measure of learning in the form of a rapid serial visual presentation paradigm (RSVP), a cover task, and binary confidence judgments, to assess how aware participants were of the statistical structure. Although there was strong evidence of participants learning the statistical structure at the group level, there was little evidence suggesting participants learned the statistical structure under the more rigorous criteria used to assess individual performance. Furthermore, participants that learned the statistical regularities at the individual level exhibited explicit, rather than implicit, learning of the structure.

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I. Literature Review

Introduction

We live in a world of patterns. Throughout daily living, we're constantly encountering patterns governed by statistical regularities. How do we make sense of all this information? To understand how humans process, learn, and discriminate between patterns, psychologists have studied classic behavioral approaches such as classical and operation conditioning. In more recent years, a compelling alternative known as statistical learning emerged. Statistical learning describes how people extract and learn joint probabilities (the likelihood of two events co-occurring at the same time) and conditional probabilities (the likelihood of one event following the occurrence of another event) from a given input of information (Klein et al., 2009), gradually reducing uncertainty within their learning environment.

Statistical learning was first studied by Saffran, Aslin, and Newport (1996), which revealed after only a single 2-minute familiarization phase, 8-month-old infants could segment words from continuous speech, based on the statistical relationships between speech sounds. Throughout this continuous speech stream, four three-syllable nonsense words (e.g. 'tupiro', 'golabu', 'bidaku', 'padoti') were repeated randomly. Word boundaries were cued with varying conditional probabilities between syllable pairs. During this phase, the within word probability was 1 in all cases, and the between word probability was 0.33 (after the presentation of a word, the next word was chosen randomly between the remaining three, with equal odds of being presented for each). Learning of these nonsense words was assessed via a test phase, which presented the nonsense words along with three-syllable non-words, containing the same syllables as used during the exposure stream. The results revealed a significant difference between listening times, with infants listening to non-words longer than the artificial words, suggesting discrimination between the two. In just 2-minutes of exposure, the infants had become more familiar with the nonsense words, due to the transitional probabilities present throughout the course of the stream.

Goals of Current Study

To preface the following literature, there were two major goals that the current project explored. Each shall later be discussed fully within the broader context of the statistical learning concepts surrounding them. The first goal of this project was to measure statistical learning at the individual level, rather than only looking at group mean differences. The second goal was to implement a task that has been found to be more effective in the measurement of individual ability, relative to more common used statistical learning tasks. This method was used to explore a debated question within the statistical learning literature: how *implicit* is visual statistical learning?

The primary focus of this project was to examine visual-temporal statistical learning at the individual level, however, it should be stressed that there are many alternatives. Since the seminal work of Saffran, Aslin, and Newport (1996), research has suggested statistical learning is a domain-general mechanism, allowing for the extraction of meaningful units of information from auditory (Endres, A.D & Mehler, 2009; Saffran, Aslin, & Newport, 1999), verbal (Pelucchi, Hay, & Saffran, 2009), nonverbal (Gebhart, Newport, & Aslin, 2009), tactile (Conway & Christiansen, 2005), and visual sequences (Kirkham, Slemmer, & Johnson, 2002). Statistical learning has been shown to occur within both the temporal and spatial domains (Fiser & Aslin, 2001; Orbán, Fiser, Aslin, & Lengyel, 2008).

This project sought to address a core issue of the statistical learning literature; much of the literature examining statistical learning considers it a unified theoretical construct, considering success to be performance above chance level within a sampled population. Due to statistical learning's suggested link with individual linguistic abilities (Christiansen, Shillcock, Greenfield; Hsu, Tomblin, and Christiansen, 2014), interest has sparked for studying statistical learning at the individual level, rather than only examining group mean differences. Siegelman, Bogaerts, and Frost (2016) argue that without significant modifications, the tasks commonly used to assess statistical learning are inadequate for assessing individual statistical learning ability. This is problematic, as many recent studies have sought to examine statistical learning at the individual level, but in doing so have made no modifications to the original task (examples: Arciuli & Simpson, 2012; Batterink, et al., 2015; Frost et al., 2013; Spencer, 2013; Turk-Browne, 2009).

Established Visual Temporal Learning Paradigms

When examining temporal visual statistical learning, tasks are commonly designed as follows; participants are seated at a white computer display, where they are exposed to a series of stimuli, consisting of novel black shapes (Fiser & Aslin, 2001; Figure 1) The stimuli are sorted into triplets, namely, each shape is presented in a fixed order with two other shapes within the sequence. The order of the sequence is random with the following rules: 1. Shapes belonging to the same triplet are always presented together, and in the same order within that triplet, and 2. The same triplet cannot be presented twice in a row. This means with a sequence of four triplets, the transitional probability between the shapes is always either 1 (within triplets) or 0.33 (between triplets).

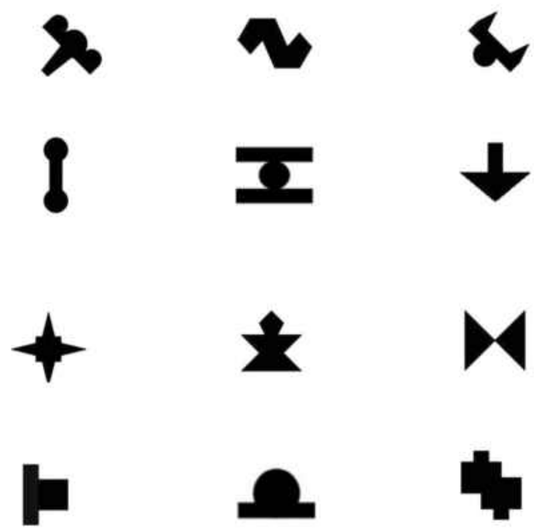

Figure 1. Example shapes for visual statistical learning task. Adapted from "Unsupervised Statistical Learning of Higher-Order Spatial Structures from Visual Scenes" by J Fiser and R.N. Aslin, 2001, Psychological Science, 12(6), p.6.

During an exposure phase, participants are exposed to each shape in a sequence, typically one by one, at the center of a computer display. This phase is usually composed of around 1200 trials (1200 single shape presentations). Each shape is presented for milliseconds to seconds, with a brief interstimulus interval (Emberson, Conway, & Christiansen, 2011; Kirkham et al., 2012). After this exposure phase, participants are tested on their knowledge of the sequence structure, typically through an alternative forced-choice completion task, where participants are instructed to complete triplets by selecting the shape they believe belongs in each triplet interval (Emberson, Conway, & Christiansen, 2011; Kirkham et al., 2012, Turke-Browne, Junge, & Scholl, 2005). In addition to this task may be a binary confidence judgment procedure, that instructs participants to indicate whether they were confident about the answer they provided on each forced-choice question interval (Bertels, Franco, & Destrebecqz, 2012).

Another task that assesses learning is rapid serial visual presentation (RSVP), which instructs participants to detect targets within a sequence of shapes (Bertels, Franco, & Destrebecqz, 2012; Bertels, Demoulin, Franco, & Destrebecqz, 2013). Here, reaction times to target shapes are compared based on the position of a shape within the triplets. Faster reaction times to the second or third shape within a triplet, compared to the first shape within a triplet, would indicate the participant has to some extent learned the sequence structure. This is due to the predictive relationship established by the transitional probabilities between shapes, as the second shape always follows the first, and the third always follows the second. The shape that occurs before the first shape within a triplet, shared a transitional probability of 0.33 with other shapes not belonging to its triplet, and therefore does not establish a predictive relationship between these other shapes. It is understood that by consistently reacting faster to the second or third shapes, they are on some level predicting these shapes will occur one after another (Bertels, Franco, & Destrebecqz, 2012).

Criticisms of Visual Statistical Learning Tasks

Siegelman, Bogaerts, and Frost (2016) offered several criticisms regarding the typical temporal visual statistical learning task and discussed several solutions to improve its predictive validity and reliability. One such criticism addresses the number of trials used within the test phase, in which psychometrically sound tasks examining individual differences require more trials than what has been used in the past for the study of individual statistical learning. In example, Spencer et al. (2014) and Turk-Browne et al. (2009), used 4 and 16 test trials respectively. This few trials would not allow for the expression of variance within the sample. Some researchers have attempted to solve this issue by introducing more trials where the same triplet is repeated, but paired against different foils (Arciuli & Simpson, 2012). Siegelman, Bogaerts, and Frost (2016) argue with these repetitions comes the concern of learning occurring during the test phase, confounding what was learned during the initial exposure. To solve address this issue, researchers should maximize the number of trials during the test phase, while minimizing the number of times triplets are repeated throughout.

This point may tie into yet another problem, that is the testing trials are all the same difficulty, leading to potential floor and ceiling effects. It's possible that individually, participants are learning the triplet structures, however, the task is not sensitive enough to detect lower levels of learning. For example, some participants might only learn part of a triplet, or a subset of triplets. If this type of partial learning occurs, less sensitive tasks may not reveal evidence that any learning has occurred. Most statistical learning studies have not reported individual performance, instead opting to report group mean differences. When studies do report individual performance, a large proportion of the sample~~s~~ perform at or below chance level (examples: Bertels et al, 2012; Endress & Mehler, 2009; Saffran et al., 1997; Saffran, et al., 1999). This sometimes results in much of the data being excluded from certain analyses, as participants may not have been aware of their own learning and are removed due to a lack of evidence of learning.

At the individual level, people may exhibit learning of statistical regularities in widely different ranges. An adequate test of statistical learning should be able to measure whether an individual has learned only part of a regularity and assess whether they can both recognize and produce the pattern. Siegelman, Bogaerts, and Frost (2016) argue because current statistical learning tasks only contain items of the same difficulty, they only measure ability within a similar area of the distribution, with low and high level statistical learning not being adequately reflected by the data. This may affect the reliability of the measure, lending some explanation as to why low correlations between statistical learning measures have been found (Erikson, Thiessen, & Berry, 2016).

New Visual Statistical Learning Task

Siegelman, Bogaerts, and Frost (2016) addressed these concerns by formulating a new visual statistical learning task. This new task consisted of 16 shapes. Unlike traditional statistical learning tasks, wherein the within triplet transitional probabilities are always 1, the transitional probabilities come in two different types. Four triplets have transitional probabilities of 0.33 between each shape, made from four possible shapes (example triplets: 1–2–3, 2–1–4, 4–3–1, and 3–4–2). A transitional probability of 0.33 indicates that after the presentation of a shape, the next shape that is presented is always one of three possible shapes, with each shape being equally probable. The other four triplets have transitional probabilities of 1 between each shape, consisting of the remaining shapes (example triplets: 5–6–7, 8–9–10, 11–12–13, and 14–15–16). A transitional probability of 1 indicates that after the presentation of a shape, the next shape that is presented is guaranteed to be a specific shape, based on the shape that was just presented (e.g. shape 5 is always followed by shape 6, which is always followed by shape 7). Each triplet appeared 24 times during the exposure phase for 800 ms, with a 200 ms ISI. The same triplet was never repeated twice in a row within a stream.

After the exposure phase, Siegelman, Bogaerts, and Frost (2016) incorporated a test phase consisting of 42-items. Items differed in terms of required response (some recognition trials, some completion trials; see Figure 2). Items also differed in terms of triplet presentation (some included all three shapes, while others only included pairs of shapes. Recognition trials instructed participants to select the pattern they felt most familiar with, among either two or four choices, by pressing the corresponding on a keyboard. Completion trials presented participants with a given triplet or pair, however, the presentation was missing a shape. On these trials, participants were instructed to select which of three shapes best completed the set.

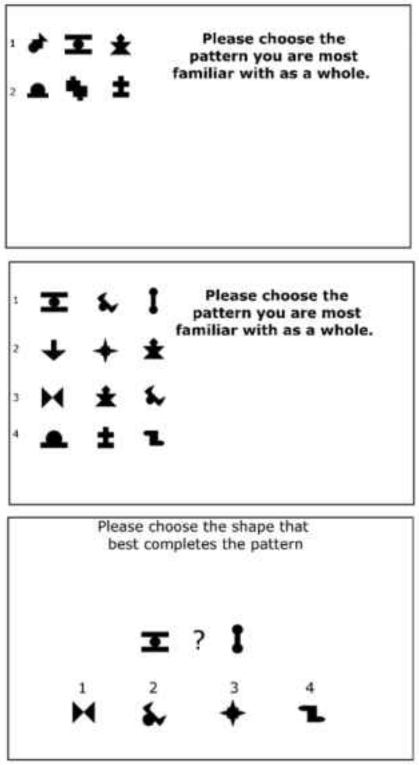

Figure 2. Examples of test phase trials

Test items differed in terms of the transitional probability of the target triplet. Triplets had a transitional probability of either 1 or 0.33. In the example triplets described above, the triplet 8-9-10 has a transitional probability of 1, as shape 8 is always followed by 9, and shape 9 is always followed by shape 10. The triplets containing shapes 1, 2, 3, and 4 have transitional probabilities of 0.33, as there are three possible shapes that can follow a given target, each with equal odds of appearing within the sequence. Test items also differed in terms of the number of foils provided (1 or 3). The degree of position violations of the foils was also manipulated, ranging from 0 to 1 degrees. For example, the triplet comprised of the shapes 4-2-7 corresponds to the correct triplets 4-3-1,1-2-3, and 5-6-7. This is because the foil triplet still has shape 4 at position one, shape 2 at position two, and shape 7 at position three, and would thusly have a 0-degree violation. The foil triplet 1-6-9 contains one shape which appears in a different position than in the actual triplet, namely the 9 that would typically be in the second position within the triplet 8-9-10. In this example there is a .33-degree position violation. If a foil triplet contained two shapes with different internal positions (e.g. 1-7-9), this would be a .66-degree position violation. If a foil triplet contained three shapes that appear in incorrect positions (e.g. 12-7-9), this would be a position violation of 1.

Siegelman, Bogaerts, and Frost (2016) argued by designing this task with variability in transitional probability of both the triplets, and the alternative choices, as well as testing both completion and recognition, the task becomes more sensitive to visual statistical learning at both lower and higher levels of learning. They argue because the transitional probabilities of triplets aren't always 1, learning the underlying structure of the sequence becomes more difficult, due to the shapes establishing a predictive relationship with more than one shape. The increased number of test trials also follows the same logic in attempting to increase the sensitivity of the measure, providing more opportunities for participants to demonstrate learning.

Their results reveal increased split-half reliability, test-retest reliability, and Cronbach's alpha coefficients in comparison to the previously outlined temporal visual statistical learning tasks which had fewer and less varied test trials (Emberson, Conway, & Christiansen, 2011; Kirkham et al., 2012, Turke-Browne, Junge, & Scholl, 2005). An item analysis revealed a significant improvement in terms of how items reflect low and high visual statistical learning outcomes. A mixed-effect logistic regression model revealed that transitional probability of foils may not have influenced test performance, however the effect of the transitional probability of target triplets was significant.

One key difference between the approach by Siegelman, Bogaerts, and Frost (2016), and the approach used by some researchers is the employment of a cover task (Bertels et al., 2012, Bertels et al., 2013). Siegelman, Bogaerts, and Frost (2016) did not use any cover task during the exposure phase, but instead instructed participants to learn the sequence of shapes. This means any learning that occurred during their task may have been in part due to intentional instructions, rather than being incidental. This is one key aspect of statistical learning research, as however reliable this new task might be, another important question is whether the knowledge acquired is incidental. This is another goal of my proposed project.

The Implicitness of Statistical Learning

Some research has suggested statistical learning occurs automatically (Fiser & Aslin, 2001; Fiser & Aslin, 2002), incidentally (Fiser & Aslin, 2005), and without awareness of the statistical structure (Turk-Browne, Jungé, & Scholl, 2005; Fiser & Aslin, 2005), indicating that this mechanism may be somewhat implicit. Aslin (2017) argues statistical learning occurs without the individual consciously making decisions about the likelihood of occurrences, or the relevance of the perceived information. Aslin (2017) also argues statistical learning occurs without receiving feedback from an instructor, and is consistent with other implicit learning tasks, such as the serial reaction time task, and artificial grammar learning. Indeed, some researchers suggest implicit memory research may facilitate a better understanding of statistical learning (Conway & Christiansen, 2006).

It’s apparent the concepts of implicit learning and statistical learning are related, as research that has examined the two topics have examined similar processes

(Perruchet & Pacton, 2006), even going as far as to use implicit learning tasks, such as the serial reaction time task, to investigate statistical learning (Hunt & Aslin, 2001). Perruchet & Pacton (2006) argue that despite both research endeavors examining one's ability to process statistical regularities, they conceptualize the unit of knowledge differently. Research investigating implicit learning often conceptualizes information processed as chunks, while statistical learning conceptualizes knowledge as statistical computations. Perruchet & Pacton (2006) posit that these two approaches aren't mutually exclusive, as it is possible the formation of chunks and statistical computations are two successive steps in the process of incidental learning. They also discuss the possibility of statistical structures being merely a by-product of the formation of chunks.

Some models of statistical learning, such as the extraction and integration framework proposed by Thiessen, Kronstein, and Hufnagle (2013) argue that sensitivity to the conditional structures often found in statistical learning paradigms are reliant on attention and working memory, contradicting how some researchers conceptualize implicit learning as being independent from these processes (Erikson & Thiessen, 2015). This idea is disputed by the findings of some research that posits statistical learning's independent from attentional processes (Evans, Saffran, & Robe-Torres, 2009; Siegelman & Frost, 2015). In the auditory domain, Batterink, Reber, and Paller (2015) assessed the implicitness of statistical learning through a forced-choice and reaction time, again using both a direct and indirect measure of learning, respectively. Their results showed both explicit learning, through word recognition, and possible implicit learning, through faster reaction times to nonsense words. These two results, however, did not correlate. This is a possible indication that implicit learning may have occurred in parallel yet was dissociable to explicit learning that occurred.

To determine how conscious statistical knowledge is, Bertels, Franco, and Destrebecqz (2012) investigated statistical learning using a visual statistical learning task, exposing participants to a sequence of novel shapes. Each shape belonged to a set of three shapes, always being presented with the other two within the sequence of shapes. This is consistent with the commonly used method developed by Fiser and Aslin (2001). After this exposure phase, participant familiarization and awareness of the sequence structure was assessed using a 4-choice completion task, rapid serial visual presentation, and binary confidence judgements. Their goal was to determine how conscious the learned information was, by using both direct and indirect measures of learning. A cover task in the form of intermittent letter presentation was also employed, to create an environment where learning of the shape's statistical regularities incidental. Their findings also revealed a relationship between participant's confidence rating and above chance performance on the completion task, indicating at least some of their knowledge was explicit, challenging the view that visual statistical learning was a solely implicit process. These findings were later replicated and expanded upon (Bertels, Demoulin, Franco, & Destrebecqz, 2013), revealing participants in a negative affective state had more conscious access to statistical knowledge than those in a control group.

There are issues with the methodology of Bertels, Franco, and Destrebecqz (2012) which this project seeks to address. As mentioned previously, Bertels, Franco, and Destrebecqz (2012) is one study that examined the awareness of learned knowledge, but only assessed it for participants that performed above chance.

Participants who performed at or below chance on the completion task were removed from the awareness analyses, as learning was not evident in those cases. As discussed previously, the typical visual statistical learning task (Emberson, Conway, & Christiansen, 2011; Kirkham et al., 2012) lacks the psychometric properties to adequately assess statistical learning at the individual level (Siegelman, Bogaerts, & Frost, 2016). Bertels, Franco, and Destrebecqz (2012) acknowledges this, stating their indirect measures of learning may have been more sensitive than the direct measure they employed. It's possible more participants would have demonstrated explicit learning of the sequence, given a more sensitive measure, thus suggesting implicit learning was not as prevalent as is suggested by their findings. If a measurement more sensitive to individual learning such as this was used, it would be clearer to indicate the individual levels of both participant learning and awareness of acquired knowledge.

Project Goals

Siegelman, Bogaerts, and Frost (2016) did not attempt to assess participant awareness of the statistical structure, as the structure was intentionally learned, rather than incidental. The task designed by Bertels, Franco, and Destrebecqz (2012) lacks the psychometric properties necessary to assess individual learning. The goal of this project was to implement both tasks to assess the implicitness of visual statistical learning at the individual level. As in Bertels, Franco, and Destrebecqz (2012), the study introduced a cover task during the exposure phase, instructing participants to respond to the presentation of black letters displayed within the sequence of shapes. The testing phase included indirect measures of learning, in the form of a rapid-serial visual presentation phase, to be completed after the testing phase. The findings of Bertels, Franco, and

Destrebecqz (2012) revealed some participants performed at chance in a completion task but demonstrated learning with indirect measures. This suggests that statistical learning might be implicit, or that prior methods of directly assessing statistical learning are not as sensitive as indirect methods.

This project investigated whether such a finding was truly due to implicit learning, or due to inadequate measurement. With a task designed to assess visual statistical learning at the individual level more adequately and having established higher predictive validity and reliability for the task, it's possible to further test participant awareness of sequence structures. If during testing, participants were not able to reproduce the patterns of the shape sequences, but showed learning through response times in the rapid serial visual presentation (RSVP) phase, this may be evidence for implicit learning. Additionally, if binary confidence judgments indicated guessing, rather than remembering the information, yet individual performance learning has occurred, this may also indicate that participants have learned the sequence implicitly. Of course, the opposite is also possible, as with a more sensitive testing phase, this may show a stronger association to the already sensitive indirect rapid serial visual presentation (RSVP) measure, indicating that learning is more explicit. Siegelman, Bogaerts, and Frost (2016) demonstrated visual statistical learning in their task, but did not use a cover task to support whether learning could be achieved under their test incidentally. This project serves a double purpose in testing the limitations of Siegelman's design, determining whether the added difficulty and variability would affect apparent implicit learning.

II. Current Study

Method

Participants

A total of 86 students (68 female; M Age = 19.9 SD = 2.43) from Eastern Kentucky University participated in exchange for course credit. As per requirement, all participants were 18 years of age or older. Informed consent was obtained from each participant. Normal or corrected to normal vision was required to participate in this study.

Materials

The experiment was conducted on an HP ProDesk computer with an intel® core i7 – 6700 processor, and a 19.2 inch (diagonal) LCD monitor set at a resolution of 1280 x 1024. PsychoPy2 (version 1.83.01; Perice, JW, 2008) was used for stimulus presentation and response recording. The 16 shapes used in the task were taken from Fiser and Aslin (2001). Each shape was presented at a height and width of 3 about centimeters.

Design and Procedure

Participants completed the experiment individually; each experimental session lasted approximately 30-minutes. After consenting to participate and being seated at a computer desk, the participants were asked to read instructions displayed on a computer monitor. Any questions the participants had were addressed at this time. The first part of the experiment consisted of an exposure phase. The exposure phase was identical to what was outlined in Siegelman, Bogaerts, and Frost (2016), (See Figure 2), with the addition of a cover task. For each participant, 16 shapes were randomly assigned to a number, ranging from 1 to 16. These shapes made up eight triplets as follows, four triplets with within triplet transitional probabilities of .33 (1-2-3, 2-1-3, 4-3-1, 3-4-2) and four triplets with within triplet transitional probabilities of 1 (5-6-7, 8-9-10, 11-12-13, 14-15-16). Each shape appeared one at a time in the center of a computer display for 800 ms, with a 200-ms interstimulus interval. The shapes were always presented within their respective triplet, in a temporal sequence. Each triplet appeared 24 times during the exposure phase. The same triplet was not repeated twice in a row. Throughout this phase, black letters appeared, acting as a cover task. These letters were sparse throughout the sequence, appearing random to the participants. The letters always appeared between the triplets, never within, to maintain the integrity of the sequence structure. Participants were instructed to pay attention to the sequence and press a key each time they saw a letter appear within the stream. In total, 30 black letters appeared throughout the sequence. This phase lasted approximately 10 minutes.

Shortly after the exposure phase, participants were presented with instructions for a rapid serial visual presentation paradigm (RSVP; Figure 3). At the beginning of each trial, a shape was displayed at the center of the computer screen for 2 seconds, along with the words “look for this shape”. A sequence of shapes then began, with each shape appearing one a time in the center of the computer display for 250-ms, with a 200-ms interstimulus interval. As in the exposure phase, the appearance of the shapes always followed the structure of the established triplets, with no triplet repeating twice in a row. Participants were instructed to detect this shape within the sequence of shapes and respond by pressing a key as soon as they see the target shape appear within the sequence. Once the participant responded with a key press, the sequence then stopped, and the next trial began. Each shape was presented six times, resulting in 96 trials.

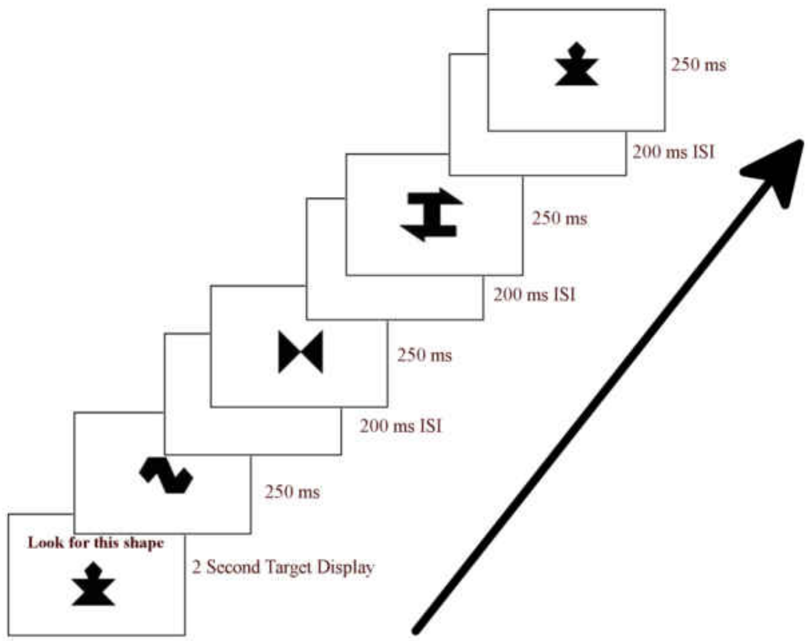

Figure 3. Example RSVP trial.

The underlying logic to this task is if learning of the sequence structure has occurred, it will be evident by analyzing the reaction times to the target shapes. If response times are faster to shapes that appear in the second or third position of a triplet, in compared to the first position, this is an indirect demonstration of having learned the sequence structure. The reasoning behind this is that throughout exposure, the shapes have established a predictive relationship with other shapes in their given triplets. If a triplet consists of the shapes 1-2-3, and the target is shape 2, 1 and 2 share a predictive relationship, allowing the participant to anticipate the occurrence of shape 2 appearing within a structured sequence. One key difference between this design and the RSVP implemented by Bertels, Franco, and Destrebecqz (2012) is the presence of varying transitional probabilities. As some shapes having lower within transitional probabilities (0.33), this variance should be reflected in learning. With some shapes belonging to different triplets, this added variance should be reflected in learning. It is predicted that target shapes belonging solely to higher transitional probability triplets will elicit faster reaction times than shapes with varying transitional probabilities. For a direct measure of learning, a second task was used. The 42-item test phase described in Siegelman, Bogaerts, and Frost (2016) was used. Some items required participants to select a familiar pattern, other items required participants to complete a pattern by selecting which shape they think is missing from it. Some items included pairs of shapes, while others will include full triplets. The number of alternative choices varied between items. Two, three, and four forced-choice items were used. As in Siegelman, Bogaerts, and Frost (2016) the alternatives varied in their position violations. After each question, participants were asked to provide a binary confidence judgment, indicating whether they guessed or remembered the answer. Lastly, at the end of the experiment participants were asked as to whether they noticed the shapes appearing in a set pattern during the exposure phase.

If statistical learning is evident within our sample, performance on the rapid serial visual presentation trial will reveal an effect of both transitional probability, and position of the shapes. If after the exposure phase the participant had learned the statistical regularities, this should be reflected in both the RSVP and direct testing phase. Average reaction times should be faster for high transitional probability targets than for targets with low transitional probability. Also, reaction times should be faster for targets within the second or third position of the triplet than the first position of the triplet. Performance on the direct test phase should also be above chance.

If statistical learning is implicit, this should be reflected in two ways. 1. An inability to produce the pattern during direct testing, coupled with strong evidence of learning during the rapid serial visual presentation task (RSVP). 2. There is no relationship between binary confidence judgments and the correctness of their responses on trials during the direct testing phase. If participants indicate they are confident in their answers on more correct trials than incorrect trials, this would indicate learning is primarily explicit.

Results

Rapid Serial Visual Presentation

Analyzing the results of the rapid serial visual presentation (RSVP), we found across the participants the average hit rate was 0.95 (SD = 0.04). To examine learning at the group level, a $3^{x}2$ repeated-measures analysis of variance (ANOVA) was conducted. Position of each shape (1, 2, and 3) was treated as an independent variable. Transitional probability of each shape (low or high) was another independent variable. The dependent variable was response time. Erroneous responses were excluded from the analysis. Inconsistent with our hypothesis, there were no significant differences in average response time when comparing the position of the shapes $F(2, 170) = 0.693$, $p = .502 > .05$, $\eta_G^2 = .002$. At the group level, response times did not significantly differ when responding to shapes in position 1 (M = 0.86, SD = 0.33), position 2 (M = 0.85, SD = 0.33), or position 3 (M = 0.83, SD = 0.32). Consistent with our hypothesis, there was a significant difference in average response time on high transitional probability trials when compared to low transitional probability trials $F(1, 85) = 6.385$, $p = .013$, $\eta_G^{\ 2} = .01$. On average, participants responded faster during high transitional probability trials (M = 0.84, SD = 0.23) than during low transitional probability trials (M = 0.88, SD = 0.40). There was no significant interaction effect of position and transitional probability on response time $F(2, 170) = 0.174$, $p = 0.84 > 0.05$, $\eta_G^{\ 2} = .0004$ (See Figure 4).

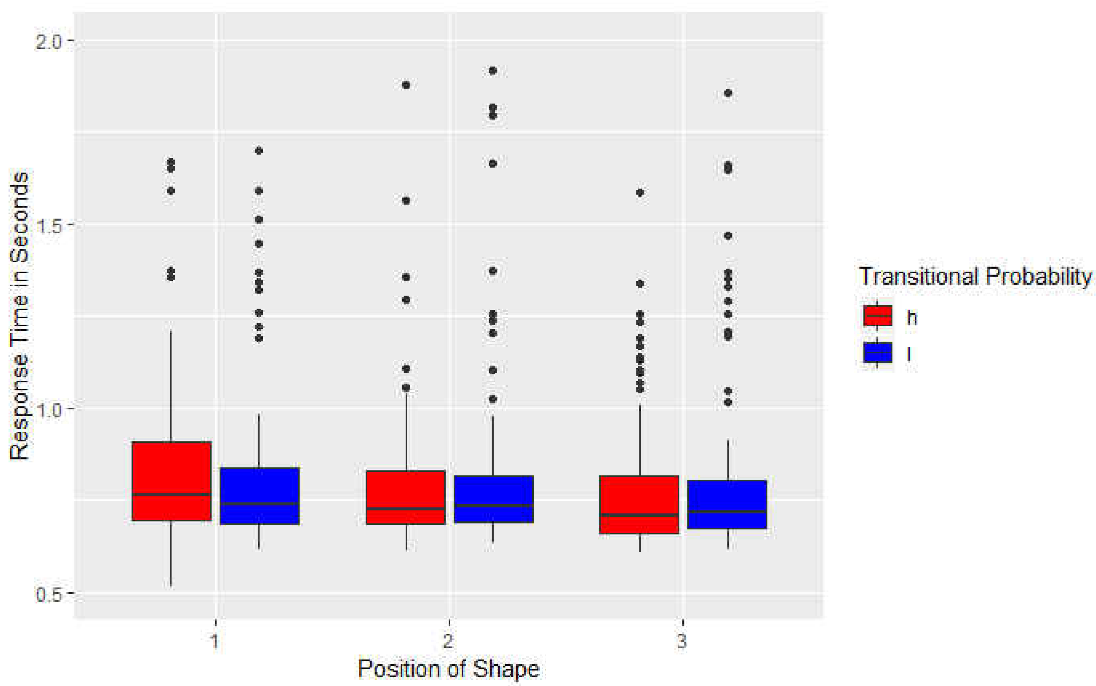

Figure 4. Mean response times by transitional probabilities and shape position.

Completion and Recognition Task

As our completion and recognition test phase was nearly identical to the method used in Siegelman, Bogaerts, and Frost (2016), the same criterion was used to assess learning in this study. Using the binomial distribution and aggregating the various probabilities of correct responses for each item, Siegelman, Bogaerts, and Frost (2016) calculated that at the group level, above chance performance on their test phase was

16.67 correct answers out of 42 total items. A total of 74 of 86 participants correctly answered 17 or more of the 42 items (M = 20.43, SD = 4.12). Calculating the individual chance level, Siegelman, Bogaerts, and Frost (2016) found, given an alpha level of .05, correctly answering 23 of the 42 items would indicate evidence of learning at the individual level. The results revealed 23 of 86 participants correctly answered 23 or more of the 42 items (M = 25.39, SD = 2.29), amounting to 27% of the participants showing evidence of learning at the individual level via this measure (See Figure 5).

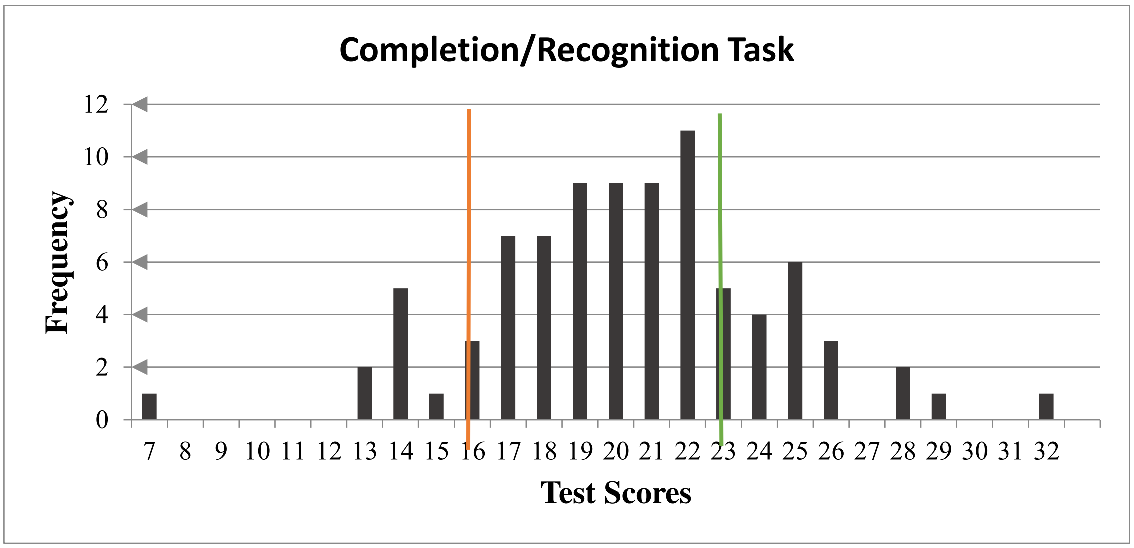

Figure 5. Individual performance on the completion and recognition task. The orange line indicates number of correct items for group level significant learning. The green line indicates number of correct items for individual significant learning

When asked if they had noticed a pattern within the sequence, 54 of the 86 participants reported noticing a pattern. A chi-squared test of was conducted to further analyze whether noticing the pattern was related to above chance performance on the completion and recognition task. $X^2 = (1, N = 86)\ 0.28$, $p = 0.59$. The results show no evidence an association between above chance performance and noticing the sequence pattern during exposure.

A 2^x2 repeated-measures analysis of variance (ANOVA) restricted to the 23 participants that showed evidence of statistical learning examined their awareness of the statistical structure. It was necessary to restrict this analysis to only participants that exhibited evidence of learning at the individual level, as the argument must be made that learning must be evident regardless of whether the participant is aware of the knowledge. This analysis used binary confidence judgments as an independent variable, and correctness of response as a second. The dependent variable was the number of responses falling into each of these categories (e.g. a correct response which was guessed, a correct response which the participant was confident in, an incorrect response which was guessed, and an incorrect response which the participant was falsely confident in). Since this sample showed evidence of learning, it's no surprise the results revealed a significant main effect of response correctness on number of responses $F(1,22) = 64.697$, $p < .001$, $\eta_G^{\ 2} = .09$. There was no evidence of a significant main effect of confidence judgment on number of responses $F(1, 22) = 0.168$, $p = 0.686$, $\eta_G^{\ 2} =$. The analysis revealed a significant response correctness, binary confidence judgments interaction effect. $F(1, 22) = 8.039$, $p = 0.009 < .01$, $\eta_G^{\ 2} = .07$. To follow up on this interaction, a simple effects analysis was conducted at both levels of confidence. When "confident" confidence judgments were made, the simple effect of response correctness was reliable $F(1,22) = 47.11$, $p < .00$, $\eta_G^{\ 2} = .01$. When "guess" confidence judgments were made, the simple effect of response correctness was not reliable $F(1, 22) = 1.88$, $p = 0.184 > .05$, $\eta_G^{\ 2} = .014$. On average, participants made more "confident" judgements when they gave correct responses (M = 14.39, SD = 6.94). than when they gave incorrect responses (M = 8.09, SD = 4.92). On average, participants also made more “guess” judgments when they gave correct responses (M = 11, SD = 7.53) than when they gave incorrect responses (M = 9.56, SD = 4.26), however, as noted this simple effect is unreliable (See Figure 6).

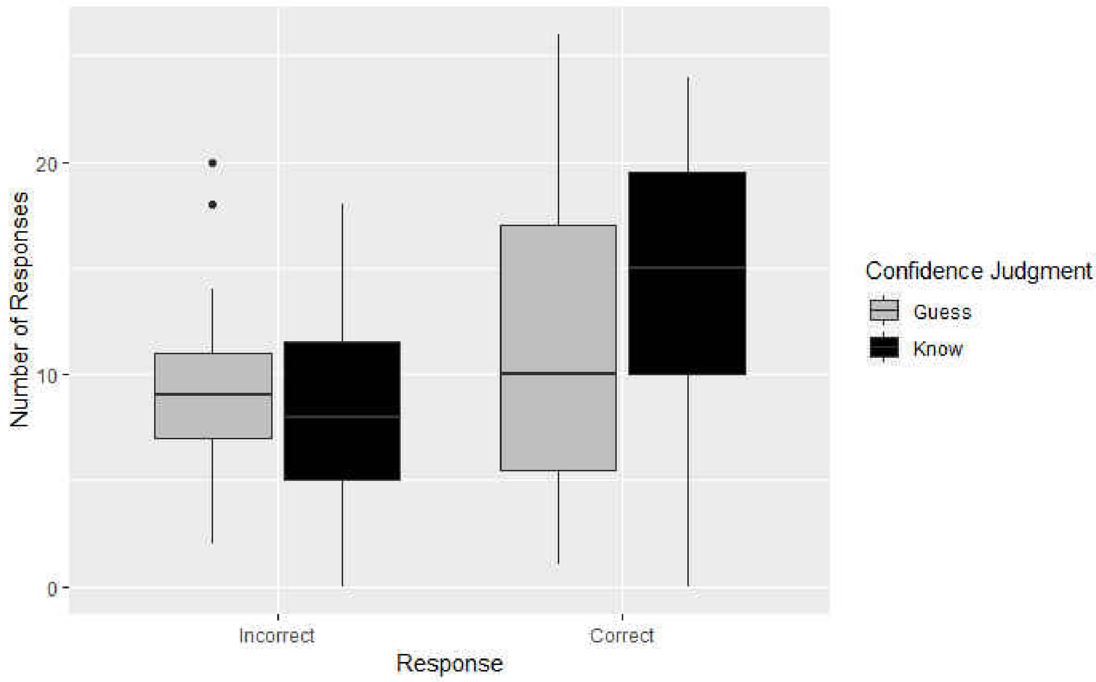

Figure 6. Mean number of responses by response correctness and confidence judgments.

The relationship between rapid serial visual presentation (RSVP) response time and direct test phase performance was examined. With the inclusion of the entire sample, there was no evidence of a relationship between response time and test performance $r(514) = -.03$, $p = .477 > .05$. Narrowing the analysis to only participants that performed above chance in the direct test phase, there was again no evidence of a relationship between response time and test performance $r(136) = .05$, $p = .54 > .05$

Discussion

The current study investigated visual-temporal statistical learning at the individual level. After an exposure phase, learning statistical structure was assessed both indirectly via a rapid serial visual presentation (RSVP) and directly using testing phase consisting of both recognition and completion items. Performance on the rapid serial visual presentation task (RSVP) at the group level indicated that participants demonstrated some learning of the statistical structure based on the transitional probabilities but did not demonstrate learning of the statistical structure based on the position of the shapes within the triplets. It was revealed that on average, performance was better on higher probability trials than on lower probability trials. This finding is not surprising, as the varying transitional probabilities were implemented to increase the difficulty of the trials for both the RSVP task and direct testing task.

Participants failing to demonstrate learning based on the position of shapes within the triplets is inconsistent with previous findings which have used the RSVP task to examine visual statistical learning (Turk-Browne, Jungé, Sholl, 2005; Kim, Feenstra, Shams, 2009; Bertels, Franco, Destrebecqz, 2012; Bertels, Demoulin, Franco, & Destrebecqz, 2013). This is the first time to our knowledge that varying transitional probabilities have been paired with an RSVP, thus, it's possible the addition of varying transitional probabilities during the exposure phase made the RSVP too complex to adequately measure learning. Future research may wish to examine the impact varying transitional probabilities has on the measure's sensitivity.

The analysis of performance on the completion and recognition task reveal that 86% of participants performed above chance at the group level, however, despite incorporating the task designed by Siegelman, Bogaerts, and Frost (2016), only 27% of participants performed above chance at the individual level. This is drastically lower than Siegelman, Bogaerts, and Frost's (2016) analyses, who found that 60% of their sample learned the statistical structure during the same task. This finding highlights the importance of analyzing the individual performance when making inferences about the learning outcomes of individuals.

It's unclear as to why most participants failed to perform above chance on the direct testing task, given Siegelman, Bogaerts, and Frost (2016) found the task was largely reliable for the measure of individual statistical learning. It's possible that the added complexity of this task, along with the addition of a cover task, adversely affects learning outcomes. A possible follow up study could compare incidental and intentional learning using this task. Our findings revealed that on average, participants who did learn the statistical structure at the individual level indicated they were confident on more trials in which they gave the correct response, than on trials on which they gave an incorrect response. It's worth noting, however, that the opposite was not true. On average, participants who performed above chance could not accurately determine whether their incorrect answers stemmed from guessing. For the purposes of this project, we defined implicit learning has learning which occurs in the absence of intention and without awareness. Because participants exhibited at least some awareness of the statistical structure, it cannot be argued that they've learned the structure implicitly. This pattern suggests that for these participants, learning of the statistical structure may have been more explicit.

Siegelman, Bogaerts, and Frost (2016) propose that possible improvements to the completion and recognition task are the implementation of weighted scoring, based on item difficulty, and adaptive difficulty based on prior item performance. Both changes could potentially improve the sensitivity of the task, however, further improvements would necessary to successfully incorporate an indirect measure of learning in addition to this task, as the varying transitional probabilities present throughout the direct measure may disturb the reliability of the RSVP measure.

Conclusion

The current study presents the combination of a direct and indirect method of measuring visual statistical learning at the individual level. This study also attempted to determine how aware participants were of the knowledge they had learned throughout exposure. Evidence for statistical learning was sparse throughout the sample. Performance on the rapid serial visual presentation (RSVP) suggested the sample did not successfully learn the statistical structure. Our findings suggest participants who successfully reached the threshold of significant learning at the individual level exhibited explicit knowledge of the statistical structure. These participants showed evidence for some awareness of the statistical structure, and thus, do not meet the criteria for implicit learning (absence of intention and awareness). No evidence was found to suggest a relationship between RSVP response times and direct testing performance. Reliability measures, similar to those of Siegelman, Bogaerts, and Frost (2016) may also be necessary to determine whether a consistent relationship between these measures exists. Finally, future research may wish to examine whether the task designed by Siegelman, Bogaerts, and Frost (2016) can adequately measure incidental learning, compared to intentional learning

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