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Los Angeles

# Modulation of Implicit Sensory and Sensorimotor Learning:

# An Investigation Within and Across Sensory Modalities

A dissertation submitted in partial satisfaction of the

requirements for the degree Doctor of Philosophy

in Psychology

by

Brandon Keith Barakat

2014

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ABSTRACT OF THE DISSERTATION

Modulation of Implicit Sensory and Sensorimotor Learning:

An Investigation Within and Across Sensory Modalities

by

Brandon Keith Barakat

Doctor of Philosophy in Psychology

University of California, Los Angeles, 2014

Professor Ladan Shams, Chair

Implicit forms of learning are what govern many aspects of human perception, cognition, and actions. This dissertation describes three studies, each of which investigated a different type of implicit learning. The first study examined visual perceptual learning. Findings from the first study suggested that, with training, people learned to detect subtle differences between rhythmic visual sequences, but their improvement depended on which sensory modalities were engaged during training. Namely, visual rhythm perception was only improved when the auditory modality was engaged during training. The second study examined whether passive exposure to sequences in multiple sensory modalities would facilitate subsequent performance in a visuomotor sequence task. However, the results failed to reveal a significant benefit of passive sequence exposure to visuomotor performance. Finally, the third study examined the effect of

statistical learning on internal stimulus representations. The results indicated that when stimuli were repeatedly presented in predictable sequences, the perceptual saliency of some of the stimuli was enhanced relative to others, depending on their degree of predictability within the sequences. Each of these studies has the potential to make a significant contribution to the research literature and, more generally, to expand our understanding of basic mechanisms of human learning.

The dissertation of Brandon Keith Barakat is approved.

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# General Introduction

When people think of learning and memory, they typically think of explicit forms, such as their ability to remember a recipe or their ability to reflect on autobiographical memories of their childhood. However, there are many forms of learning and memory that are, in fact, implicit. From the very beginning of an individual's life, mechanisms of implicit learning are what drive the fine-tuning of an infant's motor movements as she learns to walk and they are what shape her perceptions as she gains experience sensing her environment. It is likely the case that the average person does not think much about the existence of implicit forms of learning, however researchers have a great interest in understanding the mechanisms of implicit learning, as implicit forms of learning are what govern many aspects of human perception, cognition, and actions (Schacter, 1987).

This dissertation consists of three studies, each of which investigates a different type of implicit learning. The general aim of my dissertation is to examine how different types of sensory experience can influence certain forms of implicit learning and, conversely, how certain forms of implicit learning can subsequently influence one's sensory experience. In the first study, I investigated a visual form of perceptual learning. Specifically, I tested whether rhythm perception in the visual modality is susceptible to perceptual learning and, furthermore, whether training under multisensory conditions can lead to enhanced perceptual learning compared to training under unisensory conditions. In the second study, I examined a form visuomotor sequence learning. Here, I tested whether passive exposure to repeated sequences in the visual and tactile modalities can influence participants' ability to respond to those sequences in a subsequent visuomotor task. And in the third study, I looked at an implicit form of associative

learning, known as statistical learning, and found that there may be a hitherto unexplored link between statistical learning and mechanisms of perceptual learning. Specifically, I demonstrated that when stimuli are repeatedly presented in temporally predictable sequences, the perceptual saliency of predictable stimuli is enhanced relative to that of less predictable stimuli, even when the stimuli are tested outside of the context of the temporal sequences. Each of these studies either addresses a question that has not previously been examined or uses a novel methodology to challenge preexisting assumptions about how certain types of implicit learning operate. As such, each study has the potential to make a significant contribution to the research literature and, more generally, to expand our understanding of basic mechanisms of human learning.

# Study 1:

# Auditory Facilitation of Visual Rhythm Perception

## 1.1. Introduction

When a medical doctor inspects a patient's X-ray for signs of a tumor, she must know how to identify extremely subtle features within an image that contains a large amount of visual noise. This is not a simple task. In fact, it is a skill that is only acquired after a large amount of training and experience. This phenomenon of experience-based improvement in one's ability to perform a particular perceptual skill is known as *perceptual learning*. Researchers have studied perceptual learning in many different tasks, with a variety of stimuli, and in different sensory modalities (Fahle & Poggio, 2002). In the visual modality, research has largely focused on spatial tasks, such as tasks involving judgments of spatial acuity, line orientations, and motion directions (Fine & Jacobs, 2002). In comparison, temporal tasks (e.g., temporal interval discrimination) have almost exclusively been studied within the auditory modality (Karmarkar & Buonomano 2003; Wright, Buonomano, Mahncke, & Merzenich, 1997). This is most likely due to the fact that the visual modality has been shown to be dominant in the processing of spatial information (Mateeff, Hohnsbein, & Noack, 1985; Pick, Warren, & Hay, 1969), whereas the auditory modality is more adept at processing temporal information (Gebhard & Mowbray, 1959; Shipley, 1964).

The few studies that have examined temporal perceptual learning outside of the auditory modality have focused primarily on temporal interval discrimination (Bratzke et al., 2012; Lapid et al., 2009; Nagarajan et al., 1998), but another interesting domain of temporal perception to consider is rhythm perception. Studies have shown that, like other forms of temporal processing,

rhythm perception is significantly poorer in the visual modality than in the auditory modality. For instance, in tasks where subjects must discriminate or reproduce rhythmic sequences, subjects perform significantly better when the rhythms are presented in the auditory modality than in the visual modality (Collier & Logan, 2000; Glenberg et al., 1989; Saenz & Koch, 2008). However, there has been no previous study of perceptual learning in visual rhythm perception. Evidence that rhythm perception may be susceptible to perceptual learning can be found in a recent study that showed that, compared to non-musicians, individuals with musical training have superior rhythm perception in both the visual and auditory modalities (Rammsayer et al., 2012). These findings imply that musical training may result in a form of perceptual learning that improves temporal processing in multiple sensory modalities. However, Rammsayer et al. did not experimentally manipulate which subjects did and did not receive musical training; therefore the potential causal link between perceptual (i.e., musical) training and its benefit to rhythm perception remains unclear. Thus, the aim of the current study was to experimentally examine the effect of perceptual training on visual rhythm perception.

Furthermore, it is important to consider whether unisensory training alone is the best approach to training the visual modality in a temporal task. Past studies have indicated that temporal information is automatically encoded by the auditory modality, even when that information is delivered via the visual modality. Evidence for this has been obtained via behavioral methods (Guttman et al., 2005), brain imaging (Karabanov et al., 2009), and transcranial magnetic stimulation (Kanai et al., 2011). This implies that engaging the auditory modality during perceptual training may modulate visual rhythm learning. This possibility is supported by a recent study that found that auditory training in a temporal interval discrimination task led to improvements in visual interval discrimination (Bratzke et al., 2012). Furthermore,

research has shown that multisensory training can facilitate unisensory perceptual learning (Shams & Seitz, 2008). For instance, it has been shown that visual motion perception is significantly facilitated by audio-visual training compared to visual-alone training (Kim, Seitz, & Shams, 2008; Seitz, Kim, & Shams, 2006). In light of these findings, the present study examined the effect of different forms of perceptual training on visual rhythm perception by comparing the benefits of visual, auditory, and audio-visual training.

## 1.2. Method

### Participants

The participants were 94 undergraduate students 64 females, 30 males; ages 18 to 44 years) who participated for course credit or payment. All subjects had normal or corrected-to-normal vision and hearing. Each subject gave written informed consent and the research was conducted in accordance with the IRB approved by the UCLA Human Research Protection Program.

### Materials

**Apparatus.** Visual stimuli were presented on a 19" CRT monitor at resolution of 1024 × 768 pixels and frame rate of 75 Hz. Subjects' heads were positioned in a chin rest at a distance of 57 cm from the monitor. Auditory stimuli were presented with speakers positioned on the left and right sides of the monitor. Experimental tasks were delivered via custom software written in Matlab with Psychophysics Toolbox (Brainard, 1997).

**Stimuli.** The stimuli and task were adapted from Saenz & Koch (2008). The visual stimuli consisted of a white disc against a black background and gray central fixation cross. The white disc was displayed at the center of the screen and had a diameter that subtended

approximately 3 visual degrees. The auditory stimuli were beeps consisting of pure tones with a frequency of 360 Hz, as well as white noise. In all conditions, the sound pressure level was ~60 dB.

**Rhythms.** The visual stimuli were arranged into rhythms consisting of seven elements, including three elements with a short duration (50 ms) and four with a long duration (200 ms). The inter-stimulus interval (ISI) between the elements was 100 ms in duration. A standard rhythm was uniquely generated for each participant by randomizing the serial position of the seven elements, with the exception that there had to be at least three transitions between short and long elements to ensure a minimum amount of complexity within each rhythm. A schematic of an example rhythm sequence can be seen in Figure 1. Thus, a visual rhythm sequence was indicated by the onset and offset of a blinking white disc, and an auditory rhythm sequence was indicated by the onsets and offsets of pure tone beeps.

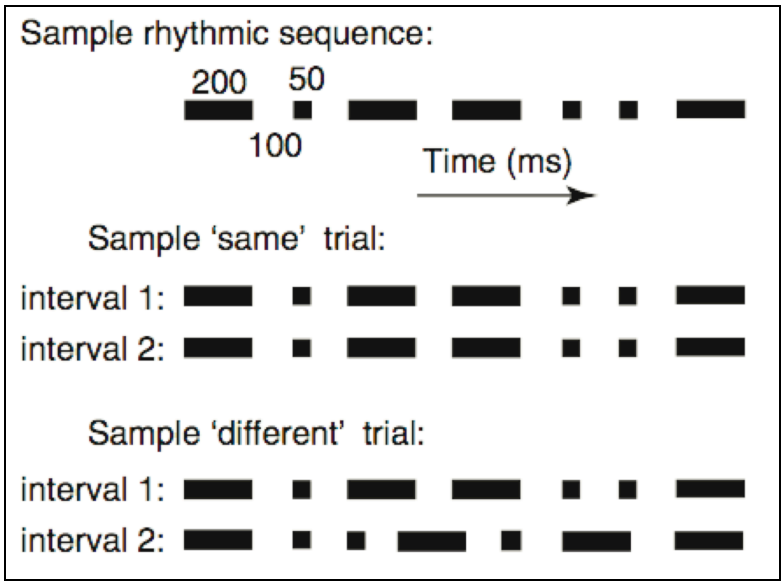



**Figure 1.** Examples of rhythm sequences used in Study 1.

**Procedure**

Participants were randomly assigned to one of three groups: a visual training group, an auditory training group, or an audio-visual training group. Each group received training and testing across 2 sessions (24 to 48 hours apart). During training and tests, subjects completed a rhythm discrimination task. This was a same-different task wherein each trial consisted of two intervals, each of which contained a rhythm sequence. The subject judged whether the two rhythms were the same or different by pressing one of two keys. On half of the trials, the standard rhythm was presented in both intervals ("same" trials). On the other half of trials, one of the intervals contained the standard rhythm, while the other contained a shuffled version of the standard rhythm ("different" trials). Specifically, the elements in positions 3 through 6 of the standard rhythm were shuffled to produce a different rhythm sequence. Subjects had up to 2 seconds to respond and were instructed to respond as quickly and accurately as possible.

For all of the groups, the pre- and post-test trials consisted of visual rhythms only (i.e., no auditory stimuli). However, the nature of the training trials differed across groups. Specifically, training trials consisted of visual rhythm sequences for the visual training group, auditory rhythm sequences for the auditory training group, and congruent auditory and visual rhythm sequences for the audio-visual training group. In order to control for the possibility that the beeps might cause the auditory and audio-visual groups to experience a general auditory alerting effect, all three training groups received a background of auditory white noise during their training trials (i.e., to equate the overall sound pressure level experienced by each group). The white noise started and stopped at the beginning and end of each rhythm sequence. Despite this white noise, the visual training group received "visual-only" training in the sense that the rhythm sequences were not represented in the auditory modality (i.e., no beeps).

In the first session, all groups completed 10 practice trials (visual stimuli only), followed by a test block (pre-test; 50 trials; visual stimuli only) and four blocks of training (50 trials per block). In the second session, subjects completed 10 warm-up trials (visual stimuli only), followed by a test block (post-test 1; 50 trials; visual stimuli only), three blocks of training (50 trials per block), and another test block (post-test 2; 50 trials; visual stimuli only). Additionally, in order to track each group's rate of visual perceptual learning during training, each training block contained 10 trials (in addition to the 50 training trials) consisting of visual-only rhythm sequences (i.e., identical to the pre- and post-test trials). A schematic of the procedure can be seen in Figure 2. Subjects received feedback during practice and training trials, but no feedback was given during pre- and post-tests. At the end of the second session, subjects completed an exit questionnaire in which they reported their number of years of formal music training, the extent of their video game experience (on a scale from 1 to 5), and whether they attempted to use any strategies during the rhythm discrimination task. The question regarding subjects' past musical training was included as a control variable, in light of research showing that musicians have significantly better visual and auditory rhythm perception compared to non-musicians (Rammsayer et al., 2012).

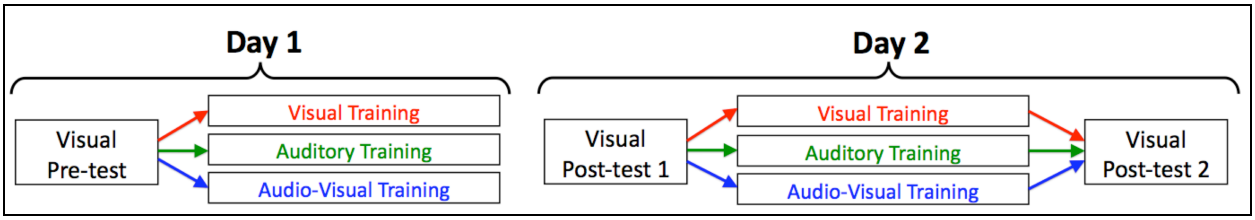



**Figure 2.** Schematic of procedure used in the first and second session of Study 1.

## 1.3. Results

To ensure initial task performance was similar across groups, subjects were omitted if their percent accuracy in the pre-test was above or below 2 standard deviations of the mean. This resulted in the exclusion of 4 subjects. Of the remaining 90 subjects, there were 30 subjects per training group. As expected from past research (Rammsayer et al., 2012), subjects' past musical experience had an effect on their visual rhythm perception, as indicated by a significant positive correlation between subjects' self-reported years of musical training and their performance in the pre-test ($r = .32$, $p = .002$). Therefore, to control for this effect, subjects' years of musical training was entered as a covariate in our analyses.

Subjects' percent accuracy in the visual rhythm discrimination task was analyzed using a 3 (group: visual, auditory, audio-visual) x 3 (test: pre-test, post-test 1, post-test 2) mixed analysis of covariance, with years of musical training entered as a covariate. There was a significant main effect of test, $F(2, 172) = 5.39$, $p = .005$, $\eta_p^2 = .06$, such that overall accuracy was higher in post-test 1 ($M = .67$, $SD = .14$) than in pre-test ($M = .63$, $SD = .10$), $t(89) = 3.49$, $p = .001$, $d = .37$, and overall accuracy was higher in post-test 2 ($M = .68$, $SD = .14$) compared to pre-test, $t(89) = 4.30$, $p < .001$, $d = .45$. And while the group by test interaction was not statistically significant, an analysis of the simple effects revealed that improvements across tests differed among the groups, such that not all of the groups displayed significant learning. Specifically, the visual group failed to show a significant increase in accuracy across tests (pre-test: $M = .63$, $SD = .11$; post-test 1: $M = .64$, $SD = .14$; post-test 2: $M = .66$, $SD = .14$), $F(2, 85) = .879$, $p = .42$, $\eta_p^2 = .02$. In contrast, a significant increase in performance was found in both the auditory group (pre-test: $M = .63$, $SD = .10$; post-test 1: $M = .69$, $SD = .14$; post-test 2: $M = .70$, $SD = .14$), $F(2, 85) = 5.22$, $p = .007$, $\eta_p^2 = .11$, and the audio-visual group (pre-test: $M = .62$, $SD = .10$; post-test 1: $M = .67$, $SD = .14$;

post-test 2: $M = .68$, $SD = .14$), $F(2, 85) = 4.80$, $p = .01$, $\eta_p^2 = .10$. The pattern of accuracy results for each group can be seen in Figure 3. A comparison of the groups' change in accuracy from pre-test to post-test 1 and post-test 2 can be seen in Figure 4.

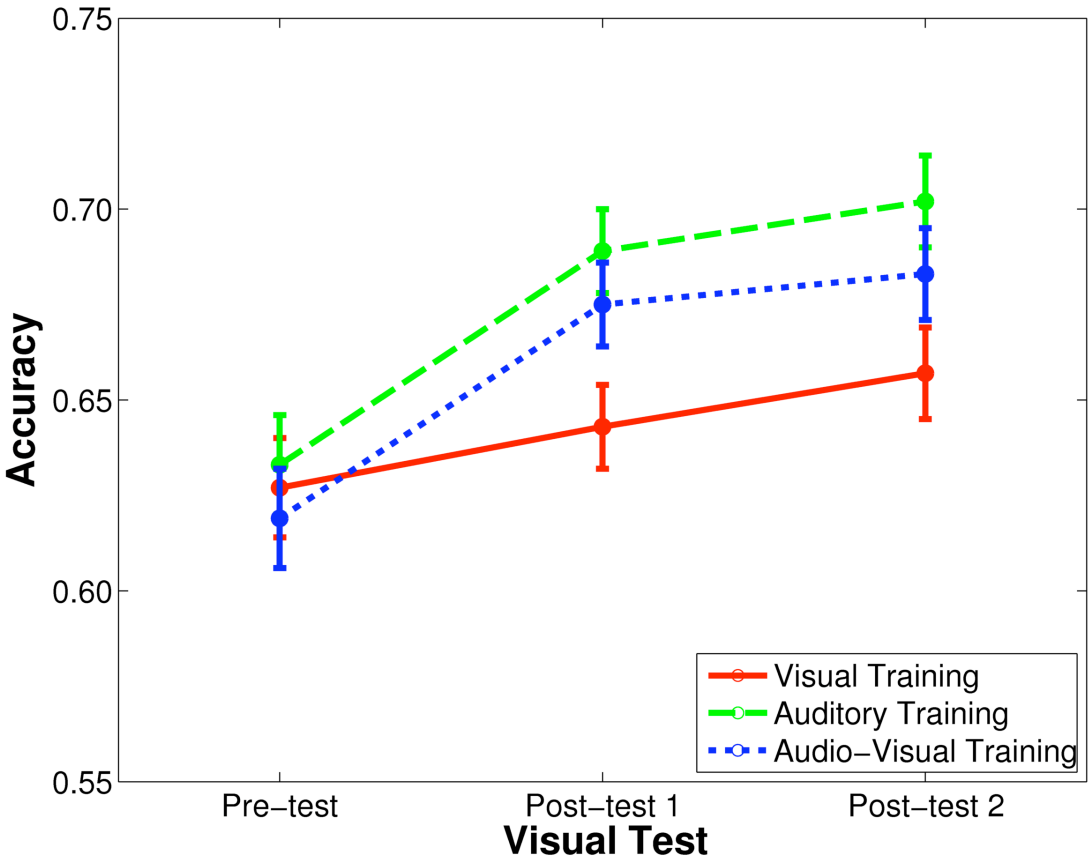



**Figure 3.** Accuracy results from Study 1. Error bars represent within-subject standard error of the mean.

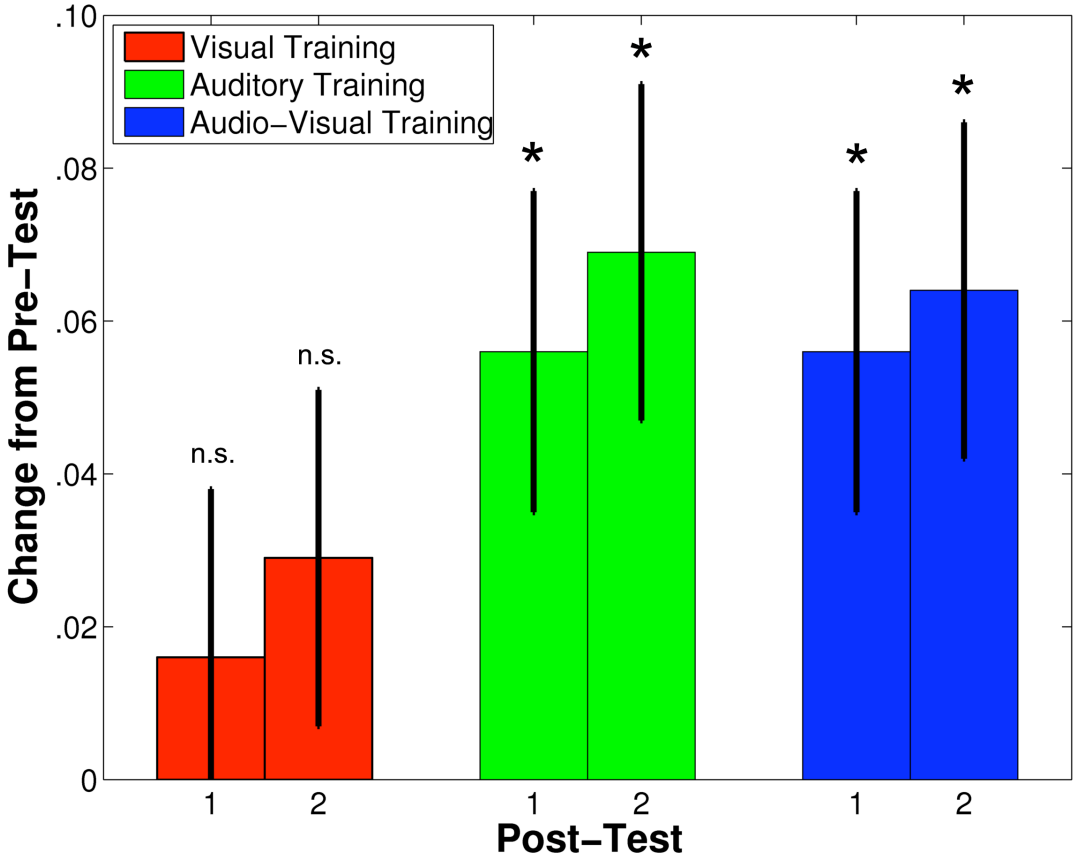



**Figure 4.** Change in accuracy from pre-test to post-test 1 and post-test 2. Error bars represent standard error of the mean difference. (* denotes $p < .01$)

## 1.4. Discussion

A main goal of this study was to examine whether visual rhythm perception could be improved via perceptual training. Based on the significant main effect of test, it appears that visual rhythm perception is in fact susceptible to perceptual learning. Furthermore, this appears to be a long-term learning effect, as the post-tests were completed 24 to 48 hours after the first session of training. Given that very few studies have examined visual perceptual learning within a temporal task and that, to my knowledge, no previous perceptual learning study has

investigated rhythm perception specifically, the current results offer a unique glimpse into these domains.

Of particular interest, despite two sessions of training, the group that received visual-only training failed to experience a significant improvement in their visual rhythm perception. In contrast, visual rhythm perception was significantly improved in the groups that received auditory and audio-visual training. This pattern of results is noteworthy, as it indicates that visual rhythm perception is not easily improved unless the auditory modality is engaged during the training process, as if the auditory modality "teaches" the visual modality. This is not an unrealistic possibility, based on what is known from past research. For instance, given that the auditory modality is known to be highly adept at processing temporal information in general (Gebhard & Mowbray, 1959; Shipley, 1964) and rhythms in particular (Collier & Logan, 2000; Glenberg et al., 1989; Saenz & Koch, 2008), it may be that subjects in the auditory and audio-visual groups were able to encode an accurate internal representation of the standard rhythm during training (i.e., better than what could have been achieved with visual-only training). Furthermore, given that temporal information delivered via the visual modality has been found to be automatically encoded by the auditory modality (Guttman et al., 2005; Kanai et al., 2011; Karabanov et al., 2009), it is possible that during the post-tests, which were visual-only trials, subjects in the auditory and audio-visual groups were able to benefit from their improved internal representation of the standard rhythm. In contrast, the subjects in the visual group, who were never presented with rhythms in the auditory modality, may have acquired a comparatively poor internal representation of the standard rhythm, which resulted in minimal improvements across the tests.

The idea that engaging the auditory modality in a given task can lead to benefits in visual perceptual learning is not new. For instance, in the domain of temporal perception, Bratzke et al. (2012) found that when subjects were trained in a temporal interval discrimination task in the auditory modality, they experienced a transfer of learning to the visual modality as well. Interestingly, they failed to find the reverse effect. That is, subjects who were trained in the visual modality did not experience a transfer of learning to the auditory modality. Another example of auditory facilitation of visual perceptual learning has been found in studies of motion perception (Kim et al., 2008; Seitz et al., 2006). These studies found that when subjects were trained in a motion discrimination task with congruent audio-visual stimuli, their subsequent visual-alone motion perception was significantly improved compared to subjects who were trained with visual stimuli only or those trained with incongruent audio-visual stimuli. The current study both complements and adds to these previous studies by demonstrating that audition can facilitate vision in a domain of temporal perceptual learning that has not previously been explored, namely rhythm perception.

Given that little is known about how malleable rhythm perception is in response to perceptual training, there are many avenues future studies can take. For example, the current study trained and tested each subject on only a single standard rhythm, however it is unclear whether the observed improvements in rhythm perception were specific to the standard rhythm or whether the subjects experienced a general improvement in their overall rhythm perception. Therefore, a natural follow-up study would be to examine the generalization of this learning, by testing whether training on a standard rhythm leads to improvements in the ability to discriminate untrained (i.e., novel) rhythms. Additionally, while the current study examined the effect of perceptual training across two sessions, it would be worthwhile to test the effect of

training across several sessions. Subjects in the current study made modest, albeit significant, improvements in performance, but with the average pre- to post-test increase in accuracy reaching only about 6%, there was clearly more room for improvement and it is unclear from the current findings whether further improvements could have been attained with additional training. Thus, it would be interesting to test the effects of longer-term training.

In general, there is a need in the perceptual learning literature for research that examines whether it is possible to improve a given sensory modality's ability to process a form of information that it is not naturally adept at processing. For instance, to what extent can the visual modality be improved in its temporal processing abilities? And to what extent can the auditory modality be improved in its spatial processing abilities? Such research would shed light on the limits of the plasticity of our sensory modalities.

# Study 2:

# Passive Sequence Exposure and Visuomotor Sequence Learning

## 2.1. Introduction

There are many skills and activities in which people must learn how to produce complex patterns of motor movements in response to stimuli that follow a particular sequence. This type of learning is what researchers often refer to as *sequence learning*, and it is believed to engage multiple brain regions, including sensory, motor, and memory systems (Keele, Ivry, Mayr, Hazeltine, & Heuer, 2003). For instance, when an individual is learning to play a piece of music on a piano, she must translate sheet music notations into a series of motor commands that cause her fingers to press the piano keys in a particular sequence. At first, this is a challenging task that requires focused concentration. However, after extensive practice, she will eventually be able to play the piece of music effortlessly, as if little or no thought is required. This kind of sequence learning is believed to arise from a coordinated interplay between sensory and motor regions of the brain, and it has become the focus of a large body of research. The current study aims to add to this literature by examining whether passive exposure to a sequence can influence performance in a subsequent visuomotor task.

A common method used to study sequence learning is the *serial reaction time* (SRT) task (Nissen & Bullemer, 1987). In this task, the subject makes speeded motor responses to a series of sensory cues, wherein each sensory cue requires a particular motor response. For instance, the onset of a visual stimulus in a particular spatial location might require a key press with the index finger, whereas a visual stimulus in another spatial location might require a key press with the ring finger, and so on. Each time the subject responds to a cue, another cue is immediately

presented, resulting in a rapid series of cued responses. Unbeknownst to the subject, during certain portions of trials, a specific sequence of cues is repeated, whereas other portions of trials consist of random cues. Throughout the task, the subject's reaction times are recorded, and the result is that subjects become increasingly fast when they are responding to the repeated sequence of cues compared to when they are responding to random cues. Such results indicate that subjects learn the repeated sequence (i.e., they are able to anticipate, and thus respond more quickly to, forthcoming sequence elements). The elegance and flexibility of the SRT task has made it a widely used method in the sequence learning literature, and it is the task that is used in the current study.

Research on certain types of implicit learning, such as *statistical learning*, has shown that when subjects passively observe a series of stimuli (e.g., geometric shapes) that are presented in pre-determined sequences, the subjects automatically learn the sequences (Fiser & Aslin, 2005; Saffran, Aslin, & Newport, 1996). Evidence of the learning can be found in the subjects' ability to later recognize or respond to the stimuli when they are presented within their pre-determined sequences versus novel sequences. For instance, Conway and Christiansen (2005) found that when subjects' fingers were vibrated in patterns that followed predetermined sequences, they were later able to accurately recognize those sequences compared to novel sequences. It is currently unknown whether this type of passive sequence learning is strictly a sensory form of learning or whether it is accessible to the motor system. Relatively few studies have examined whether the type of learning that results from passive sensory exposure to sequences can transfer to the SRT task, and these studies have produced mixed results (Howard, Mutter, & Howard, 1992; Kelly & Burton, 2001). Furthermore, these studies have been conducted exclusively within the visual modality. Given the fact that the brain areas devoted to somatosensation and motor

control are intimately interconnected (Young, 1993), it is possible that passive sequence learning in the tactile modality may readily transfer to motor performance in an SRT task. The current study examines this possibility by testing subjects' visuomotor responses in an SRT task both before and after passively exposing them to a repeated sequence in the visual and tactile modalities.

## 2.2. Method

### Participants

The participants were 50 undergraduate students (37 females, 13 males; ages 18 to 32 years) who participated for course credit and had normal or corrected-to-normal vision. Each participant gave written informed consent and the research was conducted in accordance with the IRB approved by the UCLA Human Research Protection Program.

### Materials

**Apparatus.** Visual stimuli were presented on a 19" CRT monitor at resolution of 1024 × 768 pixels and frame rate of 75 Hz. Experimental tasks were delivered via custom software written in Matlab with Psychophysics Toolbox (Brainard, 1997). Subjects' heads were positioned in a chin rest at a distance of 57 cm from the monitor. Tactile stimuli were created with the use of a computer-controlled tactile stimulation device. The device drove four vibrator components sewn into cushioned enclosures that strapped onto the subjects' fingers.

**Stimuli.** During the vibration phase, the tactile stimuli consisted of mild vibrations delivered to four fingers on each participant's right hand (i.e., index, middle, ring, and pinky finger). During the SRT task, the visual stimuli consisted of four circles that were horizontally aligned. Each circle corresponded to four keys under the fingers of the subject's right hand, such

that the first circle from the left corresponded to the index finger, the second circle corresponded to the middle finger, and so on, as depicted in Figure 5A.

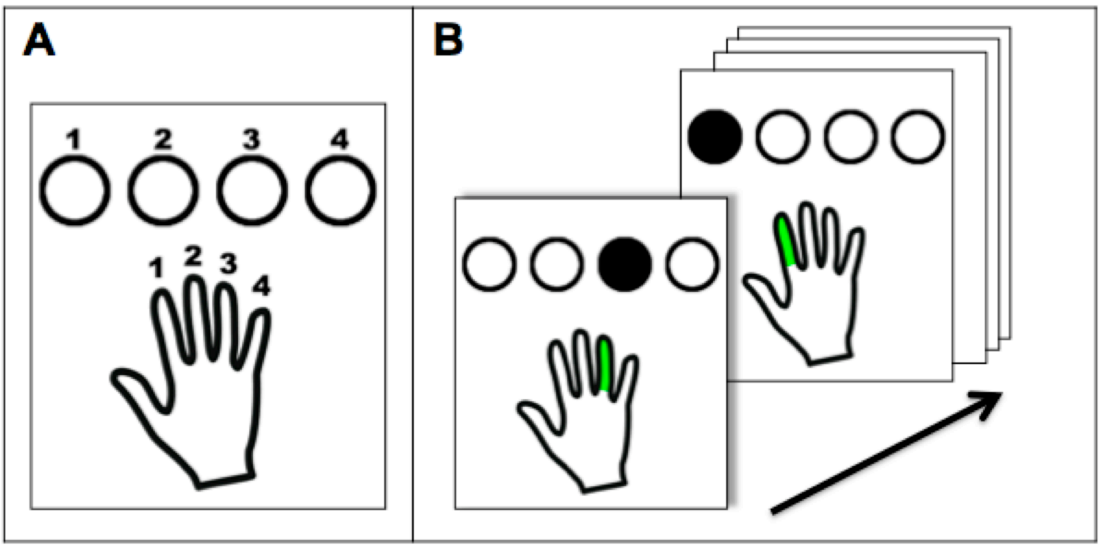



**Figure 5.** (A) Depiction of mapping between subjects' fingers and the SRT visual target locations. (B) Example trials of SRT task.

**Sequences.** Whereas in the majority of previous studies, all participants in a given study responded to the same sequence, in the current study a unique sequence was generated for each participant. By producing a unique set of sequences for each participant, we aimed to control for any sequence-specific effects on reaction time and learning (DeCoster & O'Mally, 2011). Each sequence contained 12 elements, and each element corresponded to one of the subject's fingers, as follows: *1 = index, 2 = middle, 3 = ring,* and *4 = pinky* (as depicted in Figure 5A). The sequences were randomly generated with the following constraints. To ensure each of the four element types (*1, 2, 3, 4*) occurred with equal frequency, each type was used a total of three times in a given sequence. In an effort to reduce the participants' awareness of the sequences, the elements were prevented from occurring in certain combinations, including repeats (e.g., *3-3*),

reversals (e.g., *2-1-2-1*), and ascending or descending runs (e.g., *1-2-3* or *4-3-2*), as previous studies have indicated that such combinations can be particularly salient to subjects (Reed & Johnson, 1994; Vaquero, Jimenez, & Lupianez, 2006). Finally, to ensure there were no redundancies within a given sequence, any subset of four consecutive elements within a sequence was prevented from reoccurring within the sequence (e.g., if the elements *3-1-4-3* occurred as a subset within a sequence, then that specific combination could not reoccur anywhere else within that sequence).

**Procedure**

**General Procedure.** Subjects were randomly assigned to one of two groups: a sequence-exposure group and a random-exposure group. Both groups completed an SRT task, a passive exposure phase, a 5-minute break, and then another SRT task. The details of the SRT task and the exposure phase are described in the following sections. After completing the second SRT task, participants were given an exit questionnaire that assessed their self-reported awareness of the sequences and whether they attempted to use any strategies during the SRT task.

**Serial Reaction Time Task.** Both before (pre-exposure) and after (post-test) the exposure phase, participants completed two blocks of the SRT task (four blocks in total). In each block, participants responded to 144 visual targets. Specifically, when a given target location was cued (i.e., one of the four empty circles changed to a solid black circle), the participant responded by pressing the corresponding key, as depicted in Figure 5B. After the response, another target was cued, and so on, resulting in a rapid series of trials. The time between a response and the onset of the next target, known as the response-to-stimulus interval (RSI), was 50 ms. Participants were instructed to respond as quickly and accurately as possible and they were informed that the computer was recording their reaction times and accuracy. On trials in

which the participant made an incorrect response or failed to respond within 2 seconds, the participant was presented with two brief low-pitched beeps, the trial was recorded as an error, and there was a 500 ms pause before the onset of the next target. Participants were allowed to take a short break between each block of trials.

For both groups, the second block of the pre-test and the first block of the post-test were sequenced blocks. In these blocks, the sequence that had been uniquely generated for each subject was presented for 12 repetitions. Furthermore, for both groups, the first block of the pre-test and the second block of the post-test were random blocks. That is, the order of the targets was random, with the exception that the targets followed some of the same statistical rules that were used in generating the sequences (i.e., repeats, reversals, and runs were not allowed). This was done to ensure that the overall statistical patterns of the random blocks were similar to that of the sequenced blocks.

**Exposure Phase.** In the exposure phase, participants in the sequence-exposure group were passively exposed (in both the visual and tactile modality) to the sequence they had been responding to during the SRT task. The same four circles they saw during the SRT task were displayed on the screen, and the target locations were cued in the order of the sequence for 100 repetitions of the sequence. At the same time, the tips of the subjects' fingers were vibrated (one finger at a time), in the order of the sequence, and in temporal congruency with the visual target locations. That is, when a given element of the sequence was indicated on screen at one of the target locations, the corresponding finger was simultaneously vibrated. Each visual target and each vibration had a duration of 50 ms and there was a 350 ms ISI between the sequence elements. The sequence was repeated seamlessly, with no pause or any other indication of the beginning or end of a repetition. The random-exposure group was presented with the same visual

and tactile stimuli as the sequence-exposure group, except the stimuli were presented in a random order. For both groups, the duration of the exposure phase was approximately 8 minutes.

To ensure that subjects paid attention to the visual stimuli and that they were generally attentive throughout the exposure phase, a cover task was employed. Specifically, subjects were instructed to respond (by key press) when they saw a "flashing" visual stimulus. There were a total of 24 flashing visual targets, which occurred randomly but roughly equally spaced throughout the duration of the exposure phase. The flashing visual stimuli occurred at each of the four visual target locations with equal frequency (6 times each), but in a random order. Whereas the regular visual targets were displayed for 50 ms, the flashing visual targets were displayed with a rapid onset and offset (25 ms on, 25 ms off) for 6 on/off repetitions, creating a percept of a flashing stimulus. For the sequence-exposure group, the order and occurrence of the flashing targets did not disrupt the order of the sequence.

## 2.3. Results

Subjects responded with high accuracy in the SRT task, with an overall mean accuracy of 97%. Trials wherein subjects made erroneous key presses were excluded from the reaction time analyses. The mean reaction time for each block of the SRT task was obtained by calculating the mean of the subjects' median reaction times.

First, to assess the extent of subjects' sequence learning both before and after the exposure phase, reaction times in the random versus sequenced blocks were compared via paired samples t-tests for both groups. In the pre-exposure SRT task, subjects in the sequence-exposure group responded faster in the sequenced block ($M$ = 423 ms, $SD$ = 69) than in the random block ($M$ = 434 ms, $SD$ = 67), a difference that was marginally significant, $t(24) = 1.90$, $p = .07$, $d$ =

.38. Similarly, subjects in the random-exposure group responded slightly faster in the sequenced block ($M$ = 399, $SD$ = 69) than in the random block ($M$ = 404 ms, $SD$ = 52), but this difference was not significant, $t(24) = .960$, $p = .35$, $d = .19$. However, in the post-exposure SRT task, both groups showed evidence of sequence learning. Specifically, the sequence-exposure group responded significantly faster in the sequenced block ($M$ = 369 ms, $SD$ = 51) than in the random block ($M$ = 410 ms, $SD$ = 54), $t(24) = 6.60$, $p < .001$, $d = 1.32$. Similarly, the random-exposure group responded significantly faster in the sequenced block ($M$ = 351 ms, $SD$ = 54) than in the random block ($M$ = 396 ms, $SD$ = 47), $t(24) = 8.51$, $p < .001$, $d = 1.70$. The pattern of these results can be seen in Figure 6.

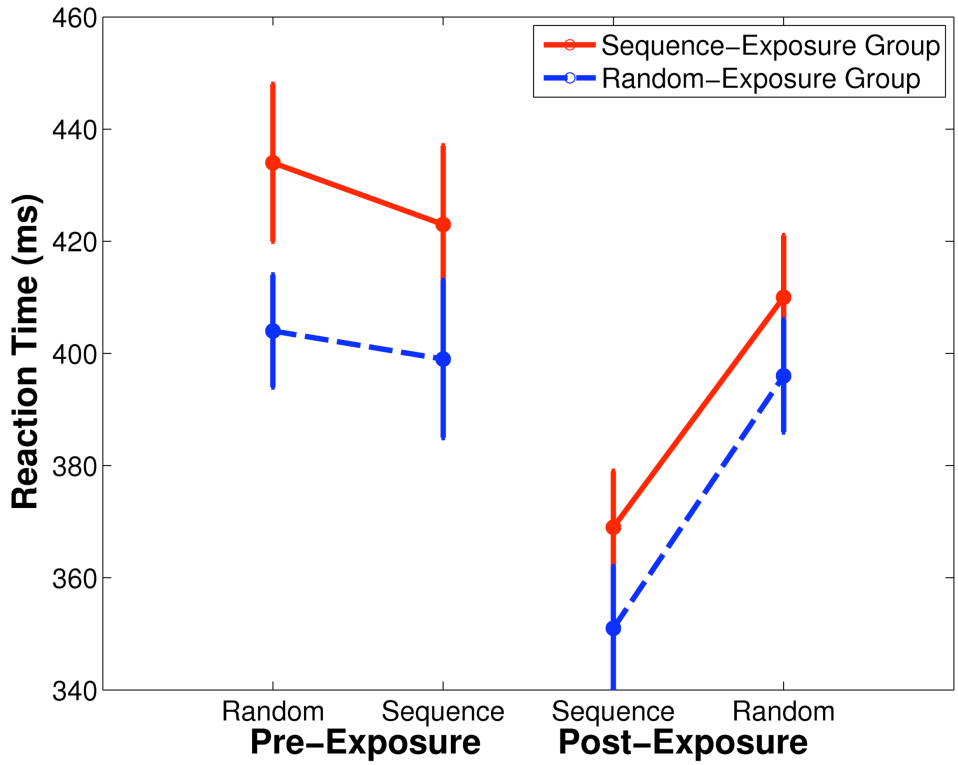



**Figure 6.** Reaction time results from the SRT task. Error bars represent between-subject standard error of the mean.

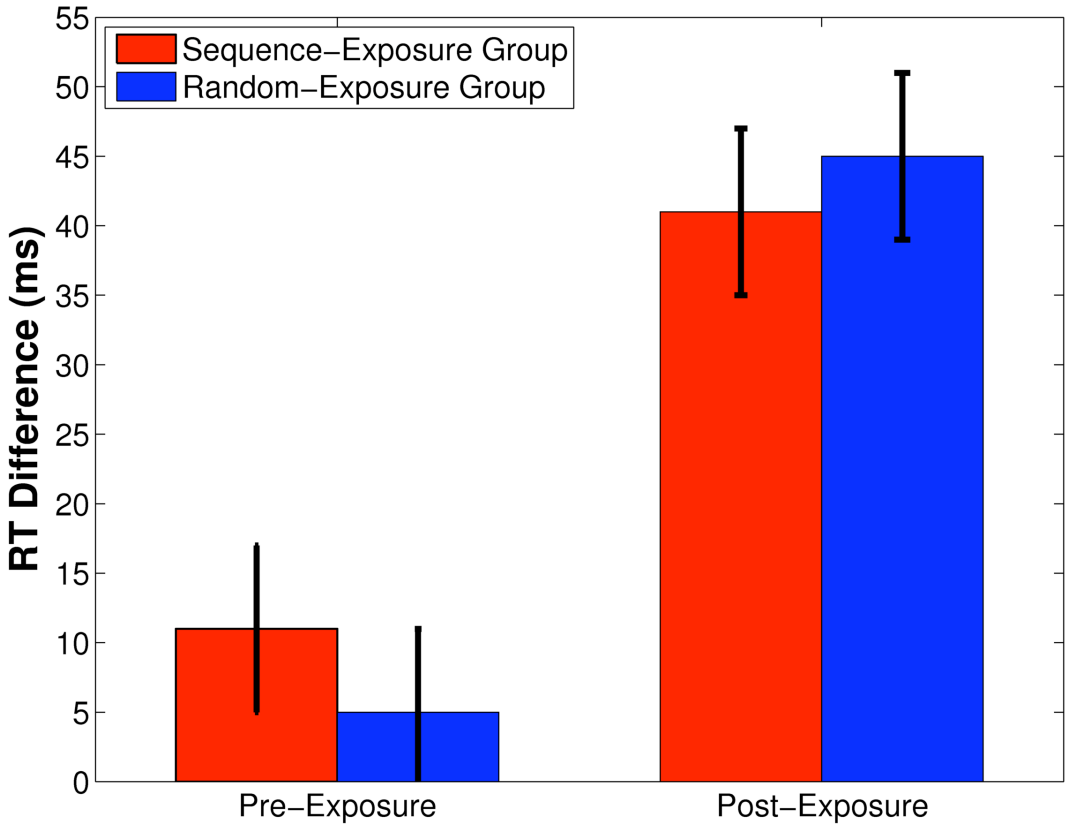



**Figure 7.** The random block vs. sequence block difference in reaction time, indicating the magnitude of the sequence learning effect. Error bars represent standard error of the mean difference.

To compare the magnitude of the sequence learning effect between the sequence-exposure group and random-exposure group, the random-minus-sequenced block difference in reaction time was calculated for both the pre-exposure and post-exposure SRT task. These reaction time differences were then analyzed with a 2 (group: sequence-exposure, random-exposure) x 2 (test: pre-exposure, post-exposure) mixed analysis of variance. The pattern of these results can be seen in Figure 7. The results revealed a significant main effect of test, such that the overall magnitude of sequence learning was greater in the post-exposure test ($M$ = 43 ms,

*SD* = 29) than in the pre-exposure test (*M* = 8 ms, *SD* = 28), $F(1, 48) = 80.38$, $p < .001$, $\eta_p^2 = .63$. However, there was no significant main effect of group ($p = .91$), nor was there a significant group by test interaction ($p = .23$). The magnitude of the sequence learning effect in the post-exposure test was significantly greater than in the pre-exposure test for both the sequence-exposure group (pre-exposure: *M* = 11 ms, *SD* = 29; post-exposure: *M* = 41 ms, *SD* = 31), $t(24) = 5.47$, $p < .001$, $d = 1.09$, and the random-exposure group (pre-exposure: *M* = 5 ms, *SD* = 28; post-exposure: *M* = 45 ms, *SD* = 27), $t(24) = 7.21$, $p < .001$, $d = 1.44$.

## 2.4. Discussion

The results of the current study indicated that both the sequence-exposure group and the random-exposure group experienced significant sequence learning, as evidenced by a highly significant effect in the post-exposure SRT task. This finding alone is noteworthy, because in the vast majority of previous SRT studies, subjects have been required to complete roughly a dozen blocks of trials, the majority of which being sequenced blocks. In contrast, the current study contained only four blocks, and only two of these were sequenced blocks. Therefore, subjects managed to acquire a significant amount of sequence learning with a relatively minimal number of repetitions of the sequence. Furthermore, the magnitude of sequence learning that was observed in the current study (i.e., approximately a 40 ms reduction in reaction time in the post-exposure sequenced block compared to the random block) was on par with that found in past studies. This indicates that the rate of learning in the SRT task is rather rapid, perhaps more so than has been acknowledged or indicated in previous research.

The main goal of the current study was to test whether passive sensory exposure to a sequence would influence subjects' visuomotor responses to that sequence in the SRT task.

Unfortunately, no such influence was found, as the sequence-exposure group and random-exposure group displayed the same magnitude of learning in the post-exposure SRT task. This was despite the fact that the sequence-exposure group was given an extensive amount of passive exposure to the sequence (i.e., 100 repetitions) in both the visual and tactile modalities. It is, perhaps, possible that the exposure phase did in fact have an effect on the sequence-exposure group's magnitude of sequence learning, but that the effect was not detectable by the measures used in the current study. For instance, it may have been too subtle of an effect to be detected by reaction time differences in the SRT task.

As previously noted, this is not the first study to examine the effect of passive exposure to a sequence on performance in an SRT task. Past studies have differed from the current study in that they have exposed subjects to a sequence in the visual modality only (Howard, Mutter, & Howard, 1992; Kelly & Burton, 2001). The results of the current study are similar to those found by Kelly & Burton (2001), who found that passive sensory exposure to sequence did not transfer to performance in a subsequent SRT task. Howard et al. (1992), on the other hand, reported significant sequence learning by subjects who passively observed a repeated sequence in the visual modality. However, this learning effect was limited to subjects who had been exposed to a short sequence (10 elements) and, furthermore, these subjects responded to 10% of the trials (i.e., it was not entirely passive observation prior to testing). Based on the results of the current study, it is clear that visuomotor sequence learning can occur very rapidly, with relatively few repetitions of the sequence. Thus, the findings by Howard et al. are not entirely indicative of passive sequence learning.

Despite the current study's lack of an effect of passive sequence exposure, future research should continue to explore this topic. It is known from other forms of implicit sequence learning

that it is possible for certain forms of sequences to be learned through passive observation, as evidenced by research on statistical learning (Saffran, Aslin, & Newport, 1996; Saffran, Johnson, Aslin, & Newport, 1999; Saffran, Newport, & Aslin, 1996) and artificial grammar learning (Reber, 1967). Thus, the question is not whether sequence learning can occur passively. The question is whether or to what extent this form of passive learning can then, by some means, be transferred to performance in a sensorimotor task. It is possible that the studies that have investigated this topic to date have not used proper measures to capture the transfer of learning. Or it may be that specific training conditions are required to facilitate the transfer of learning. For example, Huang et al. (2010) found that when subjects were given a brief lesson on how to play a song on a piano and then had the sequence of that song reinforced through passive tactile exposure on their fingers (i.e., via a specially designed tactile glove), their subsequent ability to play the song on the piano was facilitated compared to a control group who did not receive tactile exposure. It is unclear, however, whether the findings of Huang et al. were due to the subjects being explicitly aware of the to-be-learned sequence. In contrast, subjects in the current study were not explicitly informed that there was a sequence to be learned. This suggests that specific training protocols, perhaps ones that encourage explicit sequence learning, may be required for passive sequence exposure to successfully facilitate sensorimotor performance. Given that sensorimotor learning is an integral component of many everyday skills, such as playing a musical instrument, it is worthwhile for future studies to continue to explore the mechanisms between sensory and motor systems that give rise to sensorimotor sequence learning.

# Study 3:

# The Effect of Statistical Learning on Internal Stimulus Representations

## 3.1. Introduction

Statistical learning is the automatic and unconscious learning of environmental regularities (Fiser & Aslin, 2001; Kim, Seitz, Feenstra, & Shams, 2009; Saffran, Aslin, & Newport, 1996a; Saffran, Newport, & Aslin, 1996b). It is one of the most basic mechanisms of learning in human perceptual and cognitive domains, and it has been studied in relation to language acquisition (Saffran et al., 1996a; 1996b), attention (Baker, Olson, & Berhmann, 2004; Toro, Sinnett, & Soto-Faraco, 2005; Turk-Browne, Jungé, & Scholl, 2005), development (Kirkham, Slemmer, & Johnson, 2002; Saffran et al., 1996a; Saffran, Johnson, Aslin, & Newport, 1999), vision (Fiser & Aslin, 2001; 2002; 2005; Kim et al., 2009; Olson & Chun, 2001; Turk-Browne et al., 2005), audition (Saffran et al., 1999; Seitz, Kim, Wassenhove, & Shams, 2007), and haptics (Conway & Christiansen, 2005). A typical statistical learning study begins with an exposure phase in which a subject is passively exposed to a set of stimuli. Unbeknownst to the naïve subject, the stimulus set is designed to contain arbitrary inter-stimulus associations in terms of the spatial and/or temporal proximity of groups of stimuli, such that subsets of stimuli are grouped into sequences (e.g., pairs or triplets) that are repeated in the stimulus set. Subjects will then be tested on their knowledge of the stimulus groups, such as with a two-interval forced choice familiarity test (Fiser & Aslin, 2001; 2002; 2005; Saffran et al., 1999). Even though the subject is typically not consciously aware of the stimulus groups, subsequent testing of the subject's ability to recognize them reveals that implicit learning of the stimulus groups does in fact occur (Kim et al., 2009).

Research on statistical learning has focused on the mechanisms that drive the learning of associations between groups of stimuli, but it has not explored how the internal representations of the individual stimuli may also be altered as their associations are learned (e.g., O'Brien & Raymond, 2012). In fact there is a divide between the field of perceptual learning (Sagi, 2011), which concentrates on representational changes that occur during slow, explicit, training procedures, and the field of statistical learning, which emphasizes implicit, quickly developing, stimulus-stimulus associations.

One of the most common approaches used in statistical learning research has been to expose participants to groups of stimuli that are spatially and/or temporally associated and to then test the participants' sense of familiarity for those stimulus groups compared to novel groupings (Fiser & Aslin, 2001; 2002; 2005; Saffran et al., 1999). Such studies have consistently shown that participants judge learned stimulus groups as being more familiar than novel groups, however little is known about what drives this perceptual judgment. Recent neuroimaging research found that participants' sense of familiarity for learned sequential pairs was correlated with the neural processing of the second items of the pairs, but not the first items (Turk-Browne, Scholl, Johnson, & Chun, 2010). Similarly, in studies that have measured reaction time, it has been shown that when participants are exposed to repeated sequences of shapes, they are subsequently able to respond more quickly to items at the ends of the shape sequences compared to beginning sequence items (Kim et al., 2009; Olson & Chun, 2001; Turk-Browne et al., 2005). This reduction in reaction times for later group items has been interpreted as a priming effect (i.e., temporal predictability), however an unexplored possibility is that of element learning (i.e., improved internal representations of individual predictable items). In other words, it is possible that, in addition to the associative learning mechanisms that operate during statistical learning,

there may be perceptual learning mechanisms that shape the representations of individual items according to their degree of temporal predictability.

To directly address the possibility that stimulus representations change through statistical learning, we examined participants' responses to individual stimuli both within and outside of learned associative groupings. We utilized a paradigm of temporal statistical learning wherein individual items are grouped into sequences of fixed sequential order, and these groups are in turn presented repeatedly in a randomized order (Fiser & Aslin, 2002; Kim et al., 2009; Turk-Browne et al., 2005). In this paradigm, each item has a particular degree of temporal predictability according to its position within its group. For instance, an item that appears early in a given group is less predictable than an item that appears later in that group. Across three experiments, we tested participants' responses to individual items both within and outside the context of their temporal groupings, and we found clear evidence of enhanced element learning of predictable items. These findings complement previous accounts of statistical learning (Turk-Brown & Scholl, 2009) and reveal an enriched mechanism of human learning, such that learning to associate items also enhances the representations of certain items relative to others.

## 3.2. General Method

In all experiments, participants completed an exposure phase in which they observed a stream of rapidly presented visual (abstract black-and-white shapes adapted from Fiser and Aslin, 2001) and auditory stimuli (abstract computer-generated sounds from Kim et al., 2009). Visual stimuli were grouped into six associate pairs (pairs were randomly generated for each participant and paired items were presented in a fixed temporal order), whereas auditory stimuli were presented in a pseudorandomized order and acted as distractors (except in Experiment 1b

where sounds were grouped into pairs and visual stimuli were pseudorandomized and used as distractors). Visual and auditory stimuli were presented synchronously for 300 ms and with an inter-stimulus interval (ISI) of 100 ms (see Figure 8). Each pair was presented 150 times in a random order (except no pair was repeated in succession).

The visual stimuli were presented on a 19" CRT monitor at resolution of 1024 × 768 pixels and frame rate of 75 Hz (Experiments 1a & 1b) or 100 Hz (Experiment 2). Experimental tasks were delivered via custom software written in Matlab with Psychophysics Toolbox (Brainard, 1997). Subjects' heads were positioned in a chin rest at a distance of 57 cm from the monitor. The size of each visual stimulus was approximately 3° square of visual angle. Auditory stimuli were presented with speakers positioned on the left and right sides of the monitor. The duration of each auditory stimulus was 300 ms, including 5 ms on and off ramps. Sound pressure level was approximately 60 dB.

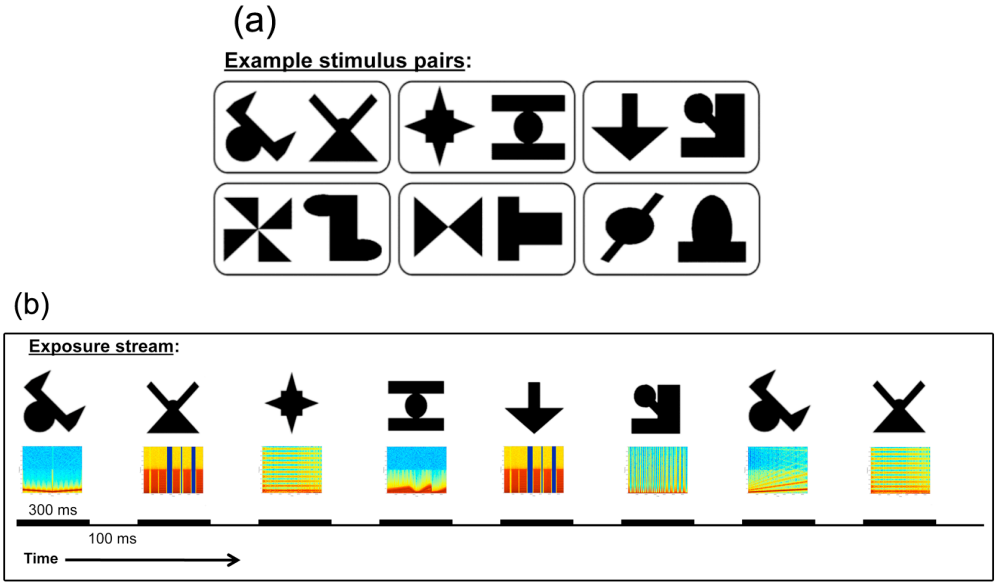



**Figure 8.** (a) Example visual stimulus set. (b) Example schematic of the stimulus stream in the exposure phase. The auditory stimuli are represented by their spectrograms.

Details of the testing procedures used in each experiment are described in the following sections. In each experiment, all test conditions were pseudorandomly interleaved and no feedback was given. For Experiments 1a and 1b, sample sizes were based on previous studies of visual (Kim et al., 2009; Turk-Browne et al., 2005) and auditory (Saffran et al., 1999; Saffran et al., 1996b) temporal statistical learning, and for Experiment 2 we conducted a power analysis to estimate the sample size needed to detect a small to medium effect size, as expected from a pilot study.

## 3.3. Experiments 1a and 1b

In our first set of experiments we used a variation of a reaction time test used in previous statistical learning studies (Kim et al., 2009; Olson & Chun, 2001; Turk-Browne et al., 2005). Our current approach is novel in that we measured reaction times both when the pairs were intact and when the pairs were broken. This allowed us to compare responses to the individual items in both the presence and absence of their learned associations.

### 3.3.1. Method

Undergraduate students (Experiment 1a: 12 participants, 19-29 years, with 5 females; Experiment 1b: 31 participants, 18-28 years, with 21 females) first completed an exposure phase in which they passively observed a stream of visual pairs (Experiment 1a; in this case the auditory stream was randomized) or auditory pairs (Experiment 1b; in this case the visual stream was randomized). Participants then completed 120 test trials where they were presented with a target stimulus, which they were instructed to detect (via a key-press) within a rapid stream of ten stimuli (see Figure 9a). In Experiment 1a each test stream consisted of visual stimuli only,

and in Experiment 1b each test stream consisted of auditory stimuli only. On all trials the target was present in the test stream, but the target's position within the stream was pseudorandomized across trials. The test stream consisted of five of the pairs from the exposure phase, presented in a psuedorandomized order with the constraint that the target item was never in the first two or last two positions of the stream. The stimulus durations and ISI were identical to those used in the exposure phase (300 ms and 100 ms, respectively). The target item was either the first or second item from one of the pairs presented during exposure and it was followed (item 1 condition) or preceded (item 2 condition) by either its pair-item (match condition) or by another item (mismatch condition) from a pair not included in the test stream. In other words, in the match condition, the target's learned item association was intact, whereas the target's item association was broken in the mismatch condition. Each stimulus was tested an equal number of times in a pseudorandom order across trials, with the constraints that the same stimulus could not be the target on consecutive trials and items from the same pair could not be targets on consecutive trials.

Participants' reaction time data were trimmed of outlier responses by removing reaction times that were 2 or more standard deviations above or below each participant's mean. Additionally, we omitted trials in which participants responded before the onset of the target. These omissions resulted in the removal of approximately 4% of responses overall.

### 3.3.2. Results

Replicating prior studies of statistical learning (Kim et al., 2009; Turk-Browne et al., 2005), we found that participants exposed to visual pairs (Experiment 1a; Figure 9b) responded faster to second items ($M$ = 334 ms, $SD$ = 26.9) than to first items ($M$ = 347 ms, $SD$ = 26.8); with

a 2 (trial type: match vs. mismatch) x 2 (target item: item 1 vs. item 2) repeated measures ANOVA showing a significant main effect of target item, $F(1, 11) = 10.90$, $p < .01$, $\eta_p^2 = .50$.

To test, whether the second item advantage was due to element learning for the second items, response times were compared between the match and mismatch trials. We found no effect of trial type, $F(1, 11) = .001$, $p = .97$, nor interaction between trial type and target item, $F(1, 11) = .015$, $p = .91$. To further examine the effect of trial type, paired *t*-tests (two-tailed) were performed. In the match condition, reaction times were faster for second items ($M = 334$ ms, $SD = 28.3$) than for first items ($M = 347$ ms, $SD = 25.9$), $t(11) = 3.60$, $p < .01$, $d = 1.04$.

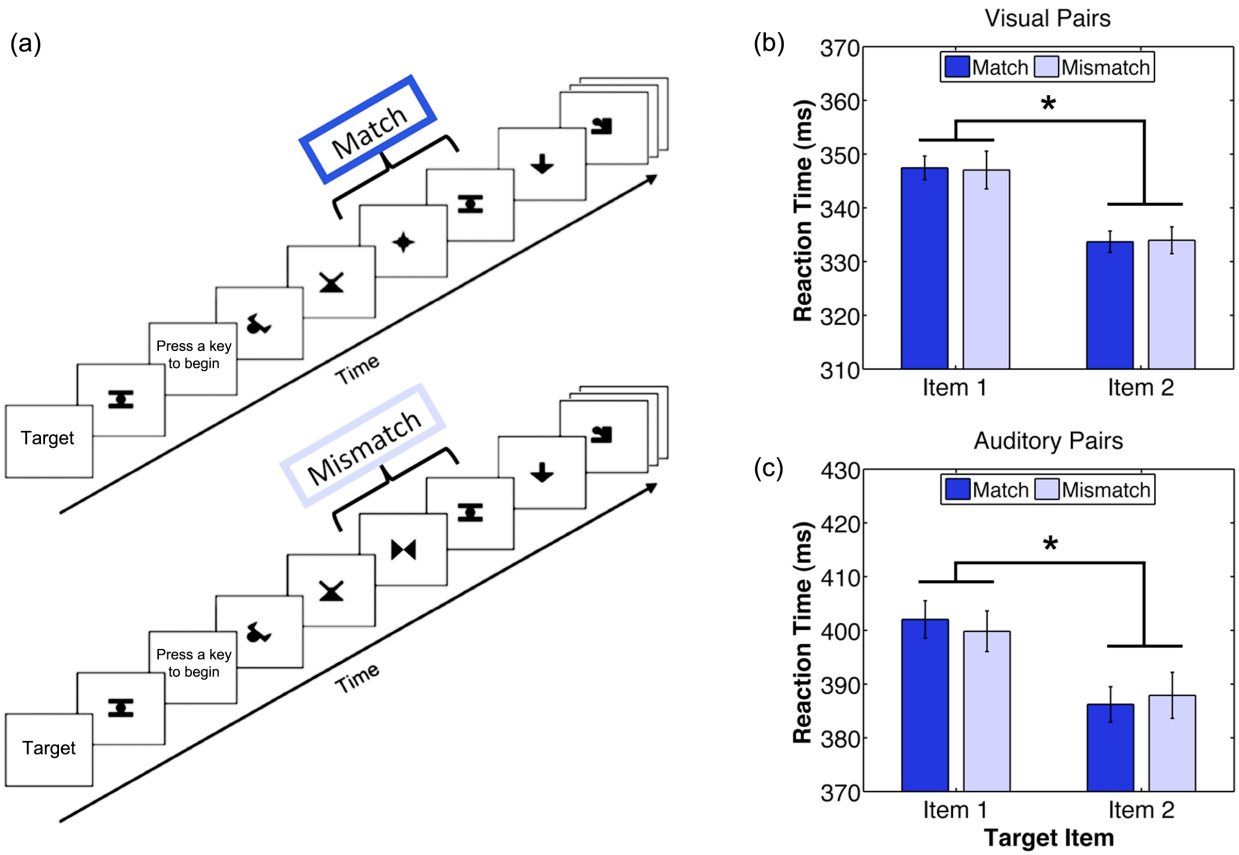



**Figure 9.** (a) Example schematic comparing a match and mismatch trial in the reaction time test used in Experiment 1a. An analogous test using auditory stimuli was used in Experiment 1b. (b) Results of Experiment 1a. (c) Results of Experiment 1b. (* denotes p < .05)

Similarly, in the mismatch condition, reaction times were faster for second items ($M$ = 334 ms, $SD$ = 25.9) than for first items ($M$ = 347 ms, $SD$ = 29.5), $t(11) = 2.24$, $p < .05$, $d = .65$. These results suggest that the speeded responses for second items may be due to differential item learning rather than priming by the first item.

To replicate this effect, we examined statistical learning for auditory pairs (Experiment 1b; Figure 9c). Here, we observed the same pattern of results, with significantly faster responses to second items ($M$ = 387 ms, $SD$ = 43) than to first items ($M$ = 401 ms, $SD$ = 46.5) as indicated by a main effect of target item, $F(1, 30) = 6.98$, $p < .05$, $\eta_p^2 = .19$, but no effect of trial type, $F(1, 30) = .004$, $p = .95$, nor interaction between trial type and target item, $F(1, 30) = .402$, $p = .53$. Given the results of Experiment 1a, we ran one-tailed paired $t$-tests for Experiment 1b. In the match condition, reaction times were faster for second items ($M$ = 386 ms, $SD$ = 46) than first items ($M$ = 402 ms, $SD$ = 43), $t(30) = 3.03$, $p < .01$ $d = .54$. Similarly, in the mismatch condition, reaction times were faster for second items ($M$ = 388 ms, $SD$ = 45) than first items ($M$ = 400 ms, $SD$ = 54), $t(30) = 1.74$, $p < .05$, $d = .31$.

Together, the results of Experiments 1a and 1b show clear evidence that speeded responses to second items are not simply due to a priming of second items by their associated first items. In both experiments, speeded responses were found for second items in the mismatch condition, where the target item was not preceded by its respective paired item. These results suggest that second item learning is responsible for the reaction time difference between first and second items. This would suggest that after statistical learning, second items should be better recognized even when presented outside of a temporal context; this was examined directly in Experiment 2.

## 3.4. Experiment 2

Experiments 1a and 1b showed a benefit for second items that could not be explained by priming by their associated first items. However, the stimulus sequence in the testing phase was very similar to the exposure phase and it may be the case that first items yield a non-specific priming to second items. Furthermore, participants were presented with the target item at the start of each trial and, therefore, the second item benefit could have originated either from top-down processes (such as attention) or bottom-up processes (such as representational changes). To address these issues, in Experiment 2 we used a two-interval forced choice shape detection test in which participants were not explicitly informed of the target item at the start of each test trial. As such, participants had to rely entirely on bottom-up sensory information to detect the target stimulus. Importantly, an individual stimulus was tested on each trial; therefore none of the paired associations from the exposure phase were present during the detection test. To control for initial saliency differences between individual items in our stimulus set, we had participants complete the shape detection test both before and after the exposure phase. Thus, our key measure of interest was participants' pre- versus post-exposure change in sensitivity for first and second items of pairs.

### 3.4.1 Method

**Exposure Phase.** Forty-three participants (ages 18-37; 33 females) underwent an exposure phase and for each subject the six visual pairs shown during the exposure phase were randomly selected from a pool of 30 visual stimuli. The exposure phase was identical to Experiment 1a except that a cover task (adapted from Turk-Browne, Scholl, Chun, & Johnson, 2009) was implemented during the exposure phase to ensure that participants attended to the

stimuli during exposure. The cover task required participants to press the spacebar whenever they saw a visual stimulus that jiggled (i.e., rapidly shifted from left to right in a shaking motion). Each stimulus jiggled on four occasions during the exposure phase and the jiggles occurred pseudorandomly with the following constraints. First, a jiggle could not occur within the first or last 12 stimulus presentations of the exposure phase nor could a jiggle occur within the 12 stimulus presentations before or after another jiggled stimulus. This ensured that jiggle occurrences were unpredictable but also evenly spaced throughout the exposure phase. The second constraint was that the same stimulus could not jiggle two or more times in a row. Finally, items from the same pair could not jiggle in succession, so as not to draw explicit attention to any of the visual pairs and to ensure that the occurrences of the jiggles were not correlated with the statistics of the embedded visual pairs.

**Shape Detection Task.** The shape detection test was completed both before and after the exposure phase (96 trials per test). On each trial, participants indicated which of two intervals contained a shape (other than the fixation cross) by pressing one of two keys. The shape (i.e., the target) was the first or second item of one of the pairs from the exposure phase. In both intervals, a forward and backward mask (described in the following section) preceded and followed the stimulus-period (i.e., the period during which the target shape could appear; see Figure 10). Each mask was displayed for 100 ms and the stimulus-period was displayed for ~10 ms. The ISI between the stimulus-period and the masking stimuli was ~40 ms (easy-ISI) or ~30 ms (difficult-ISI); the ISI values differed between participants according to a calibration run for each subject (as described below). There were an equal number of easy- and difficult-ISI trials. For the post-exposure test, the trials were divided into four blocks, which were interleaved with three brief top-up blocks of exposure stimulus stream (as described below).

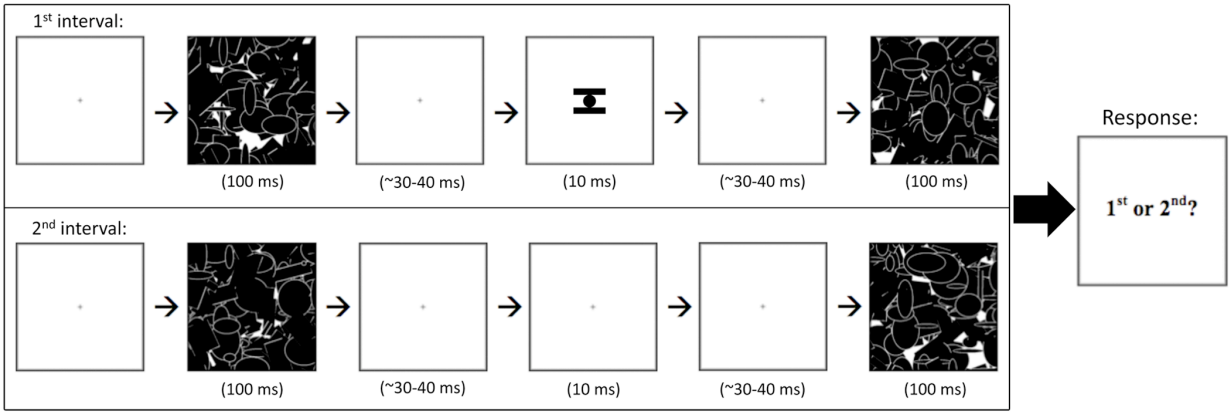



**Figure 10.** Example schematic of the two-interval forced choice shape detection test used in Experiment 2.

**Masking Stimuli.** Each mask consisted of 300 overlapping ovals and rectangles (150 each) with diameters ranging between .5° and 4° visual angle. Each oval and rectangle was black with a thin white contour line, which allowed overlapping shapes to be distinguishable from each other. In order for each masking stimulus to be unique, the sizes, orientations, and positions of the ovals and rectangles were randomized with the exception that one oval or rectangle with a size equal to or larger than the target stimulus was positioned at the center of the screen (i.e., to specifically cover the location of the target stimulus); this was done to ensure that the target stimulus was, in fact, completely masked on every trial.

**Calibration Phase.** To calibrate task difficulty for each participant, we ran a 40 trial procedure where Quest (Brainard, 1997; Watson & Pelli, 1983) was used to estimate each participant's threshold for 75% accuracy. Specifically, we varied the task difficulty by varying the ISI between the stimulus-period and the masking stimulus. The threshold estimate was then used to determine each participant's easy-ISI duration, and the difficult-ISI duration was 1 frame faster than the easy-ISI. We used two ISI durations in order to increase the experimental power

in light of the fact that this was a challenging task in which between-subject performance was variable.

**Top-Up Exposure Blocks.** The results of preliminary experiments (unpublished) indicated that the learned differences between first and second items can be diminished when participants repeatedly respond to the individual stimuli in the absence of their paired associations. In light of this, we included the exposure top-up blocks with aim of prolonging the longevity of the learning effects. The shape detection test was divided into four blocks interleaved with three brief top-up blocks of exposure stream in which participants were re-exposed to the stimulus pairings. For each exposure top-up block, the participants once again performed the jiggle task. Each exposure top-up block consisted of 25 repetitions of the visual pairs, and each item of each pair was jiggled once per block in a pseudorandom order.

### 3.4.2. Results

To examine performance difference between first and second items, we calculated participants' sensitivity (*d'*) as defined in Stanislaw and Todorov (1999). The data were analyzed using a 2 (difficulty: easy vs. difficult) x 2 (test: pre-test vs. post-test) x 2 (target item: item 1 vs. item 2) repeated measures ANOVA. As expected, there was a significant main effect of difficulty, where participants showed greater sensitivity in the easy-ISI condition ($M = 2.25$, $SD = 1.53$) compared to the difficult-ISI condition ($M = 1.22$, $SD = 1.34$), $F(1, 42) = 62.34$, $p < .001$, $\eta_p^2 = .60$. There was also a significant main effect of test, such that participants showed greater sensitivity in the post-test ($M = 1.89$, $SD = 1.41$) compared to the pre-test ($M = 1.57$, $SD = 1.40$), $F(1, 42) = 9.09$, $p < .01$, $\eta_p^2 = .21$.

A significant interaction between test and target item indicated enhanced learning for second items compared to first items, $F(1, 42) = 5.19$, $p < .05$, $\eta_p^2 = .11$ (see Fig. 4). When collapsed across difficulty, there was a significant pre-test ($M = 1.46$, $SD = 1.51$) to post-test ($M = 1.93$, $SD = 1.59$) increase in sensitivity for second items, $F(1, 42) = 18.14$, $p < .001$, $\eta_p^2 = .30$, but not first items (pre-test: $M = 1.67$, $SD = 1.36$; post-test: $M = 1.86$, $SD = 1.30$; $p = .13$). This results can be seen in Figure 11.

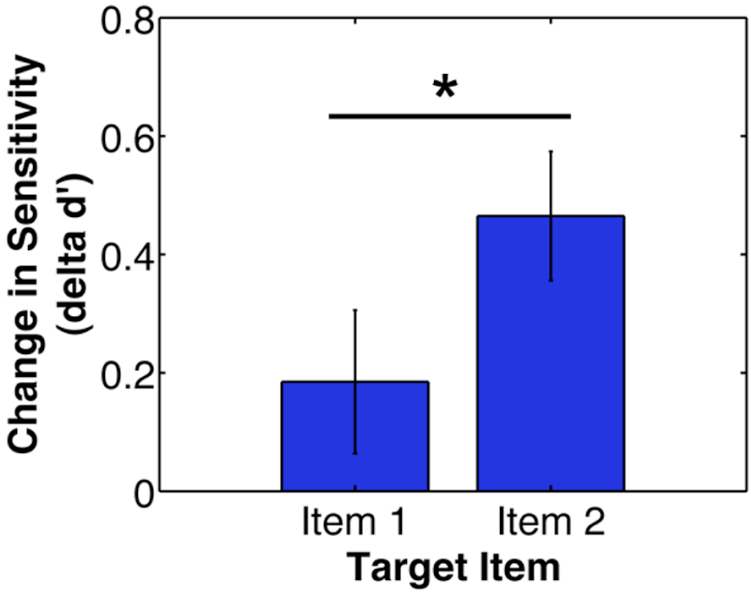



**Figure 11.** Change in sensitivity results of Experiment 2, collapsed across the easy- and difficult-ISI conditions. (* denotes $p < .05$)

As there was a noticeable pre-exposure difference between first and second items (i.e., before any learning could have occurred), to ensure this did not affect our results we performed a follow-up analysis wherein the pre-test performance for first and second items was equated. To do this, we looked at the overall pre-test accuracy for each item in our stimulus pool (i.e., collapsed across all subjects) and looked for items with particularly high or low pre-test

accuracy. We found two items that were outliers, one of which was 2 standard deviations below the mean and the other 1.9 standard deviations above the mean. After removing these items from the analysis, the pre-test performance for first and second items became equated (see Figure 12), and we once again found a significant interaction between test and target item, with enhanced learning for second items compared to first items, $F(1, 42) = 5.51$, $p < .05$, $\eta_p^2 = .12$.

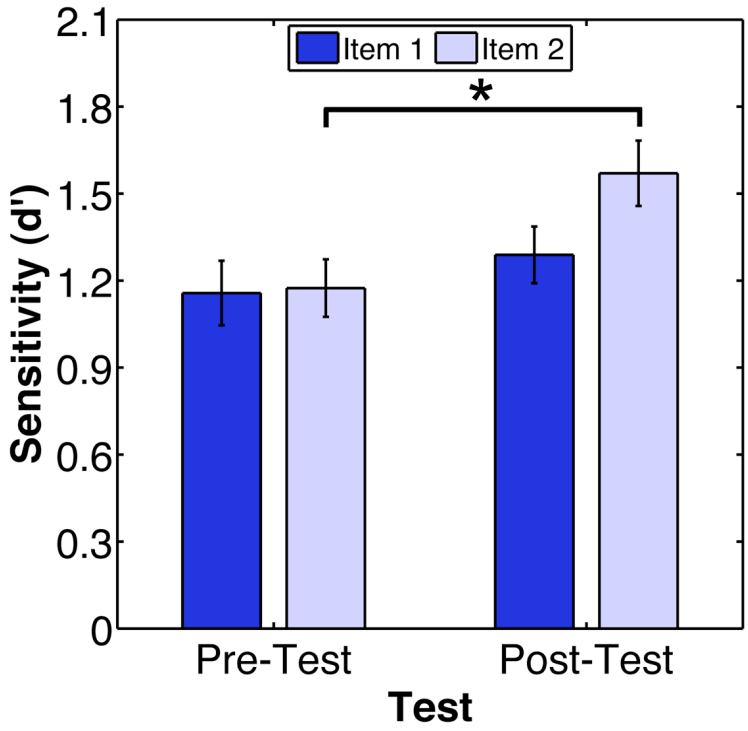



**Figure 12.** Pre- and post-test sensitivity for first and second items in Experiment 2 after removing outlier items from the analysis. Error bars indicate within-subject standard error of the mean. (* denotes p < .01)

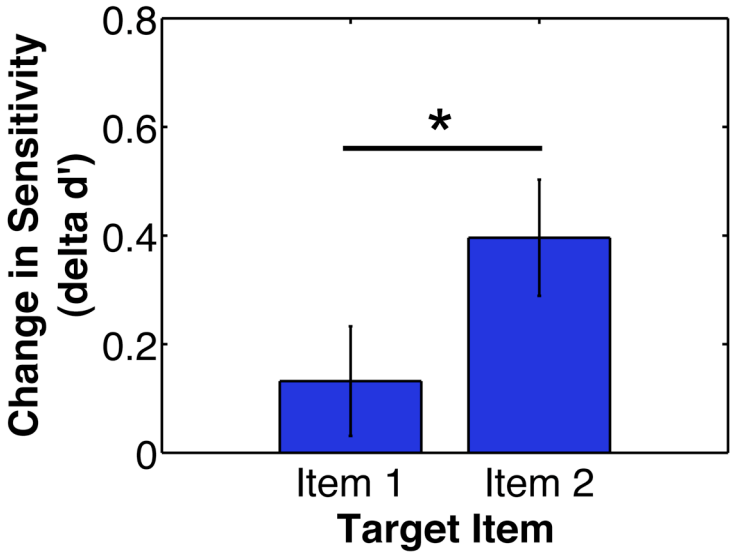



**Figure 13.** Change in sensitivity results in Experiment 2 after removing outlier items from the analysis. Error bars indicate within-subject standard error of the mean. (* denotes $p < .05$)

As in the original analysis, there was a significant pre-test ($M = 1.17$, $SD = 1.41$) to post-test ($M = 1.57$, $SD = 1.50$) increase in sensitivity for second items, $F(1, 42) = 13.63$, $p = .001$, $\eta_p^2 = .25$, but not first items (pre-test: $M = 1.16$, $SD = 1.15$; post-test: $M = 1.29$, $SD = 1.07$; $p = .20$). Thus, even when pre-test performance was equated for first and second items, there remained a significant difference in the pre- to post-test change in sensitivity for first versus second items of the pairs (see Figure 13). Additionally, an examination of simple effects revealed that the second item benefit was consistent across both levels of difficulty, such that for both the easy- and difficult-ISI conditions there was a significant pre- to post-test increase in sensitivity for second items ($ps < .01$), but not first items ($ps > .23$). These results confirm that statistical learning results in differential learning for first and second elements in temporally associated pairs.

## 3.5. Discussion

The first indications that statistical learning might differentially influence individual stimuli was found in early studies of auditory statistical learning wherein participants were exposed to sets of trisyllabic sequences (i.e., nonsense words; Saffran et al., 1996b) and tritone sequences (Saffran et al., 1999). When whole sequences were pitted against partially-mixed sequences in a familiarity test, participants were more likely to make a false alarm when the end of a partially-mixed sequence was intact compared to when the beginning was intact. In other words, there appeared to be a difference between participants' sensitivity to elements that came at the ends of the sequences compared to those at the beginning. Our study expands on this finding by showing that statistical learning can differentially influence responses to individual items, even when tested outside of their learned groupings and in a context that greatly differs from that of the exposure phase. Specifically, we found that statistical learning can lead to differences in the saliency of predictable (second) compared to less predictable (first) items.

Our results are consistent with other research showing that statistical learning can result in flexible internal stimulus representations. For instance, Turk-Browne and Scholl (2009) showed that learning of temporal associations transferred to a spatial task and, conversely, that learning spatial associations transferred to a temporal task. Such flexibility suggests that statistical learning may induce representational changes (e.g., perceptual learning) in sensory regions of the brain that are involved in processing the stimuli. Consistent with this, a recent fMRI study on visual statistical learning (Turk-Browne et al., 2009) found that brain regions involved in representing the individual stimuli (i.e., lateral occipital cortex and ventral occipito-temporal cortex) showed a change in neural processing when the stimulus stream contained a statistical structure (i.e., temporally associated stimuli) compared to when it was random. These

results are consistent with the hypothesis that sensory areas are sensitive to statistically predictable stimuli and that this may lead to a change in the saliency for these stimuli.

Still, a critical question remains: why should second items of pairs become more salient than first items, rather than the converse? And, furthermore, what underlying mechanisms are driving such changes in stimulus saliency? Although the current experiments were not designed to reveal which mechanisms might be at play, there are some plausible mechanisms about which we can speculate. Studies of statistical learning have clearly demonstrated that humans are able to learn statistical regularities in the environment and that this learning arises without instruction or intention. This implies that the brain engages in an automatic pattern-seeking behavior. This is in line with the idea, put forth by Biederman and Vessel (2006), that humans are "infovores" who have an innate drive to extract information from the environment. If we assume that the sense of familiarity that accompanies the discovery of a predictable pattern can be intrinsically rewarding, then it may be possible to consider statistical learning within the framework of reinforcement learning. In the context of the exposure phase used in the current study, it would likely be the case that an intrinsic reward would be associated with the presentation of the second item of a pair (i.e., the time point at which an anticipated pair is confirmed). Indeed, in an fMRI study of temporal statistical learning, it was found that participants' sense of familiarity for learned pairs versus novel pairs was correlated with the neural processing of second items, but not first items (Turk-Browne et al., 2010).

If the sense of familiarity related to the processing of second items can act as an intrinsic reward, then how might this affect the internal representations of first versus second items? In a review of the mechanisms of perceptual learning, Roelfsema, van Ooyen, and Watanabe (2010) note that neuromodulatory systems (e.g., dopamine) can influence the cortical representations of

stimuli that predict (i.e., occur just prior to) a reward. For instance, O'Brien and Raymond (2012) found that stimuli that were highly predictive of a monetary win or loss during an initial conditioning phase were subsequently more salient in a recognition task than stimuli that were only weakly predictive of a monetary outcome or that were predictive of no outcome. If such a mechanism were operating during the current study, then one might expect first items to undergo a greater increase in saliency than second items. However, the current results are in conflict with this interpretation, which suggests another mechanism may be at work. In fact, Roelfsema et al. describe another mechanism of perceptual learning wherein learning can occur for stimuli that are presented at behaviorally relevant times, such as with the onset of a reward. This effect has been described at length in the context of task-irrelevant perceptual learning (Seitz & Watanabe, 2005; 2009). For instance, it has been shown that when a particular visual feature (e.g., orientation or motion direction) repeatedly co-occurs with a salient event (e.g., a reward or task-related target), participants subsequently show increased sensitivity to that visual feature in a detection task (Seitz, Kim, & Watanabe, 2009; Seitz & Watanabe, 2003). When considering this in the context of the current study, it is possible that second items repeatedly co-occurred with an implicit sense of familiarity and that this caused participants to experience enhanced perceptual learning of second items compared to first items.

Another possibility is that participants' change in sensitivity to second items versus first items was due to an attentional mechanism. Recent research on temporal statistical learning has shown that attention is automatically drawn to statistically reliable stimuli (Zhao, Al-Aidroos, & Turk-Browne, 2013). Thus, in the current paradigm, it may be that when first items cue second items during the exposure phase, it leads to more attentional processing of second items, which then enhances the encoding of those items' internal representations. Of course, it is not the case

that an attentional mechanism and a reinforcement mechanism are necessarily mutually exclusive, and this highlights the need for future studies that can determine whether these or other mechanisms can account for the pattern of results observed in the current experiments.

Another aspect of the current study that needs to be addressed by future research is the extent to which the observed differences between first and second items can truly be attributed to the relative predictability of those items. In the current study, first items were always followed by their respective second item (i.e., a transitional probability of 1.0). It would be worthwhile to construct sequences containing items with different degrees of predictability (e.g., with transitional probabilities of 1.0, 0.5, 0.25, etc.) and to then test whether this influences the relative saliency of the individual items. Additionally, whereas most studies of temporal statistical learning have focused on forward transitional probabilities (i.e., for pair A-B, this would be the probability of item-B given item-A), recent studies have shown that backward transitional probabilities (i.e., the probability of item-A given item-B) may also play a role in statistical learning (Pelucchi, Hay, & Saffran, 2009; Perruchet & Desaulty, 2008). In the current study, as in most statistical learning studies, forward and backward transitional probabilities were confounded. Therefore, future studies should investigate whether forward versus backward transitional probabilities might have different effects on the internal representations of individual items.

Overall, our results suggest that temporal statistical learning can result in differences in individual item saliency. Previous statistical learning studies have, typically, exposed participants to associations and tested their ability to recognize those associations. Here, for the first time, the effect of statistical learning on the saliency of individual items was tested. Furthermore, we tested participants' ability to detect the individual items in a task that greatly

differed from the exposure phase used to induce the learning. Our findings demonstrate that temporal statistical learning is flexible and that it likely has overlapping mechanisms with perceptual learning, which highlights the need to further study what is learned through statistical learning.

# Conclusion

Each study in this dissertation examined a different type of implicit learning by exploring how learning is modulated by various aspects of sensory processing, such as multisensory interactions and internal stimulus representations. In the first study, I explored the extent to which temporal processing in the visual modality, namely visual rhythm perception, was susceptible to perceptual learning. The results indicated that, after two sessions of training, a group that received visual-only training failed to experience improvements in their visual rhythm perception. In contrast, groups that received auditory or audio-visual training experienced a significant improvement in their visual rhythm perception. To my knowledge, this was the first study to explore perceptual learning of rhythm perception and one of few studies to examine whether the visual modality's temporal processing abilities can be improved through perceptual training.

In the second study, I investigated the effect of passive sequence exposure on performance in a sensorimotor task. Specifically, subjects responded to a sequence in a serial reaction time task both before and after receiving passive and repeated exposure to that sequence in both the visual and tactile modality. Despite extensive passive exposure to the sequence, I found no evidence that passive exposure influenced subjects' performance in the sensorimotor task. This replicates findings from previous research (Kelly & Burton, 2001) and raises the question of how other studies have been able to successfully produce an effect of passive sequence exposure on subsequent motor performance (Howard et al., 1992; Huang et al. 2010). Future research should explore whether explicit awareness of the sequence is necessary for passive exposure to have an effect, as well as whether there is a potential benefit of employing a combination of passive exposure and active training.

In the third study, I examined the effect of statistical learning on internal stimulus representations. I found that when subjects were passively exposed to a set of stimuli containing repeated stimulus-stimulus associations (i.e., fixed groupings within the stimulus set), the subjects' sensitivity to some of the stimuli was increased relative to others. Specifically, the results indicated that stimuli that had greater temporal predictability during the learning phase were perceived with greater saliency during subsequent detection tests compared to stimuli that had been less predictable during the learning phase. The findings suggest that statistical learning can have effects similar to those seen in perceptual learning, indicating that these forms of implicit learning may have shared mechanisms that had not been revealed by previous studies of statistical learning.

Overall, the variety of experiments described in this dissertation indicate that implicit forms of learning and memory can influence basic human functions, such as perception and movement. As such, it is worthwhile for future research to continue to explore the factors that can modulate implicit learning, as such research will help to inform and broaden our understanding of processes that can affect human behaviors at a fundamental level.

## References


Barakat, B. K., Seitz, A. R., & Shams, L. (2013). The effect of statistical learning on internal stimulus representations: Predictable items are enhanced even when not predicted. *Cognition, 129,* 205-211.

Baker, C. I., Olson, C. R., & Berhmann, M. (2004). Role of attention and perceptual grouping in visual attention. *Psychological Science, 15,* 460-466.

Biederman, I., & Vessel, E. A. (2006). Perceptual pleasure and the brain: A novel theory explains why the brain craves information and seeks it through the senses. *American Scientist*, *94,* 247-253.

Brainard, D. H. (1997). The psychophysics toolbox. *Spatial Vision*, *10*, 433-436.

Bratzke, D., Seifried, T., & Ulrich, R. (2012). Perceptual learning in temporal discrimination: asymmetric cross-modal transfer from audition to vision. *Experimental Brain Research, 221*(2), 205-210.

Collier, G. L., & Logan, G. (2000). Modality differences in short-term memory for rhythms. *Memory & Cognition, 28*(4), 529-538.

Conway, C. M., & Christiansen, M. H. (2005). Modality-constrained statistical learning of tactile, visual, and auditory sequences. *Journal if Experimental Psychology: Learning, Memory, and Cognition*, *31*, 24-39.

DeCoster, J., & O'Mally, J. (2011). Specific sequence effects in the serial reaction time task. *Journal of Motor Behavior, 43,* 263-273.

Fahle, M., & Poggio, T. (2002). *Perceptual learning*. MIT Press.

Fine, I., & Jacobs, R. A. (2002). Comparing perceptual learning across tasks: A review. *Journal of Vision, 2,* 190-203.

Fiser, J., & Aslin, R. N. (2001). Unsupervised statistical learning of higher-order spatial structures from visual scenes. *Psychological Science*, *12*, 499-504.

Fiser, J., & Aslin, R. N. (2002). Statistical learning of higher-order temporal structure from visual shape sequences. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, *28*, 458-467.

Fiser, J., & Aslin, R. N. (2005). Encoding multielement scenes: Statistical learning of visual feature hierarchies. *Journal of Experimental Psychology: General*, *134*(4), 521-537.

Gebhard, J. W., & Mowbray, G. H. (1959). On discriminating the rate of visual flicker and auditory flutter. *American Journal of Experimental Psychology, 72*, 521–528.

Glenberg, A. M., Mann, S., Altman, L., Forman, T., & Procise, S. (1989). Modality effects in the coding and reproduction of rhythms. *Memory & Cognition, 17,* 373-383.

Guttman, S. E., Gilroy, L. A., & Blake, R. (2005). Hearing what the eyes see: Auditory encoding of visual temporal sequences. *Psychological Science, 16*(3), 228-235.

Huang, K., Starner, T., Do, E., Weiberg, G., Kohlsdorf, D., Ahlrichs, C., & Leibrandt, R. (2010, April). *Mobile Music Touch: Mobile tactile stimulation for passive learning*. In Proceedings of the SIGCHI Conference on Human Factors in Computing Systems (pp. 791-800). ACM.

Howard, J. H., Jr., Mutter, S. A., & Howard, D. V. (1992). Serial pattern learning by event observation. *Journal of Experimental Psychology: Learning, Memory, and Cognition, 18,* 1029-1039.

Kanai, R., Lloyd, H., Bueti, D., & Walsh, V. (2011). Modality-independent role of the primary auditory cortex in time estimation. *Experimental Brain Research, 209*(3), 465-471.

Karabanov, A., Blom, Ö., Forsman, L., & Ullén, F. (2009). The dorsal auditory pathway is involved in performance of both visual and auditory rhythms. *Neuroimage, 44*(2), 480-488.

Karmarkar, U. R., & Buonomano, D. V. (2003). Temporal specificity of perceptual learning in an auditory discrimination task. *Learning & Memory*, *10*(2), 141 -147.

Keele, S. W., Ivry, R., Mayr, U., Hazeltine, E., & Heuer, H. (2003). The cognitive and neural architecture of sequence representation. *Psychological Review, 110*(2), 316-339.

Kelly, S. W., & Burton, A. M. (2001). Learning complex sequences: No role for observation? *Psychological Research, 65*, 15-23.

Kim, R., Seitz, A., Feenstra, H., & Shams, L. (2009). Testing assumptions of statistical learning: Is it long-term and implicit? *Neuroscience Letters*, *461*, 145-149.

Kim, R. S., Seitz, A. R., & Shams, L. (2008). Benefits of stimulus congruency for multisensory facilitation of visual learning. *PLoS One, 3*(1), e1532.

Kirkham, N. Z., Slemmer, J. A., & Johnson, S. P. (2002). Visual statistical learning in infancy: Evidence for a domain general learning mechanism. *Cognition*, *83*, B35-B42.

Lapid, E., Ulrich, R., & Rammsayer, T. (2009). Perceptual learning in auditory temporal discrimination: No evidence for a cross-modal transfer to the visual modality. *Psychonomic Bulletin & Review, 16*(2), 382-389.

Mateeff, S., Hohnsbein, J., & Noack, T. (1985). Dynamic visual capture: Apparent auditory motion induced by a moving visual target. *Perception, 14*, 721–727.

Nagarajan, S. S., Blake, D. T., Wright, B. A., Byl, N., & Merzenich, M. M. (1998). Practice-related improvements in somatosensory interval discrimination are temporally specific

but generalize across skin location, hemisphere, and modality. *The Journal of Neuroscience*, *18*, 1559-1570.

Nissen, M. J., & Bullemer, P. (1987). Attentional requirements of learning: Evidence from performance measures. *Cognitive Psychology, 19,* 1-32.

O'Brien & Raymond (2012). Learned predictiveness speeds visual processing. *Psychological Science, 23,* 359-363.

Olson & Chun (2001). Temporal contextual cuing of visual attention. *Journal of Experimental Psychology: Learning, Memory, and Cognition, 27,* 1299-1313.

Pelucchi, B., Hay, J. F., & Saffran, J. R. (2009). Learning in reverse: Eight-month-old infants track backward transitional probabilities. *Cognition, 113,* 244-247.

Perruchet, P., & Desaulty, S. (2008). A role for backward transitional probabilities in word segmentation? *Memory & Cognition, 36,* 1299-1305.

Pick, H. L., Warren, D. H., & Hay, J. C. (1969). Sensory conflict in judgments of spatial direction. *Perceptions & Psychophysics, 6*, 203-205.

Rammsayer, T. H., Buttkus, F., & Altenmueller, E. (2012). Musicians do better than nonmusicians in both auditory and visual timing tasks. *Music Perception: An Interdisciplinary Journal, 30*(1), 85-96.

Reber, A. S. (1967). Implicit learning of artificial grammars. *Journal of Verbal Learning and Verbal Behavior, 6*(6), 855-863.

Reed, J., & Johnson, P. (1994). Assessing implicit learning with indirect tests: Determining what is learned about sequence structure. *Journal of Experimental Psychology: Learning, Memory, and Cognition, 20,* 585-594.

Roelfsema, P. R., van Ooyen, A., & Watanabe, T. (2010). Perceptual learning rules based on reinforcers and attention. *Trends in Cognitive Science, 14,* 64-71.

Saenz, M., & Koch, C. (2008). The sound of change: Visually-induced auditory synesthesia. *Current Biology, 18,* R650-R651.

Saffran, J. R., Aslin, R. N., & Newport, E. L. (1996). Statistical learning by 8-month-old infants. *Science*, *274*, 1926-1928.

Saffran, J. R., Johnson, E. K., Aslin, R. N., & Newport, E. L. (1999). Statistical learning of tone sequences by human infants and adults. *Cognition*, *70*, 27-52.

Saffran, J. R., Newport, E. L., & Aslin, R. N. (1996). Word segmentation: The role of distributional cues. *Journal of Memory and Language*, *35*, 606-621.

Sagi, D. (2011). Perceptual learning in Vision Research. *Vision Research, 51,* 1552-1566.

Schacter, D. L. (1987). Implicit memory: History and current status. *Journal of Experimental Psychology: Learning, Memory, and Cognition, 13,* 501-518.

Seitz, A. R., Kim, R., & Shams, L. (2006). Sound facilitates visual learning. *Current Biology, 16,* 1422-1427.

Seitz, A. R., Kim, R., van Wassenhove, V., & Shams, L. (2007). Simultaneous and independent acquisition of multisensory and unisensory associations. *Perception*, *36*, 1445-1453.

Seitz, A. R., Kim, D., & Watanabe, T. (2009). Rewards evoke learning of unconsciously processed visual stimuli in adult humans. *Neuron, 61,* 700-707.

Seitz, A. R., & Watanabe, T. (2003). Is subliminal learning really passive? *Nature, 422*, 36.

Seitz, A. R., & Watanabe, T. (2005). A unified model for perceptual learning. *Trends in Cognitive Science, 9,* 329-334.

Seitz, A. R., & Watanabe, T. (2009). The phenomenon of task-irrelevant perceptual learning. *Vision Research, 49,* 2604-2610.

Shams, L., & Seitz, A. R. (2008). Benefits of multisensory learning. *Trends in Cognitive Science*, *12*(11), 411-417.

Shipley, T. (1964). Auditory flutter-driving of visual flicker. *Science, 145*, 1328-1330.

Stanislaw, H., & Todorov, N. (1999). Calculation of signal detection theory measures. *Behavior Research Methods, Instruments, & Computers*, *31*, 137-149.

Toro, J. M., Sinnett, S., & Soto-Faraco, S. (2005). Speech segmentation by statistical learning depends on attention. *Cognition, 97,* B25-B34.

Turk-Browne, N. B., Jungé, J., & Scholl, B. J. (2005). The automaticity of visual statistical learning. *Journal of Experimental Psychology: General*, *134*, 552-564.

Turk-Browne, N. B., & Scholl, B. J. (2009). Flexible visual statistical learning: transfer across space and time. *Journal of Experimental Psychology. Human Perception and Performance*, *35*, 195-202.

Turk-Browne, N. B., Scholl, B. J., Chun, M. M., & Johnson, M. K. (2009). Neural evidence of statistical learning: Efficient detection of visual regularities without awareness. *Journal of Cognitive Neuroscience*, *21*, 1934-1945.

Turk-Browne, N. B., Scholl, B. J., Johnson, M. K., & Chun, M. M. (2010). Implicit perceptual anticipation triggered by statistical learning. *The Journal of Neuroscience, 30,* 11177-11187.

Vaquero, J. M. M., Jimenez, L., & Lupianez, J. (2006). The problem of reversals in assessing implicit sequence learning with serial reaction time tasks. *Experimental Brain Research, 175,* 97-109.

Watson, A. B., & Pelli, D. G. (1983). Quest: A Bayesian adaptive psychometric method. *Perception & Psychophysics*, *33*, 113-120.

Wright, B. A., Buonomano, D. V., Mahncke, H. W., & Merzenich, M. M. (1997). Learning and generalization of auditory temporal–interval discrimination in humans. *The Journal of Neuroscience*, *17*(10), 3956 -3963.

Young, M. P. (1993). The organization of neural systems in the primate cerebral cortex. *Proceedings of the Royal Society B: Biological Sciences, 252,* 13-18.

Zhao, J., Al-Aidroos, N., & Turk-Browne, N. B. (2013). Attention is spontaneously biased towards regularities. *Psychological Science, 24,* 667-677.