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The Effects of Synchronous Versus Asynchronous Temporal Patterns On Sequential Learning

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THE EFFECTS OF SYNCHRONOUS VERSUS ASYNCHRONOUS TEMPORAL PATTERNS ON SEQUENTIAL LEARNING

by

KIMBERLY MENIG ROSS

Under the Direction of Christopher M. Conway, PhD

ABSTRACT

Sequential learning refers to the ability to learn the temporal and ordinal patterns of one’s environment. The current study examines the effects of synchronous and asynchronous temporal patterns on sequential learning. Twenty healthy adults participants (11 females, 18–34 years old) performed two versions of a visual sequential learning paradigm while event-related potentials (ERPs) were recorded. Reaction times to the targets following two predictor types were also recorded. Reaction time data revealed that learning occurred in both temporal conditions, although overall the synchronous condition was responded to faster. On the other hand, the mean ERP amplitudes between 300 and 700ms post-predictor onset revealed an interaction between timing condition and predictability in the posterior regions of interest. Specifically, the ERP results indicated that learning of the statistical contingencies between items was more pronounced for the synchronous temporal condition compared to the asynchronous condition.

INDEX WORDS: Sequential learning, Temporal processing, Entrainment, ERP, P300
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KIMBERLY MENIG ROSS

A Thesis Submitted in Partial Fulfillment of the Requirements for the Degree of Masters of Arts in the College of Arts and Sciences Georgia State University 2016
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TEMPORAL PATTERNS ON SEQUENTIAL LEARNING

by

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June 2016
DEDICATION

I dedicate this work to my family, who has been by my side encouraging me through the last several years of schooling. Without the support of my husband, children, mother and stepfather, as well as countless others, I would not have had the fortitude to continue my education.
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1 INTRODUCTION

1.1 Purpose of Study

Sequential learning is the ability to learn both the temporal and ordinal patterns of one’s environment that are characteristic of a particular kind of event. For example, to learn a new routine, a dancer must be able to recognize and encode a complex, overlapping series of movements, and a jazz musician must acquire a large number of melodies (sequences of notes) and chords (concurrent notes) to draw from during improvisation. Similarly, many aspects of language—including grammar and syntax depend on sequential processing. One of the primary questions in cognitive psychology is what facilitates learning of structured events under different contexts. When patterns are not fully random but contain a degree of temporal or ordinal regularity, our brain, in general, is able to extract regularities to facilitate processing using predictive mechanisms, that is, by learning to predict future stimuli in the sequence (Selchenkova et al., 2014).

Surprisingly, whereas sequential learning studies of the ordinal structure of sequences are common, research on sequential learning of temporal patterns is scare. Most sequential learning studies focus on learning sequences of stimuli of identical durations with identical inter-stimuli intervals (e.g. Conway & Christiansen, 2005; Jost et al., 2015). However, sequential learning of sequences containing variability in the temporal characteristics, that is sequences with stimuli of various durations or with various inter-stimuli intervals, is of fundamental importance to human cognition because these types of sequences are frequent in our environment. We often process irregular temporal patterns that help us make decisions and influence our future behavior,
including when we perform motor movement coordination, and when we process language or music (Brandon et al., 2012).

To understand the human ability to process statistical sequential information better, one must look to both the ordinal and temporal pattern of that information. By integrating research in both sequential learning and temporal processing, we may begin to elucidate the varying conditions in which sequential learning is enhanced. The Dynamic Attending Theory (DAT) assumes that events with a regular pattern are processed easier than events with an irregular temporal pattern. This theory assumes that the brain creates internal oscillations, or attending rhythms, that entrain to external rhythms, creating a type of attention to future events, which facilitates learning (Jones & Boltz, 1989). The internal oscillations of the DAT are thus adaptive, allowing for enhanced processing of regular temporal structures. Therefore, the DAT implies that attention to individual items of a sequence is stimulus-driven (Jones et al., 2002). In this respect the temporal structure of a sequence becomes useful or salient to the attender.

Sequential learning can be observed behaviorally (response times) as well as indexed neurophysiologically with event-related potentials (ERP, for a recent review, see Daltrozzo & Conway, 2014). This technique has the advantage over other neurophysiological measures (i.e. fMRI) of a high temporal resolution at the millisecond scale, allowing for the exploration of neural events with precise timing. Thus, ERPs are particularly well suited for testing temporal cognition, including sequential learning of temporal and ordinal regularities. Sequential learning has been studied using the classic auditory oddball sequence task, the visual serial reaction time task, triplet paradigms and with artificial grammar learning paradigms (Brandon et al., 2012; Karabanov & Ullen, 2008; Schmidt-Kassow et al., 2009; Schwartze et al., 2011; Selchenkova et al., 2014; Selchenkova, Jones & Tillman, 2014).
In the current study I investigated how DAT entrainment affects the neural correlates of sequential learning by exploring whether the temporal regularity of patterns would enhance learning during a statistical-sequential paradigm. The expectation was that learning of structured sequences is influenced, in part, by the ability to extract temporal regularities out of events, thus enhancing attention to the ordinal structure of the sequence. To start, theories relevant to sequential learning research and temporal processing research will be briefly reviewed.

1.2 Sequential Learning: Theories and Main Findings

1.2.1 Main Theories

Sequential learning is an important topic because it underlies many aspects of human cognition. In almost all interactions we have with the environment, whether it is processing language, learning a new skill, coordinating movements, or listening to music, we must process complex structured events. To date, sequential learning research has primarily focused on the ordinal structure of sequences. Sequential learning of ordinal structure has been observed in different sensory (auditory, visual, tactile) and motor domains (Conway & Christiansen, 2006, 2009; Jost et al., 2015; Saffran et al., 1997). Within this context, studies have addressed two fundamental questions about the nature of sequential learning: 1) Are sequential learning mechanisms domain-general or modality-specific? and 2) Is sequential learning implicit or explicit in nature (or both)?

The question as to whether sequential learning is domain-general or modality-specific is still under debate (Conway & Christiansen, 2005; Reber, 1967; Saffran et al., 1997). To address this question, researchers have studied conditions for transfer effects, which occur when patterns that have been learned in one modality (visual domain) are still recognized when the patterns are re-presented in another modality (auditory domain). The classic view of sequential learning,
influenced greatly by the work of Reber, assumes that the transfer effects often seen in artificial grammar learning paradigms is due to the learning of abstract (or amodal) features of a sequence. Transfer effects, or learning from one modality to another, occurs when a task (such as memorization) implicitly supplies participants with information about the lawfulness of the stimulus sequences, so that they may efficiently perform in a transfer-recognition task (Reber, 1967). This view assumes that sequential learning is a domain-general ability. However, there is research showing modality-specific sequential learning (Conway & Christiansen, 2005; Conway & Pisoni, 2008). One of the major findings in the research regarding modality-specificity is that the auditory domain is best at processing temporal information while the visual system is best as processing spatial information (Conway & Christiansen, 2005; Emberson, Conway & Christiansen, 2011). Taken together, research seems to point in the direction of a two-system model of sequential learning, where some domain-general abilities are present, but specific modality constraints do exist (Daltrozzo & Conway, 2014). It may be that some tasks require more abstract, domain-general learning, whereas more concrete, modality-specific learning are needed for others (Conway & Christiansen, 2006) or that both systems are systematically activated whatever the modality of sequential learning.

Another important debate in sequential learning research is whether or not sequential learning is governed by unconscious, or implicit mechanisms, or by conscious, or explicit mechanisms, or both. The classic view of sequential learning is that learning occurs unconsciously, or incidentally with no explicit representations or knowledge. Several studies attribute sequential learning as an unconscious process, with evidence pointing to participants learning incidentally with no explicit knowledge of the rules or patterns existing in a sequence (Curran and Keele, 1993; Saffran et al., 1996; Rosenthal el al., 2010). However, others argue
that sequential learning comes out of a more explicit knowledge about the ordinal patterns of a sequence (Cleeremans, 2006; Haider & Frensch, 2009). Prediction and explicit awareness of a pattern is often correlated, and thus the extant to which sequential learning involves anticipatory processes has become an important question (Dale, Duran & Morehead, 2012; Willingham et al., 1989). Identifying the subsystems that are involved in sequential learning, and understanding whether they work alone or in parallel has become an important aspect of sequential learning research. Many now believe that it is a combination of both implicit and explicit systems that subserve sequential learning. For example, Karabanov and Ullen (2008) examined whether sequences could be learned implicitly using a process dissociation procedure. The process dissociation procedure is a paradigm used as a way to measure explicit knowledge obtained during a task. In this study, one group of participants were instructed to focus on the ordinal sequence of the stimuli; while a second group was instructed to focus on both the ordinal and temporal pattern of the sequence, which they had to reproduce. Karabanov and Ullen (2008) found that only those in the ordinal and temporal group were able to differentiate their performance in the inclusion and exclusion tasks. They also found that for both groups, there was a negative correlation between explicit knowledge and improvement during the serial recall task. They concluded that sequences presented ordinally were learned implicitly, whereas those presented temporally and ordinally were predominately explicitly learned. Furthermore, Singh, Daltrozzo, and Conway (2015) found that attention and consciousness of the to-be-learned patterns reorganized the cortical (event-related potential) correlates of sequential learning. They concluded that a positive ERP reflection from 200 to 700ms post-predictor onset showed different patterns depending on level of pattern consciousness. These types of results indicate
that distinct implicit and explicit systems may underlie sequential learning (Batternick et al., 2015).

The current theories of sequential learning highlight the fact that we still have many questions to answer about how we learn sequential information as well as what may aid in more efficient learning. The next section will briefly review the literature in four main areas of sequential learning research, artificial-grammar learning paradigms, triplet paradigms, the serial reaction time task and the oddball paradigm.

1.2.2 Main Findings

Sequential learning has primarily been studied using artificial-grammar learning paradigms, triplet paradigms, serial reaction time tasks and oddball paradigms. Each paradigm examines a different aspect of sequential structure and complexity, with artificial-grammar paradigms using statistical rules that are the most complex and rule based and the oddball paradigms being the simplest.

Artificial-grammar learning paradigms utilize sequences of complex grammar rules. These sequences are used as a way to study how people learn complex sequential information, much as we do with natural language, while taking out the semantic information of language. This approach allows researchers to study the processing of the grammatical structure independently of the processing of semantic knowledge (Conway & Pisoni, 2008). By creating violations to the learned grammar, researchers can explore, both behaviorally and neurally, many aspects of sequential learning, such as whether sequential learning is a domain-general or modality-specific ability.

In an artificial-grammar paradigm, Conway and Christiansen (2005) explored sequential learning in tactile, visual, and auditory sequences. Participants first learned the artificial-
grammar during a training phase and then completed a test phase. The goal of the test phase was to classify novel sequences in the same modality as either ‘legal’ or ‘illegal’ in regards to the previously learned complex artificial-grammar. The authors found that auditory sequential learning was better than both tactile and visual sequential learning, in that participants were better able to classify more sequences in the auditory domain correctly than in either the tactile or visual domain (Conway & Christiansen, 2005). This study provides support for modality-specificity; although participants demonstrated learning in all three modalities, SL was clearly better in the auditory domain.

Conway and Christiansen (2009) explored modality constraints on sequential learning using an artificial-grammar learning task in which they manipulated grammaticality and presentation rate. They employed three formats: visual input distributed spatially, visual input distributed temporally, and auditory input distributed temporally-and two rates of presentation: moderate (4 elements/second) and fast (8 elements/second). Learning abilities were best for visual-spatial and auditory-temporal conditions. Additionally, faster presentation affected the performance only for the visual-temporal condition. These results indicate that sequential learning for sequential and spatial patterns proceeds differently across different modalities (Conway & Christiansen, 2009).

Artificial-grammar learning paradigms have also been employed in neurophysiological studies exploring sequential learning. Violations of the syntactic rules of an artificial-grammar have shown to elicit both an early negative ERP component (200 – 400ms post stimuli onset) as well as a late positive ERP component (600ms post-stimuli onset). In one such study, Bahlmann, Gunter, and Friederici (2006) concluded that an early left anterior negativity component was observed when violations were at a local level of the artificial-grammar structure and a P600
component was observed when violations occurred at a local and global level. In a study examining the relationship between language and sequential learning, Christiansen, Conway, and Onnis (2012) also observed a late positive ERP component (P600) with a sequential learning task. These results suggest that the P600 index sequential learning in the artificial-grammar learning tasks.

The triplet paradigm is another way in which researchers study sequential learning. This task involves the presentation of stimuli, grouped into triplets, but presented in a seemingly continuous stream of stimuli. Participants are first introduced to the triplets during a familiarization stream. Afterwards, they are exposed to a test phase where they must classify triplets in a forced choice recognition task.

Saffran, Newport and Aslin (1996) reported one of the first findings of sequential learning in 8-month-old infants using a linguistic triplet design. They found that after a mere 2 minutes of exposure to the syllable stream, infants were able to classify triplets that they had heard often from those they had never accounted. Likewise, Saffran, Johnson, Aslin and Newport (1999) used this paradigm to investigate whether adults and 8-month-old infants could segment non-linguistic tone streams. They concluded that when presented with a continuous stream of non-linguistic auditory sequences, comprised of three syllables, participants were able to successfully identify which “words” were presented during exposure. This task has also been used to study sequential learning in the visual modality. Fiser and Aslin (2002) adapted the Saffran et al. (1996) paradigm and converted the auditory stimuli to visual stimuli, using 12 basic black shapes, grouped into triplets. Participants were able to classify 95% of the triplets in the test phase as being more familiar. This paradigm has also been used with ERP studies, albeit less frequently. Koelsch, Busch, Jentschke and Rohrmeier (2016) adapted an auditory triplet
paradigm so that the third sound in the triplet occurred with either low (10%) medium (30%) or high (60%) probability. They concluded that the triplets with both a low and medium probability sound elicited a mismatch negativity (MMN) ERP component, approximately 100ms to 180ms following the sound. This finding reflects the ability to learn the statistical transitional probabilities between items in the triplet. Overall, research using this paradigm has shown an ability to learn and encode the regularities of a sequence (Misyak, Goldstein, & Christiansen, 2012).

The serial reaction time task involves the appearance of visual stimuli at various locations on a screen, typically governed by a specific rule or pattern. The participants must respond to the pattern by pressing response buttons that correspond to each location. Behaviorally, sequential learning is indexed by shorter response times to sequences that repeat in comparison to deviant or random sequences (Eimer et al., 1996). Researchers have been interested in what facilitates learning of these types of sequences, and have often looked at the role of attention and cognitive load as a primary factor (Cohen, Ivry & Keele, 1990). Much of the behavioral evidence suggests that learning during a serial reaction time task relies heavily on attentional processing (Cohen, Ivry, & Keele, 1990; Curran & Keele, 1993; Frensch, Buchner, & Lin, 1994; Nissen & Bullemer, 1987; Schvaneveldt & Gomez, 1998).

Studies utilizing the serial reaction time task and ERP recordings have also shown correlates of sequential learning, similar to the artificial-grammar paradigms. These studies have utilized sequences derived of standards and deviants, and have concluded that a larger N200 and P300 is observed for deviant stimuli in comparison to the learned standard stimuli (Eimer et al., 1996; Schlaghecken et al., 2000). This type of serial reaction time task is often modeled after the classic oddball paradigm.
In a classic oddball paradigm, participants are exposed to a mixture of frequent “standards” and infrequent “deviants”, typically simple or complex tones. The participants’ task is typically to either count the number of deviant stimuli or respond to the deviant stimuli by pressing a response key. This paradigm elicits a larger P300 ERP component for deviant stimuli in comparison to standard stimuli. It has been suggested that the peak amplitude of this P300 component reflects the amount of attentional resources needed for detection (Polich, 2007).

The classic P300 component has been separated into two distinct neural components; the P3a and the P3b. Comerchero and Polich (1998) interpreted the P3a and P3b using a three-stimulus oddball paradigm (target, standard, non-target). They concluded that the P3a is elicited when an infrequent nontarget stimuli is inserted, and is seen in the frontal/central areas. This compares to the classic P300 (also called P3b), which is seen after a deviant stimuli in the parietal electrode sites. Some theories suggest that the distinction between the P3a and P3b emerges because the stimulus context defines the degree of attentional focus required for the primary task, which is interrupted by an infrequently occurring non-target stimulus event (Comerchero & Polich, 1998). Studies such as these further add to the domain-general vs. modality-specific debate of sequential learning. Comerchero and Polich conclude that they observed a stronger P3a effect in the auditory domain compared to the visual domain.

Polich (2007) interprets the P3a and P3b components as combining to produce a generic P300 that reflects stimulus detection. However, a more specific interpretation of the functional significance of the P300 in relation with sequential learning can also be formulated. Using a similar paradigm, van Zuijen et al. (2006) recorded a P300 to rare stimuli only when participants developed explicit knowledge of the sequence of stimuli. Therefore, the P300 may represent the detection of a probabilistic pattern, which is learned through mere exposure.
To study the P300 correlates of sequential learning, Jost et al. (2015) used a modified oddball task to examine the development of sequential learning in younger and older children and adults. Compared to the standard oddball paradigm that only contains frequent and rare stimuli, the Jost et al. paradigm contains “predictor” stimuli that are followed with various probabilities by a target stimulus. Participants were presented with a series of colored circles and asked to press a button every time they saw a circle of a particular color. Unbeknownst to them, the pattern of colored circles followed a specific ordinal pattern; with predictor stimuli followed by the target with high, low and zero predictability. By using this paradigm, ERPs time-locked to these three types of predictors showed a larger P300 with higher target probability, indicating sequential learning. What is interesting about this specific paradigm is that you are able to study the ability to encode and extract simple statistical regularities, although not specific to language. Therefore, understanding whether this paradigm is sensitive to temporal irregularity would be important for understanding general sequential learning abilities in our natural environment.

Taken together, the various paradigms used to explore sequential learning are presumably tapping into similar neural mechanisms. Although the paradigms differ in their degree of complexity and similarity to natural language, they all are catching on to a similar process, which is our inherent sensitivity to the sequential (and statistical) aspects of our environment (Misyak, Goldstein & Christiansen, 2012). Previous research on sequential learning show several common threads. Behaviorally, faster response times, or better learning of artificial grammars indicates more efficient sequential learning. Neurophysiologically, several ERP components have been linked to sequential learning, most commonly the N200, early left anterior negativity, P300 and P600. These ERP components may help in understanding the cognitive mechanisms that underlie sequential learning. The late positive ERP components will be central for this study to explore
the relationship between temporal processing and sequential learning, as I investigate the effects of entrainment to external rhythms.

1.3 Temporal Processing

1.3.1 Dynamic Attending Theory

Jones and Boltz (1989) wrote one of the first articles outlining the theory of Dynamic Attending. They suggested that events that contain an inherent rhythmic patterning affect the way people attend to them and thus process and perceive them. Rhythm is defined as an event with distinct time structures, both synchronous and asynchronous (Large & Jones, 1999). This approach has three basic assumptions. The first is that events with a regular temporal structure allow for an opportunity to direct attention to important points in time, therefore producing better performance in perceptual and memory tasks. The theory posits that the brain creates internal oscillations, also called attending rhythms, which help generate expectancies within an event through a form of rhythmic priming mechanism, with waxing and waning of attentional waves (Henry & Herrmann, 2014). The second assumption states that when stimuli correspond to the high points in these waves, performance is enhanced by affording future-oriented attending. Events such as conversations, music, dance, and so forth all have an inherent temporal structure, with some being more easily processed than others due to their varying temporal coherence. Third, oscillations are self-sustaining, which means that when an external stimulus is not present, the oscillator decays back to its intrinsic period (Henry & Herrmann, 2014).

Several studies provide evidence for the existence of attentional rhythms, as well as the ability to entrain to external rhythms (Large & Jones, 1999). In a series of seven experiments Barnes and Jones (2000) examined the role of stimulus timing properties in controlling attention to auditory sequences through time judgment tasks. Using tasks of isochronous temporal patterns
and comparison patterns, they hypothesized that attention to events, such as speech and music, is controlled, in part, by low-level stimulus-induced expectancies. In this context, stimulus-driven attention refers to a bottom-up involuntary process. They suggest that, according to the DAT, people rely on the rate and rhythm created by elements in a sequence to anticipate the “when” as well as the “what” of future elements (Jones, 1976). In another study, Lakatos et al. (2008) examined the role of entrainment as a mechanism of attentional selection in macaque monkeys. The authors hypothesized that if relevant stimuli appeared in a rhythmic and predictable pattern, neuronal oscillations would entrain (phase-lock) to the structure of the attended stimulus stream and thus serve as instruments of sensory selection. Their findings suggest that when the brain can detect a rhythm in a task, attention enforces phase resetting and entrainment of neuronal excitability oscillations to the relevant stimulus stream, thus amplifying neuronal responses to the events in that stream. These experiments provide evidence for an active oscillator that gives a running internal estimate, that is memory, of the sequence tempo, and allows for judgments of standard and comparison time intervals. Furthermore, some suggest that low frequency neural oscillations in the delta-theta range may be correlates of attentional rhythms (Henry & Herrmann, 2014; Schroeder & Lakatos, 2009).

1.3.2 SL and Temporal Processing

Previous research has demonstrated that a late positive ERP component (referred to as a P300, or P600, or other component of the P3-like family) is associated with learning of a sequential event (Jost et al., 2015; Schmidt-Kassow et al., 2009). Only a few studies have focused on the temporal regularity within a sequence of ordinal stimuli (Schmidt-Kassow et al., 2009; Schwartze & Kotz, 2015; Schwartze et al., 2011; Selchenkova et al., 2014). The main conclusions of this research is that a regular temporal pattern allows for better processing of the
sequence, with faster reaction times and a larger peak amplitude and shorter latency onset of a P3-like component occurring when the sequence has a regular temporal when compared to an irregular temporal pattern (Miniussi et al., 1999; Rohenkohl et al., 2012; Schmidt-Kassow et al., 2009; Schwartze et al., 2011). In one study, Schmidt-Kassow, Schubotz and Kotz (2009) used a classic auditory oddball paradigm, manipulating the inter-stimulus interval. They used three timing groups: isochronous, chunked and random timing. They found both an N2b and P3b component for the deviant stimuli. They concluded that the peak latency of the P3b varied as a function of the timing condition, with the shortest time-to-peak latency of the P3b occurring for the isochronous condition. The authors argued that entrainment accelerated detection of the deviant stimulus, and that according to the DAT; the deviants at expected time points were more easily processed. In a similar study using an auditory oddball task to study attention to deviant stimuli, one group of participants was asked to attend to auditory stimuli whereas another group was asked to watch a movie and to ignore the auditory stimuli (Schwartze et al., 2011). The temporal dimension of the inter-stimuli durations was also varied, with isochronous sequences having a constant inter-stimuli interval at 600ms and the random sequences having an inter-stimuli interval between 200-1000ms. The authors concluded that they saw a larger P3b effect in the isochronous condition relative to the random condition, but only in the attentive session (Schwartze et al., 2001). This result suggests that there is a difference between pre-attentive and attentive temporal processing and that for those in the attentive group, stimulus-driven attending allowed for entrainment and therefore more efficient processing, as indexed by the P3b.

Artificial-grammar learning paradigms have also been employed to explore the role of temporal representation in sequential learning. One such study by Selchenkova, Jones and Tillman (2014) utilized a pitch grammar and varied the exposure phase to have regular and
irregular temporal patterns. They reported that the group that was exposed to a regular pattern showed more complete learning of the artificial pitch grammar, suggesting that they had better expectations about the occurrence of tones in temporal space, thus facilitating learning. More simplistic auditory sequences have also been used to study stimulus-driven attending. Utilizing a time judgment task, Jones et al. (2002) conducted a series of three experiments examining the role of temporal attending in auditory sequences of tones. They found that participants were most accurate when they were judging pitches of rhythmically expected tones. They concluded that in stimulus-driven attending, temporal regularity facilitates attentional synchrony, leading to more efficient processing (Jones et al., 2002). Taken together, these studies support the idea that temporal regularity within a stream of stimuli allows for the brain to entrain to the rhythm of stimulus presentation, allowing for better perception, attention and processing during these conditions. What these studies do not examine is the effect of temporal regularity on a probabilistic sequential structure in the visual domain. To date there is little research exploring what differential learning effects are taking place in the visual domain.

1.4 Current Study

This study uses a probabilistic visual serial learning task, modeled from Jost et al. (2015), in conjunction with a manipulation of the temporal synchronicity as a way to explore the effects of temporal regularity on sequential learning. The task involved the presentation of colored circles, where participants were asked to press a response key whenever they saw a circle of specified color (the “target”). A predictor circle preceded the target circle with varying probability (high, low, and zero predictability). ERPs were time-locked to the predictor circles, and reaction times were recorded to the target circle. Jost et al. (2015) found that a central parietal P300 effect was enhanced for the high probability condition, indicating learning of the
statistical contingencies between stimuli. Whereas the literature on the relationship between sequential learning and temporal processing is scarce, there is some evidence that temporal regularity modulates sequential learning. Although the trend towards more efficient learning under temporally regular conditions has been observed using auditory artificial-grammar paradigms and auditory oddball tasks, sequential learning research would benefit from understanding any such effects in the visual domain (Rohenkohl et al., 2012). The results of previous sequential learning literature have shown that information is best learned spatially in the visual domain and temporally in the auditory domain (Conway & Christiansen, 2005, 2006, 2009). Thus, it is important to explore whether entrainment to a temporal structure can facilitate sequential learning independently of the modality of the to-be-learned sequence, that is, not only in the auditory but also in the visual domain. It is also relevant for sequential learning research to explore the effect of explicit knowledge on the learning of statistical relationships, and therefore I will be utilizing a pattern consciousness inventory to test for any effects with both ERP and reaction time data.

Research on temporal processing and sequential learning is also expected to have implications for our understanding of some disorders. For instance, certain language, cognitive and motor impairments, such as Specific Language Impairment, attention-deficit hyperactivity disorder, and dyslexia, as well as Parkinson’s disease and Schizophrenia, may be associated with temporal and entrainment deficits leading to difficulties in sequence processing (Basu et al., 2010; Calderone et al., 2014; Davalos et al., 2011; Harrington et al., 2011; Norekia et al., 2013). By exploring typical sequential learning in healthy adults and its relationship with temporal processing, this research could pave the pathway towards a better understanding of the cognitive impairments associated with these disorders.
I hypothesize that: (1) in line with Jost et al. (2015), sequential learning will be observed by a shorter latency onset and larger peak amplitude of the P300 reflecting learning of the various predictor-target contingencies (2) synchronous sequences (allowing learning of both predictor-target probability and temporal regularity) will yield larger peak amplitude and shorter peak latency onset of the P300 than asynchronous sequences. (3) Reaction times will reveal that the synchronous task will be responded to fastest, indicating enhanced learning (4) The participants’ level of consciousness, as measured by post-experiment questionnaires, will be related to the P300 effect, where more explicit knowledge of the statistical patterns allows for more enhanced attention and learning of the patterns.
2 EXPERIMENT

2.1 Participants

Twenty adult participants (11 females, 18 right-handed, 18-34 years old, average age = 20.5) without reported language, cognitive, neurological, or psychological deficits and who were native English speakers participated in this experiment. Participants were recruited through Georgia State University’s SONA system, receiving course credits for their participation. All participants provided written informed consent, which was approved by the Institutional Review Board of Georgia State University. Participants were asked to fill out a brief demographic questionnaire and the Edinburgh Handedness Inventory (Oldfield, 1971).

2.2 Procedure

The sequential learning paradigm, based on Jost et al. (2015), involved the presentation of a sequence of colored circles (brown, blue, grey, pink, orange, red, purple, yellow, green, white) in the center of a computer screen with a black background (Figure 1). Participants were asked to press a button whenever they saw a circle of a specific color (the “target”). Each trial consisted of one to five “filler” circles, followed by one of the three predictor circles (high, low, and zero predictor-target probability, chosen randomly on each trial). Depending on which predictor stimulus was presented, the next stimulus was either the target circle or the filler circle. The target circle followed the “high predictor” on 80% of the trials, with a filler circle following 20% of the time. The target circle followed the “low predictor” 20% of the time, with a filler circle following 80% of the time. The target circle never followed the “zero predictor” circle. After the target or final filler was presented at the end of the trial, the sequence repeated itself by starting off again with one to five filler circles and then the randomly chosen predictor stimulus. The color assigned to the target, predictors, and filler circles was randomly chosen for each
participant at the beginning of the task and the selection of colors for each stimulus type remained constant throughout the task for each participant. Aside from manipulating the predictor-target statistical contingency or “predictor-target probability”, there were two conditions designed to explore the effect of temporal regularities: synchronous and asynchronous sequences. In the synchronous condition, the inter-stimulus interval (ISI) was held constant at 1000ms. In the asynchronous condition, the ISI was randomly assigned to a value in the 600 to 1400ms range (Schwartze et al., 2011) so that on average across trials in this condition the ISI remained the same as in the synchronous condition, i.e. 1000ms

Figure 1: Visual Sequential Learning Task
Visual SL task layout [high probability, HP; low probability, LP; zero probability, Z]. In this example, three filler circles precede the predictor stimuli, but this number could range from one to five. After the appearance of either a target or filler at the end of the trial, a new sequence begins. In this example, the target stimuli are green, but in reality the colors of the standard, predictors and target stimuli were randomly assigned for each participant.
The experimental conditions were separated into two separate tasks, the synchronous and asynchronous tasks. Each task was also programmed with two color sets. Set one contained the colors gray, yellow, pink, orange and blue. Set two contained the colors brown, white, red, purple and green. The assignment of set colors as well as order of each task were counterbalanced across participants, so that each participant received a different set of colors for each task. Each task lasted approximately 25 minutes, and included the presentation of 180 trials through 6 blocks of 30 trials each. Compared to the Jost et al. (2015) paradigm that included the presentation of 150 trials, the overall number of trials was increased to 180 trials to increase the signal to noise ratio, allowing better comparison of ERP effects between the first and second half of the sequential learning task. After participants completed both sequential learning tasks, they completed a pattern consciousness inventory, to assess the overall level of consciousness of the probabilistic structure of the sequence (Appendix A).

2.3 Recording Technique

The electroencephalograph (EEG) was measured from 256 scalp sensors using an Electrical Geodesic Inc. (EGI) EEG net. Net Station Version 4.3.1 was used to process the EEGs and ERPs. Active electrode impedances were kept below 50 kΩ. Recordings were made with a 0.1 to 30 Hz bandpass filter and digitized at 250 Hz. The EEG was segmented into epochs -100 to +1000ms with respect to the predictor onset. An artifact detection operation removed trials containing noise from eye blinks and other movements. Separate ERPs were computed for each participant, experimental condition, electrode and block. All experimental sessions were conducted in a 132 square foot double-walled, sound-deadened acoustic chamber.
2.4 Data Analysis

Statistical calculations were performed on the individual mean amplitude and latency ERPs within the time-window of interest (300-700ms post-predictor onset), estimated from previous research and visual inspection (Jost et al., 2015), using Net Station Version 4.3.1. To analyze the effect of cortical topography, nine regions of interest were defined (ROIs, Figure 2): left (LAn), middle (FRz), and right anterior (RAn); left (LCn), middle (CNz), and right central (RCn); and left (LPo), middle (POz) and right posterior (RPo) regions. Based on previous research, we expected the ERP effects of learning to be focused in the posterior central (POz) region (Jost, et al., 2015). Visual inspection of the grand averages confirmed a sequential learning effect in all three posterior regions, the left posterior (LPo), central posterior (POz) regions and the right posterior (RPo), and so all analyses were conducted on these three combined regions (posterior ROIs). Mixed-measures ANOVAs on the individual mean amplitudes and latencies were conducted with the following within-participant factors: Predictor (“high predictor” or HP, “low predictor” or LP, and “zero predictor” or Z), temporal regularity (synchronous, asynchronous) and block (first three blocks vs. last three blocks) and the between-subject factor: whether they saw the synchronous or asynchronous task first (task order). One participant was excluded from the ERP statistical calculations because the number of segments containing artifacts was high (synchronous condition 82%, asynchronous condition 94%).
Response times to target stimuli were analyzed with a mixed-measure ANOVA with predictor, temporal regularity, and block as within-participant factors and task order as the between subject factor. One participant was also excluded from response time calculations, due to a computer error.

Consciousness scores were calculated for each participant for each task. Three raters were used to come up with an average consciousness score for each person. Chronbach alpha showed high reliability for each task (Synchronous = .94, Asynchronous = .93). Correlations were then computed between ERP amplitude scores and consciousness scores as well as reaction times and consciousness scores.

All statistical analyses were conducted with SPSS (PAWS Statistics 18 – Release 18.0.3 September 9, 2010). All reported p-values were adjusted with the Greenhouse–Geisser correction for non-sphericity, when appropriate. Partial eta-squared is reported as a measure of effect size.
for all ANOVAs (Cohen, 1988; Olejnik & Algina, 2003). Reported p-values of the posthoc tests were Šidák corrected.
3 RESULTS

3.1 Reaction Times

Table 1 displays the mean reaction time data for both the synchronous and asynchronous tasks, separated by the first half and second half of each in order to observe effects of learning that might be present following a certain amount of exposure to the patterns. A 2 (timing: synchronous or asynchronous) x 2 (predictability: HP or LP) x 2 (block: 1st half or 2nd half of task) x 2 (task order: synchronous first or asynchronous first) mixed-measures Analysis of Variance (ANOVA) was done on reaction times in milliseconds. Reaction times were only recorded to the target circle, and therefore no reaction times followed the zero predictor (Z) condition. The ANOVA revealed a significant main effect of Timing \( [M_{syn} = 373.4, SD = 11.7, M_{asy} = 392.9, SD = 9.4, F(1,16) = 4.90; p = .042, \eta^2_p = .23] \), Predictability \( [M_{LP} = 392.7, SD = 8.2, M_{HP} = 373.6, SD = 11.8F(1,16) = 9.12; p = .008, \eta^2_p = .36] \) and a main effect of Block \( [M_{1stHalf} = 390.1, SD = 9.1, M_{2ndHalf} = 376.6, SD = 10.5, F(1,16) = 12.32; p = .003, \eta^2_p = .44] \), but no significant interactions. These data indicate that the synchronous condition was overall responded to faster than the asynchronous condition. It also shows that the HP condition was responded to significantly faster than the LP condition across both halves of both tasks. Finally, the main effect of block suggests that participants improved on their performance of the task in the second part of the tasks, regardless of predictor type. Overall, these results suggest that participants showed facilitation with responding to targets when the HP stimulus was present, indicating learning of the ordinal structure in both the synchronous and asynchronous versions of the task, although overall the synchronous task was responded to faster.
Table 1: Mean (SD) reaction time scores by timing condition, predictor and block

<table>
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<tr>
<th></th>
<th>Synchronous</th>
<th>Asynchronous</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>1st Half</td>
<td>2nd Half</td>
</tr>
<tr>
<td>HP</td>
<td>379.9 (59.4)</td>
<td>357.1 (66.0)</td>
</tr>
<tr>
<td>LP</td>
<td>385.7 (45.9)</td>
<td>379.9 (50.7)</td>
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</tbody>
</table>

3.2 ERP Amplitude Data

Figure 3 displays the grand averaged ERPs for each task across all participants, time-locked to the three predictors (HP, LP, & Z) at the posterior regions of interest used for topographic analyses during both the first and second half of the task. Visual inspection suggests a larger positivity between about 300ms and 700ms for the HP predictor compared to the LP and Z predictors in the second half of the task for the synchronous but not asynchronous conditions.

Another way to visualize the ERP data is to display the mean average for each of the three predictor conditions for each task across the two blocks. Figure 4 shows the means for the posterior ROIs from 300 to 700ms post predictor-onset. From visual inspection, it is very clear that the timing condition appears to be affecting the ERPs elicited by each predictor type in different ways. Specifically, whereas in the first half of both tasks, the ERP effects do not appear to differ, they do differ in the second half for the synchronous but not the asynchronous task, presumably reflecting participant’s learning of the varying predictor-target probabilities.
Figure 3: Grand average ERPs
Grand average ERPs observed in the posterior regions of interest in response to the high probability condition (HP, red line), low probability condition (LP, blue line), and zero probability condition (Z, green line) (vertical axis: electrical potential in $\mu V$, positivity upward; horizontal axis: time in milliseconds) in the first and last three blocks of each task. The synchronous task is shown in the two upper panels and the asynchronous task in the lower two panels.
Figure 4: Means Line Graph
Line graph depicting the means in microvolts ($\mu V$) for the posterior regions of interest (300-700ms post-predictor onset) for each of the three predictors in the first half versus the second half of the task.

A $2 \times 2 \times 2 \times 3$ mixed-measures ANOVA confirmed that there was an interaction between Timing and Predictability 300ms to 700ms poststimulus onset [$F(2,34) = 4.01; p = .027, \eta_p^2 = .19$] indicating a significant difference between HP and Z in the synchronous condition but not the asynchronous condition ($p = .01$).

There was also a significant Block and Predictability interaction [$F(2,34) = 7.74; p = .002, \eta_p^2 = .31$] 300ms to 700ms poststimulus onset, indicating that the difference between HP and LP ($p =$
.023) and HP and Z (\(p = .005\)) was larger in the second half of the experiment, regardless of timing condition.

Although there was no significant three-way interaction between Predictability, Timing and Block, two 2 (block) x 3 (predictor) repeated measures ANOVAs indicate an effect only in the synchronous condition. There was a significant Block and Predictability interaction in the synchronous condition \([F(2,36) = 5.94; p = .006, \eta^2_p = .25]\), indicating differences between means from the first to the second half of the task. Posthoc tests revealed significant differences between HP and LP from the first half to the second half \((p = .006)\) as well as significant differences between HP and Z from the first half to the second half \((p = .01)\). A repeated measures ANOVA found no significant interaction between Block and Predictability in the asynchronous condition.

There was also an interaction between Timing and whether the participant completed the synchronous or the asynchronous task first \([F=(1,17) = 11.14, p = .004, \eta^2_p = .40]\), indicating that for the synchronous task, the ERP means were significantly higher if the participant saw the asynchronous task first. However, for the asynchronous task, whether the participant saw the asynchronous or synchronous task first had no effect on average ERP amplitude (Figures 5 & 6). There was also an interaction between block and which timing condition was completed first \([F(1,17) = 11.19, p = .04, \eta^2_p = .22]\). These results indicate that mean ERP amplitudes showed opposite effects according to which task you saw first. If a participant saw the synchronous task first, their overall ERP means decreased from the first half to the second half of the task. However, for those who saw the asynchronous task first, their overall ERP amplitudes increased as the task progressed (Figure 7). The mixed-measures ANOVA results can be found in Tables 2 and 3.
Figure 5: Interaction between Task and Timing
Grand average ERPs observed in the posterior regions of interest in response to the high probability condition (HP, red line), low probability condition (LP, blue line), and zero probability condition (Z, green line) (vertical axis: electrical potential in μV, positivity upward; horizontal axis: time in milliseconds) for the entire experimental session, broken up into which task the participant saw first. The synchronous task is shown in the two upper panels and the asynchronous task in the lower two panels.
Figure 6: Timing x Task Interaction
Line graph depicting the means in microvolts ($\mu V$) for the posterior regions of interest for the interaction between Timing condition and which task (Syn or Asy) the participant saw first.

Figure 7: Block x Task Interaction
Bar graph depicting the means in microvolts ($\mu V$) for the posterior regions of interest for the interaction between Block and which task (Syn or Asy) the participant saw first.
Table 2: Mixed-Measures ANOVA 300-700ms posterior ROIs

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<td>.57</td>
<td>.03</td>
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* S1 vs. A1 = Synchronous task first vs. Asynchronous task first
Table 3: Mean (SD) ERP amplitudes 300-700ms posterior ROIs

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<tr>
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<th>Standard Deviation</th>
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<tr>
<td>Asy_Z_2ndHalf</td>
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<td>1.32</td>
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n = 19
3.3 ERP Latency Data

A 2 (timing) x 2 (block) x 2 (task order) x 3 (predictor) mixed-measures ANOVA of the peak latency from 300-700ms in the posterior regions of interest showed a significant main effect of predictor \[ F(2,34)= 7.67, \, p = .002, \, \eta^2_p = .93 \]. Post hoc tests indicated that the P300 peaked earlier in the zero predictor condition, compared to both the high \((p = .007)\) and low \((p = .004)\) predictor conditions (Figure 8). There were no significant interactions.

![Mean Latency](image)

Figure 8: Main Effect of Predictor
The means for the main effect of predictor for the latency scores 300-700ms post predictor onset in the posterior regions of interest.

3.4 Consciousness Inventory

The consciousness inventory produced an average rating per participant, for each temporal condition \((M_{asy} = 2.1, \, SD = .78, \, M_{syn} = 2.2, \, SD = .77)\). A paired-sample t-test revealed no significant differences between timing groups \((t(18)= -.304, \, p = .77)\). However, consciousness scores were significantly correlated with the mean ERP amplitudes for each predictor condition in the second half of the synchronous task: HP \((r=.577, \, p=.01)\), LP \((r=.732, \, p<.001)\) and Z
(r=.673, p =.002) from 300-700ms post-predictor. These results show that for the synchronous condition, in the second half of the task, there was a positive relationship between one’s level of consciousness of the probabilistic patterns and the ERP amplitudes. There were no significant correlations for the asynchronous condition (Tables 4 & 5).
### Table 4: Correlation of synchronous condition and consciousness scores

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* * p < .05  
** ** p < .01

### Table 5: Correlation of asynchronous condition and consciousness scores

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<td>2. Z_{1stHalf}</td>
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<td>3. HP_{1stHalf}</td>
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* * p < .05  
** ** p < .01
In this study I explored the effects of temporal regularity on the neural correlates of visual sequential learning using behavioral and neurophysiological evidence (ERPs). I used a modified oddball task as a way to explore learning of statistical contingencies. The main findings of this research are that (1) under the synchronous temporal conditions only, the ERPs indicated a significant effect of predictor type in the last 3 blocks of the task, with greater P300-like amplitudes for the HP condition; (2) ERPs indicated that if participants were presented with the asynchronous task first, their neural response was heightened, indicated by higher ERP means; (3) reaction time data showed that the target was responded to faster following the presentation of the high predictor compared to the low predictor, which indicated learning for both temporal conditions and (4) reaction time data also showed that participants responded faster to the target during the synchronous temporal condition. Together, these findings support the theory that regularly structured events allow for enhanced perceptual processing by allowing individuals the opportunity to direct their attention to salient information within a stream of stimuli.

The ERP results of the synchronous condition mirrors those of Jost et al. (2015), who also observed a P300-like ERP component for the HP predictor, reflecting the learning of the probabilistic contingencies between stimuli. The fact that this P300 effect was not seen in either the first three or the last three blocks of the asynchronous task highlights the fact that processing and binding of statistical regularities was heightened during trials that had highly regular rhythms. This shows that variability in timing may influence the P3b, which is typically seen 300-500ms over central and parietal electrode sites (Schwartze et al., 2011). However, contrary to previous research, we found no significant latency effects that would indicate that the
regularly timed condition elicited an earlier peak latency of the P300 (Schmidt-Kassow, Schubotz & Kotz; 2009).

Overall, the ERP results fit well within the context of the DAT, which predicts that events with highly regular temporal rhythms produce entrainment of oscillatory waves, so that perception and encoding are enhanced because stimuli are being presented during the highest point in the wave of attention (Jones & Boltz, 1989). My findings fit well within the expectation of the DAT that temporal regularity provides an opportunity to direct attention to salient information, in this case, the onset of the stimuli being presented, which led to improved encoding of the statistical regularities. The larger P300 effect in the synchronous condition may indicate stimulus-driven synchronization of attention that leads to an improvement of stimulus processing and an advantage in learning (Schmidt, Schubotz & Kotz, 2009; Schwartze et al., 2011).

Whereas the classic oddball paradigm is used to explore the effect of deviant stimuli in a stream of input, the modified oddball paradigm that was applied in the present study (based on Jost et al., 2015), that includes predictor-target statistical contingencies, allows for the exploration of the extraction of sequential probabilities out of a serial input stream. The results from this study highlight that after a certain amount of exposure to the serial pattern, the participants’ brain treated the high predictor stimuli as if it were the target itself, producing a larger P300. While most of the research conducted on sequential learning and temporal processing has been conducted in the auditory domain, this study shows that sequential learning of visual stimuli is also sensitive to temporal regularities. The P300 may reflect expectations about when the target stimulus occurs, and therefore stimuli that occur at expected time points are processed more efficiently. Because we do not always experience events in a regular
temporal fashion, understanding how we process events structured with a varying temporal regularity has important implications for human cognition, especially for incidental and implicit learning.

Interestingly, ERP data also showed an effect of which task participants were presented with first. These results indicate that the asynchronous task created a heightened arousal response to the task, with ERP means being significantly higher when participants saw this task first. The data also suggest that if you were presented with the synchronous task first, your ERP means decreased from the first half to the second half of the task, whereas for the asynchronous task your ERP means increased from first to second half. Altogether, I interpret these data to mean that if participants were exposed to the asynchronous task first, their overall level of arousal was heightened. However, this heightened arousal did not facilitate learning of the statistical patterns within the sequence.

Unexpectedly, reaction time data showed learning effects in both timing conditions in the last 3 blocks of the task, although overall the synchronous condition was responded to faster. One interpretation of the lack of interaction between timing, block and predictor could be that reaction times could represent the implicit learning of the patterns, whereas the ERP effects index attention-dependent processes that were affected by entrainment. The consciousness scores revealed a significant positive correlation with ERP means in the synchronous condition in the last half of the experiment, suggesting that as one’s level of consciousness increased, so did their neurophysiological responses. The P300 is known to be affected by attentional manipulations (Polich, 2007), so taken together, these findings suggest that temporal regularity results in increased attentional processing of the patterns (explicit knowledge) while leaving implicit learning more or less unaffected (for a similar argument that sequential learning relies upon both...
implicit and explicit learning processes, see Batterink et al., 2015). Karabanov and Ullen (2008) found that when participants focused only on the ordinal structure of a sequence, they learned it mainly implicitly, while focusing on both ordinal and temporal structure led to mainly explicit learning. If temporal irregularity forced a mainly local level processing (ordinal features only), implicit learning might remain intact, reflected by the behavioral results. On the other hand, there was a main effect of timing, indicating that the synchronous condition led to an overall facilitation in responses (i.e. quicker responding); thus, there simply may not be enough power to detect these interaction effects behaviorally.

In addition to using larger sample sizes, another limitation of this study is that we did not collect data on the participant’s ability to entrain to external stimuli. Although we infer from the results that participants were entraining to the synchronous, but not the asynchronous condition, this would need to be explored in future studies with a task designed to measure entrainment, such as a finger-tapping task (Leong & Goswami, 2014; Patel et al., 2005; Repp, 2005). Furthermore, it would be important to explore the effects of temporal regularity in the auditory domain. Previous research has suggested that sequential learning has modality-specific constraints, and thus it is may be possible that temporal regularity effects may be different in the auditory modality (Conway & Christiansen, 2005; Emberson, Conway & Christiansen, 2011).

Future studies might also explore different ways of varying the temporal structure of input sequences. For instance, in line with previous research (Brandon et al., 2012; Essens & Povel, 1985; Selchenkova et al., 2014), a metrical framework might be adapted and tested using this predictor-target paradigm. Selchenkova et al. (2014) manipulated the temporal structure of sequences by using both metrical and isochronous structures in an artificial grammar-learning paradigm. They found that the highly metrical condition showed a larger P300 component in the
exposure phase and an earlier N2 component in the test phase, in comparison to the isochronous condition. Similarly, Brandon et al. (2012) conducted two experiments investigating temporal structure learning based on Inter-Onset-Intervals in the presence of an uncorrelated second dimension (ordinal structure) with metrically organized temporal structures. The authors used an adaptation of the classic serial reaction time paradigm and found that reaction times significantly slowed when a novel temporal structure was introduced. Studies like these suggest that a complex interplay between metricality and temporal regularity can have a dramatic effect on sequential learning, and thus it may be advantageous to further explore these dimensions.

Finally, the current research on temporal processing and sequential learning is expected to have implications for our understanding of certain impairments. Language, cognitive and motor impairments, such as Specific Language Impairment, attention-deficit hyperactivity disorder, and dyslexia, as well as Parkinson’s Disease and Schizophrenia, appear to be associated with temporal and entrainment deficits that in turn could lead to difficulties in sequence processing (Basu et al., 2010; Hsu & Bishop, 2014; Davalos et al., 2011; Harrington et al., 2011; Noreika et al., 2013; Soltész et al., 2013). For example, dyslexia is thought to be due, in part, by inefficient rhythmic entrainment, leading to less preparatory brain activity (Leong & Goswami, 2014; Soltész et al., 2013). Future research ought to explore entrainment and sequential learning in typical and atypical participants in order to better characterize the nature of the deficits that these individuals are experiencing. One possibility is that sequential learning is impaired in these populations because of a lessened ability to dynamically attend to stimuli, leading to inefficient processing of both auditory and visual stimuli. This research approach is expected to advance our comprehension and assessment of several types of cognitive impairments affecting language, attention, motor coordination, and more generally a wide range of cognitive systems.
By exploring sequential learning in healthy adults and its relationship with temporal processing, this research could pave the pathway towards a better understanding of the cognitive impairments of these clinical populations.
REFERENCES


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APPENDIX: CONSCIOUSNESS INVENTORY

SANDAL -- Experimenter Questions

1. Think about the first task with circles of different colors. Tell me about your perception of the task.
   (Allow 10s to respond without prompting to anything and record as verbatim as possible.)

2. What about in the second task you did with circles of various colors? Did you notice anything about these circles? Tell me about your perception of the task.
   (Allow 10s to respond without prompting to anything and record as verbatim as possible.)

3. Do you think the first task of circles of various colors occurred randomly?
   • Yes
   • No
   • If yes which one?________________________________________(describe)

4. Do you think the second task of circles of various colors occurred randomly?
   • Yes
   • No
   • If yes which one?________________________________________(describe)

5. Did you notice a particular rhythm to either the 1st or the 2nd task?

6. Was there a pattern or anything regular in the order that the circles of various colors were presented?
   1st Task:
   • There was definitely a pattern
   • There was a pattern at certain times
   • There may have been a pattern
   • The circles of various colors occurred somewhat randomly
   • There was absolutely no pattern at all
2nd Task:
- There was definitely a pattern
- There was a pattern at certain times
- There may have been a pattern
- The circles of various colors occurred somewhat randomly
- There was absolutely no pattern at all

7. If you noticed a pattern, at what point did you notice it?
   a. **Asynchronous Task**: Before 1\textsuperscript{st} break, after 1\textsuperscript{st} break, after 2\textsuperscript{nd} break, after 3\textsuperscript{rd} break, after 4\textsuperscript{th} break
   b. **Synchronous Task**: Before 1\textsuperscript{st} break, after 1\textsuperscript{st} break, after 2\textsuperscript{nd} break, after 3\textsuperscript{rd} break, after 4\textsuperscript{th} break

   **ANSWER ONLY IF YOU NOTICED A PATTERN**

8. Did the first task help you to find a pattern in the second task?

9. Do you feel that the target circle was preceded by a circle of specific color?
   1\textsuperscript{st} task:
   2\textsuperscript{nd} task:

10. Were the tasks easy or difficult? Yes/ No

    Was one more difficult than the other? Which one? 1\textsuperscript{st} task/ 2\textsuperscript{nd} task

11. Were the tasks too long? Yes/ No

12. Did you get tired during either or both of those tasks?

    At what point did you start getting tired?

   a. **Asynchronous Task**: Before 1\textsuperscript{st} break, after 1\textsuperscript{st} break, after 2\textsuperscript{nd} break, after 3\textsuperscript{rd} break, after 4\textsuperscript{th} break
   b. **Synchronous Task**: Before 1\textsuperscript{st} break, after 1\textsuperscript{st} break, after 2\textsuperscript{nd} break, after 3\textsuperscript{rd} break, after 4\textsuperscript{th} break