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Ross, Kimberly M.
Conway, Christopher M.

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Temporal Structure Modulates ERP Correlates of Visual Sequential Learning

Kimberly M. Ross (Kross25@student.gsu.edu)
Department of Psychology, P.O. Box 5010, Atlanta, GA 30302 USA

Christopher M. Conway (Cconway@gsu.edu)
Department of Psychology, P.O. Box 5010, Atlanta, GA 30302 USA

Abstract

Sequential learning (SL) refers to the ability to learn the temporal and ordinal patterns of one's environment. Whereas research on the learning of ordinal patterns is common, the learning of temporal patterns within sequential events has been far less studied. The current study examines the effects of synchronous and asynchronous temporal patterns on visual sequential learning. We hypothesize that entrainment (i.e. exposure to a regular rhythmic pattern) allows for better processing of the ordinal structure of sequential events. Twenty healthy adult participants (11 females, 18–34 years old) performed two versions of a visual sequential learning paradigm while event-related potentials (ERPs) were recorded. The SL task involved the visual presentation of colored circles, wherein a target circle was embedded that was partially predictable based on preceding predictor stimuli. One version of the task incorporated synchronous temporal presentation of the stimuli whereas the other version involved asynchronous presentation of stimuli using a randomized ISI on every trial. Reaction time data demonstrated that learning occurred in both temporal conditions. On the other hand, the mean ERP amplitudes between 350 and 750ms post-predictor onset in the posterior regions of interest revealed that learning of the statistical contingencies between stimuli was disrupted for the asynchronous temporal condition but intact for the synchronous condition. These neurophysiological data suggest that the brain processes regular and irregular timing events differently, with statistical learning of ordinal visual patterns being improved by a synchronous temporal structure, possibly a result of heightened attention to the stimuli due to entrainment.

Keywords: Sequential learning; statistical learning; temporal processing; entrainment; ERPs

Introduction

An important question in cognitive science is what facilitates learning of structured events under different contexts. When events are not fully random but contain a degree of temporal or ordinal regularity, our brain is able to extract these regularities to facilitate processing using predictive mechanisms, that is, by learning to predict future stimuli in the sequence (Selchenkova et al., 2014). In this manner, we are able to generate expectancies about future events, an ability that that allows us to improve our responses and execution of actions (Rohenkohl et al., 2012).

Sequential learning (SL) is the ability to learn incidentally the ordinal patterns of one's environment (i.e., sequences of items that unfold in time, such as a melody or a gymnastics routine). Surprisingly, whereas SL studies of the ordinal structure of sequences are common, research on SL of temporal patterns is scare. Most SL studies focus on learning sequences of stimuli with identical durations and identical inter-stimuli intervals (e.g. Conway & Christiansen, 2005; Jost et al., 2015). However, SL of sequences containing temporal irregularity, that is with stimuli of varying durations or with different 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 examine both the ordinal and temporal information available in any given context. The Dynamic Attending Theory (DAT) proposes 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.

SL can be observed behaviorally (response times) as well as indexed neurophysiologically with event-related potentials (ERPs, for a recent review, see Daltrozzo & Conway, 2014). The ERP technique has been used to study SL using variations of the classic auditory oddball sequence task, the serial reaction time task (SRT) and with artificial grammar learning (AGL) 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). The ERP technique has the advantage 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 examining temporal cognition, including SL of temporal and ordinal regularities.

The Current Study

The current study uses a probabilistic visual serial learning task (Jost et al., 2015) with a manipulation of the temporal

synchronicity as a way to explore the effects of temporal regularity on SL. Whereas the literature on the relationship between SL and temporal processing is scarce, there is some evidence that temporal regularity modulates SL. 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 (Rohenkohl et al., 2012; Schmidt-Kassow et al., 2009). However, because most of the studies exploring the effect of the temporal regularities on SL have been conducted in the auditory domain, it is important to test this relationship in the visual domain (Rohenkohl et al., 2012). The results of previous SL literature have shown that perceptual modality (i.e., visual vs. auditory patterns) influences SL (Conway & Christiansen, 2005). Thus, it is important to explore whether entrainment to a temporal structure can facilitate SL independently of the modality of the to-be-learned sequence, that is not only in the auditory but also in the visual domain.

We hypothesize that: (1) Reaction time data will show better learning in the synchronous condition compared to the asynchronous condition; (2) ERP data will show that the synchronous sequences yield larger peak amplitudes of the P300 than asynchronous sequences, suggesting a facilitative effect for processing statistical regularities in temporally regular events.

Method

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 credit 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).

Procedure
The SL 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. In the synchronous temporal condition, the stimuli appeared on the screen for 500ms with a 1000ms (black screen) ISI. In the asynchronous temporal condition, stimuli appeared on the screen for 500ms, with a randomized ISI, ranging between 600ms and 1400ms so that on average across trials the ISI remained the same as in the synchronous condition (1000ms).
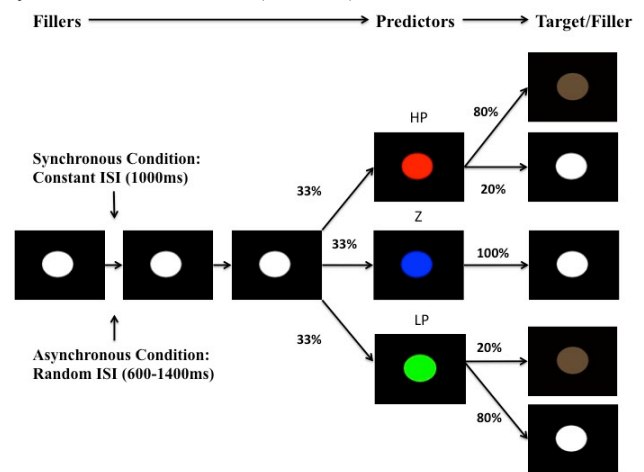

Figure 1: Visual SL task layout [high probability, HP; low probability, LP; zero probability, Z]. In this example, three filler circles precede the predictor stimuli, but this number could range from one to five. After the appearance of either a target or filler at the end of the trial, a new sequence 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, synchronous and asynchronous. 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 trails, the overall number of trials was increased to 180 trials to increase the signal to noise ratio, allowing us to better compare ERP effects between the first and second half of the SL task. After participants completed both sequential learning tasks, they completed a pattern consciousness inventory, a measure that tested the

overall level of consciousness of the probabilistic structure of the sequence.

Recording Technique

The electroencephalograph (EEG) was measured from 256 scalp sensors using an Electrical Geodesic Inc. (EGI) EEG net (Figure 2). Net Station Version 4.3.1 tools were used to process the EEGs. 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 -200 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.

Statistical Analysis

Statistical calculations were performed on the individual mean amplitude ERPs within the time-window of interest (350-750ms 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 an SL effect in both the left posterior (LPo) and central posterior (POz) regions, and so all analyses were conducted on these two combined regions (posterior medial-left). Repeated-measure ANOVAs on the individual mean amplitudes 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). One participant was excluded from the ERP statistical calculations due to a high percentage (over 60%) of trials containing artifacts (Synchronous, 94%; Asynchronous, 82%).

Response times to target stimuli were analyzed with repeated-measure ANOVAs with predictor, temporal regularity, and block as within-participant factors. One participant was also excluded from response time calculations, due to a computer error.

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.
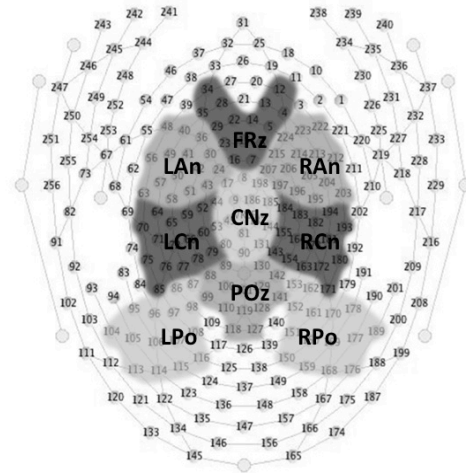

Figure 2: 256 sensors EEG net with the highlighted nine regions of interest.

Results

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 2x2x2 repeated measures ANOVA revealed a significant main effect of Predictability [$F(1,18) = 11.79$; p = .003, $\eta_p^2 = .40$] and a main effect of Block [$F(1,18) = 6.63$; p = .02, $\eta_p^2 = .27$], but no significant interactions. These data indicate that the HP condition was responded to significantly faster than the LP condition across both halves of both tasks. The main effect of block also suggests that participants improved on their performance of the task in the second part of the tasks, regardless of predictor type and task synchronicity. 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. Note that numerically the synchronous condition displayed improved RTs for the HP condition from the 1st half to 2nd half of the task (379.9 vs. 357.1 ms); although the asynchronous condition also showed a similar facilitation, the effect was smaller (387.2 vs. 372.0 ms). However, this difference in effects was non-significant, likely due to lack of statistical power [$F(1,18) = .112$; p = .74, $\eta_p^2 = .006$].

Table 1: Mean (SD) reaction time scores by timing condition, predictor and block.

	Synchronous		Asynchronous	
	1st Half	2nd Half	1st Half	2nd Half
HP	379.9 (59.4)	357.1 (66.0)	387.2 (43.1)	372.0 (63.0)
LP	385.7 (45.9)	379.9 (50.7)	406.7 (40.9)	389.3 (46.8)

The ERP data, however, presents a more nuanced picture. 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 medial-left 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 350ms and 750ms 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.
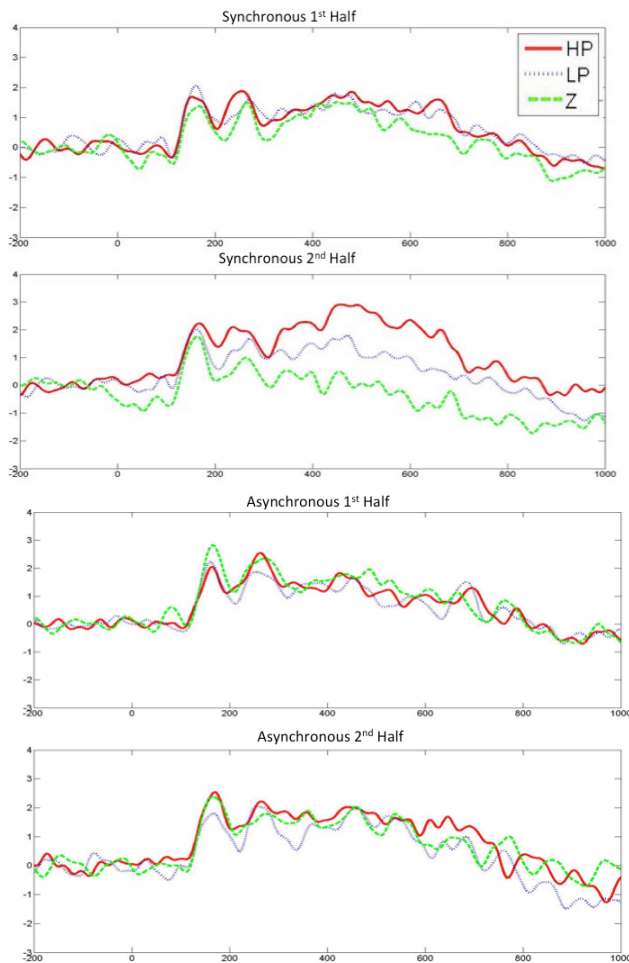

Figure 3: Grand average ERPs observed in the posterior medial and left regions of interest in response to the high probability condition (HP, red line), low probability condition (LP, blue line), and zero probability condition (Z, green line) (vertical axis: electrical potential in μV, positivity upward; horizontal axis: time in milliseconds) in the first and last three blocks of each task. The synchronous task is shown in the upper panels and the asynchronous task in the lower panels.

Figure 4 shows the means for the posterior medial-left region for each of the three predictors in the first three blocks of the task versus the last three blocks of the task in both timing conditions. 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 differences in participants' learning of the varying predictor-target probabilities.
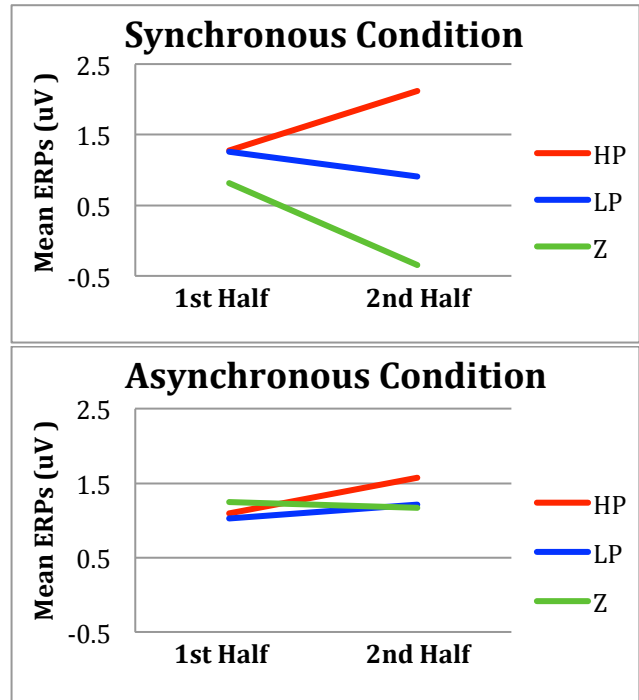

Figure 4: Line graph depicting the means in microvolts (μV) for the posterior medial-left region for each of the three predictors in the first half versus the second half of the task 350-750ms post-predictor onset.

A 2x2x3 repeated measures ANOVA confirmed that there was an interaction between Timing and Predictability 350ms to 750ms poststimulus onset [F(2,36) = 6.01; p = .006, η_p^2 = .25] indicating a significant difference between HP and Z in the synchronous condition but not the asynchronous condition (p = .009). There was also a significant Block and Predictability interaction [F(2,36) = 4.13; p = .040, η_p^2 = .19] 350ms to 750ms poststimulus onset, indicating that the difference between HP and LP (p = .03) and HP and Z (p = .02) was larger in the second half of the experiment, regardless of timing condition.

While there was no significant three-way interaction between Predictability, Timing and Block, two 2x3 repeated measures ANOVAs indicate an effect only in the synchronous condition. We found a significant Block and Predictability interaction in the synchronous condition [F(2,36) = 5.77; p = <.001, η_p^2 = .24], 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 = .013) 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.

The consciousness inventory produced an average rating per participant, for each temporal condition. A paired-sample t-test revealed no significant differences between timing groups (t(18)= -.304, p =.77). However, the consciousness scores were significantly correlated with the mean ERP amplitudes for each predictor condition in the second half of the synchronous task: HP (r=.608, p=.006), LP (r=.614, p=.005) and Z (r=.603, p =.006) from 350-750ms post-predictor. This suggests 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.

Discussion

This study explored the effects of temporal regularity on the neural correlates of visual SL using neurophysiological evidence (ERPs). The main findings of this research are that (1) reaction time data showed that the target was responded to faster following the presentation of the high predictor compared to the low predictor, regardless of temporal condition, indicating learning for both conditions; (2) 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.

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 was enhanced 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 (Schmidt-Kassow, Schubotz & Kotz; 2009). According to the predictions made by the DAT, 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). Our 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.

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. While most of the research conducted on SL and temporal processing has been conducted in the auditory domain, this study shows that SL 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. Since 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, reaction time data showed learning effects in both timing conditions in the last 3 blocks of the task, which seems to stand in contrast to the ERP findings. One interpretation of this discrepancy is that reaction times could represent the implicit learning of the patterns, while 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 awareness of the sequence 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 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) On the other hand, the means of the reaction times go in the direction that would be expected if the synchronous condition led to improved learning; thus, there simply may not be enough power to detect these effects behaviorally.

In addition to using larger sample sizes, future studies might explore different ways of varying the temporal structure of input sequences. For instance, in line with previous research (Brandon et al., 2012; 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. Studies like these suggest that a complex interplay between metricality and temporal regularity can have a dramatic effect on SL, and thus it may be advantageous to further explore these dimensions.

Finally, the current research on temporal processing and SL is expected to have implications for our understanding of certain pathologies. Language, cognitive and motor impairments, such as Specific Language Impairment (SLI), attention-deficit hyperactivity disorder (ADHD), 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).

For example, SLI is thought to stem from an impairment of the procedural memory system, which in turn may affect both sequential and temporal processing (Hsu & Bishop, 2014). Future research ought to explore entrainment and SL in typical and atypical participants in order to better characterize the nature of the deficits that these individuals are experiencing. One possibility is that SL is impaired in these pathological 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 SL 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 pathological populations.

Acknowledgments

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