Behavioral and Neurophysiological Correlates of Sequential Learning are Associated with Language Development in Children

Joanne A. Deocampo (jdeocampo@gsu.edu)
Department of Psychology, Georgia State University, P.O. Box 5010, Atlanta, GA 30302

Christopher M. Conway (cconway@gsu.edu)
Department of Psychology, Georgia State University, P.O. Box 5010, Atlanta, GA 30302

Leyla Eghbalzad (leghbalzad1@student.gsu.edu)
Department of Psychology, Georgia State University, P.O. Box 5010, Atlanta, GA 30302

Jerome Daltrozzo (Jerome.daltrozzo@gmail.com)
Department of Psychology, Georgia State University, P.O. Box 5010, Atlanta, GA 30302

Abstract

Sequential learning (SL) is believed to be an essential component of language development. Despite support from behavioral studies, neural evidence of this relationship, especially in children, is scarce. The current study measured 7-12-year-olds' ERPs to a visual SL task involving incidental learning of probabilistic relationships between predictors and targets presented within a serial input stream. Various aspects of language and cognitive development were assessed with standardized tests. Results on the SL task showed that children demonstrated SL as determined by differences in ERP amplitudes and response times for predictor conditions that varied with the probability of predicting the target. Crucially, the amplitude of ERP difference waveforms was positively correlated with language ability and cognitive control. These findings validate the use of a probabilistic visual predictor-target task to investigate SL in children and, most importantly, provide neural evidence of a close relationship between SL, language development and cognitive control.

Keywords: sequential learning; language development; event-related potentials (ERP); cognitive development; cognitive control

Introduction

Spoken language development depends upon basic processing mechanisms that encode structural regularities in the input (e.g., Gervain and Mehler, 2010; Gogate & Hollich, 2010; Kuhl, 2004; Saffran, Senghas & Trueswell, 2001; Ullman, 2004). One such mechanism, structured sequence processing or sequential learning (SL), is used to learn about structured patterns of information in the environment that unfold over time (Conway et al., 2010; Conway & Pisoni, 2008; Saffran, 2003; Udden & Bahlman, 2012). SL can take place through any sensory modality and is used across multiple domains, including language and communication, motor and skill learning, music perception and production, problem solving, and planning (e.g., Conway et al., 2011; Conway, Pisoni, & Kronenberger, 2009).

In particular, research suggests that SL is an essential component of language development. For example, in a recent study of deaf children with cochlear implants,

Conway et al. (2011) found that children's scores on a visual SL task were positively correlated with their scores on a standardized measure of verbal language ability involving syntax, even after controlling for verbal short-term memory and vocabulary skill (also see Conway, Pisoni, & Kronenberger, 2009). In addition, Shafto, Conway, Field, and Houston (2012) demonstrated an empirical link between visual sequence learning and vocabulary development in typically hearing infants. However, neural evidence for the relationship between SL and language processing, especially in children, is scarce.

One exception is Christiansen, Conway, and Onnis (2012), who measured event-related potentials (ERPs) while adult participants performed both a SL task and a language processing task. They found that both tasks elicited a centro-parietal late latency ERP component, called the P600, when structural incongruities were encountered. As this component is known to be an index of syntactic processing in natural language, it was concluded that the same neural mechanisms may be recruited for both syntactic processing of linguistic stimuli and more general SL processes. Even so, this study focused on adults only, and so it remains an open question as to whether the same relationship between the neural mechanisms of SL and language processing holds true for children.

In an attempt to extend this research to examine the possible connection between the neural mechanisms of SL and language ability in children, we measured ERPs in 19 children aged 7-12 years while performing a visual SL task. These children were also administered a number of standardized neuropsychological assessments that measured language development, cognitive ability, and executive function.

The SL task was modified from the task used by Jost et. al (2011) that was used to investigate the neurophysiological correlates of visual statistical learning in adults and children. Jost et al.'s (2011) task in turn was based on the classic visual oddball paradigm, modified to include sequential regularities between a predictor and a target. Participants viewed a stream of visual stimuli that included targets to which participants were instructed to respond by pressing a

button. Participants were not told that embedded in this stimulus stream were predictor stimuli that predicted the occurrence of the target with varying levels of probability (high, low, and zero probability). Jost et al. (2011) demonstrated that children and adults' learning of the transitional probabilities between predictors and targets embedded within the serial input patterns elicited a mid- to late-latency (between 300 to 600ms post-predictor onset) centro-parietal positivity. This ERP component was elicited specifically by the high-probability predictor that was the strongest predictor of the upcoming target.

For the present study, we used a similar SL task modified to be more child-friendly by making it into a game with a background story (i.e., the "magician" task). Like Jost et al. (2011), we measured ERPs time-locked to each predictor presentation. In addition, we administered a number of assessments of language and other cognitive abilities in an attempt to determine whether performance on these assessments was correlated with the above-mentioned ERP index of SL.

Method

Participants

Nineteen typically developing and hearing children between the ages of 7 and 12 years (M = 8.95 years; 9 female) participated. Two additional participants were excluded, one due to software failure, and one due to inability to reduce impedances to 50 kΩ. All children were recruited from the Atlanta metropolitan area.

Sequential Learning Task

Children were told a story about an inconsistent magician who tried to make food for his children using his magic hat. Participants were told to "catch" the sporadically presented food by pressing a button. Children then viewed a stream of stimuli consisting of hats of different colors presented one at a time. Occasionally, a target hat with food depicted above it was presented within the stream. Unbeknownst to participants, hats of three different colors each differentially predicted the occurrence of the target hat, which we refer to as high-probability predictors, low-probability predictors, and standards. When the high-probability predictor was presented, it was immediately followed by the target 90% of the time and the standard 10% of the time. The low-probability predictor was followed by the target 20% of the time and the standard 80% of the time. In addition, the target was occasionally presented directly after a standard without a preceding predictor (referred to as no-predictor). Figure 1 shows a schematic of the sequence learning task.

If children learned either implicitly or explicitly, the transitional probabilities between each type of predictor and the target, it was expected that there would be differences in both response times (RTs) to the targets and ERPs to the predictors based on whether a trial was a high-probability, low-probability, or no-predictor trial. Either of these differences would constitute evidence of sequence learning.

Each stimulus was presented on screen for 500ms on a black background, followed by a black screen for 500ms (Stimulus Onset Asynchrony: 1000ms). There were 60 trials in each experimental condition presented in pseudorandom order in 6 blocks of 30 trials each. Blocks were interspersed with 30s breaks during which children watched a stop-action cartoon related to the magician story.
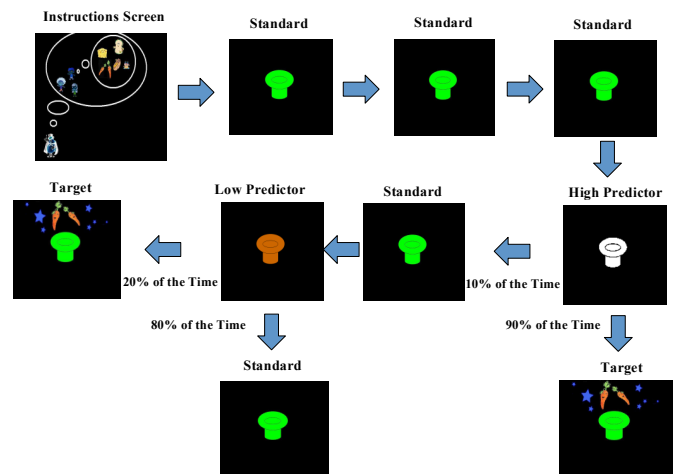

Figure 1: Schematic representation of the sequential learning task. The target followed the high predictor on 90% of high predictor trials but only on 20% of low predictor trials. In the no-predictor condition, the target was presented immediately after a standard with no preceding predictor.

ERP Recording and Analysis

ERPs reflecting stimulus-time-locked changes in electrical potential on the scalp during the SL task were collected using a 32-channel sensor net and processed using Net Station Version 4.3.1 (Electrical Geodesics, Inc.). Impedances were kept below 50 kΩ. Data were acquired with a 0.1 to 30 Hz bandpass filter and digitized at 250 Hz.

ERPs were time-locked to the onset of each predictor stimulus or in the case of the no-predictor condition, the standard that preceded the target (epochs: -200ms to +1500ms). This resulted in 60 trials for each of the three predictor conditions (high-probability, low-probability, and no-predictor). Automatic rejection was applied for eye blinks, movements, and other artifacts. Data from channels with poor signals were replaced with data extrapolated from surrounding channels using a bad channel replacement operation. Channels were grouped into 7 regions of interest (ROIs) containing four sensors each (see Figure 2): frontal, left anterior, right anterior, central, left posterior, centro-posterior, and right posterior. Data from the facial sensors were not included in analyses due to electrooculogram noise.

Neuropsychological Assessments

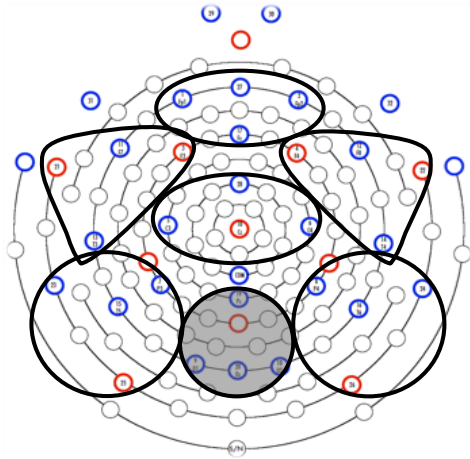Children's receptive vocabulary was assessed using the

2116

Figure 2: ROI mapping. The centro-posterior ROI is shaded.

Peabody Picture Vocabulary Test, Fourth Edition (PPVT-4; Dunn & Dunn, 2007). Two subtests of the Comprehensive Assessment of Spoken Language (CASL; Carrow-Woolfolk, 1999) were also administered as assessments of language development: *Grammaticality Judgment*, in which children are asked to judge sentences' grammatical correctness; and *Sentence Completion*, wherein sentences are read without their final word , and children are asked to give a semantically and grammatically correct word ending.

Short-term and working memories were assessed with the *Forward and Backward Digit Span* subtest of the Wechsler Intelligence Scale for Children, Fourth Edition Integrated (WISC-IV Integrated; Kaplan et al., 2004). Spatial ability was assessed with the *Block Design* subtest of the WISC-IV.

Finally, executive function and cognitive control were assessed with the Stroop Color and Word Test: Children's Version (Golden, Freshwater, & Golden, 2002). This test takes advantage of the well-known Stroop Effect. Children read as many color words (red, blue, and green) in a list as they can in 45 seconds, then name as many colors (red, blue, and green) as they can in 45 seconds, and finally name the incongruent ink color in which color-words are written as many times as possible in 45 seconds. This test measures the degree of inhibitory control to semantic interference between automatic and controlled semantic processing.

Results

Statistical Analyses

Repeated-measures ANOVAs were Greenhouse-Geisser-corrected for sphericity when appropriate. Posthoc tests were Sidak-corrected for multiple testing.

Response Times.

A one-way repeated measures ANOVA comparing mean RT by predictor type (high-probability, low-probability, no-predictor) revealed a significant effect of predictor type ($F(1.359, 24.459) = 6.482$, $p = .011$). Posthoc tests showed

that RTs for high-probability predictor trials ($M = 420$ ms, $SD = 88$) were significantly faster than those for the no-predictor trials ($M = 490$ ms, $SD = 86$; $p = .029$). The low-probability predictor mean RT ($M = 471$ ms, $SD = 70$) was not significantly different from that for either the high-probability predictor ($p = .101$) or no-predictor (p = .293) conditions. These response time analyses suggest that participants learned the transitional probabilities between the high-probability predictor and the target.

ERPs

Visual inspection of the grand-averaged ERPs for the three predictor conditions (Figure 3) revealed a centro-parietal late (between about 300-750 ms) positivity similar to a P300 component that increased with the transitional probability between predictors and targets.
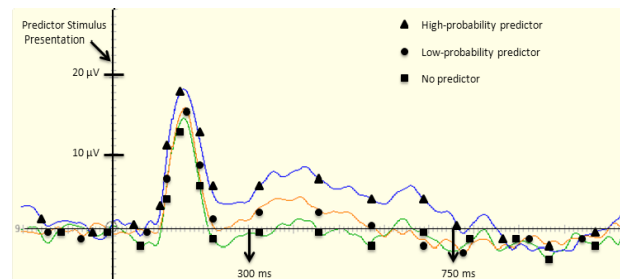

Figure 3: Grand-averaged ERP in the centro-posterior ROI (Figure 2) to high-probability (triangles), low-probability (circles), and no-predictor (squares) trials (Positivity upward in microVolts; time in milliseconds).

A repeated measures ANOVA with Predictor (high, low, and no) and ROI (Figure 2) within-participants factors on the mean ERPs in the 300-750ms post-predictor onset window showed a Predictor X ROI interaction ($F(2.910, 52.381) = 3.727$, $p = .018$).

A repeated measures ANOVA comparing the three predictor conditions (high, low, and no) conducted on ERPs from only the centro-posterior ROI showed a significant effect of predictor ($F(1.30, 25.12) = 6.36$, $p = .011$). Posthocs showed a larger positivity to high-probability predictors ($M = 3.77$ µV, $SD = 2.02$) than to no predictor trials ($M = -0.22$ µV, $SD = 5.15$; $p = .038$) and a marginally significant higher positivity to high-probability predictors ($M = 1.55$ µV, $SD = 3.42$) than to low-probability predictor trials ($p = .085$). ERPs did not differ significantly between the low-probability predictor and no-predictor conditions during this window ($p = .183$). These neurophysiological data suggest that children learned the transitional probabilities between predictors and targets. These findings roughly parallel the behavioral findings and validate the use of ERPs as a measure of learning in this task.

Neuropsychological Assessments

Means and standard deviations for all neuropsychological assessments are reported in Table 1. Mean scores on all

tasks fall roughly into the average expected ranges as reported in each test manual. Age-normed, scaled scores were used in analyses for all neuropsychological assessments.

Table 1: Means and standard deviations (SD) for each neuropsychological assessment.

Assessment Score	Mean	SD	N
PPVT Standard Score	99.58	18.158	19
PPVT Percentile	48.53	35.195	19
Grammaticality Judgment	97.56	13.080	18[1]
Sentence Completion	102.61	12.939	18
Stroop Interference T-Score	55.83	10.972	18
Block Design	8.05	2.915	19
Digit Span	10.00	2.867	19

Correlations

The no-predictor condition provides a baseline-measure for RTs and ERPs given no warning that the target was about to be presented. Thus, a decreased RT or an ERP deviation from these baselines on low- and high-probability predictor trials ought to reflect SL. To compare levels of learning, we created difference scores between the no-predictor and low-probability predictor and between the no-predictor and high-probability predictor for both the mean response times and mean ERP amplitudes. Response time difference scores and amplitude difference scores for the centro-posterior region were then correlated with each other and with neuropsychological assessment scores using a Spearman's correlation (see Table 2). This non-parametric statistic was used because the small sample size may mean that data are not normally distributed. Correlations among different neuropsychological tests are not of main interest in the present study and therefore are not reported in the text. In addition, age was not significantly correlated with any of the SL measures, thus age was not included in further analyses.

Response Times. Response time difference score correlations with both ERP wave differences and neuropsychological assessments were non-significant. This is likely related to high variability in children's response times due to any of the following: lack of motivation to react as quickly as possible, responding to the predictor in

---

[1] One participant did not complete some of the neuropsychological assessments resulting in an n of 19 for some assessments and an n of 18 for others.

anticipation of the target once the transitional probabilities had been learned, and variability in fine motor control.

ERP Effects and Neuropsychological Assessments. The low-no ERP effect was significantly positively correlated with the CASL Sentence Completion standard scores ($\rho_s(16) = .502$, $p = .034$), and marginally positively correlated with the Stroop Interference T-Score ($\rho(16) = .416$, $p = .054$). In addition, the high-no ERP effect was significantly positively correlated with the Stroop Interference T-Score ($\rho_s(16) = .539$, $p = .021$). These results suggest that better SL, as indexed by greater differences between high- and low-probability predictor ERP amplitudes and the baseline (no-predictor) ERP amplitude, are associated with: (1) greater ability to complete the last word of a sentence based on previous sentence context (Sentence Completion score) and (2) greater cognitive control and flexibility (Stroop Interference score).

Discussion

Results from this investigation confirm the primary findings from the Jost et al. (2011) study: children's ERPs show a P300-like positivity between about 300ms to 750ms post stimulus onset in response to predictors of varying probability, with the positivity being greater for high probability predictors compared to low probability or no predictors. These findings validate the use of this type of embedded predictor-target task as a way to examine the behavioral and neural correlates of SL in children (as well as adults). This paradigm thus paves the way for exploring the developmental progression of SL mechanisms across the lifespan and their relationship with language ability.

It is possible that differences in ERPs in comparison with the baseline-measure may be exaggerated due to the known increase in P300 to infrequent stimuli with respect to frequent stimuli. This is true because although the high and low predictors were presented an equal number of times, the standard (no predictor) was presented much more frequently. However, differences between conditions in ERPs parallel the observed differences between conditions in RT, which are not subject to the P300 effect. In addition, Jost et al. (2011) did not have this potential confound and yet presented similar ERP results. Thus, we believe these ERP differences to reflect SL *per se* rather than frequency-encoding mechanisms.

The findings from the present study also revealed positive relationships between the neurophysiological measures of SL and two standardized assessments measuring language development (i.e., Sentence Completion) and executive function (i.e., Stroop Interference T-score). These correlations are not just indicative of general cognitive level as measures of memory and spatial cognition did not show significant correlations with neurophysiological measures of SL. Instead, these results are consistent with other recent findings showing a connection between SL and both language and cognitive control. For example, considering the correlation with the Sentence Completion task first,

Table 2: Correlation Matrix.

		PPVT	Grammaticality Judgment	Sentence Completion	Stroop Interference	Block Design	Digit Span	ERP High-No Difference	ERP Low-No Difference	RT No-High Difference	RT No-Low Difference
PPVT	Spearman's ρ	1	.824	.710	.034	.714	.385	.265	.374	-.125	.091
	p-value	.	.000	.001	.893	.001	.103	.272	.114	.611	.710
Grammaticality Judgment	Spearman's ρ	.824	1	.535	.024	.670	.404	.304	.216	.025	.126
	p-value	.000	.	.022	.924	.002	.096	.221	.390	.922	.618
Sentence Completion	Spearman's ρ	.710	.535	1	.042	.310	.418	.378	.502	.143	.125
	p-value	.001	.022	.	.867	.211	.084	.122	.034	.573	.621
Stroop Interference	Spearman's ρ	.034	.024	.042	1	-.355	-.528	.539	.461	.079	.215
	p-value	.893	.924	.867	.	.148	.024	.021	.054	.756	.391
Block Design	Spearman's ρ	.714	.670	.310	-.355	1	.366	.019	-.034	-.153	-.002
	p-value	.001	.002	.211	.148	.	.123	.940	.889	.533	.994
Digit Span	Spearman's ρ	.385	.404	.418	-.528	.366	1	-.202	-.019	-.076	-.002
	p-value	.103	.096	.084	.024	.123	.	.407	.937	.756	.994
ERP High-No Difference	Spearman's ρ	.265	.304	.378	.539	.019	-.202	1	.811	.205	.296
	p-value	.272	.221	.122	.021	.940	.407	.	.000	.399	.218
ERP Low-No Difference	Spearman's ρ	.374	.216	.502	.461	-.034	-.019	.811	1	.116	.367
	p-value	.114	.390	.034	.054	.889	.937	.000	.	.637	.123
RT No-High Difference	Spearman's ρ	-.125	.025	.143	.079	-.153	-.076	.205	.116	1	.481
	p-value	.611	.922	.573	.756	.533	.756	.399	.637	.	.037
RT No-Low Difference	Spearman's ρ	.091	.126	.125	.215	-.002	-.002	.296	.367	.481	1
	p-value	.710	.618	.621	.391	.994	.994	.218	.123	.037	.

Conway et al. (2010) found that adults' performance on a visual SL task and performance on an auditory sentence perception task that required implicit prediction of the final word in a sentence were positively correlated. Conway et al. (2010) concluded that the skill required for both tasks that lead to their association was the ability to encode underlying statistical structure contained in input sequences--both in the visual SL task and in natural language—and then using such knowledge to facilitate the processing of subsequent input (also see Misyak, Christiansen, & Tomblin, 2010 for a similar conclusion). In the same way, the correlation observed in the present study between visual SL as measured by differences in ERP amplitudes and the Sentence Completion test suggests that children's ability to provide grammatically and semantically appropriate endings to sentences is based in part on SL and implicit prediction processes. However, we believe our results are the first evidence of this relationship in children and the first correlation of SL with a standardized assessment of sentence prediction. Finding a relationship with a standardized measure of sentence prediction is the first step in fleshing out the clinical implications for developing language interventions using SL.

The other correlation observed here, between ERP correlates of SL and the Stroop Interference T-score, may highlight the role of inhibitory processes required for both tasks. In the Stroop task, a high interference t-score translates to a low level of interference, meaning that the participant is able to inhibit the automatic process of reading color words in order to quickly name the incongruent color of the ink in which the word is displayed. In the SL task, learning the probabilistic contingencies between predictors and targets may also require inhibition of responding to non-relevant stimuli in the task. Interestingly, associations between Stroop performance and language processing have been found in healthy adults (January, Trueswell, & Thompson-Schill, 2009) and in children with cochlear implants (Conway et al., under revision). Likewise, neuroimaging evidence suggests that sequence processing and cognitive control both engage left frontal areas of the brain (Bahlmann, Korb, Gratton, & Friederici, 2012). However, to our knowledge, this is the first direct, within-subject evidence of a link between neural correlates of SL and a measure of cognitive control and flexibility. Future research is needed to further elucidate the ways in which language development, sequence processing, and cognitive control are related.

Further research is also necessary to confirm the causal nature of the relationships among these variables. The current study shows only correlations only and does not speak to the direction of the causal relationships or even whether there are other unobserved variables that account for associated performance on SL, language, and cognitive control tasks. However, there is reason to believe that SL does in fact causally impact language processing. Shafto et al. (2012) recently showed that visual SL in 8.5 month-olds predicted infants' comprehension of communicative gestures five months later, suggesting a causal link in which better SL leads to better language development. On the other hand, SL and receptive vocabulary were also concurrently positively correlated at 8.5 months leaving open the possibility that better language understanding actually leads to better SL ability or that there is a third variable underlying performance on both skills. Further support for a causal relationship between SL and language was found in a recent mediational analysis of adaptive training of SL and its impact on language processing (Smith et al., under review). We believe that a combination of

longitudinal designs (as espoused by Arciuli & Torkildsen, 2012 and Conway et al., 2011) and training interventions (Smith et al., under review) will provide further insight as to the causal relationships among these constructs.

In conclusion, the findings of this study validate the use of a modified visual oddball task to study SL in children. These findings also support a growing body of evidence suggesting a tight coupling between sequential learning, language processing, and cognitive control (Bahlmann et al., 2012; Christiansen et al., 2012; Conway et al., 2010; Conway et al., 2011; January et al. 2009; Misyak et al., 2010; Shafto et al., 2012). Importantly, we believe this study contributes some of the only data that link neural measures of such learning processes in children to behavioral measures of language ability and cognitive control, bringing us one step closer to elucidating the multiple processes underlying language development.

Acknowledgements

References

Arciuli, J. & Torkildsen, J.K. (2012). Advancing our understanding of the link between statistical learning and language acquisition: The need for longitudinal data. *Frontiers in Psychology*, *3*, 324.

Bahlmann, J., Korb, F.M., Gratton, C., & Friederici, A.D. (2012). Levels of integration in cognitive control and sequence processing in the prefrontal cortex. *PLoS ONE*, *7*(8), e43774.

Carrow-Woolfolk, E. (1999). *Comprehensive Assessment of Spoken Language.* Circle Pines, MN: AGS.

Christiansen, M.H., Conway, C.M., & Onnis, L. (2012). Similar neural correlates of language and sequential learning: Evidence from event-related potentials. *Language and Cognitive Processes, 27*(2), 231-256.

Conway, C.M., Bauernschmidt, A., Huang, S.S., & Pisoni, D.B. (2010). Implicit statistical learning in language processing: word predictability is the key. *Cognition, 114, 356–371.*

Conway, C.M., & Pisoni, D.B. (2008). Neurocognitive basis of implicit learning of sequential structure and its relation to language processing. *Annals of the New York Academy of Sciences*, *1145*, 113–131.

Conway, C.M., Pisoni, D.B., Anaya, E.M., Karpicke, J., & Henning, S.C. (2011). Implicit sequence learning in deaf children with cochlear implants. *Developmental Science*, *14*, 69-82. PMC3050521

Conway, C.M., Pisoni, D.B., & Kronenberger, W.G. (2009). The importance of sound for cognitive sequencing abilities: the auditory scaffolding hypothesis. *Current Directions in Psychological Science*, *18*, 275–279.

Conway, C.M., Walk, A.M., Deocampo, J.A., Anaya, E.M., & Pisoni, D.B. (under revision). Processing sentences as strings of unrelated words: Use of sentence context by deaf children with cochlear implants. *Journal of Speech, Language, and Hearing Research.*

Dunn, L.M. & Dunn, D.M. (2007). *Peabody Picture Vocabulary Test* (4th ed.). Circle Pines, MN: AGS.

Gervain, J., & Mehler, J. (2010). Speech perception and language acquisition in the first year of life. *Annual Review of Psychology*, *61*, 191-218.

Gogate, L.J., & Hollich, G. (2010). Invariance detection within an interactive system: A perceptual gateway to language development. *Psychological Review*, *117*, 496-516.

Golden, C. J., Freshwater, S. M., & Golden, Z. (2002). *Stroop Color and Word Test: Children's Version.* Wood Dale, IL: Stoelting.

January, D., Trueswell, J.C., & Thompson-Schill, S.L. (2009). Co-localization of Stroop and syntactic ambiguity resolution in Broca's area: Implications for the neural basis of sentence processing. *Journal of Cognitive Neuroscience, 21,* 2434-3444.

Jost, E., Conway, C. M., Purdy, J. D., & Hendricks, M. A. (2011). Neurophysiological correlates of visual statistical learning in adults and children. In L. Carlson, C. Hoelscher, & T.F. Shipley (Eds.), *Proceedings of the 33rd Annual Conference of the Cognitive Science Society* (pp. 2526-2531). Austin, TX: Cognitive Science Society.

Kaplan, E., Fein, D., Kramer, J., Delis, D., & Morris, R. (2004). *Wechsler Intelligence Scale for Children - Fourth Edition Integrated*. San Antonio, TX: Harcourt Assessment Inc.

Kuhl, P.K. (2004). Early language acquisition: Cracking the speech code. *Nature Reviews Neuroscience*, *5*, 831-843.

Misyak, J. B., Christiansen, M. H., & Tomblin, J. B. (2010). Sequential expectations: The role of prediction-based learning in language. *Topics in Cognitive Science*, *2*, 138-153.

Saffran, J.R., 2003. Statistical learning learning: Mechanisms and constraints. *Current Directions in Psychological Science*, *12*(4), 110-114.

Saffran, J.R., Senghas, A., & Trueswell, J.C. (2001). The acquisition of language by children. *Proceedings of the National Academy of Sciences*, *98*, 12874–12875.

Shafto, C.L., Conway, C.M., Field, S.L., & Houston, D.M. (2012). Visual sequence learning in infancy: Domain-general and domain-specific associations with language. *Infancy*, *17,* 247-271.

Smith, G.N.L., Conway, C.M., Bauernschmidt, A., & Pisoni, D.B. (under review). Exploring the causal relationship between structured sequence processing and language using adaptive computerized training. *PLOS ONE*.

Uddén, J, & Bahlmann, J (2012) A rostro-caudal gradient of structured sequence processing in the left inferior frontal gyrus. *Philosophical Transactions of the Royal Society: B Biological Sciences*, *367*, 2023-2032.

Ullman, M. T. (2004). Contributions of memory circuits to language: The declarative ⁄ procedural model. *Cognition, 92*, 231–270.