A Developmental Shift in the Relationship Between Sequential Learning, Executive Function, and Language Ability as Revealed by Event-Related Potentials

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Abstract

Previous research has shown a link between sequential learning (SL) and language as well as links between executive function (EF) and both language and SL. However, little research has focused on both the development of the relationship between these factors and their neurological underpinnings. Here we report a study of the event-related potential (ERP) correlates of SL and behavioral measures of language and EF in a sample of 7-12-year-old children. Results revealed that both SL and EF had independent associations with language development but that the contribution that both made toward language development shifted dramatically between the ages of 7 to 11-12 years. The results furthermore suggest that this developmental shift may be due in part to the maturation of EF abilities and changes due to neural entrenchment and commitment as a consequence of language acquisition.

Keywords: language development; sequential learning; statistical learning; executive function; event-related potentials (ERP)

Introduction

The ability to encode statistical structure in temporally ordered sequences and make predictions about the world based on that structure is referred to as structured sequence processing or sequential learning (SL). There is a growing body of evidence suggesting that SL is an important mechanism underlying spoken language acquisition (e.g., Conway, Bauernschmidt, Huang, & Pisoni, 2010). For example, infants and adults can both learn artificial spoken languages in the laboratory based only on transitional probabilities (e.g., Romberg & Saffran, 2013, adults; Saffran, Aslin, & Newport, 1996, infants). Auditory statistical learning tasks can also uniquely predict adults' ability to comprehend English sentences (e.g., Misyak & Christiansen, 2012). In addition, several studies have linked individual differences in visual SL (VSL) to individual differences in various aspects of language, including, for example, adults' incidental learning of a grammar in a sequential memory task correlating with their ability to predict words in a spoken sentence (Conway, et al. 2010), individual differences in children's VSL independently predicting their ability to comprehend English syntax (Kidd & Arciuli, 2015), and VSL abilities of children with cochlear implants correlating with their performance on language measures (Conway, Pisoni, Anaya, Karpicke, & Henning, 2011). One recent study found that infants' VSL predicted later vocabulary and gesture comprehension (Shafto, Conway, Field, and Houston, 2012). In addition, there is some neural evidence showing a connection between SL and language. For instance, Christiansen, Conway, and Onnis (2012) found that an event-related potential (ERP) component that is typically considered an index of syntactic processing in natural language was elicited by incongruities in both an SL task and a natural language processing task in adults.

Recent research also suggests strong positive relationships between executive function (EF) and both SL (e.g., Bahlmann, Korb, Gratton, & Friederici, 2012) and language (e.g., January, Trueswell, & Thompson-Schill, 2009). Because SL is the ability to make predictions about the world based on statistical structure in temporally ordered sequences, it makes sense that some EF mechanisms, such as attention, cognitive control, cognitive flexibility, working memory, and inhibition, would contribute to SL ability in the same way that it does to language ability. In addition, as with SL and language, there is some evidence for an overlap in the neural mechanisms underlying SL and EF (Bahlmann et al., 2012).

However, there is very little research that addresses the developmental trajectory of the relationship between SL, EF, and language ability, especially in combination with neural measures. In light of this, we aimed to examine the relationship between SL as measured by ERPs, EF, and spoken language ability throughout a 5-year period in childhood. We chose the age range 7-12 years for two reasons: 1) there has been relatively less research on SL in middle childhood, with the bulk of the research having been done on infancy through preschool and adolescence through adulthood, and 2) as brought up in the Discussion, 7 years and 12 years appear to be ages at which there are major changes in the development of both SL and language (Janacsek, Fiser, & Nemeth, 2012; Johnson & Newport, 1989). We hypothesized that because EF skills appear to contribute to both SL and language abilities and SL is an important component of language development, EF and SL would both directly predict language ability, but that EF would also affect language through the mediator of SL. In addition, we hypothesized that because of the protracted nature of EF's development (e.g., Best & Miller, 2010), these relationships would differ at various ages, suggesting age as a moderator (see Figure 1).

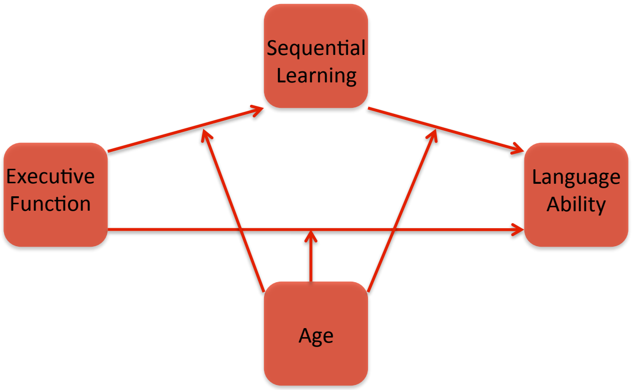

Figure 1: Conceptual model of the proposed relationships between EF, SL, language, and age.

Method

Participants

Thirty-eight typically developing and hearing monolingual English-speaking children between the ages of 7 and 12 years (*M* = 9.13 years, *SD* = 1.9 years; 15 female) participated.

Sequential Learning Task

Children were told a story about a 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 (for each: 500ms stimulus, 500ms black screen; SOA: 1000ms). 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 (HP) predictor was presented, it was immediately followed by the target 90% of the time and the standard 10% of the time. The low-probability (LP) 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 (no-predictor, NP). Figure 2 shows a schematic of the sequential learning task.

Based on previous results using a similar task (Jost, Conway, Purdy, Walk, & Hendricks, 2015), it was expected that if children learned the transitional probabilities between the predictors and the target, there should be differences in both response times (RTs) to the targets and ERPs to the predictors based on whether a trial was a HP, LP, or NP trial. These differences would constitute evidence of SL. Although RT findings supported the ERP findings, to conserve space, they will not be discussed in this paper.

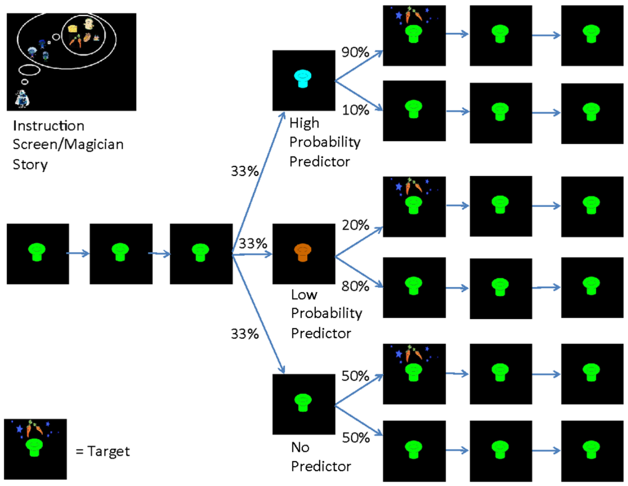

Figure 2: Schematic representation of the sequential learning task. The target followed the high predictor on 90% of HP trials but only on 20% of LP trials. In the NP condition, the target was presented immediately after a standard with no preceding predictor. A random number of standards were presented before each predictor (or NP)..

ERP Recording and Analysis

ERPs were collected using a 32-channel sensor net and preprocessed using Net Station Version 4.3.1 (Electrical Geodesics, Inc.). ERPs were time-locked to the onset of each predictor stimulus or in the case of the NP condition, the standard that preceded the target during the SL task. This resulted in 60 trials for each of the three predictor conditions (HP, LP, and NP).

The remainder of processing was done using custom scripts in MATLAB (version R2012b 8.0.0783; MathWorks) and the EEGLAB Toolbox (version 10.2.2.24a, Delorme & Makeig; 2004) for MATLAB to remove artifacts and replace bad channels. Participants were required to have a minimum of 20 good epochs per condition in each half of the SL task to be included in further analyses.

Executive Function Task

Executive function (EF) was assessed with a version of the Eriksen Flanker Task, which is thought to tap into selective attention, conflict response, and response inhibition mechanisms, all of which fall under the umbrella of EF. Horizontal arrays of arrows were presented on a computer screen, and children were told to respond only to the arrow in the center. They were to indicate whether the arrow was pointing left or right while ignoring the flanking arrows which could be facing the same direction (congruent) or opposite direction (incongruent). Response times to incongruent and congruent trials were recorded separately and average incongruent RTs subtracted from average congruent RTs to give a Flanker score (a higher score indicates higher EF).

Language Assessment

We assessed children's language ability with the Sentence Completion subtest of the Comprehensive Assessment of Spoken Language (CASL; Carrow-Woolfolk, 1999). In this test, sentences are read without their final word, and children are asked to give a semantically and grammatically correct single word ending. We chose this assessment because it parallels a sentence prediction task that was positively associated with adults' SL (Conway et al., 2010).

Results

ERP Analyses

Based on the ERPs to the SL task described in Jost et al. (2015), we chose to analyze the ERP time window 400-700 ms post-stimulus presentation from the medial posterior region of sensor net. This is the time window and region in which Jost et al. (2015) found ERP effects in a very similar paradigm and with children of similar ages. Visual inspection of the grand averaged ERP waveforms (Figure 3) suggests that there was a P300-like positivity in the posterior medial region within a similar window as that found by Jost et al. (2015). This positivity was especially visible for the HP condition in the second half of the task (Figure 3B), consistent with the notion that learning the predictor-target contingencies occurred toward the end of the task, after sufficient exposure to the statistical probabilities (as was also observed in Jost et al., 2015). Furthermore, based on visual inspection, this positivity appears to consist of two different peaks where the predictor conditions appear to be differentiated: 300-600 ms and 600-750 ms post stimulus presentation. Therefore, we chose to analyze each of these time windows separately. Results for the 600-750ms window are presented here, although both windows yielded similar results. This 600-750ms window has the advantage of being within the time window analyzed by Jost et al. (2015) with children as well as within the window where Christiansen et al. (2012) found overlap between ERPs to a language task and an SL task.

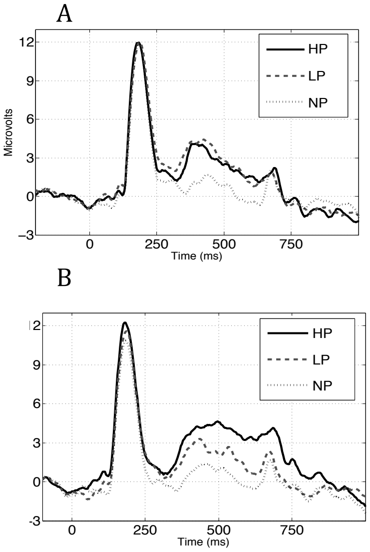

Figure 3: Grand-averaged ERP (n=38) in the medial posterior region to high-probability predictor (HP, solid line), low-probability predictor (LP, dashed line), and no-predictor (NP, dotted line) trials for first block (A) and second block (B) (Positivity upward in microVolts; time in milliseconds).

A 3 (predictor: high probability predictor, low probability predictor, or no predictor) x 2 (block: 1st half SL task or 2nd half SL task) repeated measures ANOVA was done on ERPs in the 600-750ms window to examine the effects of predictor type and block on the mean ERP amplitudes. Results revealed a significant main effect of predictor, $F(2, 74) = 7.67$, $p = .001$, $\eta_p^2 = .17$, and a significant interaction between predictor and block, $F(2, 74) = 5.08$, $p = .009$, $\eta_p^2 = .12$. The main effect of block was not significant. Predictor effect post hoc pairwise comparisons revealed that HP ERP amplitude was significantly greater than both LP ($p = .039$) and NP amplitudes ($p = .004$). For the interaction, post hoc pairwise comparisons showed that only HP increased across blocks ($p = .002$). All posthoc tests were Sidak corrected for multiple comparisons.

Conditional Process Model

To test the conceptual model of the relationship between EF, SL, language, and age depicted in Figure 1 in which EF has both direct and indirect effects (mediated by SL) on language and all relationships with language are moderated by age, we constructed a statistical conditional process model. First, we created composite SL scores to capture the level of learning across the task. First, the ERP amplitude difference of HP minus LP was calculated to capture the amount of differentiation between high and low probability predictors, which indicates a basic level of learning. Then, HP-LP for the 1st block was subtracted from HP-LP for the 2nd block to show change over time during the task, which indicates the amount that learning increased as the task progressed. We refer to this measure as "HP-LP change".

The conditional process model was tested using Hayes's (2013) PROCESS macro Model 59 with bootstrapping in SPSS. Bootstrapping was used to ameliorate the relatively small sample size. One additional participant was removed at this point because she met outlier criteria for the regression. We tested the model with HP-LP changes as the SL variable. For the EF measure, we used the Flanker score (congruent RT minus incongruent RT), and we used a continuous measure of age. Standard Sentence Completion score was the outcome measure.

Both predictive models, that between EF and SL with SL as the outcome and that predicting language (Sentence Completion) as the outcome from EF and SL, were significant (see Tables 1 and 2). SL does mediate the relationship between EF and language, but only with age moderating both the predictive link between EF to SL and the predictive link between SL to language. In addition, the EF measure, Flanker, significantly positively predicted language as measured by Sentence Completion. SL and age also positively predicted language (although SL only did so marginally). Age significantly moderated the relationships between EF and SL and between SL and language and marginally significantly moderated the relationship between EF and language, suggesting that the relationships between all of these constructs change with age. To visualize these changes in relationships that occur with age, we divided participants into three age groups of approximately equal size, 7-year-olds (n = 12), 8-10-year-olds (n = 13), and 11-12-year-olds (n = 12), and produced scatter plots to show each relationship (see Figure 5).

Table 1: Regression table with SL (HP-LP change) as the outcome

Variable	*B*	*SE B*	*p*
EF (Flanker)	-.006	.004	.181
Age	.044	.426	.917
EF x Age	-.005	.002	.016
R^2	.263		.017

Table 2: Regression table with language (Sentence Completion) as the outcome

Variable	*B*	*SE B*	*p*
SL (HP-LP change)	1.27	.739	.096
EF (Flanker)	.047	.010	.0001
Age	-3.82	1.54	.019
SL x Age	.985	.329	.005
EF x Age	.013	.007	.064
R^2	.371		.0000

Inspection of the scatter plots reveals that all three relationships are quite different for older (11-12 years) versus younger (7 years) children. Younger children exhibited a positive relationship between EF and SL, which was expected given Bahlmann et al.’s (2012) findings and our prediction that EF would underlie SL abilities. The older children’s negative relationship between EF and SL is more puzzling, but seems to be driven by two participants who had high SL scores but low EF scores. For the remaining plots, younger children (and even middle age children) seem to have a relatively strong positive relationship between EF and language skills while there is practically no relationship for older children. The opposite is true for SL and language: older children have a strong positive relationship while younger have little relationship or even a negative relationship. Thus, it appears that EF is a more important contributor to language development for our younger children while SL is more important for our older children.

To further inspect differences between the oldest and youngest children, we created separate ERP waveforms for the two age groups to look for evidence of differences in SL patterns (see Figures 6 and 7). Visual inspection of the waveforms reveals that for the 7-year-olds, there is a P300-like positivity that is most pronounced for the HP condition in the second block of the task. On the other hand, for the

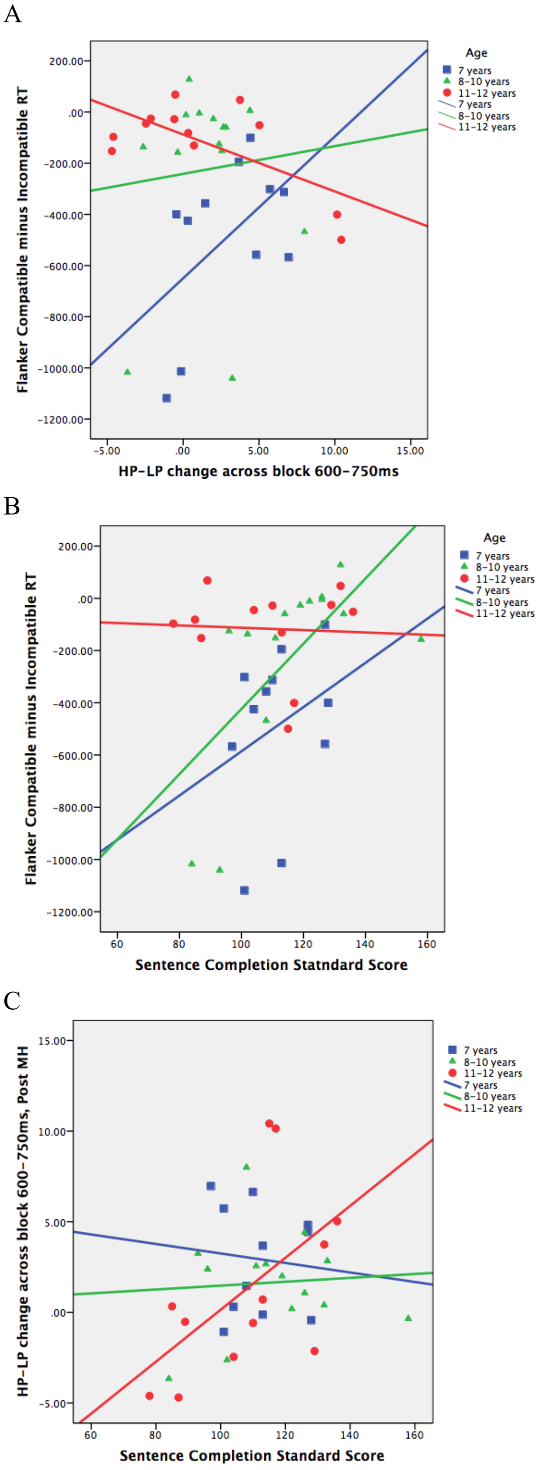

Figure 5: Scatter plots depicting the relationships between A) EF and SL, B) EF and language, and C) SL and language for three age groups: 7 years (blue squares), 8-10 years (green triangles), 11-12 years (red circles).

11-12-year-olds, the HP and LP waveforms are not clearly differentiated; in addition, there does not appear to be much difference between the first and second blocks.

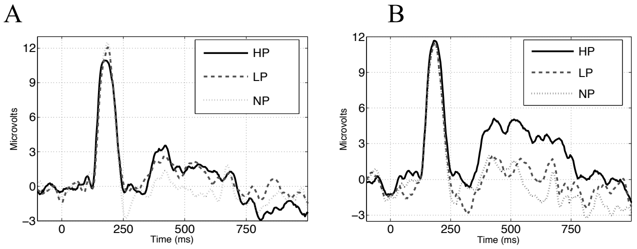

Figure 6: 7-year-old age group's grand-averaged ERP (n=12) in the medial posterior region to HP (solid), LP (dashed), and NP (dotted) trials for first block (A) and second block (B) (Positivity upward in microVolts; time in milliseconds).

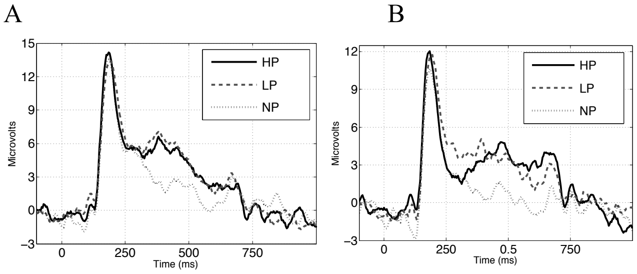

Figure 7: 11-12-year-old age group's grand-averaged ERP (n=12) in the medial posterior region to HP (solid), LP (dashed), and NP (dotted) trials for first block (A) and second block (B) (Positivity upward in microVolts; time in milliseconds).

2(block) x 3(predictor) ANOVAs for each of the two age groups revealed a significant main effect of predictor, $F(2,20) = 3.69$, $p = .043$, $\eta_p^2 = .27$ and significant block x predictor interaction, $F(2, 20) = 8.87$, $p = .002$, $\eta_p^2 = .47$ for 7-year-olds but no significant effects for 11-12-year-olds. This may suggest that while 7-year-olds showed SL over time, 11-12-year-olds did not evidence SL over time. For the 7-year-olds, predictor differences did not hold for post hoc tests, but posthoc pairwise comparisons for the interaction indicated that only HP increased from the first half to the second half ($p = .015$), although there was a trend toward NP decreasing across blocks ($p = .065$).

Discussion

This study sought to examine how sequential learning (SL) and executive function contribute to language across development. In a sample of 7-12 year old children, we used ERPs to measure the neural correlates of SL in a visual statistical-sequential learning task. The ERPs revealed that the youngest children showed evidence of statistical learning whereas the oldest did not (however, see Arcuili & Simpson, 2011, for evidence of increased SL with age using a different SL task). In addition, we used a conditional process model to assess the extent that SL in conjunction with EF was associated with a behavioral measure of language development for the different age groups. The results of this model revealed that both SL and EF had their own independent contributions to language development, but the relationship between both SL and language and EF and language showed dramatic shifts occurring between 7 years and 11-12 years of age.

As SL has been considered to be an implicit process, and implicit learning has been argued to be developmentally invariant (e.g., Reber, 1993; Vintner & Perruchet, 2000; though see Thomas et al., 2004, for an opposing view), the observed finding that there may be a developmental change in SL is particularly important. Further, this development of SL seems to be accompanied by a counterintuitive developmental change to the relationship between SL and language ability.

Although the finding that younger children show better sequential learning than older children and that there may be opposite relationships between SL and language across ages may seem puzzling, some previous findings may provide clarity. For example, in examining SL across the lifespan, Janacsek, Fiser, and Nemeth (2012) found that 4-12-year-olds had the strongest learning effects as measured by RTs with a dramatic decrease in SL ability around 12 years that continued to decline across the lifespan. However, accuracy scores were worst in the children and elderly participants with highest scores at the middle ages. Janacsek et al. (2012) suggested that these findings may be the result of tapping into two separate systems, with accuracy related to voluntary attentional control (an under-developed EF mechanism in early childhood) and RT related to involuntary attention mechanisms. Jost, Conway, Purdy, and Hendricks (2011) also presented findings that younger children may display heightened statistical learning abilities compared to older children and adults. Similarly, McNealy et al. (2011) found that younger children (5-7 years old) showed greater neural activation to weak statistical cues governing a novel stream of nonsense syllables, compared to older children (9-10 and 12-13 year olds) and adults. It may be advantageous to have efficient information processing mechanisms for detecting statistical patterns early in development, which could provide an explanation for why young children are able to learn natural language so effectively.

According to Kuhl (2004), infants and young children who have had relatively little experience are extremely open to learning; however, the more they learn, the more entrenched and neurally committed their brains become to the specific statistical and prosodic patterns of their own language. This may allow children and adults to readily process sequential structure of their native language, but may also have the side effect of making it more difficult to learn other sequential structures. This shift can be seen around 9 months when infants begin to stop using and recognizing sounds from non-native languages but improve in their ability to use and recognize sounds from their native language (Kuhl, 2004); another shift appears to occur around 7 years and at adolescence, both times at which learning a foreign language fluently becomes much more difficult (e.g., Johnson & Newport, 1989).

Thus the anchor ages that we tested (7 and 12 years) are precisely at points when previous research has found changes in both SL and language that amount to both decreases in performance of unfamiliar items and increases in performance involving familiar items (e.g., native language and its underlying statistical structure). Voluntary attentional control (an EF mechanism improving over this period) and involuntary attention (an already developed mechanism) may also play a role in the relationships between SL, language, and age. We suggest that at around 7 years of age, continued openness to unfamiliar sequence structures is detrimental to language development. By 12 years, SL is lower in general than it is for 7-year-olds, but within that lower level individuals with higher SL combined with overall higher EF provides a benefit to language ability. As suggested by Arciuli and Torkildsen (2012), longitudinal research is necessary to fully flesh out the complicated interrelationships between sequential learning, language, executive function and age. Although these findings are still preliminary, we expect this research to lead to valuable information about the basic nature of the neurocognitive mechanisms of language development.

Acknowledgments

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