

Statistical Learning Ability Can Overcome the Negative Impact of Low Socioeconomic Status on Language Development

Leyla Eghbalzad (leghbalzad1@student.gsu.edu)

Department of Psychology, Georgia State University, P.O. Box 5010, Atlanta, GA 30302

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

Abstract

Statistical learning (SL) is believed to be a mechanism that enables successful language acquisition. Language acquisition in turn is heavily influenced by environmental factors such as socioeconomic status (SES). However, it is unknown to what extent SL abilities interact with SES in affecting language outcomes. To examine this potential interaction, we measured event-related potentials (ERPs) in 38 children aged 7-12 while performing a visual SL task consisting of a sequence of stimuli that contained covert statistical probabilities that predicted a target stimulus. Hierarchical regression results indicated that SL ability moderated the relationship between SES (average of both caregiver's education level) and language scores (grammar, and marginally with receptive vocabulary). For children with high SL ability, SES had a weaker effect on language compared to children with low SL ability, suggesting that having good SL abilities could help ameliorate the disadvantages associated with being raised in a family with lower SES.

Keywords: statistical learning; language development; socioeconomic status, event-related potentials (ERP); cognitive development

Introduction

All typically developing children learn how to comprehend and produce language, suggesting the existence of common biological and/or environmental mechanisms for language development. On the one hand, language acquisition may depend on intrinsic factors such as mental and genetic components (e.g., Chomsky, 1965; Crain & Lillo-Martin, 1999). On the other hand, language development may rely less on internal factors and more on external interactions with social and environmental contexts (Bronfenbrenner, 1979, 1988). The universality and variability in language development suggest that a combination of these perspectives might provide the most appropriate approach for studying language development (Hoff, 2006). In particular, it may be beneficial to study language development in children by focusing on the interaction between intrinsic (e.g., cognitive skills) and extrinsic factors (e.g., social/linguistic environment).

Social environmental factors appear to be essential for the development of language (Kuhl, 2010). For instance, according to the "social gating" hypothesis (Kuhl, 2007),

social interactions influence learning in children by increasing their attention span and, therefore, the amount of knowledge retained from the environment. Social environmental factors such as socioeconomic status (SES) also impact language learning (Feldman et al., 2003; NICHHD, 2000; Hoff et al., 2012). SES consists of many components and each component could potentially influence various aspects of child development differently. Primary Caregivers' education level and income are among the most important indicators of SES (Roberts et al., 1999). Children who live in low SES families are reported to have less exposure to linguistic stimulation, which could detrimentally impact their language development (Rowe and Goldin-Meadow, 2009; Sheridan et al., 2012). In addition, there is increasing evidence suggesting that environmental factors can impact brain regions that are associated with executive functions and language. For instance, the prefrontal cortex in children seems to be strongly impacted by their SES (Sheridan et al., 2012). Consequently, children with low SES do not perform as well as children with higher SES on tasks that represent cognitive control, memory, and language (Farah et al., 2006).

Certain biological factors and cognitive mechanisms also play an important role in language development in children. Specifically, statistical learning (SL) abilities appear to be essential for detecting and encoding structured patterns of information in the environment, including language (Conway et al., 2010; Saffran, 2003). Indeed, research suggests that SL is a crucial component of language processing in newborns (Saffran, Aslin & Newport, 1996; Shafto, Conway, Field & Houston, 2012), children (Kidd & Arciuli, 2015; Lum et al., 2012), and adults (Christiansen, Conway, & Onnis, 2012; Misyak, Christiansen, & Tomblin 2010). Shafto, Conway, Field, and Houston (2012) demonstrated an empirical link between visual SL in infants and their subsequent vocabulary development. SL appears to be used to learn the underlying patterns inherent in linguistic signals, which facilitates the prediction of upcoming units (Conway et al. (2010). In an electroencephalography study, Christiansen et al. (2012) reported that the same neural mechanisms appear to be utilized for processing syntactic rules of language and SL. Overall, these studies suggest that SL may be a prerequisite

for language learning and that variations in SL can affect language development.

In sum, language development appears to be highly dependent on both the environment that the child is raised in and his or her cognitive skills. What is not known is the extent to which these two factors might interact to impact language development. For instance, it is possible that having better intrinsic learning abilities could help offset the deleterious effects of being raised in an impoverished social environment.

The specific aim of this study is to examine the relationship between the neural mechanisms of SL, social environmental factors, and language in typically developing children. Specifically, we explored the possible impact of SL as a moderator of the relationship between SES and language development in children. We measured SL by using the event-related potential (ERP) technique while children were performing a computerized visual SL task. We also measured children's vocabulary and grammatical judgment using standardized language assessments.

Method

Participants

We recruited 42 typically developing children aged 7-12 from the Atlanta metropolitan area with English as their native and only language (age mean = 9 years; 25 male). Four participants were excluded from this study, one due to computer software difficulties during ERP data acquisition, and three due to having too many noisy trials in the ERP task (see EEG section below). The final analyses were done using data from 38 participants (Age mean = 9 years; 23 male, 15 female; 13 black or African American; 18 white; 7 more than one race). Participants and their parent/caregiver came to the Psychology Department at Georgia State University for their laboratory visit. During their visit, both parents and children were informed about the goal and details of the study and provided written informed consent and assent to participate. Participants were offered a toy, worth \$10 for participating. Additionally, the parents received monetary compensation of \$50 for the session.

Socioeconomic Status (SES)

Parents of the participants completed a questionnaire regarding their socioeconomic status (SES) and demographics. This questionnaire consisted of questions about their individual and household income, education, and demographics of the PC and secondary caregiver (SC). In the analysis, we used average of both PC and SC education level as a measure of SES. Each caregiver's education level was measured using the following scale: 0= Less than High School, $N=5$; 1= High School, $N=14$; 2= Some college, $N=8$; 3= Associate's degree, $N=3$; 4= Bachelor's degree, $N= 15$; 5= Master's degree, $N=16$; 6= PhD, $N=5$; 7= Professional degree, $N=10$. Household income was not used in the analyses due to missing data from more than half of the participants.

Statistical Learning Task

The visual SL task was based on a task recently developed by Jost et al. (2015), which in turn is similar to the classic visual oddball paradigm, but with statistical regularities embedded in the stimuli. We made the Jost et al. (2015) task more child-friendly by making it into a game with a background story ("the Magician task"). This task was presented as a game on a laptop computer. In this task, children were told a story about an inconsistent magician who tries to make food for his children using his magic hat. Children viewed a stream of flashing stimuli consisting of hats of different colors presented with a black background one at a time. Occasionally, a target hat with food was presented within the stream. Children were instructed to "catch" the presented food by pressing a button. Participants were not told that hats of different colors each differentially predicted the probability of occurrence of the target hat. Each target followed a predictor in the sequence with three conditions: high (90% probability of target following), low (20% probability of target following), and no predictor (target presented with no preceding predictor). Each experimental condition (high, low, and no) contained 60 trials, for 180 trials total. Each stimulus was presented on the screen for 500 milliseconds and was followed by a black screen for 500 milliseconds. Six blocks were separated by 30-second breaks during which children watched a short cartoon related to the magician story. Figure 1 shows a schematic presentation of the magician task. It took the participants about 20 minutes to complete the task after net application. If children learned the probabilistic patterns between each type of predictor and the target, it was expected that there would be significant differences in their response times (RTs) to the targets and/or the amplitude differences of ERPs of the predictors based on whether a trial was a high-probability (HP), low-probability (LP), or no-predictor (NP) type. Either of these differences would be evidence of SL¹.

Electroencephalography (EEG) Recording

We collected EEG data measuring changes in electrical potential on the scalp during the statistical learning task using a 32-channel high-density EGI (Electrical Geodesics, Inc.) sensor net and followed standard net application techniques for the EGI system. EEG data were collected in a sound-attenuated room. We used the NetStation 4.3.1 acquisition software (Electrical Geodesics, Inc.) to transform and record the data to digital form. Before starting the SL task, participants were instructed to sit still and avoid excessive blinking. Data were acquired with a 0.1 to 30 Hz bandpass filter and digitized at 250 Hz.

¹ The no-predictor condition in the "Magician" task is the same as the standard stimuli, which means participants saw it more frequently than the high- and low- probability conditions; therefore, ERP responses to the no-predictor condition may be influenced by this difference in frequency of occurrence.

Impedances were kept below 50 k Ω . ERP recordings were time-locked to the onset of each predictor stimulus and continued for 1500ms after onset for a total segment length of 1700ms. In the no-predictor condition, the ERPs were time-locked to the standard preceding the target stimulus. After data acquisition, data from channels with poor or noisy signals was replaced with data induced from surrounding sensors using the computational MATLAB software (version R2012b 8.0.0783; MathWorks). Additionally, trials containing muscle activity such as eye movement and blinks were removed using an artifact detection process.

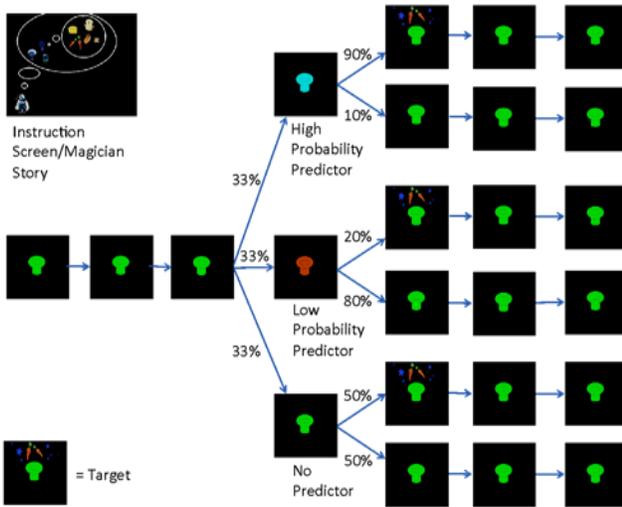


Figure 1: A schematic representation of the statistical learning “Magician” Task.

Language Assessments

The Grammaticality Judgment subtest of the Comprehensive Assessment of Spoken Language (CASL; Carrow-Woolfolk, 1999) was administered as an assessment of syntactic language development. In this test, a sentence with or without grammatical errors was read to the child, and the child was asked whether it sounded correct and if not to fix it by changing only one word. This assessment was administered in a separate room with a trained experimenter after removal of the EEG sensor net. The standardized scores of this test were computed based on participants’ age.

Children’s receptive language was measured using the Peabody Picture Vocabulary Test, Fourth Edition (PPVT-4; Dunn & Dunn, 2007). During this test, an experimenter showed the participants 4 pictures and asked them to point to the picture that best represented the presented word. This assessment was administered by a trained experimenter in a quiet room before the EEG net application.

Results

The descriptive statistics of the language tests are reported in Table 1. We used the standard scores for these measures

which take age into account. The average score for both the grammaticality judgement subtest of the CASL and PPVT is 100 with a standard deviation of 15 points. The participants’ average scores were slightly higher than average on the grammaticality judgement and the PPVT tasks (yet still within normal limits); but there was a wide range of scores for both language tests.

Table 1: Means and standard deviations for language tasks

Assessment	Mean	SD	Range
PPVT Standard Score	111.58	19.20	73-146
Grammaticality Judgment Standard Score	105.53	13.42	69-132

N=38

Statistical Learning Measure

Based on Jost et al. (2015), who observed a P300-like ERP component in the posterior region of the scalp in conjunction with SL in the 400-700 milliseconds window following the predictor onset, we focused our analyses on a pre-defined region of 6 electrodes in the posterior region for the same time window (see Figure 2). To assess the behavioral and neural correlates of learning during the SL task, we ran 2 one-way ANOVAs to determine whether the 3 probability conditions (high, low, and no) in ERP amplitudes and reaction times (RT) were significantly different from one another.

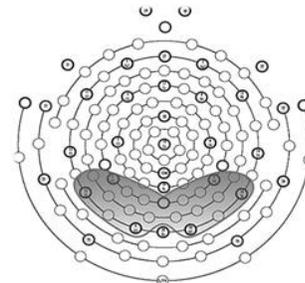


Figure 2: The map of 32-sensor EEG net with posterior region of interest highlighted.

ERP Amplitudes Figure 3 displays the grand average ERP waveforms in the posterior region. Visual inspection suggests that there may be a late positivity roughly 400-700 msec for the high and low predictor conditions. This was confirmed with a one-way ANOVA comparing ERP amplitudes for the 3 probability conditions in the 400-700 ms time-window after predictor onset, which revealed a significant effect of probability condition, $F(2, 74) = 16.60$, $p < .000$. Paired-sample t tests with Sidak adjustment revealed that the ERP wave amplitude was significantly higher for the high-probability condition ($M = 2.42$, $SD = 2.52$) compared to the low-probability condition ($M = 1.59$, $SD = 2.39$), $t(37) = 2.41$, $p < .05$, and no-predictor condition ($M = 0.28$, $SD = 1.94$), $t(37) = 5.19$, $p < .001$. The ERP wave amplitude was also significantly higher for

the low-probability condition compared to the no-predictor condition, $t(37) = 3.60, p < .001$. These results provide neurophysiological evidence that children demonstrated sensitivity to the different probability conditions, measured by the EEG data, which is consistent with the findings of Jost et al. (2015). These results suggest that as a group, children's learning of the predictor-target statistical patterns was reflected by a larger amplitude for the high predictor stimuli, and to a lesser extent, for the low predictor stimuli.

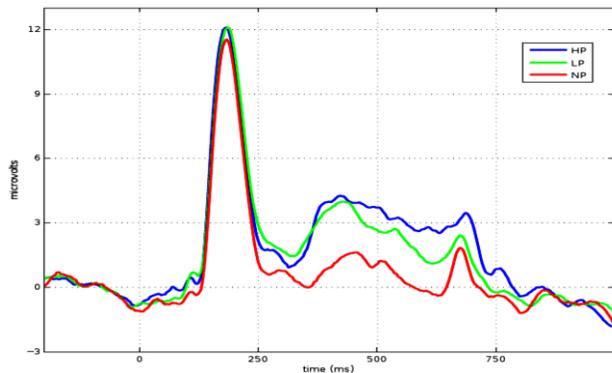


Figure 3: ERP waveform in the posterior region showing 3 different probability conditions. High-probability line is on the top (blue), low-probability line is in the middle (green), and no-predictor line (baseline) is at the bottom (red).

Reaction Times Similarly, the behavioral analyses provide evidence of statistical learning. The results of the second one-way ANOVA comparing RT in each predictor condition showed that participants responded significantly differently to the 3 predictor conditions, $F(2, 70) = 31.04, p < .001$, sphericity assumed. Paired-sample t tests revealed that the RT was significantly lower to the target following the high-probability stimuli ($M = 388.97, SD = 78.84$) compared to when the target followed the low-probability stimuli ($M = 465.08, SD = 65.89$), $t(35) = -4.96, p < .001$, and the no-predictor stimuli ($M = 493.20, SD = 67.59$), $t(35) = -6.21, p < .001$. The RTs were also significantly lower for the target when it followed the low-probability condition compared to the no-predictor condition, $t(35) = -4.18, p < .001$.

Furthermore, difference scores were created for both the ERPs and the RT data between the high and no predictor conditions to explore the magnitude of the learning effects. Because the target was preceded by a standard in the no-predictor condition, we used it as the measure of baseline for both ERPs and RTs as it essentially constituted a measure of ERP or RT that would occur without any predictor. Thus, we defined SL by the difference between baseline and high-predictor conditions. This created one variable for ERP amplitude difference, high probability – no-predictor (H-N), and one variable for RT difference, no-predictor – high probability (N-H). Note that for the RTs, the difference scores were calculated to be positive since the high predictor condition elicited lower RTs than the no predictor condition.

Correlations

The relationship between ERP amplitude difference scores, RT difference scores, and language assessments were examined using Pearson's correlation analyses. The H-N ERP variable ($M = 2.11, SD = 2.59$) was significantly positively correlated with N-H RT ($M = 104.23, SD = 100.71$), $r = .54, p = .001$. Consistent with past research, SES ($M = 3.67, SD = 2.06$) was positively correlated with scores on PPVT ($M = 111.58, SD = 19.20$), $r = .63, p < .001$, and Grammaticality Judgement test ($M = 105.53, SD = 13.42$), $r = .59, p < .001$. However, SES was not correlated with any of the SL measures (r 's $< 0.3, p$'s $> .07$). Surprisingly, we did not find significant correlations between SL and either language measure (r 's $< 0.3, p$'s $> .07$). Partial correlation analyses with age as the controlled variable, did not result in any significant changes in these correlations.

Moderation Analyses

Hierarchical multiple regression analyses were conducted to examine if SES as the independent variable predicts language outcome in children and whether SL ability modifies this relationship. The predicting variables were standardized (converted to z scores) prior to data analyses. The results reveal that SL ability (H-N ERP variable) moderated the relationship between the caregivers' education level and grammar, $R^2_{adj} = .50, F(3, 34) = 13.13, p < .001$, and marginally moderated the relationship between the caregivers' education level and receptive vocabulary in children, $R^2_{adj} = .45, F(3, 34) = 11.18, p = .058$ (see Figure 4). In addition, the SL reaction time for N-H condition was a significant moderator of the relationship between SES and grammar scores, $R^2_{adj} = .367, F(2, 33) = 7.75, p < .001$, but not with receptive vocabulary, $R^2_{adj} = .373, F(2, 33) = 8.33, p = ns$. We controlled for potential covariates in each model by including 3 widely-used cognitive measures: Stroop (inhibitory control and attention), Block Design (visuo-spatial memory), and Digit Span (short-term memory) in each regression analysis separately. None of these measures were significant predictors of variance in grammar scores in addition to SL. However, Block Design and Digit span tasks were significant predictors of variance in receptive vocabulary scores, $\beta = 7.42, p < .05$ and $\beta = 7.47, p < .05$, respectively. In addition, we controlled for age as a potential covariate in all analyses which did not result in any significant explanation of variance in either language measure. The overall effect that can be seen in Figure 4 is that SES has a larger effect on language scores for the children with lower SL ability; SES has a much weaker influence on children with higher SL. This figure also shows that there is a good distribution of caregivers' average education level in our sample.

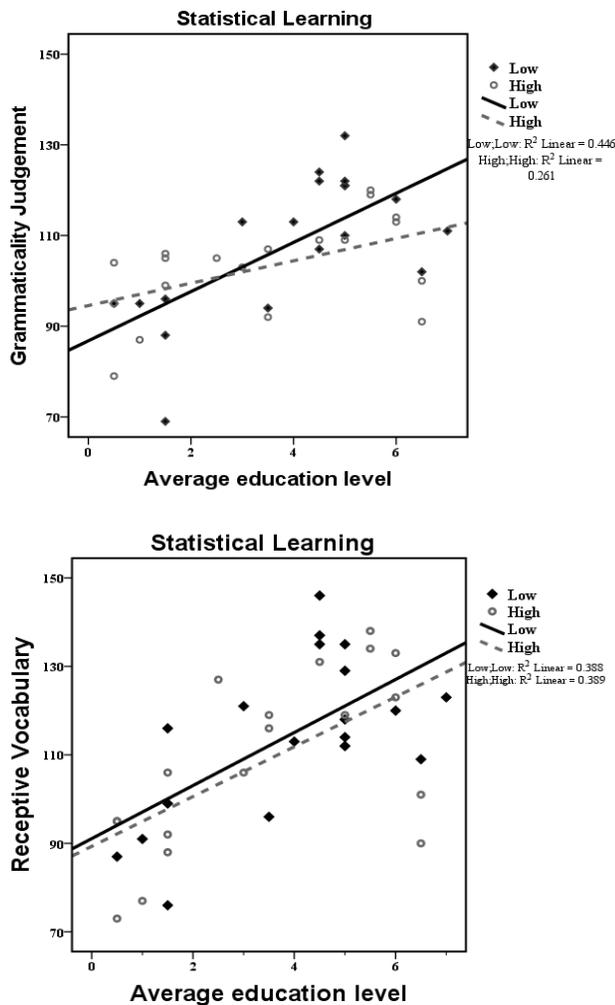


Figure 4: Scatter plots of the interactions between language scores and SES for low and high SL. For the purpose of illustration, SL variable was separated into low SL and high SL by a median split of the data.

Discussion

In this study, we investigated whether SL moderates the known relationship between SES and language outcome. In the SL task, children demonstrated different sensitivity to the different probability conditions, indicating learning of the statistical probabilities. The reaction time results were consistent with the ERP results in demonstrating evidence of SL. Consistent with previous findings, there was a positive relationship between children's SES level and their language ability (Feldman et al., 2003; Hoff & Tian, 2005; NICHD, 2000). These results replicate previous studies demonstrating a relationship between primary caregiver's education level and language development in children (Stanton-Chapman et al., 2002). Children with more highly educated mothers demonstrated better language skills in both receptive vocabulary and grammar measures compared to those children whose mothers are not highly educated.

More importantly, the results of the moderation analysis revealed that children with high SL appeared to have more robust language ability that was less affected by their SES. In other words, the negative effect of low SES on language appeared to be dampened by high SL ability. On the other hand, for children with lower SL ability, their language scores were much more sensitive to the effects of SES. Thus, children who were raised in less advantaged families showed more typical language development if they had good SL skills whereas if they had low SL their language scores were lower. These results are the first to suggest that intrinsic cognitive abilities, specifically SL, may play a moderating role in the relationship between SES and language skills in children. The negative effect of low SES on language is more apparent when a child's SL ability is low compared to when SL ability is high.

Results also showed that SL had a stronger moderating effect for grammar compared to receptive vocabulary scores. This distinction could possibly be explained by the declarative/procedural model of language, which posits that procedural learning and grammar share a common neurological substrate (Ullman, 2004). Thus, it makes sense that SL ability has a greater moderating effect on grammatical ability compared to vocabulary.

It is important to mention that sample size of 38 participants may be relatively small for the type of analyses used in this study, and so future research with a larger sample size is needed to confirm the observed interaction between SES, SL, and language. In addition, although up to this point we have considered SL an intrinsic or biological factor and SES an environmental one, it is also possible that children's SL ability may have been shaped by the environment they are raised in while differences in SES level could be due to biological or genetic factors.

In sum, this research provides an important examination of the relationship between learning abilities, the socio-linguistic environment, and language development in children. The results suggest that having good SL abilities can help ameliorate the language disadvantages associated with being raised in a lower SES home environment, offering intriguing new ways to think about the relations between learning, language development, and the social/linguistic environment in which a child is raised. One possible implication of these findings is the possibility of designing intervention programs for children of families with low SES. Recent research has demonstrated that it may be possible to improve SL abilities through targeted computerized training (e.g., Smith, Conway, Bauernschmidt, & Pisoni, 2015). Thus, by promoting SL abilities in children raised in low SES families, it may be possible to facilitate children's development by minimizing the impact of being raised in a less than optimal social and linguistic home environment.

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