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The Moderating Effect of Statistical Learning on the Relationship between Socioeconomic Status and Language: An Event-Related Potential Study

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THE MODERATING EFFECT OF STATISTICAL LEARNING ON THE RELATIONSHIP BETWEEN SOCIOECONOMIC STATUS AND LANGUAGE: AN EVENT-RELATED POTENTIAL STUDY

by

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Under the Direction of Christopher M. Conway, PhD

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.

INDEX WORDS: Statistical learning, Language development, Socioeconomic status, Event-related potentials (ERP), Cognitive development

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DEDICATION

I would like to express my gratitude to my family and friends who provided me support for completing this project successfully.

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1 INTRODUCTION

Early language acquisition and production in childhood are essential to children's cognitive development and success in school. 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 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; Bronfenbrenner & Morris, 1998, p. 996). 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).

1.1 Extrinsic Environmental Influences on Language Development: Socioeconomic Status

Social environmental factors appear to play an important role in the development of language (Kuhl, 2010). For instance, according to the "social gating" hypothesis (Kuhl, 2003), social interactions influence learning in children by increasing their attention span and thus the amount of knowledge retained from the environment. Social environmental factors such as socioeconomic status (SES) also impact learning (Feldman et al., 2003; Hoff & Tian, 2005; NICHHD, 2000; Pan, Rowe, Singer, & Snow, 2005; Hoff et al., 2012). Whitehurst (1997) reported that children with low SES tend to receive lower scores on vocabulary tests compared to those with high SES. Some studies also reported lower executive function ability in children with low SES (Ardila, Rosselli, Matute, & Guajardo, 2005; Hughes & Ensor, 2005). Children who live in low SES families are reported to be less exposed to linguistic stimulation (Rowe and Goldin-Meadow, 2009; Sheridan et al., 2012). SES consists of many components and each component may influence various aspects of development differently. Caregivers' education level is among the most important indicators of SES (Roberts et al., 1999). More specifically, low parental education, as a measure of SES, is found to be a strong predictor of language impairments in children (Stanton-Chapman et al. 2002). In a study comparing children with low and high parental education level, Hupp et al., (2011) found that twenty-month-old children with well-educated mothers demonstrated better language production skills compared to those whose mothers were not well-educated. They suggest that this difference could be due to the absence of a learning-friendly home environment in families with low SES.

Growing research findings in neuroscience provide strong evidence supporting the impact of environmental factors on brain regions that are associated with executive functions and language. For instance, Sheridan et al. (2012) reported that the prefrontal cortex in children seems to be strongly impacted by their SES. High brain activation of the prefrontal cortex in low SES children was measured by fMRIs during a stimulus-response mapping task. In this task, participants had to learn to associate one of four buttons with a certain family of stimuli and another button with the second family of stimuli. This rule learning task has been associated with high prefrontal cortex activity. They conclude that this excessive activation in the prefrontal region could be due to children with low SES needing more time to learn the associations which leads to greater reliance on this brain region (Sheridan et al., 2012). In addition, 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). Given these research findings, the lack of exposure to language and cognitive stimulation may impact certain brain regions in children with low SES and contribute to difficulties in academic learning and achievements.

1.2 Intrinsic Cognitive Influences on Language Development: Statistical Learning

Statistical learning is a cognitive skill that plays an essential role in language development by allowing individuals to detect and encode structured patterns of information in the environment (Conway et al., 2010; Conway & Pisoni, 2008; Saffran, 2003; Udden & Bahlman, 2012). The detection of these patterns helps us predict visual and auditory events in the environment that unfold over time. Statistical learning helps us recognize familiar sequences in any sensory domain and make predictions accordingly without having a conscious awareness of it (Cleeremans & McClelland, 1991). For example, according to Conway et al. (2010), statistical learning is used to learn the underlying patterns inherent in linguistic signals, which facilitates the prediction of upcoming units of speech. Indeed, research suggests that statistical learning is an essential component of language processing in infants (Ellis, Robledo & Deák, 2014; Saffran, Aslin & Newport, 1996; Shafto, Conway, Field & Houston, 2012; Teinonen et al., 2009), children (Conway, Pisoni, Anaya, Karpicke & Henning, 201; Lum et al., 2012), and adults (Christiansen, Conway, & Onnis, 2012; Misyak, Christiansen, & Tomblin 2010; Pena et al., 2002). In a study by Ellis, Robledo, and Deák (2014), 6-month-old infants' performance on a visual statistical learning task was associated with their vocabulary production at 22 months. Similarly, Saffran, Aslin, and Newport (1996) reported that 8-month-old infants are able to learn the transitional probabilities in a continuous speech stream. Furthermore, Shafto, Conway, Field, and Houston (2012) demonstrated an empirical link between visual statistical learning in 8 to 9-month-old infants and their subsequent vocabulary development. Conway, Pisoni, Anaya, Karpicke, and Henning (2011) reported that performance on a visual statistical learning task is related to language development in deaf children with cochlear implants.

In a study by Christiansen et al. (2012), brain activity in adults was measured by using electroencephalography (EEG) while engaged in a language reading task and a statistical learning task. Adults showed a P600 effect when sequential violations or ungrammatical information were encountered. The P600 is an ERP component that is elicited by hearing or reading a grammatical error. Christiansen et al. (2012), suggest that the same neural mechanisms seem to be utilized for processing syntactic rules of language and statistical learning. Furthermore, in a magnetoencephalography (MEG) study by Dikker and Pylkkänen (2013), enhanced activation in prefrontal cortex has also been observed in contexts of language with high word-predictability patterns compared to no predictability conditions. This study provides neural evidence for the importance of prediction in language processing. Prediction is essential for recognizing grammatical versus ungrammatical rules in language. When we learn a specific sequence, we tend to be able to predict what comes next in the "grammatical" sequence; however, if we encounter an "ungrammatical" sequence, our predictions would not be accurate. Similarly, in statistical learning we learn the statistical properties of sequences of events or stimuli and make predictions accordingly. The studies by Christiansen et al. (2012) and Dikker and Pylkkänen (2013) provide neural evidence for the existence of this similarity between statistical learning and language processing.

In summary, behavioral and neurophysiological evidence support the existence of a relationship between statistical learning and language development in children and adults. Specifically, high statistical learning ability has been associated with better performance on grammar and receptive vocabulary subsets of language. Overall, these studies suggest that statistical learning may be a prerequisite for language learning and a required component for typical language development.

Taken together, language development is highly dependent both on children's intrinsic cognitive skills and the environment in which they are raised. What is not known is the extent to which these two factors might interact to impact language development in children. For instance, it is possible that having better cognitive learning abilities could help offset the deleterious effects of being raised in an impoverished social environment. On the other hand, low SES may dilute the positive impact of high cognitive abilities on language development. In this study, we aimed to investigate the relationship between these factors in a sample of young, typically-developing children.

1.3 Purpose of the Study

The specific aim of this study was to examine the relationship between the neural mechanisms of statistical learning, parental education level as an indicator of SES, and language development in typically developing children ages 7-12 years. First, we explored the relationship between statistical learning ability, SES, and language performance in typically developing children. Then, we investigated the potential impact of statistical learning on the relationship between SES and language development. We were interested in exploring statistical learning's role as a moderator of the relationship between SES and language. In other words, we investigated whether the relationship between SES and language development changes according to children's statistical learning ability. We measured statistical learning by using the event-related potential (ERP) technique while children were engaged in a computerized visual statistical learning task; SES was measured by the average of both caregiver's reported education level. Finally, we measured children's receptive vocabulary and grammar by using 2 standardized neuropsychological assessments.

1.4 Expected Results

First, we expected a significant relationship between statistical learning, SES, and language performance in children. More specifically, we expected statistical learning and language, statistical learning and SES, and SES and language to be positively correlated. The strong relationship between statistical learning ability and language performance as well as the relationship between SES and language performance in children have been reported by previous research reviewed earlier. Additionally, in a study by Kaufman and colleagues (2010), they reported that statistical learning ability is strongly related to personality variables such as openness to experience and intuition. However, the relationship between statistical learning and social/ environmental factors such as SES has never been explored before. Due to the similarities reported earlier between statistical learning and language, we expect that children's statistical learning ability to be related to social/environmental factors such as their SES.

Finally, we expected a moderating effect of statistical learning on the relationship between SES and language outcome. Specifically, we predicted that high statistical learning ability reduces the negative effect of low SES on language development by providing some amount of resiliency for children who receive less linguistic exposure at home. If a child with high statistical learning ability is exposed to impoverished or lack of linguistic input, their heightened learning abilities may allow them to learn the regularities or rules of language easier. On the other hand, we predicted that low statistical learning ability may magnify the negative effect of low SES on language development. That is, for children with low statistical learning who are raised in a low SES family, their statistical learning ability would not be able to help compensate for the lack of a linguistically-rich environment and thus their language development will be negatively impacted.

2 METHOD

2.1 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, 17 female). We chose this age range due to the difficulties of collecting EEG data in children younger than 7 on our particular learning task. Children with any reported cognitive, neural, or language impairments were not considered for participation. Four participants were excluded from this study. One of them was excluded due to computer software difficulties during ERP data acquisition (12 years, female). Three of them were excluded during EEG data processing (see EEG section below) due to having too many noisy trials in the ERP task (7 years, 1 female, 2 male). The final analyses were done using data from 38 participants (Age mean = 9 years; 23 male, 15 female). Participants' demographic information is listed in Table 1.

2.2 Procedure

Participants and their parent/caregiver visited the Psychology Department at Georgia State University for 2 sessions. Both parents and children were informed about the goal and details of the study and provided written informed consent and assent to participate. During the first session, we collected information on demographics by using parent questionnaires. SES was measured by using the average of highest education level reported for both caregivers. We measured statistical learning by using the event-related potential (ERP) technique while children were performing a computer visual statistical learning task. Additionally, we measured children's vocabulary and grammaticality judgment using standardized neuropsychological assessments. In addition, we used 4 cognitive assessments to measure the participants' general cognitive ability to assure that our participants' general cognitive performance is similar to what is expected for this age range and to use these cognitive assessments as control variables in some of the analyses. The cognitive data were collected in 2 sessions in addition to other measures which were not used for the purpose of this study. Participants were offered a toy, worth $10 for participating and the parents received monetary compensation of $50 for each session they completed. This study is part of a larger NIH funded study that aims to examine the relationship between statistical learning and language outcomes in children with cochlear implants. Some preliminary data were collected from typically hearing children; however, new measurements and analyses were added to the existing procedures with the help of this funding in order to carry out the proposed aim of this study.

Table 1 *Demographic characteristics of the participants*

		Female	Male	Total
Race	Black or African	6	7	13
	White	6	12	18
	More than one race	3	4	7
Ethnicity	Non-Hispanic or Latino	15	23	38
Mean age		8.73	9.39	9.13
Caregiver's education level		Primary	Secondary	Mean
	Did not graduate high school	3	2	2.5
	High School	4	10	7
	Some college	5	3	4
	Associate's degree	1	2	1.5
	Bachelor's degree	9	6	7.5
	Master's degree	10	6	8
	Ph.D.	3	2	2.5
	Professional degree	3	7	5

N = 38

2.1.1 *Parent Questionnaire*

Parents of the participants completed a questionnaire regarding their socioeconomic status (SES) and demographics. This questionnaire consists of questions about their individual and household income, education, and demographics of the primary caregiver and secondary caregiver. In the analysis, we used both primary and secondary caregivers' education level as a measure of SES. Household income was not used in the analyses due to missing data from more than half of the participants.

2.1.2 *Statistical Learning Task*

The visual statistical learning task is 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 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. Sometimes, other objects appeared in the hat instead of food and participants were told to avoid pressing the button when they saw those objects. Participants were not aware that hats of different colors 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 which produced 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, low-probability, or no-predictor trial. Either of these differences would constitute evidence of statistical learning (Jost et al., 2011). Due to some technical issues, the response times for 2 participants were not recorded during the ERP data acquisition, however, the ERP responses for these participants were recorded. Therefore, we excluded these participants only in analyses that include response time data (*N*= 36; 21 male, 15 female).

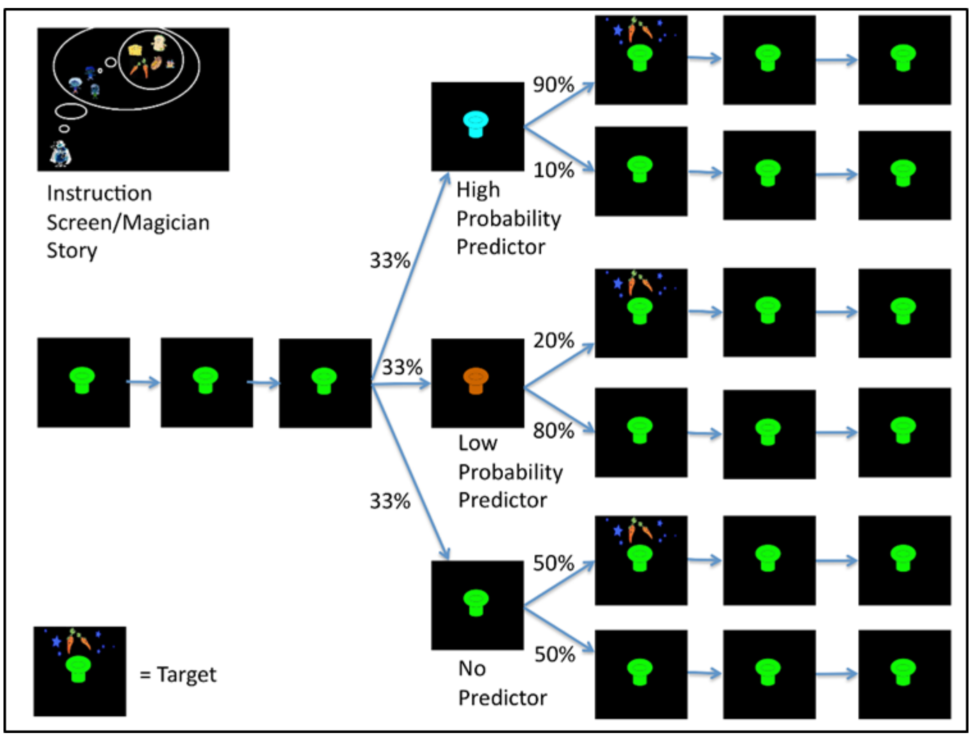

Figure 1 *Schematic Representation of the Magician Task*

The low predictor and high predictor were presented on the same number of trials; however, the target followed the high predictor on 90% of high predictor trials but only followed the low predictor on 20% of low predictor trials. In addition, on some trials, the target was presented directly after a standard with no preceding predictor.

2.1.3 *Electroencephalography (EEG)*

We collected EEG data to show the changes in electrical potential on the scalp during the statistical learning task by using a 32-channel high-density EGI (Electrical Geodesics, Inc.) sensor net. Standard net application techniques for the EGI system were followed. EEG data were collected in a sound-attenuated room to stop any unwanted noise from interfering with the data. We used the NetStation 4.3.1 acquisition software (Electrical Geodesics, Inc.) to transform and record the data to a digital form. Before starting the statistical learning task, we instructed the participants to sit still and avoid excessive blinking during the task because these muscle movements could affect the quality of data collected through EEG system. Data were acquired with a 0.1 to 30 Hz bandpass filter and digitized at 250 Hz. Impedances were kept below 50 kΩ. We excluded data from 14 sensors from the analyses due to electrooculogram noise and other undesirable noise. 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 any stimulus preceding the target stimulus. After data acquisition, segments containing activity associated with eye blinks and other movements during the task were removed for each participant by using the computational MATLAB software (version R2012b 8.0.0783; MathWorks). Three of the participants were excluded due to having too many “noisy” segments in this step of the analyses.

2.1.4 *Language Assessments*

We used 2 standardized language measures to assess our participants’ grammar and receptive vocabulary. These assessments were administered by a trained experimenter in a separate room.

2.1.4.1 ***Grammar***

We measured children's grammatical language ability because the underlying mechanisms involved in syntax processing have been reported to be highly related to mechanisms that underlie statistical learning ability (Christiansen et al., 2012; Conway et al., 2010; Ullman, 2014). 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 sounds correct and if not to fix it by changing only one word. A high internal consistency has been reported for this subset of the CASL, $\alpha = 0.90$. 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 used to take the participants' age into account. The average score for the grammaticality judgement subtest of the CASL is 100 with a standard deviation of 15 points. Additionally, this subtest has been widely-used and will serve as a valid and reliable measure of grammar in our study.

2.1.4.2 ***Receptive Vocabulary***

In addition to grammar, previous research reported a strong relationship between statistical learning ability and receptive vocabulary in infants and children (Ellis, Robledo & Deák, 2014; Shafto, Conway, Field & Houston, 2012). 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 represents the presented word. This measure is reported to have a very high internal consistency, $\alpha = 0.97$. This neuropsychological assessment was administered by a trained experimenter in a quiet room before the EEG net application. The average score for

PPVT is 100 with a standard deviation of 15 points. The PPVT has been used widely in the literature as a valid measure of receptive vocabulary.

2.1.5 *Cognitive Assessments*

We used 3 cognitive measures to assess our participants' attention and general cognitive ability as well as to control for any cognitive mechanisms that could explain variance in language in addition to statistical learning (see Results section). These assessments were administered by a trained experimenter in a separate room.

2.1.5.1 *Attention and Inhibitory Control*

One of these measures is the Stroop Color and Word Test: Children's Version (Golden, Freshwater, & Golden, 2002). This task measures cognitive mechanisms such as selective attention capacity (Howieson et al., 2004), processing ability (Lamers, 2010), and executive function (Spreen et al., 2006) with a test-retest reliability of .73 (Golden, 1975). In the Stroop task, participants are presented with series of words that are names of colors and are printed in either the same color as the word describes (e.g. "Red" printed in red ink) or in a different color ink from the word (e. g., "Red" printed in green ink). The participants are instructed to name the color ink the word is written in. it is more common for participants to make fewer errors when the ink color matches the written name of the color. However, if the ink color and name of the color do not match, participants tend to read the word instead of naming the color ink it is written in. Participants experience difficulty with inhibition of reading the written color name which interferes with their perception of ink colors.

2.1.5.2 ***Working and Spatial Memory***

In addition, we used 2 subtests of the fourth edition of Wechsler Intelligence Scale for Children Fourth Edition Integrated (WISC-IV Integrated; Kaplan et al., 2004): block design and digit pan. The block design test is reported to be a measure of visual spatial ability. In this assessment, children were presented with a picture of an abstract pattern and were instructed to recreate the same pattern by using red and white blocks. The participants were scored for accuracy and completion speed. Digit span subtest was administered to assess children's short-term and working memory. In this test, the examiner read a random sequence of digits that had no logical relationship to each other and the participants were asked to recall the digits in the exact same order. In the second part of the test, the participants were instructed to recall the digits in reverse order. Participants tend to perform better on the forward digit span task compared to backward digit span because there are more cognitive steps (processes) involved in repeating a list of digits backward. The average score for each of the cognitive measures is 10 with a standard deviation of 3 points. Additionally, these tests have been widely-used and will serve as valid and reliable measures of cognitive abilities in our study.

2.2 Data Analyses

The data were preliminarily analyzed to ensure that assumptions of multicollinearity, normality, homoscedasticity, and linearity were met or corrected for.

2.2.1 ***Statistical Learning***

Based on Jost et al. (2015), who observed a P300 ERP component in the centro-posterior region of the scalp in conjunction with statistical learning 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). P300 component suggests learning of the probabilities between predicting and target stimuli.

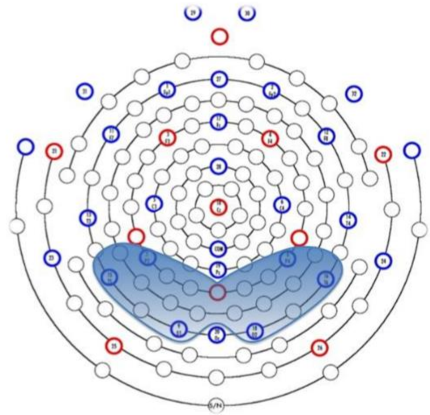

Figure 2 *Sensor Map for the EEG 32-Sensore Net*

To assess the behavioral and neural correlates of learning during the statistical learning task, we ran 2 one-way ANOVAs to determine whether the 3 probability conditions (high, low, and no) were significantly different from one another in terms of their ERP amplitudes and reaction times (RT). Furthermore, we created difference scores for RT and difference scores for ERPs between the 3 conditions to explore the magnitude of this difference which would indicate the presence of statistical learning. Since, in the no-predictor condition, the target was preceded by a random predictor, we used it as the measure of baseline for both ERPs and RTs. Thus, we defined statistical learning by the difference between baseline and each low- and high- conditions. This resulted in 2 variables for ERPs: high probability – no-predictor (H-N) and low probability – no-predictor (L-N), and 2 variables for RT. However, for the response time, the difference scores were calculated to be positive: no-predictor – high probability (N-H) and no-predictor – low probability (N-L).

2.2.2 *The Relationship between Statistical Learning, SES, and Language*

To answer the first question, we examined the relationship between statistical learning difference scores for ERP and RT data, SES, and both standardized language measures using Pearson's correlation analyses.

2.2.3 *Statistical Learning as a Moderator in the Relationship between SES and Language*

To examine the moderating effect of statistical learning on the relationship between SES and language, we used a hierarchical multiple regression model recommended by Aiken and West (1991). Before entering the variables in the hierarchical regression, SES (IV) and statistical learning scores (moderator) were standardized and converted to z scores to reduce multicollinearity between the variables. Next, we multiplied SES and statistical learning variables to create an interaction term which would potentially measure the variance in language explained by both the IV and the moderator. We conducted separate regression analyses for ERP amplitudes and RT measures with each of the two language scores (grammar or vocabulary) as a dependent variable in each regression analysis. In the first step of each regression, language (PPVT or Grammaticality Judgement) was entered as the dependent variable, SES as the independent variable, and statistical learning (ERP or RT) as the moderator. In the second block, we entered the interaction term of SES and statistical learning. We controlled for potential covariates in the model by including the 3 widely-used cognitive measures: Stroop, Block Design, and Digit Span in each regression analysis separately.

3 RESULTS

3.1 Analyses of Variance in Statistical Learning

Figure 3 displays the grand average ERP waveforms in the posterior region. The visual inspection of the ERP waves suggests that there may be a late positivity roughly 400-700 ms 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 suggested that the ERP wave amplitude was significantly higher for high-probability condition ($M = 2.42$, $SD = 2.52$) compared to low-probability condition ($M = 1.59$, $SD = 2.39$), $t(37) = 2.41$, $p < .05$, and no-predictor condition ($M = 0.28$, $SD = 1.94$), $t(37) = 5.19$, $p < .001$. ERP wave amplitude was also significantly higher for low-probability condition compared to no-predictor condition, $t(37) = 3.60$, $p < .001$. These results provide neurophysiological evidence that children demonstrate sensitivity to the different probability conditions, measured by the EEG data, which is consistent with the findings of Jost et al.(2015) suggesting that children learned the statistical pattern of predictor and target stimuli in the task. Additionally, 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.

Similarly, the behavioral analyses provide evidence of statistical learning. The results of the second one-way ANOVA comparing RT in each predictor condition suggested that participants responded significantly differently to the 3 conditions, $F(2, 70) = 31.04$, $p < .000$, sphericity assumed. Paired-sample *t* tests revealed that the RT was significantly lower for high-probability condition ($M = 388.97$, $SD = 78.84$) compared to low-probability condition (M =

465.08, SD =65.89,), *t* (35) = - 4.96, p < .001, and no-predictor condition (M = 493.20, SD = 67.59), *t* (35) = - 6.21, p < .001.

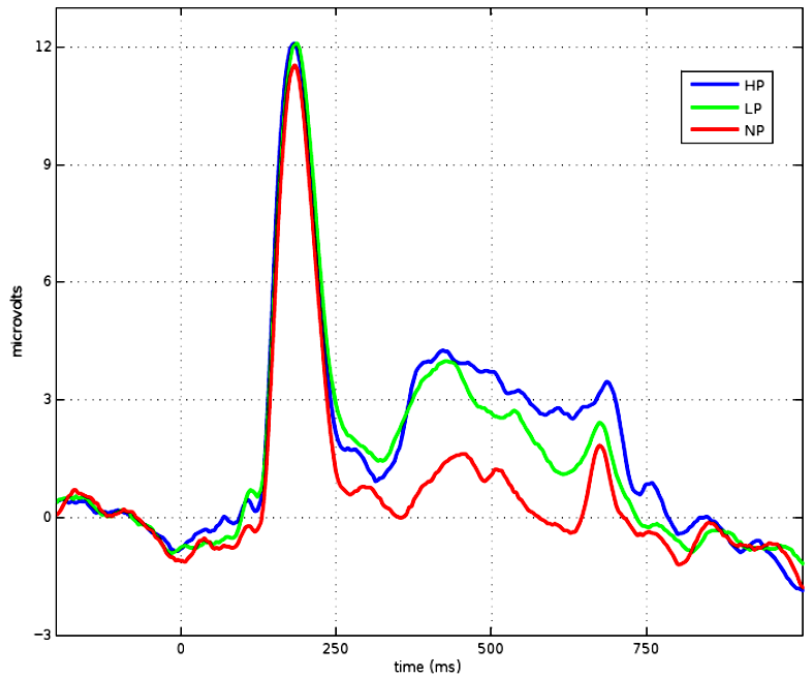

Figure 3 *ERP Waveform in the Posterior Region Showing 3 Different Probability Conditions*
High- probability line is in blue, low-probability line is in green, and no-predictor line (baseline) is in red.

The RT was also significantly lower for low-probability condition compared to no-predictor condition, *t* (35) = - 4.18, p < .001. These behavioral results suggest that participants responded faster to the target stimulus when it was preceded by the high-probability predictor stimulus compared to when it was preceded by the low-probability predictor stimulus and no-predictor stimulus. The participants also responded faster to the target when it was preceded by the low-probability predictor compared to no-predictor stimulus. These findings provide neurophysiological and behavioral evidence that the participants learned the predictor-target contingencies of the statistical learning task.

3.2 Correlations

The relationship between statistical learning ERP amplitude and RT difference scores, SES, and neuropsychological assessments (language and cognitive measures) were examined using Pearson's correlation analyses (Table 2). In addition, partial correlation analyses were conducted between these variables with age as the control variable (see Appendix A). For the purpose of this study, we will only report the correlations between variables of interest. The descriptive statistics of all measures are reported in Table 2.

Table 2 *Correlations Matrix*

Variables	1	2	3	4	5	6	7	8	9	10	11
1. Average Education	—										
2. PPVT	.63**	—									
3. Grammar	.59**	.81**	—								
4. Statistical Learning (H-N)	.02	-.19	-.20	—							
5. Statistical Learning (L-N)	-.18	-.25	-.30	.62**	—						
6. Response Time (N-H)	.15	.01	.13	.54**	.11	—					
7. Response Time (N-L)	.12	-.12	.03	.21	0.25	.41*	—				
8. Block Design	.57**	.65**	.63**	-.34*	-.45**	.00	.00	—			
9. Digit Span	.14	.49**	.56**	-.18	-.18	-.01	-.10	.44**	—		
10. Stroop	-.14	-.40*	-.18	.25	.21	.22	.30	-.43**	-.15	—	
11. Age	.00	.14	-.22	-.10	.11	-.50**	-.27	.08	-.18	-.48**	—
Mean	3.67	111.58	105.53	2.12	1.31	104.23	28.12	10.39	10.95	53.37	9.13
SD	2.06	19.20	13.42	2.59	2.25	100.71	40.39	3.88	3.09	9.38	1.91
Range	0.5 - 7	73 - 146	69 - 132	-3.49 - 8.42	-3.66 - 5.64	-39.46-307.98	-49.72-120.41	3 - 17	3 - 19	34 - 76	7 - 12
N	38	38	38	38	38	36	36	38	38	38	38

**$p < .01$

*$p < .05$

3.2.1 *ERPs and RTs*

The H-N ERP variable (M = 2.11, SD = 2.59) was significantly correlated with N-H RT (M = 104.23, SD = 100.71), r = .54, p = .001. However, the L-N ERP variable (M = 2.11, SD = 2.59) and N-L RT (M = 2.11, SD = 2.59) were not significantly correlated, r = .54, p = .001.

3.2.2 *SES, Statistical Learning, and Language*

Comparable to previous research, we found significant correlations between SES and performance on language assessments. 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 scores on Grammaticality Judgement test (M = 105.53, SD = 13.42), r = .59, p < .001. These results suggest that higher SES leads to children performing better on language assessments. Surprisingly, neither of the statistical learning measures (ERPs and RTs) were significantly correlated with SES nor with either of the language measures. In addition, we did not find a significant correlation between statistical learning and language measures even after controlling for age of the participants in the partial correlation analyses.

3.3 Moderation Regression

Hierarchical multiple regression analyses were conducted to examine if SES as the independent variable predicts language outcome in children and whether statistical learning ability modifies this relationship. All the variables were standardized (converted to z scores) prior to data analyses. Analyses of standard residuals showed that the data contained no outliers. The assumptions of normality and linearity, and homoscedasticity were met according to the scatter-plots and histograms of standardized residuals of the data.

3.3.1 *SES, Statistical Learning, and Grammaticality Judgement*

The results of the regression analyses with SES and H-N ERP as independent variables and Grammaticality Judgement test scores as the dependent variable suggested that overall the model significantly explained 38% of the variance in children's performance on Grammaticality Judgement test, R^2_{adj} = .357, F(2, 35) = 11.28, p < .001. SES was a significant predictor of Grammaticality Judgement test, β = 7.95, p < .001, however, statistical learning (H-N) was not a significant predictor of Grammaticality Judgement test scores, β = -2.90, p = ns. Adding the interaction term to the model significantly increased the variance explained to 50%, R^2_{adj} = .496, F(2, 35) = 13.13, p < .001. The summary of these regression coefficients are presented in Table 3. Tests of the assumption of collinearity indicated that multicollinearity was not a concern (Tolerance = .999, VIF = 1.001).

Similar results were evident for the regression analyses with SES and Grammaticality Judgement when L-N ERP variable was entered as the moderator. Overall, the model was predicative of 35% of variance in performance on Grammaticality Judgement test, R^2_{adj} = .348, F(2, 35) = 10.89, p < .001. SES was a significant predictor of these grammar scores, β = 7.39, p

Table 3 *Summary of Regression Analysis of Moderating Effect of Statistical Learning on the Relationship between SES and Grammaticality Judgment Scores*

Conditions and Models			ERP Amplitude					
			b	*SE*	*β*	*t*	*Adj. R2*	*ΔR2*
H-N								
	Model 1	SES	7.95	1.77	0.59	4.45**	0.36	
		SL	-2.90	1.77	-0.22	-1.64		
	Model 2	Interaction Term	-5.55	1.70	-0.42	- 3.26*	0.50	0.15**
L-N								
	Model 1	SES	7.39	1.81	0.55	4.08*	0.35	
		SL	-2.68	1.81	-0.20	-1.48		
	Model 2	Interaction Term	-4.95	1.96	-0.34	-2.52*	0.44	0.10*
			Response Time					
N-H								
	Model 1	SES	7.81	1.92	0.58	4.07**	0.31	
		SL	0.62	1.96	0.04	0.31		
	Model 2	Interaction Term	-1.86	0.92	-0.58	-2.03*	0.37	0.08*
N-L								
	Model 1	SES	7.97	1.91	0.59	4.18**	0.31	
		SL	-0.63	1.95	-0.05	-0.32		
	Model 2	Interaction Term	-1.56	0.99	-0.52	-1.57	0.34	0.05

N = 38, *p < .05, **p < .01,

< .001 but, statistical learning was not a significant predictor, β = - 2.68, p = ns. The interaction term significantly increased the explained variance of the model to 43%, $R^2_{\text{adj}} = .435$, $F(3, 34) = 10.50$, $p < .001$. The summary of these regression coefficients are presented in Table 3. Tests of the assumption of collinearity indicated that multicollinearity was not a concern (Tolerance = .966, VIF = 1.035).

In both of these analyses, the significant interactions between SES and statistical learning imply that the effect of SES on grammar development in children was moderated by their statistical learning ability. This effect is depicted in Figure 4. For children who showed high statistical learning, SES had a weaker effect on grammar scores compared to children who showed low statistical learning. The cognitive measure tests were not significant predictors of variance in performance on Grammaticality Judgement task in any of the regression analyses for any of the ERP amplitude scores.

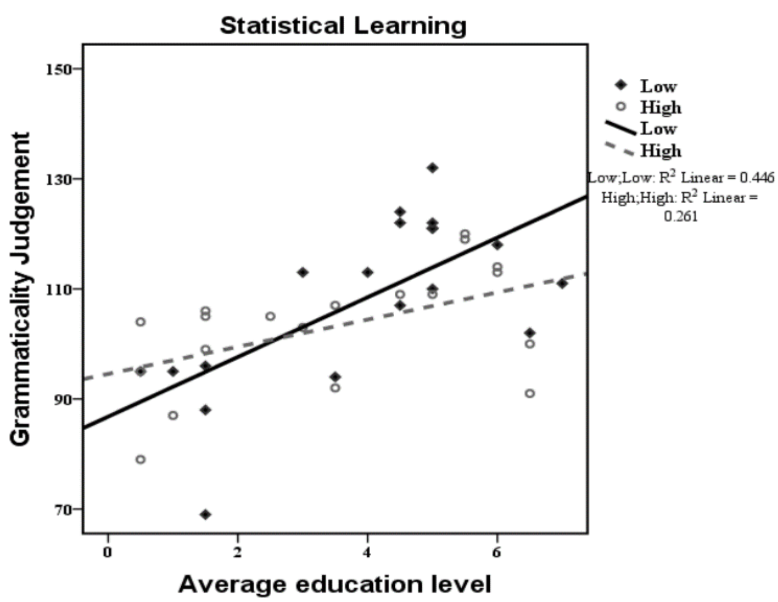

Figure 4 *Scatter Plots of the Interaction between Grammar Scores and SES for Low Statistical Learning and High Statistical Learning (H-N) ERP Amplitudes*

Caregivers' average education levels: 0= Less than High School, 2= Some college, 4=Bachelor's degree, 6= PhD. For the purpose of illustration, statistical learning variable was separated into low statistical learning and high statistical learning by a median split of the data.

The behavioral data regression results with SES and RT N-H variables suggested that overall, SES and N-H explained 31% of variance in performance on Grammaticality Judgement, $R^2_{adj} = .306$, $F(2, 33) = 8.73$, $p = .001$. SES was the significant predictor in this model, $\beta = 7.39$, $p < .001$. The interaction term in model 2 was also a significant predictor of grammar scores, $\beta = 7.39$, $p < .001$ and significantly increased the explained variance by the model to 37%, $R^2_{adj} = .367$, $F(2, 33) = 7.75$, $p < .001$. As a result, the response time to statistical learning condition N-H was a significant moderator of the relationship between SES and language scores. Tests of the assumption of collinearity indicated that multicollinearity was not an issue in this analysis (Tolerance = .977, VIF = 1.023). These behavioral results were consistent with the ERP results for the same probability condition which provides support for the reliability of the neurophysiological results.

Finally, the regression analysis model with SES and RT N-L, significantly explained 31% of variance in Grammaticality Judgement scores, $R^2_{adj} = .307$, $F(2, 33) = 8.74$, $p = .001$. SES was a significant predictor of grammar scores, $\beta = 7.39$, $p < .001$, but N-L was not a predictor, $\beta = -.63$, $p =$ ns, as evident in all other regression analyses that we conducted. The interaction term in this model was not a significant predictor of grammar scores, $\beta = -1.56$, $p =$ ns which suggest that response time of statistical learning in the N-L condition was not a moderator of the relationship between SES and grammar. Tests of the assumption of collinearity indicated that multicollinearity was not a concern (Tolerance = .985, VIF = 1.015). The summary of these regression coefficients are presented in Table 3.

3.3.2 *SES, Statistical Learning, and PPVT*

The results of the regression with SES and H-N ERP as independent variables and PPVT as dependent variable indicate that overall, the model significantly explained 41% of variance in children's performance on PPVT , R^2_{adj} = .408, F(2, 35) = 13.73, p < .001. Individually, SES was a significant predictor of PPVT scores, β = 12.19, p < .001. However, statistical learning (H-N) did not significantly predict children's performance on PPVT, β = -3.97, p = ns. The interaction term for SES and statistical learning was added to the second step of the regression and was marginally significant in predicting variance in PPVT scores, β = - 5.0, p = .058. Overall, the model that included the interaction term explained 45% of variance in PPVT scores R^2_{adj} = .45, F (3, 34) = 11.18, p < .001. The summary of these regression coefficients are presented in Table 4.

Table 4 *Summary of Regression Analysis of Moderating Effect of Statistical Learning on the Relationship between SES and PPVT Scores*

Conditions and Models			ERP Amplitude					
			b	*SE*	*β*	*t*	*Adj. R2*	*ΔR2*
H-N								
	Model 1	SES	12.19	2.43	0.64	5.02**	0.41	
		SL	-3.97	2.43	-0.21	-1.64		
	Model 2	Interaction Term	-4.98	2.54	-0.26	-1.96	0.45	0.057
L-N								
	Model 1	SES	11.61	2.53	0.61	4.6**	0.38	
		SL	-2.63	2.53	-0.14	-1.04		
	Model 2	Interaction Term	-2.13	2.96	-0.1	-0.72	0.37	0.01
			Response Time					
N-H								
	Model 1	SES	12.19	2.43	0.64	5.02**	0.41	
		SL	-3.97	2.43	-0.21	-1.64		
	Model 2	Interaction Term	-4.98	2.54	-0.26	-1.96	0.45	0.057
N-L								
	Model 1	SES	11.61	2.53	0.61	4.6**	0.38	
		SL	-2.63	2.53	-0.14	-1.04		
	Model 2	Interaction Term	-2.13	2.96	-0.1	-0.72	0.37	0.01

N = 38, **p* < .05, ***p* < .01,

After adding the cognitive measures to this regression model, as potential covariates, the results indicated that Digit Span task was a significant predictor of PPVT scores, $\beta = 7.45$, $p < .05$. Adding this measure significantly increased the explained variance by the first model to 55%, $R^2_{\text{adj}} = .545$, $F(3, 34) = 15.77$, $p < .001$. However, after adding this measure, the interaction term for SES and statistical learning remained non-significant, $\beta = -3.09$, p = ns. Similarly, Block design task was a significant predictor of PPVT scores, $\beta = 7.71$, $p < .05$, and significantly increased the variance explained to 49%, $R^2_{\text{adj}} = .487$, $F(3, 34) = 12.7$, $p < .001$. After adding this covariate to the model, the interaction term was not significant, $\beta = -3.86$, p = ns. These results indicate that the H-N ERP score is not a moderator of the relationship between SES and language outcome when we control for working and spatial memory. Additionally, Stroop was not a significant predictor of PPVT scores and did not contribute to the variance.

Next, we examined the relationship between SES, statistical learning and PPVT scores by using the L-N ERP variable as the moderator. The first model of the hierarchical regression explained 38% of variance in PPVT scores $R^2_{\text{adj}} = .382$, $F(2, 35) = 12.41$, $p < .001$. Similarly, in this model SES was the only significant predictor of performance on PPVT, $\beta = 11.61$, $p < .001$ and statistical learning (L-N) was not a significant predictor of PPVT scores, $\beta = -2.63$, p = ns. The interaction term added to the second step was not a significant predictor of PPVT, $\beta = -2.13$, p = ns. However, the model remained significant due to the strong relationship between SES and PPVT scores, $R^2_{adj} = .373$, $F\ (3, 34) = 8.33$, $p < .001$.

In this analysis, statistical learning was not a moderator in the relationship between SES and language. The summary of these regression coefficients are presented in Table 4. After entering Block Design, and Digit Span measures in the model, none of them were significant predictors of PPVT scores and they did not significantly contribute to the model.

In both of these analyses, statistical learning does not appear to moderate the effect of SES on children's vocabulary development. The lack of a moderating effect is depicted in Figure 5.

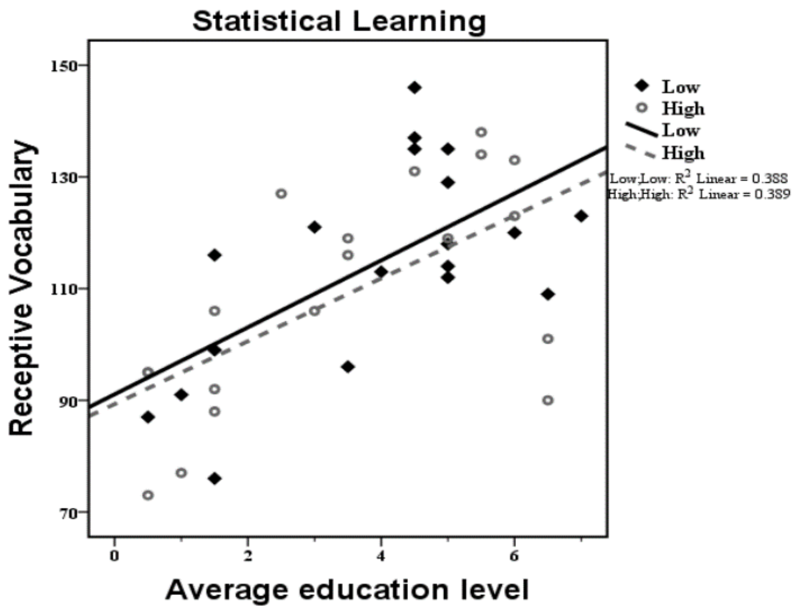

Figure 5 *Scatter Plots of the Marginally Significant Interaction between Vocabulary Scores and SES for Low Statistical Learning and High Statistical Learning (H-N) ERP Amplitudes*
Caregivers' average education levels: 0= Less than High School, 2= Some college, 4=Bachelor's degree, 6= PhD. For the purpose of illustration, statistical learning variable was separated into low statistical learning and high statistical learning by a median split of the data.

The results of regression analyses with the response time data were similar to the ERP results in regards to predicting vocabulary scores in children. The first model with SES and RT N-H variable significantly explained 37% of variance in PPVT, $R^2_{\text{adj}} = .368$, $F(2, 33) = 11.19$, $p < .001$, with SES as the only significant predictor, $\beta = 11.95$, $p < .001$. However, the interaction term did not significantly explain variance in PPVT scores, $\beta = -1.76$, p = ns; thus, the behavioral measure in N-H condition did not moderate the relationship between SES and PPVT scores. Next, the analysis with SES and N-L variable as predictors show that overall, the model explained 40% of variance in PPVT scores, $R^2_{\text{adj}} = .401$, $F(2, 33) = 12.73$, $p < .001$. SES was a significant predictor in the model, $\beta = 12.16$, $p < .001$. There was a marginally significant interaction effect of SES and N-L on PPVT scores, $\beta = -2.45$, $p = .059$. The summary of these regression coefficients are presented in Table 4. After adding the cognitive measures to this regression model, as potential covariates, the results indicate that the Digit Span task was a significant predictor of PPVT scores, $\beta = 7.47$, $p < .05$, and the effect of the interaction term for SES and statistical learning was no longer marginally significant $\beta = -1.56$, $p =$ ns. Similarly, the Block Design task was also a significant predictor of PPVT scores in this model, $\beta = 7.42$, $p < .05$. This measure, significantly increased the variance explained by model one to 49%, $R^2_{adj} = .487$, $F(3, 32) = 12.10$, $p < .001$. Interestingly, after adding the Block Design task to our model, the significant predictive effect of the interaction term between SES and statistical learning increased, $\beta = -2.30$, $p = .055$. These behavioral results suggest that statistical learning RT did not have a marginal moderating effect after we controlled for these cognitive measures.

4 DISCUSSION

In this study we aimed to investigate the relationship between intrinsic cognitive (statistical learning) and extrinsic environmental (SES) factors impacting language development in typically developing children by investigating whether statistical learning moderates the well-known relationship between SES and language outcome. Overall, the findings do indicate that statistical learning (as measured both behaviorally and neutrally) moderates the affect that parental education has on syntactic knowledge in children. This and the other main findings of this study will be discussed in detail below.

In terms of the visual statistical learning task, children's ERPs demonstrated sensitivity to the different probability conditions, indicating learning of the statistical probabilities embedded in the sequences of stimuli. The reaction time results were consistent with the ERP results in demonstrating evidence of statistical learning with quicker responding to targets when they followed the high predictor stimuli.

In terms of the relationship between SES and language, 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; NICHHD, 2000; Pan, Rowe, Singer, & Snow, 2005; Hoff et al., 2012). These results replicate previous studies demonstrating a relationship between primary caregiver's education level and language development in children (Stanton-Chapman et al., 2002; Hupp et al., 2011) suggesting that higher SES leads to children performing better on language assessments. Children with highly educated caregivers demonstrated better language skills in both receptive vocabulary and grammar measures compared to those children whose caregivers are not highly educated. A potential explanation for this relationship is parents with higher education level may also provide more complex linguistic input resulting in their children's better learning of words and grammatical rules of language compared to children with low CEL. According to the Federal Interagency Forum on Child and Family Statistics (2005), children in low SES families are less likely to be read to by their parents. Additionally, children with low SES have been reported to own less books and also have less exposure to them at home (Lee & Burkam, 2002; Whitehurst & Lonigan, 1998). These are only a few potential explanations for the relationship between SES and language development in children.

We hypothesized that children with high SES would demonstrate higher statistical learning ability due to being raised in a learning- friendly environment created by high SES. However, we did not find a significant correlation between statistical learning and SES. This lack of relationship may be explained if statistical learning ability is less sensitive to differences in the environment, hence its presence reported in studies with infants (Ellis, Robledo & Deák, 2014; Saffran, Aslin & Newport, 1996; Shafto, Conway, Field & Houston, 2012; Teinonen et al., 2009) and nonhuman primates (Hauser, Newport & Aslin, 2001). If statistical learning is age-invariant and less affected by experience, then the lack of social/environmental resources may not be a strong deterrent of its development in children. On the other hand, SES may be affecting statistical learning indirectly. According to Kuhl (2003) social interactions influence learning in children by increasing their attention span and, therefore, the amount of knowledge retained from the environment. Additionally, attention has also been linked to performance on statistical learning tasks in infants (Yoshida et al., 2006). One possibility may be that attention may be mediating this indirect relationship between social factors and statistical learning ability. Future research is needed to investigate whether attention span may be the link between social factors and implicit statistical learning ability.

Contrary to previous findings, we did not find a relationship between statistical learning and language measures. There may be many explanations for this finding. First, this finding may be due to the age of our participants. Previously, the relationship between statistical learning and language has been reported in younger children and adults. For example, Jost et al. (2011) reported that younger children may utilize different mechanisms in statistical learning which are more automatic and implicit compared to older children using more controlled and explicit mechanisms. Language and statistical learning may be using the same underlying mechanisms only when there is no conscious awareness during learning of the embedded statistical sequences which is reported to be evident in younger children (Jost et al., 2011). However, this relationship may change over development. On the same note, the relatively young age of our participants may have created some level of difficulty in the interpretation of EEG data during the statistical learning task. This issue may be a disadvantage of using the EEG technique in children. As mentioned earlier, muscle movement is recorded by the EEG system and may block or distort the ERP waves. Children tend to be more physically active than adults and it is difficult for them to sit quietly and still for the duration of the task. It is notable that in this study only 3 out of 42 participants were excluded due to this reason, however, it still stands as a potential reason for the lack of relationship between Statistical Learning and language measures. With previous knowledge of the potential difficulty of collecting EEG in children, we still utilized this technique because it provides an on-line measure of neural processing occurring in real time, providing greater sensitivity to the biological mechanisms supporting statistical learning than behavioral responses alone. Third, the “Magician” task also measures the frequency effects of different probability conditions in addition to statistical probabilities of stimuli in different conditions. The no-predictor condition in the 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 as well as difference in statistical probability of conditions. The relationship between statistical learning and language might have been observed if the frequency effect of different conditions were controlled for in the task. Fourth, we used ERP’s to capture temporal precision of responses of the participants in the statistical learning task, however, most of previous studies on statistical learning in children did not use ERP. Most statistical learning studies in infants measured statistical learning ability by using eye- statistical learning, recording looking time, and other nonverbal cues inferring preference for certain stimuli conditions. Most statistical learning studies with older children and adults measure statistical learning ability by directly recording participants' verbal and/or physical responses to different probability conditions.

Perhaps the most important finding of this study is that the moderation analyses revealed that children with high statistical learning appeared to have more robust syntactic knowledge that was less affected by their SES. In other words, the negative effect of low SES on grammar knowledge appeared to be deterred by high statistical learning ability. On the other hand, for children with lower statistical learning ability, their grammar scores were much more sensitive to the effects of SES. Thus, children who were raised in less advantaged families showed more typical syntax development if they had good statistical learning skills whereas if they had low statistical learning their language scores were lower. These results are the first to suggest that intrinsic cognitive abilities, specifically statistical learning, 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 statistical learning ability is low compared to when statistical learning ability is high. A potential explanation for this relationship is that when children receive poor linguistic input (due to low SES), those with good statistical learning ability can still detect and extract the embedded regularities in speech that they need to acquire language satisfactorily. However, children with low statistical learning ability may not be successful in extracting necessary regularities in language unless they are in a linguistically rich environment. Parents' high education level may help create this linguistically rich environment which can lead to better language development in children.

Results also showed that statistical learning did not have a moderating effect for receptive vocabulary scores. The results suggest that having low SES may not be as detrimental for vocabulary development if children demonstrate a strong statistical learning ability. This distinction could possibly be explained by the declarative/procedural model of language, which posits that procedural learning and grammatical processes share a common neurological substrate and declarative learning and the mental lexicon also share common neurological systems (Ullman, 2004). In this model, Ullman (2004) suggests that rule-based sequences are learned implicitly by using procedural systems that are also utilized in learning of new syntax and processing existing syntactic rules in language. These common brain regions include but are not limited to basal ganglia and Broca's area (Ullman, 2004). This model may help explain why our results indicate that statistical learning ability has a strong relationship with grammar scores and not with vocabulary scores of the participants. Further neuroimaging research is needed to explore the common areas that are involved in both statistical processing of stimuli and language processes.

In sum, this research provides an important examination of the relationship between intrinsic biological factors, the socio-linguistic environment, and language development in children. As a matter of fact, the neurophysiological evidence of this association between statistical learning and language outcome has never been explored in children. These results suggest that having good statistical learning abilities can help ameliorate the disadvantages associated with being raised in a lower SES home environment, offering intriguing new ways to think about the relations between intrinsic learning abilities, language development, and the social/linguistic environment in which a child is raised. Our results emphasize the importance of considering environmental factors in models exploring behavioral and neurophysiological aspects of cognitive and language development in children. 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 statistical learning abilities through targeted computerized training (e.g., Smith, Conway, Bauernschmidt, & Pisoni, 2015). Thus, by promoting statistical learning 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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APPENDICES

Appendix A *Partial Correlation Matrix with Age as the Controlling Variable*

Control Variable		1	2	3	4	5
Age	1. PPVT	—				
	2. Grammar	.87**	—			
	3. Statistical Learning (H-N)	-.18	-.24	—		
	4. Statistical Learning (L-N)	-.27	-.29	.63**	—	
	5. Response Time (N-H)	.04	.00	.57**	.19	—
	6. Response Time (N-L)	-.11	-.05	.19	.29	.33

**. $p < .01$

N =38