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Visual Statistical Learning Deficits in Children with Developmental Dyslexia: an Event Related Potential Study

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Abstract

A growing body of research suggests that individuals with developmental dyslexia perform below typical readers on non-linguistic cognitive tasks involving the learning and encoding of statistical-sequential patterns. However, the neural mechanisms underlying such a deficit have not been well examined. The aim of the present study was to investigate the ERP correlates of sequence processing in a sample of children diagnosed with dyslexia using a probabilistic visual serial learning paradigm. The behavioral results revealed that whereas age-matched typically developing children (n=12) showed learning in the task as reflected by their response times, the children with dyslexia (n=8) likely showed difficulty in learning. In conjunction with these behavioral results, the ERPs of the typically developing children showed a P300-like response indicative of this paradigm (Jost et al., 2015); whereas, the children diagnosed with a reading disorder showed no such ERP effects. These findings are consistent with the idea that differences in statistical-sequential learning ability might underlie the reading deficits observed in developmental dyslexia.

Keywords: Developmental dyslexia; statistical learning; sequential learning; implicit learning; ERPs.

Introduction

Statistical-sequential learning refers to the ability to learn statistically structured sequential patterns from the environment (Lashley, 1951; Saffran, Aslan, Newport, 1996). Statistical learning is thought to be important for the acquisition of language. For instance, in spoken language, linguistic units (e.g., phonemes, syllables, words) are organized in statistically structured sequences according to the specific language's phonology, phonotactics, semantics, and syntax. A growing body of research suggests that variations in statistical learning ability are associated with spoken language ability, in adults (Conway, Bauernschmidt, Huang, & Pisoni, 2010; Misyak, Christiansen, & Tomblin, 2010), children (Kidd, 2012), and infants (Shafto, Conway, Field, & Houston, 2012). Recent research also suggests that this same relationship between statistical learning and spoken language may hold true for statistical learning and written language. For instance, visual statistical learning was found to be related to reading ability in adults and children, even after controlling for age and attention (Arciuli & Simpson, 2012). Similarly, performance on a variant of the serial response time (SRT) task has also been shown to predict reading ability in a sample that included both healthy controls and adults diagnosed with dyslexia (Bennet, Romano, Howard, & Howard, 2008).

Developmental dyslexia (DD) is a learning disability that specifically impairs a person's ability to read despite having normal intelligence and ample opportunity for learning. Common characteristics among people with dyslexia are difficulty with phonological processing (the manipulation of sounds) (Bradley & Bryant, 1983; Snowling, 2000) and spelling (NINDS, 2011; Gabrieli 2009). In the standard view of dyslexia, individuals present with difficulty in reading but appear to process other information in a typical manner. In recent decades, however, it has become apparent that developmental dyslexia may be associated with impairments to other cognitive abilities such as motor functioning (Orban, Lungu, & Doyon, 2008), implicit learning (Du & Kelly, 2013), and cerebellar dysfunction (Nicolson, Fawcett, & Dean, 2001).

Of the many studies suggesting that there may be broader cognitive impairments underlying developmental dyslexia, a single commonality underlies many: sequential learning ability. For instance, individuals with dyslexia have been shown to perform below typical reading peers in variations of the SRT and other related sequence learning paradigms (Du & Kelley, 2013; Howard, Howard, Japiske, & Eden, 2006; Jiminez-fernandez, 2011; Vicari, Marotta, Menghini, Molinari, & Petrosini, 2003). Thus, there is mounting behavioral evidence for dyslexia to be associated with impairments in implicit statistical-sequential learning mechanisms. However, the neural mechanisms associated

with this proposed learning deficit have not been well explored. Furthermore, many of the previously mentioned tasks involved a motor component to learning; as such it is important to determine whether impaired sequential learning is due solely to difficulties with motor learning or whether deficits are also found using tasks that are not as dependent upon motor responses.

The Current Study

The purpose of the current study was to examine the neural correlates of statistical learning in children who have been diagnosed with DD compared to age-matched, typically-reading children. To this aim, we measured event-related potentials (ERPs) while children were engaged in a visual statistical learning paradigm previously used by Jost, Conway, Purdy, Walk, and Hendricks (2015). Eight children previously diagnosed with DD and twelve TD children participated. The learning task involved the presentation of a series of visual stimuli wherein target stimuli could be probabilistically predicted based on the preceding stimulus. ERPs to three different types of predictor stimuli reflecting high, low and zero probability of being followed by the target were compared across DD and TD groups. Based on the Jost, Conway, Purdy, Walk & Hendricks, (2015) study that demonstrated a P300-like ERP component that was associated with learning in the task, we investigated waveforms within the same 400-700ms time-window as used by Jost et al., (2015). We also examined behavioral correlates of learning as measured by response times (RTs) to the target stimuli. We predicted that if developmental dyslexia is associated with a deficit to general-purpose statistical learning mechanisms, the children with DD would be poorer at learning the predictor-target statistical patterns, as reflected by both the behavioral and ERP data, compared to the TD children. Furthermore, because the ERP effects are time-locked to the presentation of the predictor stimuli before any motor responses are made, any observed differences in the waveforms would suggest that the locus of impairment is at a perceptual or cognitive level, rather than only at the motor response level of processing.

Method

Participants

Twenty children (ages 8-12 years) were recruited from the greater Saint Louis region, eight of whom had a prior diagnosis of reading dyslexia (DD group) and the remaining had no prior diagnoses of cognitive, emotional, or learning disorders (TD group). The TD group was recruited through advertisements or by word of mouth and the DD group was recruited through a flier placed in the newsletter of a city school that specializes in teaching children with learning disorders. All participants' families were compensated $30.00- $40.00 for a 2 hour testing session and travel, and each child was given a small toy ($5.00-$10.00 in value). The resulting average age of the children across groups was similar, though the DD group [*M*=10.7] was slightly older than the TD [*M*=9.4] group on average. [*t*(18)=-1.707, *p*=.105] (and are still similar when one TD group participant was removed due to missing data on the cognitive tests[1]). Table 1 shows the demographic characteristics for the two groups.

Table 1: Descriptives for the children with developmental dyslexia (*DD*) and age-matched typically developing (*TD*) children [*see procedure below for explanation*].

	N	Gender	Mean Age
DD	8	5M, 3F	10.7 years
TD	12	8M, 4F	9.4 years

Table 2: Cognitive (raw) scores for both groups and Reading (raw) scores for the *DD* group

	DD*(N=8)*	TD*(N=11)*
BD	33.50	26.27
DS	15.38	13.91
WR	22.25	-
PD	11.00	-

Procedure

In addition to the statistical learning task (described below), we administered 2 sub-tests from the Wechsler Intelligence Scale for Children IV (WISC) (Wechsler, Kaplan, Fein, Kramer, Morris, Delis, & Maelender, 2003). We assessed participants' level of perceptual reasoning using the Block Design (BD) subtest. This test assesses visual-motor and visual-spatial skills by requiring children to recreate a 2-dimensional printed figure using 3-dimensional blocks, within a specific time frame. We also used the Digit Span (DS) sub-test as an index of short-term memory capacity as it provides a measure of a child's ability to retain new information, concentrate and manipulate input, thus demonstrating cognitive flexibility. The results of the BD and DS assessments are provided in Table 2. As one can see, the two groups of children obtained very similar scores, which were not statistically significant from one another for either subtest [BD: *t*(17)=-1.288, *p*=.215 and DS: *t*(17)=-1.259, *p*=.225].

[1] The resulting average age of the children across groups was similar, though the DD group [*M*=10.7] was slightly older than the TD [*M*=9.4] group on average. [*t*(17)=-1.678, *p*=.112]

The DD children were also administered the Pseudoword decoding and Word Reading sub-tests of the Wechsler Individual Achievement Test-II (WIAT) (Wechsler, 2005). The Word Reading (WR) sub-test assesses basic phonological skills and the Pseudoword Decoding (PD) sub-test assesses the child's ability to use phonetic decoding skills while reading from a list of nonsense words. The results of these two subtests are shown in Table 2. These scores indicate that the DD group performed at least two standard deviations below age matched peers on both WIAT sub-tests.

Statistical Learning Task

In the statistical learning task, children were presented with consecutive series of colored circles on a computer monitor one at a time (Figure 1). Stimuli were presented electronically using E-Prime 2.0.8.90 software (Psychology Software Tools, Pittsburgh, PA), on a Dell Optiplex 755 computer. Each visual stimulus was presented in the center of the screen on top of a dark background, displayed for 500ms Participants were instructed to press a button on a button box each time a target (T) color appeared. Every trial began with one to five occurrences of a standard (S) stimulus in the center of the screen. Following the presentation of these S stimuli, one of three possible predictor stimuli appeared, with each one predicting the target stimulus with varying levels of probability. When a high predictor (HP) color appeared, the target color followed 90% of the time; when a low predictor (LP) color appeared, the target color followed 20% of the time. When T did not appear (10% of the time for HP; 80% of the time for LP) the S followed instead. A zero-predictor (ZP) color was never followed by T, but always followed by S. The end of one trial was

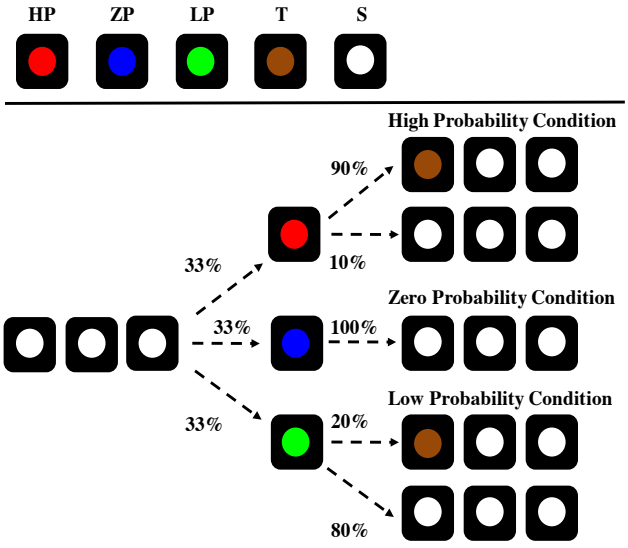

Figure 1. Diagram of the Statistical learning task

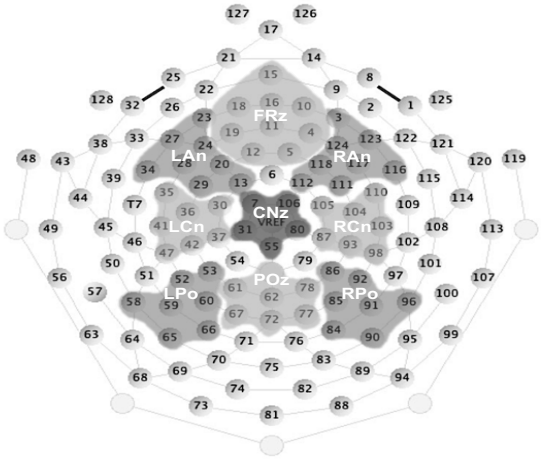

Figure 2: 128 sensors
EEG net with the highlighted nine regions of interest.

immediately followed by the next trial. Each of the three predictor colors occurred with the same frequency and the assignment of colors (red, blue, green, brown, white) to the three predictors, Ss, and Ts, was determined randomly for each participant. Note that Figure 1 shows an example depiction of the task with the HP being assigned to the red stimulus, ZP to the blue stimulus, etc.

Each predictor condition (HP, ZP and LP) was presented 50 times. Within each block, the trials were presented randomly and the end of one trial segued seamlessly into the next trial, so that participants could not distinguish the onset or offset of one trial from another. There were 50 trials of each predictor (for a total of 150 trials). Note that participants were given no instruction of the predictor-target statistical contingencies. Instead, the participant was expected to implicitly learn the statistical relationships between each predictor and the target, with learning to be expected to be observed through both response times and ERPs (as per Jost et al., 2015).

Electroencephalography Acquisition

The electroencephalograph (EEG) was acquired from 128 scalp sites using an Electrical Geodesic Inc. sensor net (Figure 2) and was pre-processed using Net Station Version 4.3.1 with subsequent processing using custom scripts written in Matlab (version R2012b 8.0.0783, The MathWorks) and the EEGLAB toolbox (version 10.2.2.2.4a; Delorme & Makeig, 2004). Electrode impedances were kept below 50 kΩ. The EEG was acquired with a 0.1 to 100 Hz band-pass at 250 Hz and then low-pass filtered at 30 Hz. The continuous EEG was segmented into epochs -200ms to +1000ms with respect to the predictor onset. ERPs were baseline-corrected with the 200ms prestimulus data and averaged-referenced. Individual ERPs were computed for each participant, probability condition, and electrode.

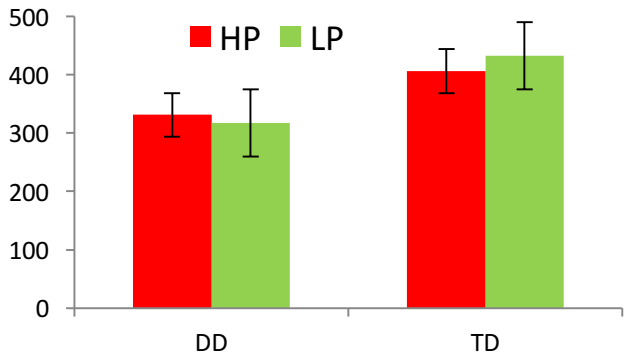

Figure 3: Response times (RT) across the two groups for the high (red) and low probability condition (green)

Statistical Analysis

Statistical calculations were performed on the individual mean amplitude ERPs within 400-700ms (as used by Jost et al, 2015). To analyze the effect of cortical topography, nine regions of interest (ROIs, Figure 2) were defined: left (LAn), middle (FRz), and right anterior (RAn); left (LCn), middle (CNz), and right central (RCn); and left (LPo), middle (POz), and right posterior (RPo) regions.

Behavioral analyses were conducted across DD and TD groups for response times. Pearson correlations were also performed on both groups with the WISC sub-tests as well as with the DD group and the WIAT sub-tests.

Results

RT data (Figure 3) was examined for only 10 TD children and on 6 of the DD children (due to missing data for 2 children in both groups). A 2 X 2 ANOVA with 2 levels of predictor (HP/ LP) and 2 groups (TD/DD) with RT as dependent variable revealed a significant main effect for predictor only *[*$F(1, 28) = 24.018$. $p < .001$]. The effect for group [$F(1, 28) = .086$. $p = .772$] and the group x predictor interaction were non-significant [$F(1, 28) = 1.03$. $p = .319$]. Even though the predictor X group interaction was non-significant (likely due to lack of statistical power), visually, it appears that RTs were quite different for the TD and DD groups, with the TD group showing the expected facilitation in RTs for the HP compared to the LP predictors, but the DD group not showing this same effect. This could indicate that for the DD children, the subtle differences between the HP/ LP were left undetected. However, a larger sample size is needed before making strong claims.

Figure 4 (left panel) displays grand average ERPs for the DD participants, within the 400-700ms range. Visual inspection indicates that the waveforms for the HP and LP predictors have the same amplitude but are larger than the ZP predictor. Figure 4 (right panel) displays grand average ERPs for the TD participants for each predictor condition, within the 400-700ms (across all 9 ROIs). Visual inspection indicates that the waveform for the HP predictor has a larger amplitude compared to the ZP and LP predictor waveforms.

Two one–way ANOVAs were performed separately for each group (DD, TD) within the 400-700ms window with EEG amplitude as the dependent variable and predictor conditions (HP, ZP and LP) as the independent variables. In the DD group, there were significant differences among predictor conditions [$F(2, 1941) = 24.762$, $p<.001$]. However, Tukey's post hoc-tests indicated that there were no significant differences between the HP and LP groups ($p=.865$) but there were significant differences between HP and ZP ($p<.001$) and LP and ZP ($p<.001$). Analyses for the TD group revealed that there were significant differences between the predictor conditions [$F(2, 2913) = 4.325$, $p=.02$]. Tukey's post hoc tests indicated significant differences between the HP and LP ($p=.01$), and HP and ZP ($p<.05$) but not between the ZP and LP groups ($p=.918$).

Pearson correlation analyses for all but one child with

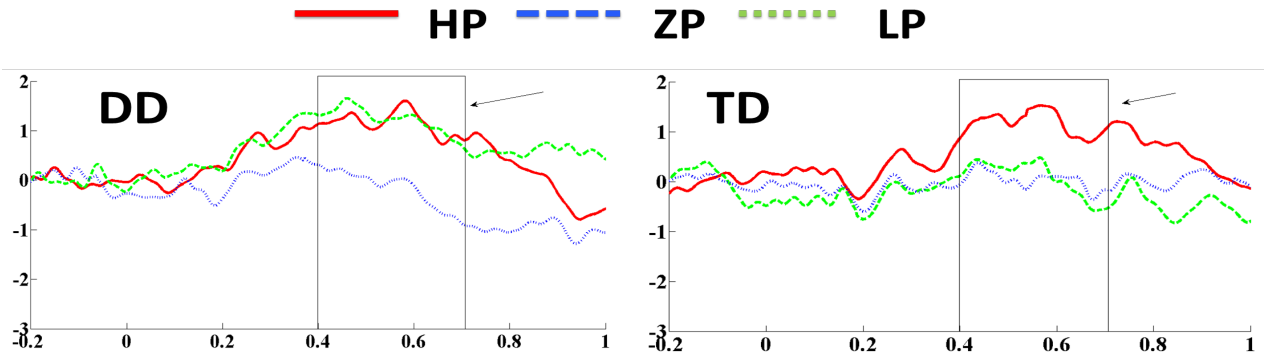

Figure 4: Grand averages are in response to the high predictors (*HP*, red solid line), zero predictors (*ZP*, green dotted line) and low predictor (*LP,* blue dashed line) (vertical axis: electric potential in μV, positivity upward; horizontal axis: time in seconds).

missing data (N=19) indicated that scores on the Digit span (DS) sub-test were strongly correlated with scores on the Block design (BD) sub-test [r(17)=.543; p=.02]. Pearson correlation analyses for only the DD group (N=8) children showed that scores on the Pseudoword Decoding (PD) sub-test were strongly correlated with scores on the Word Reading (WR) sub-test of the WIAT [r(6)=.967; p<.001]. Additionally, non-significant correlations were observed between: WR and statistical learning: [r(6)=.375, p = .360] and PD and statistical learning: [r(6)=.520, p = .186]. The lack of significant correlations is largely due to a small sample size issue.

Discussion

In this study, we examined the neural correlates of visual statistical-sequential learning in children who have been diagnosed with a reading disorder. The results showed that: (1) Relative to the TD group, typical learning patterns in RT data from children diagnosed with DD seemed less apparent, indicating unlikely encoding of the predictor-target relationships; and (2) the DD group showed atypical ERP waveforms within the 400-700ms time-window, compared to TD controls.

In a previous study using this same visual paradigm with a group of TD children, Jost et al. (2015) observed a P300-like component elicited by the HP but not the LP or ZP stimuli, similar to what we observed in the current sample of TD children. The P300 is regarded as an index of target detection and evaluation (van suijen et al., 2006) and has also been observed in other learning tasks (Baldwin & Kutas, 1997; Carrion & Bly, 2007; Russeler et al., 2003). Jost et al. (2015) suggested that the P300, typically observed during the occurrence of an infrequent target stimulus, "shifted" earlier in the input stream so that it now occurred in response to a stimulus that predicted the target with a high level of probability. That is, after sufficient exposure to the sequential statistics of the input array, the participants' brains treated the high predictor stimulus as if it were the target itself, displaying the prototypical P300 response. Regardless of the actual cognitive interpretation of the P300, it is clear that it reflects the participants treating the high predictor stimulus differently than both the low and zero predictor stimuli, presumably on the basis of having learned that this stimulus predicts the target with a high level of reliability.

In contrast, the DD group showed both a lack of facilitation of reaction times and an atypical ERP waveform pattern. Rather than showing the P300 effect to the HP stimulus, the DD group showed it for both the HP and the LP stimuli. This suggests that these children were unlikely to have encoded the statistical probabilities between predictors and target. Rather than learning that the HP stimulus was "special" in terms of its predictive power, it appears that these children learned that both the HP and LP were predictive of the target. On this account, they have not learned the subtle distinction in terms of the predictor-target probabilities that differentiate the HP from the LP stimulus (in terms of predicting the target with a 90% vs. 20% probability). This pattern of performance is also reflected in their RTs, by not responding faster to targets following the HP stimulus. Thus, it would appear that the children with developmental dyslexia were unable to learn even the most basic of statistical-sequential dependencies contained within this visual input stream.

How do the current findings relate to some of the prominent theories about the causes of developmental dyslexia, namely the phonological deficit and magnocellular deficit theories? The phonological deficit explanation is a prominent theory suggesting that dyslexia is a language-based disorder characterized by difficulties in single-word decoding (Orton, 1995) and phonological processing (Snowling, 2000). According to this theory, these individuals experience difficulties in perceiving and parsing phonemes, resulting in the inability to establish phoneme-grapheme connections. Although prominent, this theory does not explain other low-level visual, sensory, and motor coordination deficits that have also been associated with dyslexia. These shortcomings can instead be accounted for by the magnocellular deficit theory (Eden, Van- Meter, Rumsey, & Zeffiro, 1996). This theory postulates weaknesses in the perception of visual, rapid moving stimuli. Such degraded visual input is due to poor binocular fixation while reading. Its physiological manifestation is at the central nervous system level with impaired sensitivity of cells within the retinocortical magnocellular pathway (Stein, 2001). In the context of the present findings, the magnocellular theory would seem to be most relevant as it might help account for difficulties the DD children encountered while performing the visual statistical learning task. Future work will need to explore the specificity of this statistical learning deficit, that is, to what extent is it also apparent for other statistical learning tasks such as those incorporating auditory (non-linguistic) input streams or even visual-spatial patterns.

In conclusion, our findings suggest that children with DD show difficulty in implicitly learning statistical-sequential visual patterns. Because learning was indexed at the perceptual level by ERPs, and was not dependent upon a motor response, it appears that the learning deficit is not based on motor learning but reflects a more perceptual or cognitive learning problem. Additional research is required at both cognitive and neurophysiological levels in order to clarify the nature of this impairment and how it relates to or causes reading disability.

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