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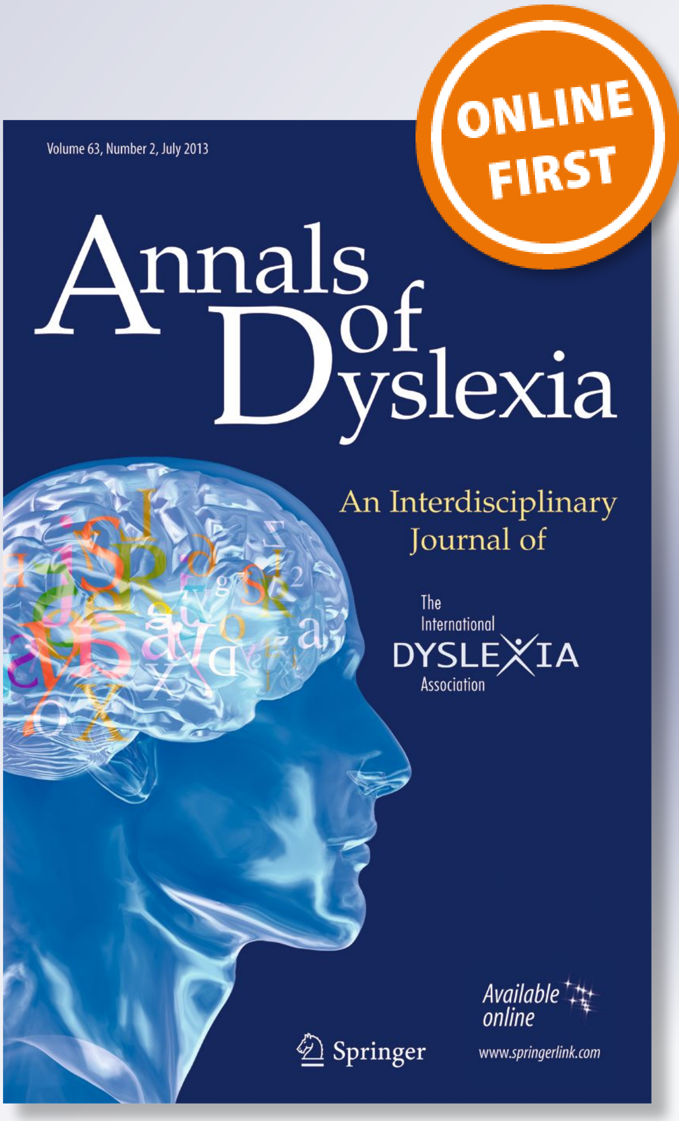

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Atypical predictive processing during visual statistical learning in children with developmental dyslexia: an event-related potential study

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Abstract Previous 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 event-related potential (ERP) correlates of sequence processing in a sample of children diagnosed with dyslexia using a non-linguistic visual statistical learning paradigm. Whereas the response time data suggested that both typical and atypical readers learned the statistical patterns embedded in the task, the ERP data suggested otherwise. Specifically, ERPs of the typically developing children ($n = 12$) showed a P300-like response indicative of learning, whereas the children diagnosed with a reading disorder ($n = 8$) showed no such ERP effects. These results may be due to intact implicit motor learning in the children with dyslexia but delayed attention-dependent predictive processing. These findings are consistent with other evidence suggesting that differences in statistical learning ability might underlie some of the reading deficits observed in developmental dyslexia.

Keywords Developmental dyslexia · ERPs · Implicit learning · Sequential learning · Statistical learning

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Introduction

Statistical learning refers to the ability to learn statistically structured patterns from the environment and is thought to be important for the acquisition of language (Saffran, Aslin, & Newport, 1996). For instance, in spoken language, linguistic units (e.g., phonemes, syllables, words) are organized in a non-random manner. This structured arrangement of units can be described in terms of statistical probabilities (e.g., the conditional probability that "X" is followed by "Y"). In terms of written or oral language, this arrangement ultimately results in the formation of that 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; Kidd & Arciuli, 2016), and infants (Shafto, Conway, Field, & Houston, 2012; Romberg & Saffran, 2010). Recent research also suggests that the 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). The current study investigates whether atypical statistical learning abilities are associated with developmental dyslexia in children, as measured by event-related potentials (ERP).

In general, the act of reading requires the mapping of alphabetic characters to the spoken words that they represent. It is this orthography to phonology mapping ability that may be impaired in individuals with dyslexia (Shaywitz et al., 1998). 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 individuals with dyslexia are difficulty with phonological processing (the manipulation of sounds) (Bradley & Bryant, 1983; Snowling, 2000) and spelling (Gabrieli, 2009). These features are consistent with the phonological deficit hypothesis of dyslexia (Swan & Goswami, 1997). 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 DD may be associated with impairments to other cognitive abilities such as motor functioning (Orban, Lungu, & Doyon, 2008), implicit learning (Laasonen et al., 2014; Du & Kelly, 2013; Folia et al., 2008; Bennett et al., 2008; Sperling et al., 2004), statistical learning of sequences (Gabay, Thiessen, & Holt, 2015; Conlon et al., 2011), and cerebellar function (Nicolson, Fawcett, & Dean, 2001).

Of the studies suggesting that there may be broader cognitive impairments underlying DD, a single commonality underlies many: the learning of statistical-sequential patterns. For example, performance on a variant of the serial reaction time (SRT; Nissen & Bullemer, 1987; Robertson, 2007) task has been shown to predict reading ability in a sample that included both healthy controls and adults diagnosed with dyslexia (Bennett, Romano, Howard, & Howard, 2008). In the SRT task, participants are presented with sequences containing cues as to what response is to be made (button press) but are not informed about the structure governing the presentation of the sequences (i.e., either the same sequence repeated multiple times or statistical probabilities that govern the occurrence of individual items within each sequence). As participants extract the sequential regularities, their response times (RTs) decrease, indicating learning. In addition, individuals with dyslexia have been shown to perform below typical reading peers in variations of the SRT and other related sequence learning paradigms (Du & Kelly, 2013; Howard, Howard, Japiske, & Eden, 2006; Jiménez-Fernández et al., 2011; Vicari, Marotta, Menghini, Molinari, & Petrosini, 2003).

Despite accumulating evidence that dyslexia is associated with impairments to implicit statistical-sequential learning abilities, the neural mechanisms associated with this proposed learning deficit have not been well explored (Sawi & Rueckl, 2018; Schmalz et al., 2017). Furthermore, many of the previously mentioned tasks involved a motor component to learning; as such, it is important to determine whether impaired statistical 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 and are more perceptual in nature.

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 developing (TD) readers. 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). The ERP approach involves fitting the participant with a snug sensor net designed to measure electrical activity generated in the brain in response to a specific sensory, cognitive, or motor event (Polich, 2007). The resulting brain wave data are referred to as event-related potentials (ERPs) and have been used to examine the underlying neural correlates of dyslexia (Papagiannopoulou & Lagopoulos, 2017). The non-invasive nature of ERPs makes it an appealing measure, which can provide complementary information to standard behavioral responses.

Eight children with a previous clinical diagnosis of DD and 12 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 et al. (2015) study that demonstrated a P300-like ERP component (typically a measure of target detection for infrequent stimuli that peaks between 250 and 500 ms after stimulus exposure) that was associated with learning in the task, we investigated waveforms within the same 400–700 ms time window as used by Jost et al. (2015). We also examined behavioral correlates of learning as measured by RTs to the target stimuli. An advantage of our task design over previous SRT tasks is that the ERPs index the cognitive processing associated with each predictor type before the target appears and before any motor response is made. Thus, in the current design, the ERPs likely index perceptual or attentional neural processes associated with making a prediction about the upcoming stimulus. Conversely, the RT data are collected after target presentation and so reflect a motor response that may index a form of implicit learning (see Batterink et al., 2015 for a similar argument), though decision processes occurring prior to the motor response could also impact latencies.

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. On the other hand, given that the ERP and RT data at least partially index separate processes, it is also possible that the children with DD will exhibit intact learning as measured by RTs, but atypical neural responses.

Method

Participants

Twenty children (ages 8–12 years) were recruited from the greater Saint Louis region, eight of whom had a prior diagnosis of dyslexia (based on parent report) or other type of reading disorder (DD group) and the typical readers had no prior diagnoses of cognitive, emotional, or learning disorders (TD group). The TD group was recruited through fliers placed in the Saint Louis University daily online newsletter and 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-h 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$, $p = .105$]. Table 1 shows the demographic characteristics for the two groups.

To confirm the presence of a reading disorder, 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 word recognition skills and the pseudoword decoding (PD) sub-test assesses the child's ability to use phonetic decoding skills while reading from a list of non-sense words. The results of these two sub-tests are shown in Table 1. These scores indicate that the DD group on average performed approximately two standard deviations below the norms on WR and PD measures of the WIAT, confirming the validity of the diagnosis of a reading disorder.

Procedure

In addition to the statistical learning task (described below), we administered two sub-tests from the Wechsler Intelligence Scale for Children IV (WISC) (Wechsler et al., 2003). We assessed participants' level of perceptual reasoning using the block design (BD) sub-test. This test assesses visual-motor and visual-spatial skills by requiring children to recreate a two-dimensional printed figure using three-dimensional blocks, within a specific time frame. We

Table 1 Descriptives for the children with developmental dyslexia (DD) and age-matched typically developing (TD) Children. [BD: block design; DS: digit span; WR: word reading; PD: pseudoword decoding; st: standardized; sc: scaled]

		DD	TD
N		8	12
Gender		5M, 3F	8M, 4F
Mean age		10.7 years	09.4 years
BD sc	*M*	10.5	9.64[a]
	SD	2.73	2.54[a]
DS sc	*M*	10.5	9.55[a]
	SD	2.88	1.97[a]
WR st	*M*	74.63	–
	SD	8.03	–
PD st	*M*	77	–
	SD	5.88	–

[a] $N = 11$; one participant had missing data

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. These sub-tests were included to document equivalence on cognitive sub-skills across the two groups. The results of the BD and DS assessments are provided in Table 1. The two groups (N=19 for the DD group; one participant had missing data) of children obtained very similar scores, which were not statistically significant from one another for either sub-test [BD: $t(17)=-1.288$, $p=.215$ and DS: $t(17)=-1.259$, $p=.225$].

Statistical learning task

In the statistical learning task, children were presented with a consecutive series of colored circles on a computer monitor one at a time (Fig. 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 500 ms. Participants were instructed to press a button on a button box each time a target color appeared. Every trial began with one to five occurrences of a standard stimulus in the center of the screen. Following the presentation of these standard 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 the target did not appear (10% of the time for HP; 80% of the time for LP), the standard followed. A zero predictor (ZP) color was never followed by the target but was always followed by a standard. The end of one trial was 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, standard, and target was determined randomly for each participant. Note that Fig. 1 shows an example depiction of the task with the HP being assigned to the red stimulus, ZP to the blue stimulus, etc.

There were five blocks in the task, with each block containing 10 trials of each predictability condition (HP, LP, ZP) or 30 trials total per block and 150 trials total in the task. Within each block, trials were presented randomly and the end of one trial flowed seamlessly into the next trial, so that participants could not distinguish the onset or offset of one trial from another. Participants were given no instruction of the predictor-target statistical contingencies. Rather, because the participants' task was to press a button whenever they saw the target stimulus appear, it was expected that participants would implicitly learn the statistical relationships between each predictor and the target, with learning 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 (Fig. 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 with vertex reference and then re-referenced to the average reference of all sensors and low-pass filtered at 30 Hz. Signals containing non-stereotypical artifacts,

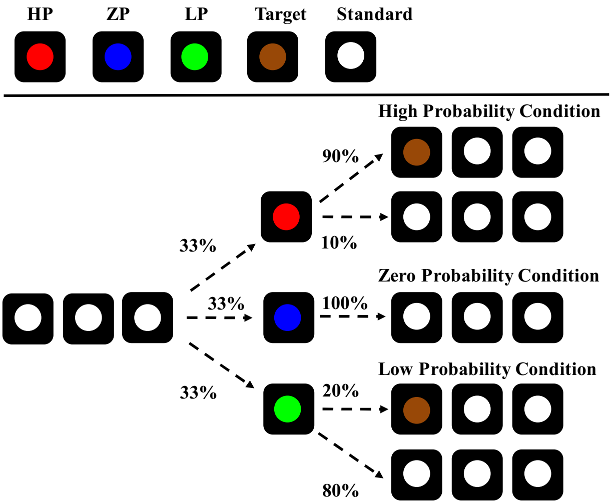

Fig. 1 Diagram of the visual statistical learning task

including high-amplitude, high-frequency muscle noise, and electrode cable movements, were rejected (approximately 25% of trials). Prior to segmentation, stereotypical artifacts such as vertical eye blinks and horizontal eye movements were corrected with an extended Infomax independent component analysis using EEGLAB (Lee, Girolami, & Sejnowski, 1999). The continuous EEG was then segmented into epochs −200 to +1000 ms with respect to the predictor onset. Note that ERPs were collected in response to the predictor stimuli, not the target itself, because it was expected that if learning had occurred, there would be a characteristic ERP effect distinguishing the HP, LP, and ZP stimuli (as per Jost et al., 2015). ERPs were baseline-corrected with the 200 ms pre-stimulus data. Individual ERPs were computed for each participant, predictor type, and electrode.

Statistical analysis

Statistical calculations were performed on the individual mean amplitude ERPs within 400–700 ms (as used by Jost et al., 2015) in the POz (centro-posterior) region of interest (ROI; see Fig. 2), where Jost et al. (2015) reported the strongest ERP effects related to learning in the task. Based on Jost et al. (2015), larger amplitudes for the HP compared to the LP condition is expected to reflect learning. A 2 × 3 mixed measures ANOVA was run with a Greenhouse-Geisser correction, with experimental group (TD/DD) as the between-group variable and predictor condition (HP/LP/ZP) as the within-group variable and ERP amplitude as the dependent variable. Analyses were collapsed across blocks, unlike the Jost et al. (2015) study that treated block as a within-group variable, as visually there did not appear to be differences in the ERPs across blocks. Thus, for increased power and signal-to-noise-ratio, statistical analyses were run with block collapsed.

Behavioral analyses were conducted across DD and TD groups for response times to the target stimuli for the HP compared to the LP stimuli. Shorter RTs to the target stimuli for the HP compared to the LP stimuli are expected to reflect learning. A 2 × 2 mixed measures ANOVA was run with Greenhouse-Geisser correction, with experimental group (TD/DD) as the between-group variable, predictor condition (HP/LP) as the within-group variable, and RT

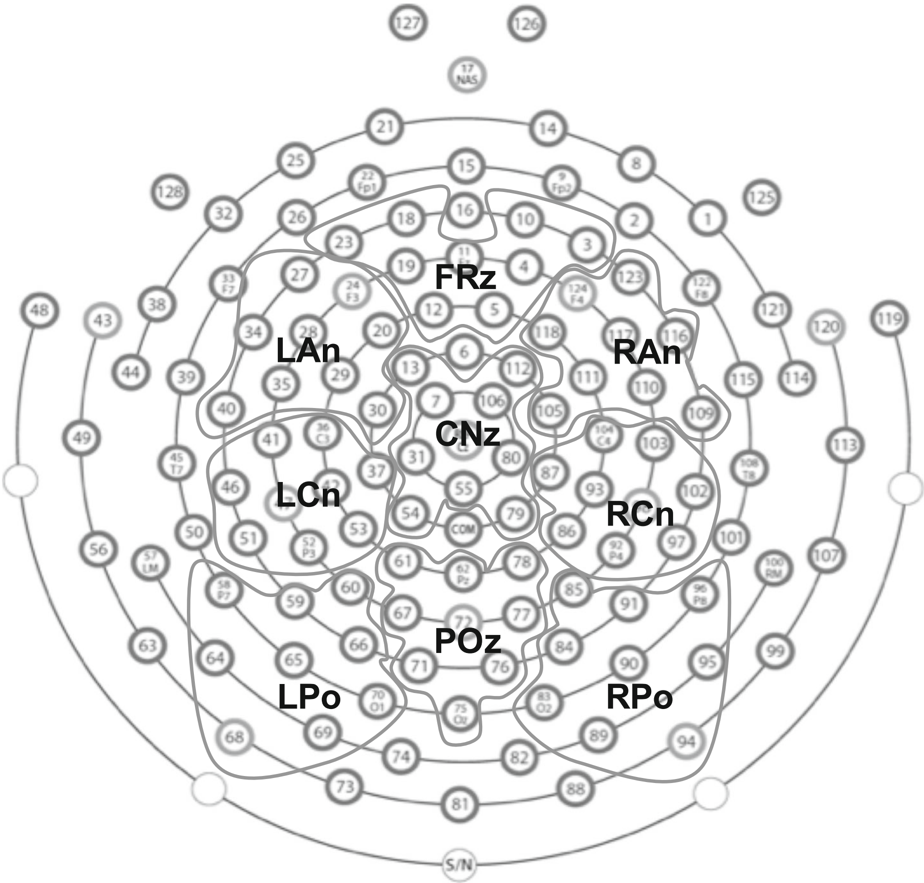

Fig. 2 One hundred and twenty-eight sensor EEG nets with the highlighted nine regions of interest: left (LAn), middle (FRz), and right anterior (RAn); left (LCn), middle (CNz), and right central (RCn); and left (LPo), central (POz), and right posterior (RPo) regions

as the dependent variable. Pearson correlations were also performed on both groups with the WISC sub-tests and statistical learning task as well as with the DD group and the WIAT sub-tests. For this analysis, statistical learning was operationalized as a difference score of the average response times for the LP condition minus the HP condition.

Results

Behavioral

Response time (RT) data (Fig. 3) was examined for only 10 TD children (due to missing data for 2 children for both groups) and on 6 of the DD children. The 2 × 2 mixed ANOVA revealed a significant main effect for predictor only [$F(1, 14) = 30.841$; $p < .001$; $\eta^2 = 0.688$]. There were no significant effects for group [$F(1, 14) = .070$; $p = .795$; $\eta^2 = 0.005$] nor was there a significant group × predictor interaction [$F(1, 14) = 1.323$. $p = .269$; $\eta^2 = 0.086$]. It appears that

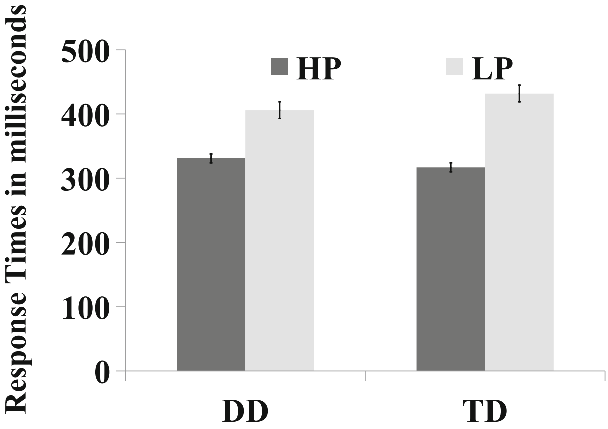

Fig. 3 Response times (RTs) in milliseconds, across the two groups for the high (dark gray) and low probability condition (light gray)

performance was comparable across groups, with quicker RTs to the target when it was preceded by the HP compared to the LP stimuli, suggesting that both groups of children learned the predictor-target probabilities.

ERP results

Figure 4 (left panel) displays grand average ERPs for the DD participants averaged across all nine ROIs, with the 400–700 ms time window outlined. 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 the same grand average ERPs for the TD participants (averaged across ROIs). Visual inspection indicates that the waveform for the HP predictor has a larger amplitude compared to the ZP and LP predictor waveforms. Thus, the two panels in Fig. 4 appear to indicate different ERP profiles for the DD and TD participants.

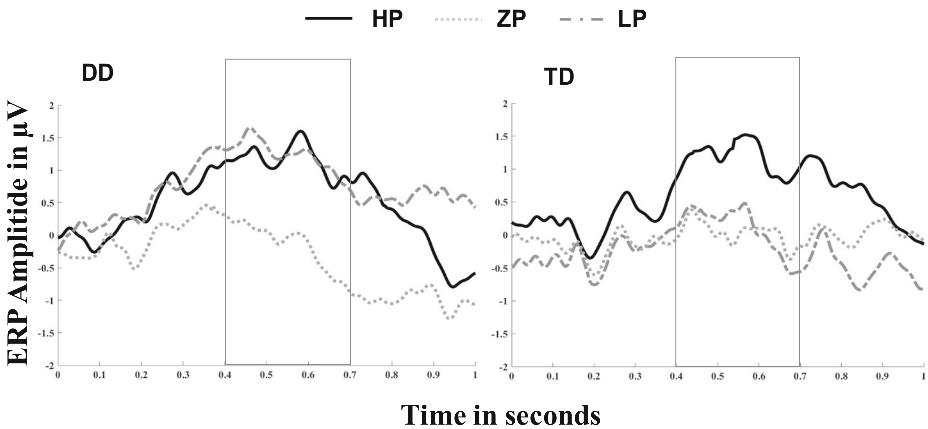

Fig. 4 Grand averages across all nine ROIs are in response to the high predictors (HP, solid line), zero predictors (ZP, dotted line), and low predictor (LP, dashed line) (vertical axis: electric potential in µV, positivity upward; horizontal axis: time in seconds)

Figure 5 displays grand average ERPs for the DD participants, for each of nine ROIs separately, whereas Fig. 6 displays grand average ERPs for the TD participants (for each ROI separately). Visual inspection of the waveform patterns indicates different ERP profiles similar overall to that displayed in Fig. 4. That is, for the DD participants, the HP and LP waveforms show similar amplitudes in most ROIs, whereas for the TD participants, the HP and LP waveforms are generally separate from one another.

The mixed ANOVA analyzing the ERP data for the POz ROI within the 400–700 ms time window revealed a main effect for predictor [$F(1.844, 328.316) = 20.963$; $p = < .001$; $\eta^2 = 0.105$] but not for group [$F(1, 178) = 2.602$; $p = .108$; $\eta^2 = 0.014$]. However, there was a significant interaction between predictor condition and group [$F(1.844, 328.316) = 4.158$; $p = .019$; $\eta^2 = 0.023$]. Follow-up Bonferroni pairwise comparisons revealed that there were significant differences between each of HP and ZP ($p = < .001$), ZP and LP ($p = .023$), and HP and LP ($p = .001$) predictor conditions, at this ROI. In line with the group by predictor interaction, the "learning effect" or the difference between the ERP amplitude means for HP vs. LP is larger in the TD group, HP [$M = -0.012$; $SD = 0.014$] vs. LP [$M = -0.069$; $SD = 0.014$], compared to the DD group, HP [$M = 0.011$; $SD = 0.017$] vs. LP [$M = -0.009$; $SD = 0.017$]. In addition, to further explore differences between groups for each predictor condition, three separate one-way ANOVAs were run. There was no significant difference between TD and DD for the HP condition [$F(1, 1618) = 0.792$; $p = .373$]. There was a significant group difference for the ZP condition [$F(1, 1618) = 10.953$; $p = .001$] as well as for the LP condition [$F(1, 1618) = 0.15.155$; $p = .000$].

Pearson correlation analyses (see Table 2) for the DD group ($N = 6$) children showed that (standard) scores on the pseudoword decoding (PD) sub-test were strongly correlated with scores on the word reading (WR) sub-test of the WIAT [$r = .963$; $n = 6$; $p = .002$]. Additionally, positive but non-significant correlations were observed between statistical learning as

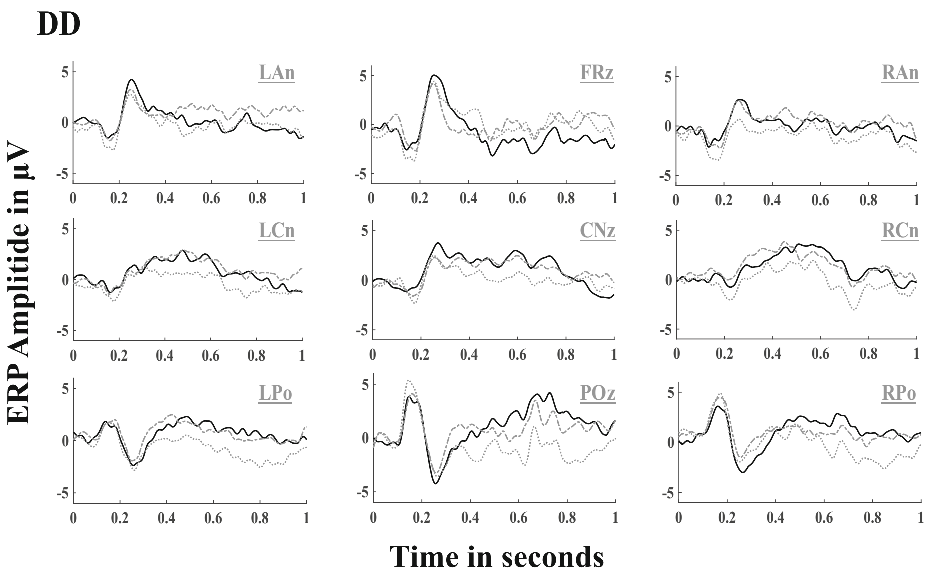

Fig. 5 DD grand averages for each of the nine ROIs are in response to the high predictors (HP, solid line), zero predictors (ZP, dotted line), and low predictor (LP, dashed line) (vertical axis: electric potential in µV, positivity upward; horizontal axis: time in seconds)

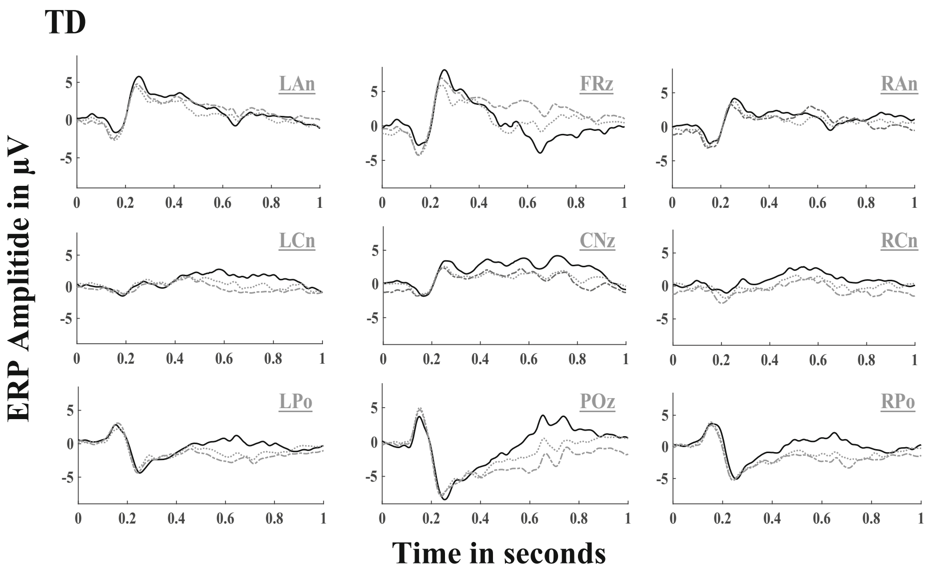

Fig. 6 TD grand averages for each of the nine ROIs are in response to the high predictors (HP, solid line), zero predictors (ZP, dotted line), and low predictor (LP, dashed line) (vertical axis: electric potential in µV, positivity upward; horizontal axis: time in seconds)

measured with RT difference scores and both WR (standard scores) [$r = .465$, $n = 6$; $p = .353$] and PD (standard scores) [$r = .281$, $n = 6$; $p = .589$]. The lack of significant correlations is likely due to the small sample size.

We also ran Pearson correlation analyses for both TD and DD group children together ($N =$ 15; one participant was removed due to lack of data; see Table 3). There was a positive non-significant correlation between BD (standard scores) and DS (standard scores) [$r = .432$, $n =$ 15; $p = .108$]. There was also a negative non-significant correlation between statistical learning as measured with RT difference scores and DS [$r = .-334$, $n = 15$; $p = .224$].

Discussion

In this study, we examined the neural and behavioral correlates of visual statistical-sequential learning in children who have been diagnosed with a reading disorder compared to age-matched typical readers. Interestingly, RTs showed learning effects in both groups. In contrast, the DD group showed atypical ERP waveforms within the 400–700 ms time window, compared to TD controls. In a previous study using this same visual paradigm with a group of TD children and adults, Jost et al. (2015) observed a P300-like component elicited by the HP but not the LP or ZP stimuli, similar to what was observed in the current sample of TD

Table 2 Table of correlations for only developmental dyslexia (DD) groups ($N = 6$). [WR: word reading; PD: pseudoword decoding; $^{**}p < .01$]

	PD	WR	SL
PD	1		
WR	0.963**	1	
SL	0.281	0.465	1

Table 3 Table of correlations for both typically developing (TD) and developmental dyslexia (DD) groups ($N = 15$). [BD: block design; DS: digit span]

	BD	DS	SL
BD	1		
DS	0.432	1	
SL	− 0.089	− 0.334	1

children. The P300 is regarded as an index of target detection and evaluation (van Zuijen et al., 2006) and has also been observed in other learning tasks (Baldwin & Kutas, 1997; Carrión & Bly, 2007; Rüsseler 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 began to view the high predictor stimulus as if it were the target itself, displaying the conventional 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 the current study, although the DD group showed facilitation of response times that suggests learning in the task, their performance showed atypical ERP waveforms. Rather than showing the P300 effect to the HP stimulus alone, the DD group showed it for both the HP and the LP stimuli. Rather than discerning that the HP stimulus was "special" (represented by a larger mean ERP amplitude difference for HP-LP) in terms of its predictive power, it appears that the DD children learned that both the HP and the LP were predictive of the target, but not differentially so. This could indicate a possible delay in or difficulties with learning 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). Jost et al. (2015) reported that learning occurred only after sufficient exposure to the input contingencies in the second half of the task. Thus, perhaps the children with dyslexia are less efficient and slower to learn the statistical contingencies; it is possible that with additional or modified exposure, more typical ERP effects might be observed.

One explanation for the performance disparity between the RTs and the ERPs is that RTs may reflect implicit pattern learning, whereas the ERP effects demonstrate attention-dependent or more explicit processes, as suggested by Batterink et al. (2015). Under this proposal, the children with DD have intact implicit learning abilities but their attentional resources were not adequately focused on the HP stimulus that occurs in TD children. Shaywitz and Shaywitz (2008) emphasized the dependency of attention in automatic information processing tasks such as reading ability and its possible contribution to reading difficulties observed in dyslexia. Another related possibility is that the ERPs measure predictive processing because they are elicited before the target occurs. That is, for typical learners, the P300 effect for the HP could be a reflection of a predictive process that heightens attentional resources in expectation of the target stimulus. Because predictive processing in sequence learning tasks appears to be at least partly based on explicit processing (Dale, Duran, & Morehead, 2012), this is again consistent with ERP effects being an index of attentional or explicit processing and the motor responses an index of implicit processing. Overall, based on the neural findings, the current results suggest atypical processing of the predictor-target contingencies, possibly due to atypical devotion of attentional or cognitive resources in the service of prediction.

It is important to evaluate the current findings in the context of some of the existing theories regarding the underlying causes of developmental dyslexia. For instance, the phonological deficit theory suggests that dyslexia is a language-based disorder characterized by difficulties in single-word decoding (Orton, 1995) and phonological processing (Snowling, 2000). Although phonological processing deficits are most frequently reported when comparing typical and atypical readers, other cognitive processes might also be important contributing factors in reading disability. Present consensus on the etiology of dyslexia proposes what might be described as a phonological core, multiple deficit model (Pennington, 2008; Willcutt et al., 2008), a model that is perhaps aligned with current results (see Elliott & Grigorenko, 2014). According to their model, a plethora of factors might alter neurodevelopmental systems that are responsible for reading. From this perspective, the heterogeneity of the many cognitive weaknesses observed within reading disorders cannot be traced back to a single theory. Instead, dyslexia might be better conceptualized as a complex disorder characterized by a multifactorial etiology.

Another theory that could account for the visual learning deficits is the magnocellular deficit theory (Eden, VanMeter, Rumsey, Maisog, Woods, & 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). The current findings also appear to be in line with the cerebellar deficit theory (Nicolson & Fawcett, 1999), according to which, a large majority of children with dyslexia show evidence of cerebellar abnormality as reflected by impairments in skill automatization, time estimation, and most importantly, execution of an automatic sequence and error elimination (Nicolson, Fawcett, & Dean, 2001). Optimum performance in the present study hinges on statistical-sequential learning and, to a certain extent, the awareness and estimation of time are important factors used in predicting the upcoming target. This interpretation is made with caution as the present results only indicate dysfunction in DD children at the neurophysiological and not at the behavioral level, as in previous work (Nicolson, Fawcett, & Dean, 2001). A very similar explanation is the procedural learning hypothesis, according to which, automatization is affected by procedural learning impairments and is suggestive of a more domain general procedural learning impairment in DD (Gabay, Thiessen, & Holt, 2015; see also Krishnan, Watkins and Bishop, 2016). Finally, according to the temporal processing deficit account, children with DD have trouble integrating sensory (visual) information, especially when it is presented rapidly (Hood & Conlon, 2004). Because the current task requires learning of sequential-statistical relationships, perhaps the DD group was unable to learn the high frequency predictor-target association as a result of temporal processing deficits, as observed by ERPs. Thus, although the current findings do not differentiate between theories, the results are interpreted as consistent with most or all the above mentioned causal theories of dyslexia but perhaps provide a slightly different perspective: that the reading deficits could in fact be due to difficulties with learning of statistical-sequential patterns specifically. In fact, the current data complement other research that have reported impairments in children with dyslexia in statistical learning using artificial grammar learning tasks (Pavlidou & Williams, 2014; Schiff, Sasson, Star, & Kahta, 2017) and the SRT task (Gabay et al., 2015; Menghini et al., 2008; Nigro et al., 2016; Vicari et al., 2003). Although Menghini et al. (2008) used neuroimaging to examine learning differences, the current study is one of the first to examine ERP differences in visual statistical learning in children with dyslexia.

There are limitations to the current study, the most prominent being the small sample size. It is possible that with greater statistical power, differences in RTs between the DD and TD groups might have been observed. It is also important to emphasize that the aim of the current study was to uncover possible links between statistical learning and dyslexia but it is not possible with the given data set to make causal claims between statistical learning and reading disability. Finally, based on study design recommendations by Goswami (2015), a future study might benefit from matched controls on reading level rather than chronological age. Also, the current design does not account for any potential confounds that may have been the result of undiagnosed attention-related disorders such as attention deficit hyperactivity disorder (ADHD). This is an important area of future research, as there are clearly attentional demands in the learning task. Future research should account for reading ability in the control group as well as further explore for the dyslexia group whether the child specifically had trouble in phonemic awareness, reading comprehension, reading fluency, or other similarly challenging areas within reading disability.

In conclusion, the findings from the current study suggest that children with DD show atypical learning and processing of statistical-sequential visual patterns. Because learning was measured in two ways, indexed at the perceptual level by ERPs, and at the motor level by RTs, it appears that the learning deficit is not based on motor learning but reflects a more perceptual or cognitive learning problem. Another explanation is that children with DD show intact implicit pattern learning but have atypical or delayed neural responses that reflect a sluggish allocation of attention to stimuli that are highly predictive of an upcoming target. That is, the children with DD show atypical predictive processing but intact motor responses following the target. Additional research is required at both cognitive and neural levels in order to clarify the nature of this impairment and how it relates to or causes reading disability.

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