Decoding of speech information using EEG in children with dyslexia: Less accurate low-frequency representations of speech, not “Noisy” representations

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1. Introduction

Dyslexia is a disorder of development. Classically, a child has shown apparently typical language acquisition and cognitive development until faced with the task of learning to read. Suddenly, the affected child shows a specific problem with reading and spelling that cannot be accounted for by low intelligence, poor educational opportunities, or obvious sensory or neurological damage. Reading is the process of understanding speech when it is written down. To acquire early reading skills, the child must learn the visual code used by their culture for representing speech as a series of symbols. Logically, individual differences in acquiring reading could be related developmentally to either spoken language processing or visual code processing or both (Snowling, 2000; Stein & Walsh, 1997). However, it is important to recognise that the visual code that must be learned is not a neutral visual stimulus. It is a culturally-specific code that is taught directly using symbol-sound correspondences, such as the alphabetic correspondences used to represent English phonology (the sound system of the language). Learning this visual code typically begins a few years into the development of a spoken language system, and it is now widely recognised that individual differences in children’s pre-reading phonological awareness (their ability orally to recognise or manipulate phonological units in words such as syllables, rhymes or phonemes) is a causal determinant of how readily their visual code learning progresses (Ziegler & Goswami, 2005, for cross-language review). Indeed classically, ‘deficits’ in the representation and use of phonological information have been seen as critical in the etiology of developmental dyslexia (Catts, 1993; Snowling, 2000; Stackhouse & Wells, 1997; Stanovich & Siegel, 1994; Swan & Goswami, 1997).

To understand the nature of this ‘phonological deficit’ in dyslexia, longitudinal studies that begin with infants are required. Evidence from both electrophysiological and behavioural measures suggests that infants at family risk (genetic risk) for dyslexia already exhibit deficits in the auditory processing of speech and non-speech sounds in their first year of life, which could be expected to affect novel word learning. It is well known that the speech signal provides a rich repertoire of acoustic cues that infants exploit to learn new words (Saffran, 2001). Although very few neurophysiological longitudinal studies of at-risk infants exist,
EEG studies suggest atypical detection of changes to the acoustic features of speech and non-speech sounds (e.g., F0 frequencies, vowel length, and consonant voice onset time) in newborns and two-month-olds, and there are also differences in their hemispheric distribution of the neural responses to these acoustic stimuli (Guttorm, Leppanen, Hämäläinen, Eklund, & Lyytinen, 2010; Guttorm et al., 2005; Leppänen et al., 2010; see also van Zuijen, Plakas, Maassen, Maurits, & van der Leij, 2013).

Regarding the atypical development of phonological representations for words that characterise older children once they are diagnosed with dyslexia, the most commonly accepted hypothesis is that these phonological representations are somehow “noisy” or “imprecise” (Snowling, 2000; Swan & Goswami, 1997). As explained in detail by Ramus and Sznovkivits (2008), the general idea concerning “noisy” representations is that a dyslexic child’s neural representations of the speech signal are somehow fuzzier, for example having a lower resolution than they should, or preserving too many acoustic or allophonic details (Adlard & Hazan, 1998; Bogliotti, Serniclaes, Massignoud-Galinou, & Sprenge-Chorolles, 2008; Elbro, Borstrom, & Petersen, 1998; Mann et al., 1997; Mody, Studdert-Kennedy, & Brady, 1997; Serniclaes & Seck, 2018; Serniclaes, Van Hecke, Mousty, Carré, & Sprenge-Chorolles, 2004; Snowling, 2000). Other terms used in the literature to describe dyslexic children’s phonological representations are “imprecise” or “under-specified”. Ramus and Sznovkivits (2008) disputed this idea about “noisy” representations, arguing that the phonological representations of individuals with dyslexia may be quite normal. The phonological ‘deficit’ might arise instead from problems in accessing these normal representations when required for phonological awareness and other oral tasks. For example, Boets et al. (2013) explored the phonetic representations of adults with dyslexia in an fMRI connectivity study, and reported that functional connectivity between auditory cortices and left inferior frontal gyrus was impaired, which they argued could suggest reduced accessibility to intact phonetic representations. Although access is not mechanistically defined by Boets and colleagues, Ramus and Sznovkivits expect access to be more difficult when a task requires lots of phonological information to be stored in short-term memory, or a task requires speeded or repeated retrievals of phonological information, or it requires the extraction of speech information from noise (Ramus & Sznovkivits, 2008). To our knowledge, however, neural studies have not yet been able to contrast the “noisy representations” view of the phonological ‘deficit’ in dyslexia with the opposing view of Ramus and Sznovkivits that the phonological representations developed by the dyslexic brain are “normal”. We describe an initial neural approach to exploring this contrast here.

In the last 5 years, neural studies with children with dyslexia have been applying novel computational methods to EEG and MEG data to try to measure the quality of children’s phonological representations directly. These methods either use original speech features such as the envelope to predict the brain’s neuroelectric responses (forward models, from speech envelope to brain response, Di Liberto et al., 2018), or reconstruct speech-based representations of envelope information from the brain’s neuroelectric responses to speech input (backward or speech reconstruction models, from brain response to speech signal, Power et al., 2016; Destoky et al., 2020). These studies use a linear approach to stimulus reconstruction or to neural prediction, namely temporal response functions (TRFs, Di Liberto, O’Sullivan, & Lalor, 2015; Cross, Di Liberto, Bednar, & Lalor, 2016). Backward TRF models reconstruct either the envelope of the neural signal, or the envelopes in different frequency bands (such as 0.5–1.5 Hz or 2–8 Hz; Destoky et al., 2020). Such studies are still rare in the literature, and only one of them to date has used natural speech (Di Liberto et al., 2018) rather than degraded speech (vocoded speech, Power et al., 2016) or speech-in-noise (Destoky et al., 2020). Nevertheless, all studies to date show atypical low-frequency encoding of the speech signal by children with dyslexia, with speech envelope information < 10 Hz encoded reliably less accurately by dyslexic children compared to age-matched control children.

These prior TRF studies also included younger children matched for reading level to the children with dyslexia. This is an important experimental control for the effects of learning on the developing brain. It is known that learning to read in itself changes phonological representations, as orthographic knowledge gained through reading affects performance in oral listening tasks for both children and adults (Ehri & Wilce, 1980; Ziegler & Ferrand, 1998). In principle, younger reading-level-matched (RL match) children provide a control for the effects of reading experience on the developing language system. Both of the prior EEG studies using both backward and forward TRF models reported significantly greater stimulus reconstruction accuracy (Power et al., 2016) or neural response accuracy (Di Liberto et al., 2018) regarding low-frequency acoustic speech information for their RL controls compared to their dyslexic participants. Accordingly, in EEG studies the dyslexic brain shows less accurate speech encoding of low-frequency envelope information than the brains of younger children matched for reading experience, suggesting a fundamental difference in encoding certain aspects of linguistic information. The exception was the MEG study using speech-in-noise tasks, and the authors explained their null result by suggesting that discriminating speech in noise may be facilitated by learning to read (Destoky et al., 2020). If speech-in-noise performance depends on the level of reading attained, then children with dyslexia should perform at the same level as younger matched children for reading, as found by Destoky et al. (2020).

To date, therefore, data from neural TRF studies do not suggest that the phonological representations of words developed by children with dyslexia are “normal” regarding the encoding of low-frequency acoustic information. At the same time, however, it is not clear that these representations are “noisy” or “fuzzy” regarding this low-frequency information. Rather, low-frequency acoustic information in the speech signal appears to be represented less accurately in the neural mental lexicons of children with dyslexia. This suggests that speech itself may be perceived differently by children with dyslexia. Rather than being a noisy signal for the dyslexic brain, the signal itself may be represented in an atypical manner, with less accurate representation of low-frequency information (Goswami, 2022). This reduced accuracy for envelope information may possibly be compensated by an over-weighting of allophonic and other information (Bogliotti et al., 2008), which may be represented with greater specificity by children with dyslexia. It is also possible that both low-frequency envelope information in the speech signal and other speech features like voicing are represented inaccurately by the brains of children with dyslexia.

These potential differences in the encoding of different types of acoustic information can be assessed in part with psychophysical methods (Goswami, Fosker, Huss, Mead, & Szucs, 2011; Serniclaes & Seck, 2018; Serniclaes et al., 2004). For example, Goswami et al. (2011) presented a phonetic contrast (ba/da) to children with dyslexia and age-matched and RL controls, changing “ba” to “wa” either by varying amplitude rise time in synthetic syllables or by varying frequency rise time. The children with dyslexia were significantly poorer at discriminating “ba” from “wa” when the phonetic change depended on amplitude rise time, but were significantly better than both age-matched and RL controls when the phonetic change depended on frequency rise time. These differences in the encoding of acoustic information appear to impair dyslexic children’s performance in classical phonological awareness tasks while enhancing their performance in some speech-based psychophysical tasks such as categorical perception (Bogliotti et al., 2008; Serniclaes et al., 2004). These representational differences regarding speech information would also complicate the process of learning to read, since any visual symbol system that is being learned will have been designed for learners who hear speech differently from children with dyslexia. This would apply whether the visual code is an alphabetic system or any other orthographic system (see Goswami, 2022).
were then computed, and the accuracy of these models was compared developed by the children with dyslexia could not be designated as phonological representations that do not encode low-frequency acoustic information as accurately as control children, then the between-group comparison should reveal significant differences in the accuracy of the decoding models. In such a case, the phonological representations developed by the children with dyslexia could not be designated as “normal”. If children with dyslexia are encoding “noisy” or “fuzzy” representations of the speech signal, then the within-child comparison should also reveal significant differences in the accuracy of the models at the group level. The averaged within-child models of low-frequency envelope information for the children with dyslexia should be less accurate than the averaged within-child models for the control children, as the speech-based representations of this low-frequency information developed by children with dyslexia should be less consistent. To investigate these possibilities, EEG was recorded while children listened to a 10-minute story presented as audio-only. Backward TRF models were then computed, and the accuracy of these models was compared for the canonical delta, theta and alpha (control) bands using both between-group and within-child comparisons. The alpha band was utilised as a control band, as Temporal Sampling (TS) theory (Goswami, 2011) would not predict group differences for this band. In adults, alpha band oscillations are mostly related to working memory and attention, but some studies have suggested that the alpha band plays an important role in auditory processing as well regarding continuous speech perception (Dimitrijevic, Smith, Kadis, & Moore, 2017; Strauß, Wöstmann, & Obleres, 2014). In the adult literature, cortical activity in the delta band is mostly associated with prosodic, intonational and phrasal features of speech (Ding & Simon, 2014), while cortical activity in the theta band helps to identify the onsets of syllables, contributing to speech parsing (Di Liberto et al., 2015; Ding & Simon, 2014; Keshavarzi & Reichenbach, 2020; Keshavarzi, Kegler, Kadir, & Reichenbach, 2020).

For the between-group comparisons, we expected to replicate the finding in the literature that low-frequency acoustic speech information is encoded less accurately by children with dyslexia in the delta and theta bands. Regarding the “noisy” representations question, given the frequent observation that children with dyslexia appear to show no difficulties in speaking and listening tasks that do not tax phonological knowledge, it may be that the children are operating with perceptually stable phonological representations at the speech envelope level that are not “noisy” for their users.

2. Material and methods

2.1. Participants

Fifty-one children were participated in this study. Twenty-one participants were typically developing children (mean age of 109.3 ± 5.4 months) and thirty participants had developmental dyslexia (mean age of 110.7 ± 5.6 months). The unequal group sizes arose due to Covid-19, which necessitated the cessation of testing part-way through the study, thereby also preventing testing of the recruited RL control group. One of the dyslexic children only completed 5 min of the EEG session, due to lots of head movement, not listening to the story, and taking out the earphone phone during data collection. We therefore excluded this child from further analysis. The children with dyslexia did not have any additional learning difficulties (e.g., ADHD, dyspraxia, autistic spectrum disorder, developmental language disorder), and were recruited through learning support teachers. The absence of the additional learning difficulties was confirmed based on school and parental reports and our own behavioural testing. All participants had a nonverbal IQ above 84, and their first language spoken at home was English. All children received a short hearing screen across frequency range of 0.25–8 kHz (0.25, 0.5, 1, 2, 4, 8 kHz) using an audiometer, and they all were found to be sensitive to sounds within the 20 dB HL range. SES data were not formally collected, but children were attending state schools (equivalent to US public schools) situated in a range of towns and villages near a university town in the United Kingdom. Participants and their parents gave informed consent for the EEG study in accordance with the Declaration of Helsinki, and the study was approved by the Psychology Research Ethics Committee of the University of Cambridge.

2.2. Behavioural tests

A series of standardised tests (see Table 1) of written and spoken language were administered in schools prior to the EEG session to assess cognitive development (please see Keshavarzi et al., 2022, for a full description of each test; the current participants also received the repetitive speech task employed in that study). Reading and spelling were assessed using the British Ability Scales (BAS, Elliott, Smith, & McCall, 1996) and the Test of Word Reading Efficiency (TOWRE, Torgesen, Wagner, & Rashotte, 1999). Four subscales from the Wechsler Intelligence Scale for Children (WISC-V, Wechsler, 2016) including two verbal (vocabulary and similarities) and two non-verbal (block design and matrix reasoning) scales were administered. Full-scale IQ was then estimated following the approach of Aubry and Bourdin (2018). In addition, the British Picture Vocabulary Scale (BPV3S) measure was used to assess receptive vocabulary and the Phonological Assessment Battery (PhAB, Frederickson, Frith, & Reason, 1997; GL Assessment) was administered to assess phonological awareness at the rhyme and phoneme levels, along with rapid naming of objects and digits (RAN). The children’s amplitude rise time thresholds were estimated using 3 psychoacoustic threshold tasks based on (1) sine tones; (2) tones made from speech-shaped noise; (3) a synthetic syllable “ba”. As shown in Table 1, the children with dyslexia had significantly poorer reading and spelling skills than the control children, significantly poorer phonological skills, and significantly poorer amplitude rise time discrimination in

Table 1

|                          | Dyslexic | Age-Matched Control |
|--------------------------|----------|---------------------|
| N                        | 30       | 25                  |
| Age (months)             | 110.7 (5.6) | 109.3 (5.4)       |
| WISC FSIQ                | 101.7 (10.1) | 103.6 (12.0)       |
| BAS Reading SS           | 81.0 (8.0)* | 95.9 (6.2)         |
| BAS Reading Age in months| 85.5 (11.0)** | 105.6 (11.7)      |
| BAS Spelling SS          | 79.9 (7.5)** | 97.1 (6.1)         |
| TOWRE SWE SS             | 79.5 (12.8)** | 101.1 (7.7)       |
| TOWRE FDE SS             | 79.2 (10.9)** | 98.0 (8.6)        |
| PhAB Rhyme SS            | 92.6 (11.7)** | 102.4 (5.9)       |
| PhAB Phoneme SS          | 97.6 (9.8)** | 105.1 (9.4)       |
| PhAB RAN objects SS      | 91.9 (15.0)* | 101.2 (13.0)      |
| PhAB RAN digits SS       | 85.8 (15.8)** | 97.4 (13.3)       |
| Rise time sine tone ms   | 174.7 (61.7) | 139.7 (84.5)      |
| Rise time SSN ms         | 221.9 (56.7) | 215.0 (54.9)      |
| Rise time “ba” ms        | 101.5 (43.8)* | 70.8 (34.6)       |

Note: *p < 0.001; **p < 0.01; *p < 0.05; p = 0.052. WISC FSIQ = Wechsler Intelligence Scale for Children, estimated Full Scale IQ; BPVS = British Picture Vocabulary Scales; SS = standardised mean score = 100; BAS = British Ability Scales, SS = standardised score = 100; TOWRE SWE = Test of Word Reading Efficiency; SS = standardised score = 100; TOWRE PDE = Phon Decoding Efficiency Scale, SS = standardised score = 100; PhAB = Phonological Awareness Battery; SS = standardised mean score = 100; RAN = Rapid Automated Naming; Rise time = threshold in rise time task in ms; SSN = speech-shaped noise.
a synthetic syllable task (discriminating differences in rise time of the syllable “ba”).

2.3. Experimental set-up and stimuli

The children were seated in an electrically shielded soundproof room. The auditory stimuli (through earphones) were presented at a sampling rate of 44.1 kHz to the participant while EEG data were collected at a sampling rate of 1 kHz using a 128-channel EEG system (HydroCel Geodesic Sensor Net). The stimuli were natural speech presented as a 10-minute long story for children, *The Iron Man: A Children’s Story in Five Nights* by Ted Hughes. The story was read in child-directed speech and was presented in ten sections, each of which lasted about one minute followed by a 2 s gap. During the experiment, participants were instructed to listen to the speech carefully and to look at a red cross (+) shown on the screen that was in front of them.

2.4. Auditory stimuli and EEG data pre-processing

In this study, we first obtained the broad-band envelopes by calculating the absolute value of the analytical signal of the speech stimuli. The broad-band envelopes were then filtered at frequency range of 0.5–8 Hz to extract the low frequency envelopes. The low frequency envelopes were used for the analyses used here.

The collected EEG data were referenced to Cz channel and then band-pass filtered into frequency range of 0.5–48 Hz using a zero phase FIR filter with low cutoff (–6 dB) of 0.25 Hz and high cutoff (–6 dB) of 48.25 Hz (EEGLab Toolbox; Delorme & Makeig, 2004). Bad channels were detected and interpolated through spherical interpolation (EEGLab Toolbox). The EEG data were downsampled to 100 Hz and filtered to extract delta (0.5–4 Hz), theta (4–8 Hz) and alpha (8–12 Hz) frequency bands. The data were further downsampled to 50 Hz to reduce the computational costs, and then epoched into the 1-minute story parts.

2.5. Stimulus reconstruction using backward TRF model

To investigate how accurately the children were encoding the low-frequency information in the speech signal, we used a decoding accuracy method based on the backward TRF model (Crosse et al., 2016). Given the focus of TS theory on the envelope, and given that the speech envelope carries the most critical low-frequency acoustic information aiding linguistic decoding, the speech envelope was chosen as the decoding target in our study. The TRF model was used to reconstruct the stimuli envelopes from the EEG signals at each frequency band. For each frequency band of interest (delta, theta, alpha), we used a randomly-selected subset of control children ($C_{train} = 11$) for training 11 backward TRF models. A final model was obtained by averaging across all 11 individual trained models. This final averaged model was then tested separately on the rest of the control children ($C_{test} = 10$) and on the 29 dyslexic children. We next computed the mean correlation values for the tested control children and the dyslexic children, resulting in a single value for each group (control, dyslexic). This procedure was then repeated 100 times, using random permutations across all the control children, in order to use different combinations of 11 versus 10 ($C_{train}$ and $C_{test}$) control children for training and testing the model, resulting in 100 normative (averaged) models. Accordingly, 100 correlation values were generated for the control children and 100 correlation values were generated for the dyslexic children, providing an averaged correlation value for each group. This then enabled us to assess whether there were differences in speech decoding accuracy regarding low-frequency envelope information between children with dyslexia and age-matched controls. In essence, the reconstruction accuracy for the typically-developing children was utilised as a benchmark to compare with the reconstruction accuracy obtained for the dyslexic children. Fig. 1 provides a schematic diagram of the analytic approach used for the between-group backward TRF analysis.

2.7. Within-child backward TRF analysis

To discover whether the perceptual experience of low-frequency envelope information in the speech signal is consistent (or stable) for any individual child, we also built a single backward TRF model for each child in the study based on the data from that child. This within-child approach enabled us to assess whether the speech-based representations developed by children with dyslexia are less consistent, “fuzzy” or “noisy” for each frequency band of interest. This was achieved by using 80% of the data (eight story sections) for each child to train the TRF model for that child, and then using the remaining data from that child (two story sections) to test the model. We calculated the Pearson correlation between the estimated speech envelope and the actual speech envelope for each child separately for each frequency band. This resulted in a single correlation score for each band for each child. These scores were then summed by group for each band and compared between groups. Fig. 2 provides a schematic diagram of the analytic approach used for the within-child backward TRF analysis.

We also applied the Wilcoxon rank sum test to compare the ridge parameter values for the within-child model between the control and dyslexic groups separately for the three frequency bands. The results showed that there was no significant difference between the two groups for all three bands (Wilcoxon rank sum test; delta, $z = -1.34, p = 0.18$; theta, $z = 0.71, p = 0.48$; alpha, $z = -0.68, p = 0.50$).

2.8. Computation of the chance level for backward TRF

To check the statistical significance of stimulus reconstruction accuracy as estimated by the backward TRF models (both between-group and within-child), we computed null models for each frequency band of
interest. To obtain the null models, we randomly selected ten control children and EEG data were permuted across different story sections for each child. We then built a single model for each child. To achieve this, 80% of the data for each child were used to train the null model for that child, and the remaining data were used to test the null model. The Pearson correlation between the estimated speech envelope and the actual speech envelope for each child separately for each frequency band was then calculated for these null models, resulting in a single correlation value for each band and for each child. We finally computed the mean reconstruction accuracy by averaging across the accuracy scores obtained for the selected children. This was done 100 times for each band, in order to calculate the probability density functions (PDF, a statistical measure that determines the probability distribution of a variable) for the null models and thereby establish chance levels. Note that the area under the PDF curve should be 1, hence for our data the smaller the range of Pearson correlations on the x axis, the higher the value required for the PDF on the y axis.

3. Results

3.1. Does the accuracy of speech envelope decoding vary between control and dyslexic children?

To investigate whether the accuracy of speech envelope decoding estimated from EEG recorded from the dyslexic brain is different from that recorded from the typically-developing brain, the Between-Group Backward TRF analysis (see Section 2.6) was applied separately for each frequency band. To check the statistical significance of the stimulus reconstruction accuracy obtained for each frequency band by group, we first compared decoding accuracy in each band to decoding accuracy for the null models (the estimate of chance level for each band, see Section 2.8). Statistical significance by band and group is shown in Fig. 3. The modelling showed that stimulus-reconstruction accuracy was significantly greater than chance in the delta band only (Fig. 3A). Reconstruction accuracy in the theta and alpha bands was not statistically different from the noise values in these bands for either group (Fig. 3B, C).

To compare the accuracy of decoding between the control and dyslexic groups in the delta band, we applied the Wilcoxon rank sum test. This showed that reconstruction accuracy for the control group in the delta band as derived from 100 TRF models was significantly greater than reconstruction accuracy for the dyslexic group (Wilcoxon rank sum test, \( z = 3.72, p = 0.0002 \)). This difference in speech envelope decoding suggests that control brains encode a more accurate neural representation of the speech envelope in the delta band compared to dyslexic brains, as shown in Fig. 4.

3.2. Do children with dyslexia develop “Noisy” representations of low-frequency information in speech?

To explore whether children with dyslexia have “noisy” or “fuzzy” representations of the low-frequency envelope information in the speech

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**Fig. 1.** Schematic diagram for the model used for the between-group analysis. Panel A shows the procedure used to train the model and panel B shows the procedure applied to test the model. \( P_{ci} (i = 1, 2, \ldots, 21) \): the \( i \)th control participant; \( P_{di} (i = 1, 2, \ldots, 29) \): the \( i \)th dyslexic participant; \( r_{ci} (i = 12, 13, \ldots, 21) \): decoding accuracy for the \( i \)th control participant; \( r_{di} (i = 1, 2, \ldots, 29) \): decoding accuracy for the \( i \)th dyslexic participant.

**Fig. 2.** Schematic diagram for the model used for the within-child analysis. Panel A shows the procedure used to train the model and panel B illustrates the procedure applied to test the model. \( P_{ci} (i = 1, 2, \ldots, 21) \): the \( i \)th control participant; \( P_{di} (i = 1, 2, \ldots, 29) \): the \( i \)th dyslexic participant; \( r_{ci} (i = 1, 2, \ldots, 21) \): decoding accuracy for the \( i \)th control participant; \( r_{di} (i = 1, 2, \ldots, 29) \): decoding accuracy for the \( i \)th dyslexic participant.
signal, the Within-Child Backward TRF analysis method (see Section 2.7) was employed separately for each frequency band. The statistical significance of the stimulus reconstruction accuracy obtained for each frequency band for the within-child analyses was computed by considering chance level for that band (the null models, see Section 2.8). Comparisons with the null models showed that stimulus-reconstruction accuracy was above chance-levels ($\alpha = 0.05$) for both groups in all three frequency bands (Fig. 5).

Fig. 6 shows the box plots for stimulus reconstruction accuracies for the control and dyslexic groups based on the backward TRF models from individual children (shown as dots) by band, separated by group. To compare reconstruction accuracy between the two groups, we employed the Wilcoxon rank sum test. The results by band showed that there was no difference between the two groups in any band (delta band, Fig. 6A; Wilcoxon rank sum test, $z = -0.59$, $p = 0.55$; theta band, Fig. 6B; Wilcoxon rank sum test, $z = -1.30$, $p = 0.19$; alpha band, Fig. 6C; Wilcoxon rank sum test, $z = -0.81$, $p = 0.42$). We also applied Bayesian factor analysis to quantify the strength of the evidence for the alternative model. Bayesian factor analysis estimates the strength of the evidence for the alternate hypothesis $H_1$ that the groups differ in their stimulus reconstruction accuracy over the null hypothesis $H_0$ that they do not. The results indicated greater evidence in favour of the null model for all three bands (Bayesian factor analysis; delta band, $BF_{10} = 0.2$; theta band, $BF_{10} = 0.9$; alpha band, $BF_{10} = 0.3$). Accordingly, as shown in Fig. 6, the backward TRF model can reconstruct the stimulus envelopes for each individual child in each band consistently from that child’s EEG data. Furthermore, this envelope information is reconstructed above chance levels for each individual child in all three bands, in contrast to the reconstruction consistency achieved for the between-group analysis, in which decoding accuracy was only above chance for both groups of children in the delta band condition (Fig. 5). The within-child group comparisons (Fig. 6) show that the consistency of decoding accuracy is always above chance, and is not statistically different irrespective of whether the child is a child with dyslexia or a control child. The modelling indicates that the neural representation of the low-frequency envelope information in the speech signal for each child is consistent for that child, providing them with a stable percept of this aspect of speech.

4. Discussion

Here we employed backward TRF models to estimate stimulus reconstruction accuracy of bands of low-frequency acoustic information in the speech signal (delta- and theta-band speech envelope information) along with alpha-band speech envelope information (control band) in children with and without dyslexia matched for age. Two different group comparison approaches (between-group and within-child) were employed to investigate whether the speech-based representations for low-frequency envelope information being developed by the dyslexic brain were “noisy” or “normal”. If decoding accuracy varies by group for the between-group TRF models, then the speech-based representations of low-frequency acoustic information developed by children with developmental dyslexia cannot be considered “normal”. However, if decoding accuracy is equal irrespective of group for within-child TRF models, then the speech-based representations of low-frequency
envelope information developed by children with developmental dyslexia cannot be considered “noisy”. The modelling suggested that the dyslexic brain does not develop “noisy” representations of low-frequency envelope information, but neither are these representations “normal”. The between-group models showed that the speech-based representations developed by children with dyslexia were less accurate than the speech-based representations developed by children without dyslexia regarding low frequency envelope information. These differences were restricted in the current study to the delta band (Fig. 4). The between-group modelling generated lower decoding accuracies than the within-child modelling, as can be seen by comparing the correlation values in Figs. 4 and 6. Between-group decoding accuracy for the theta and alpha bands did not exceed chance levels as estimated by the null models. Therefore, the conservative conclusion is that encoding of low-frequency speech information in the delta band is atypical in 9-year-old children with developmental dyslexia.

At the level of an individual child, however, the modelling did not support the classical theoretical view (including our own earlier view, see Swan & Goswami, 1997) that the phonological representations of speech developed by children with dyslexia are “fuzzy”, “noisy” or “imprecise” (see also Elbro et al., 1998; Snowling, 2000). Although we only decoded the low-frequency envelope information in speech, the quality of the speech-based representations for each child as indexed by the neural decoding method were similar consistency whether the child was dyslexic or not, for all frequency bands explored. This finding suggests that even if acoustic information is weighted differently in the speech-based representations developed by children with dyslexia, the experience of speech processing regarding low-frequency envelope
information is perceptually stable for the children themselves. Never-
theless, a linear decoding approach to stimulus reconstruction is only
one method for assessing whether neural stimulus representations of
low-frequency envelope information are “noisy” or not, and converging
neural methods are required. Furthermore, the question of whether
other features of the speech signal such as voicing may be represented in
a “noisy” manner by the dyslexic brain is not addressed by our data.

The delta-band between-group difference in decoding accuracy found
here was predicted by TS theory (Goswami, 2011, 2019), which
provided the conceptual framework for the current study. TS theory has
proposed that dyslexic difficulties in discriminating amplitude envelope
rise times, difficulties found for dyslexic children in 7 languages to date
(see Goswami, 2015, for a review), are associated with atypical neural
encoding of acoustic information within the amplitude envelope < 10
Hz, related to perceptual impairments in processing speech rhythm. Rise
times are one neural trigger for oscillatory phase-resetting, an automatic
process that aids multi-timescale speech-brain cortical tracking in adults
(Doelling, Arnal, Ghita, & Poeppel, 2014; Giraud & Poeppel, 2012;
Lizarazu, Lallier, Bourguignon, Carreiras, & Molinaro, 2021). A recent
MEG study with adults with dyslexia has shown that rise times do not
provide an efficient phase-resetting mechanism in the dyslexic brain
during natural speech listening (Lizarazu et al., 2021). The between-
group data presented here suggest that this inefficient phase-resetting
may particularly affect the encoding of speech envelope information in
the delta band during childhood. This delta-band information is a
critical feature of the speech signal.

The current study has several limitations. As already noted, the
quality of dyslexic children’s speech-based representations for features
other than the envelope is not addressed by our backward decoding
method. Further, although the backward TRF model has been used as
the most popular model for decoding stimulus information from neural
responses, it has some general limitations. Firstly, the model assumes a
linear relationship between the input stimuli and the neural responses.
Secondly, the performance of model when generalising to unseen testing
data sets depends on the estimate of large number of unknown param-
eters and on the size of the data used for training the model. It should be
noted that the forward TRF model also has these two latter limitations.
However, many adult studies focus on backward (decoding) models, as
they have several advantages over forward (encoding) models, as
described by Crosse et al. (2016).

In conclusion, the current study converges with the three preceding
studies of children with dyslexia that measured speech-based repre-
sentations directly using neural methods (Destoky et al., 2020; Di Lib-
erto et al., 2018; Power et al., 2016). These studies all reported that
children with dyslexia show atypical encoding of low-frequency infor-
mation in the speech amplitude envelope. Together with the current
study, these studies suggest that the speech-based representations
developed by children with dyslexia for low-frequency envelope informa-
tion < 10 Hz are not “normal”, supporting TS theory. Our results
(Between-Group analysis; see Section 3.1) suggested that children with
dyslexia encode less accurate prosodic (delta band) speech-based in-
formation in their phonological representations for words in comparison
to typically-developing children. TS theory proposes that these differ-
ences in encoding low-frequency envelope information affect phono-
logical awareness at all linguistic levels via the linguistic hierarchy,
which is governed by the prosodic level, and that this then impacts the
process of learning to read and spell. At the same time, the current study
corrects a novel child-by-child neural decoding approach that reveals
that the perceptual world of the dyslexic child regarding low-frequency
envelope information in speech is a consistent one. At the level of the
individual child, the speech-based representations of low-frequency
envelope information developed by children with dyslexia are not
“fuzzy” or “noisy”. This finding contributes to a long-standing debate in
the psycholinguistic literature regarding whether the phonological
‘deficit’ that characterises individuals with dyslexia across languages
stems from differences in phonological representation or in
phonological access (e.g., Adlard & Hazan, 1998; Elbro et al., 1998;
Manis et al., 1997; Mody et al., 1997; Serniclaes et al., 2004; Bogliotti
et al., 2008; Snowling, 2000; Ramus & Sznukovits, 2008). The neural
decoding method employed here suggests that differences in phono-
logical representation are indeed present for low-frequency speech in-
formation. This conclusion accords well with the linguistic data
gathered by recent longitudinal studies of infants at family risk for
developmental dyslexia, who show amplitude rise time discrimination
difficulties from age 10 months as well as poorer early word learning
and poorer phonological development (Kalashnikova, Goswami,
& Burnham, 2018; Kalashnikova, Goswami, & Burnham, 2019a; Kalash-
nikova, Goswami, & Burnham, 2019b; Kalashnikova, Goswami, &
Burnham, 2020). Nevertheless, the strongest test of this conclusion
about phonological representations would be a demonstration that
speech production is also atypical in dyslexia regarding the specification
of speech prosody. If speech prosody is not encoded accurately in the
dyslexic brain, yet this atypical encoding is consistent and perceptually
stable for the child, then speech output of prosodic information should
also be affected.

CRediT authorship contribution statement

Mahmoud Keshavarzi: Conceptualization, Methodology, Visualiza-
tion, Formal analysis, Writing – original draft. Kanad Mandke:
Methodology, Investigation, Writing – review & editing. Annabel
Macfarlane: Investigation, Data curation. Lyla Parvez: Investigation.
Fiona Gabrieleczyk: Investigation, Data curation. Angela Wilson:
Investigation, Data curation. Sheila Flanagan: Investigation, Writing –
review & editing. Usha Goswami: Conceptualization, Funding acquis-
tion, Methodology, Resources, Supervision, Writing – original draft.

Declaration of Competing Interest

The authors declare that they have no known competing financial
interests or personal relationships that could have appeared to influence
the work reported in this paper.

Data availability

Data will be made available on request.

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