# Neural processing of natural speech by children with developmental language disorder (DLD): EEG speech decoding, power and classifier investigations

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## Highlights

- Cortical decoding accuracy for speech envelope information < 10 Hz is intact in DLD.
- Children with DLD show greater EEG power in delta, theta, and low gamma frequencies.
- Low-gamma EEG power yields the best DLD classification performance (AUC = 0.81).


## Abstract

The sensory/neural Temporal Sampling (TS) theory of developmental language disorder (DLD) is based on the sensory and linguistic impairments in rhythm processing that are found in children with both developmental dyslexia (DD) and DLD. These sensory/linguistic impairments include decreased sensitivity to amplitude rise times (ARTs), syllable stress patterns and speech rhythm. They are explained via a neural oscillatory speech processing framework drawn from the adult literature. Notably, at the neural level TS theory predicts impairments in the cortical tracking of different rates of amplitude modulation (AM) in the speech signal <10Hz. To date, the accuracy of low-frequency cortical tracking in natural continuous speech has not been measured in children with DLD. Here, EEG was recorded during story listening from children with and without DLD aged around 9 years, and decoding analyses in the delta, theta and alpha (control) bands were carried out. EEG power was computed in the delta, theta and gamma bands, as was phase-amplitude versus phase-phase coupling (PAC, PPC) between bands. The expectation that the accuracy of low-frequency decoding (delta, theta) of the speech signal would be impaired in DLD was not supported. Further, theta-delta and theta-gamma PAC were not atypical, contrary to prediction. EEG power in all bands was elevated for the DLD group, however. Receiving-operator-characteristic (ROC) curves estimated using support vector machine and logistic regression showed that these simple band power measures provided classifier models with the highest areas under the curves (AUC). The data are discussed using TS theory.

## Keywords

Developmental language disorder, EEG, speech decoding, backward mTRF, band-power, classification

## 1. Introduction

The potential sensory/neural causes of developmental language disorder (DLD) are poorly understood. Children with DLD show language difficulties that cause functional impairments in many aspects of linguistic processing, yet to date there is no agreed biomedical aetiology. For example, the CATALISE multi-national study of DLD identified linguistic processing problems with syntax, such as distinguishing grammatical from ungrammatical sentence forms, problems with word semantics, such as showing a limited understanding of word meanings, impairments in verbal short-term memory, and difficulties with phonology (Bishop et al., 2017). Given this wide range of impairments, the underlying biomedical aetiology seems likely to affect fundamental sensory/neural aspects of processing the speech signal. One prior avenue of interest has been whether hemispheric asymmetries during linguistic processing may be important in aetiology (Bishop, 2013). Using fMRI, it has been shown that left frontal and temporal cortical areas show reduced activation in DLD children during language processing (Asaridou and Watkins, 2022, for review). However, the fMRI findings do not demonstrate which speech processing mechanisms may be affected, and indeed laterality differences per se do not seem as fundamental as once thought (Parker et al., 2022). Prior MEG studies of DLD using speech processing tasks are consistent with the fMRI literature in that they demonstrate atypical left hemisphere function, particularly in temporal regions (Helenius et al., 2009, 2014). Again, however, these MEG demonstrations have not provided mechanistic information about aetiology at the biomedical level.

By contrast, the Temporal Sampling (TS) theory of childhood language disorders, originally proposed on the basis of experimental data from children with developmental dyslexia (DD, Goswami, 2011), does enable predictions concerning aetiology. TS theory builds on recent mechanistic advances in the neuroscience of speech processing, specifically the oscillatory framework proposed by Giraud and Poeppel (2012), which offers new opportunities

for understanding developmental language disorders like DD and DLD (Goswami, 2011, 2015, 2022). Regarding DLD, TS theory utilises acoustic parameters of the speech signal related to processing speech rhythm and prosody, such as amplitude (loudness) and frequency (pitch) modulation (AM, FM). AM and FM changes in the continuous speech signal characterise all languages, and the processing of rhythm has been shown to be impaired in children with DLD in a range of languages (Corriveau et al., 2007; Corriveau & Goswami, 2009; Przybylski et al., 2013; Cumming et al., 2015; Richards & Goswami, 2015, 2019; Sallat & Jentschke, 2015; Bedoin et al., 2016). Indeed, sensitivity to speech rhythm is thought to be a cross-language precursor of language acquisition by infants (Mehler et al., 1988; Nazzi et al., 1998). Furthermore, speech rhythm patterns in the continuous speech signal are cued by amplitude rise times (ARTs; Greenberg et al., 2003), and children with DLD exhibit impaired discrimination of ART in non-speech tasks (Corriveau et al., 2007; Fraser et al., 2010; Beattie & Manis, 2012; Cumming et al., 2015; Richards & Goswami, 2015, 2019). To date, however, ART studies have only been carried out in English-speaking children with DLD.

To explain the speech rhythm impairments that characterise children with DLD, TS theory has proposed that sensory/neural impairments in the cortical tracking of low-frequency AM rates < 10 Hz (known to carry information about prosody, see Goswami, 2011; Greenberg, 2006), already known to characterise children with DD (Goswami, 2022, for recent review), may also characterise children with DLD. A key focus of TS theory is the different bands of low-frequency AMs that are nested within the speech amplitude envelope (AE) of child-directed and infant-directed speech, particularly bands of AMs centred on ~2 Hz and ~5 Hz (corresponding to the EEG delta and theta bands, 0.5-4 Hz and 4-8 Hz respectively; see speech modelling studies by Leong & Goswami, 2015; Leong et al., 2017). These different AM bands underpin both rhythm perception and neural speech encoding across languages (Daikoku & Goswami, 2022, for review). Meanwhile, the speech modelling studies of infant- and child-

directed speech (IDS, CDS) show that *phase relations* between these bands of AMs (bands centred on ~2Hz and ~5Hz) enable the parsing of phonological information at the prosodic and syllabic levels ('acoustic-emergent phonology', see Leong & Goswami, 2015; Leong et al., 2017). Accordingly, the accurate cortical tracking of delta- and theta-band speech information and phase-phase coupling during infancy and early childhood may support the development of an emergent linguistic system (Leong et al., 2017). By TS theory, prosodic learning in all languages may be related to AM-based speech encoding mechanisms that are present from birth, with the accuracy of encoding lower frequencies <10 Hz of particular developmental importance (Goswami, 2022). Low-frequency speech-brain cortical tracking is already measurable in infancy (Kalashnikova et al., 2018; Jessen et al., 2019; Ortiz Barajas et al., 2021; Attaheri et al., 2022; Menn et al., 2022).

Regarding DLD therefore, by TS theory neural encoding of low-frequency speech envelope information would be expected to be impaired in children with DLD. To our knowledge, the fidelity of the cortical tracking of continuous speech by oscillatory neural networks has yet to be investigated in children with DLD. This is surprising, as studies of the cortical tracking of continuous speech by children with DD are frequent in the literature, using both EEG and MEG approaches (Power et al., 2016; Molinaro et al., 2016; Di Liberto et al., 2018; Destoky et al., 2020, 2022; Keshavarzi et al., 2022a; Mandke et al., 2022). In these DD studies, the cortical tracking of speech by children with dyslexia was selectively impaired in frequency bands below 10Hz, supporting TS theory. Affected children in English, French and Spanish all showed decreased speech-brain synchronisation in the delta (and sometimes theta) bands, in both sentence listening and story listening tasks. Furthermore, longitudinal TS-driven studies of infant language acquisition show that the accuracy of cortical tracking of continuous speech in the delta band measured at 11 months is a significant predictor of language outcomes at 2 years (Cambridge BabyRhythm study, Attaheri et al. 2024). The Cambridge BabyRhythm

study included 120 TD infants, and also reported that the accuracy of theta-gamma phase-amplitude coupling (PAC) to continuous speech was a second predictor of enhanced language outcomes. Meanwhile, infants exhibiting higher theta power (power spectral density, PSD) and a higher theta/delta ratio during continuous speech listening had worse language outcomes (Attaheri et al., 2024). These prior TS-driven developmental data suggest that children with DLD might be expected to have poorer delta band cortical tracking of continuous speech, excessive theta power when listening to continuous speech, and worse theta-gamma PAC.

Oscillatory EEG and MEG studies with children with DLD are beginning to appear in the literature, but to date these studies have not utilised continuous speech stimuli such as sentences or stories. Instead, current studies rely on paradigms using single words or speech features within words (such as target phonemes), or even nonspeech stimuli or no task. Prior resting state studies may be indicative of oscillatory differences that are related to language development. For example, Lum et al. (2022) reported a negative correlation between resting state power in the theta band and TD children's scores on the Clinical Evaluation of Language Fundamentals (CELF; Wiig et al., 2017) Recalling Sentences task, which is a diagnostic measure of DLD in English. No other associations between CELF scores and oscillatory power were found. Theta band resting state findings were also reported in a study with TD Chinese-speaking children, who were aged around 10 years (Meng et al., 2022). Meng et al. reported that resting state theta power was negatively associated with a vocabulary subtest of the Wechsler Intelligence Scale for Children (Vocabulary Definitions subtest). Accordingly, resting state studies are suggestive of enhanced oscillatory power in TD children with poorer language development. In an MEG study with DLD children aged 10-15 years, the first (to our knowledge) oscillatory study of word listening reported atypical oscillatory responses compared to age-matched typically-developing (TD) children (Nora et al., 2024). Nora et al. reported that early cortical decoding (100 ms latency) of individual words in Finnish did not

differ between children with DLD and TD children, for either amplitude envelope or speech spectrogram measures. However, at longer latencies (at ∼200-300 ms lags) the data from the children with DLD showed poorer cortical representation of the AE information. Impaired representation of the AE is consistent with TS theory. This finding was interpreted by Nora et al. (2024) as reflecting poorer retention of acoustic–phonetic information in short-term memory, consistent with the verbal memory problems that characterise children with DLD across languages.

The oscillatory framework that motivated TS theory (Giraud & Poeppel, 2012) also identifies speech-brain synchronisation at faster rates such as beta (~15-25Hz) and gamma (> 30 Hz). In the Giraud and Poeppel framework, phonemic information in the speech signal is encoded neurally by gamma band responses (Lehongre et al., 2011, 2013). Phonemic representation in DLD is known to be impaired from nonword repetition studies, in which affected children make phoneme-level errors when repeating nonwords such as 'loddernapish' and 'fenneriser'. Interestingly, *prospective* studies of infants at potential family risk for language disorders indicate that resting state power in the faster gamma band is associated with later DLD. These studies all used non-speech stimuli such as pairs of tones (Benasich et al., 2008; Choudhury and Benasich, 2011; Gou et al., 2011; Cantiani et al., 2016, 2019). Some of these infant studies also measured resting state theta power, which was not found to predict later language outcomes (Cantiani et al., 2016). Accordingly, the oscillatory infant and child data available to date, which are primarily resting state data, appear to identify at least two neurophysiological frequency bands as potentially atypical in DLD, the gamma band in infancy and the theta band in childhood. However, as none of these infant studies involved linguistic processing, these studies cannot provide a test of the TS framework.

One exception to the DLD field's reliance on single word or nonspeech paradigms is a TS-driven oscillatory EEG study that used a story listening task (Araújo et al., 2024). Araújo

et al. reported that children with DLD aged on average 9 years had significantly greater delta-theta PAC compared to TD children during natural speech listening. This may suggest that low-frequency oscillatory dynamics are atypical in the DLD brain during natural speech listening. However, only 7 children with DLD were in tested this study. A further TS-inspired EEG study conducted with the same 9-year-old children tested here measured neurophysiological responses to rhythmic speech (repetition of the syllable "ba" at a 2 Hz repetition rate) (Keshavarzi et al., 2024a). When administered to children with DD, the rhythmic speech paradigm reliably reveals an atypical preferred phase in the delta band (Power et al., 2013; Keshavarzi et al., 2022b). This could be suggestive of the DD brain encoding a less-accurate representation of low frequency envelope information. Accordingly, by TS theory a similar delta-band impairment could be anticipated in DLD. However, the participants with DLD did not show atypical preferred phase in the delta band. Instead, they showed enhanced theta and low gamma band power during the entrainment period, with significantly greater power than the TD control children. Further, when group differences (DLD vs TD) in resultant phase were computed in exploratory analyses, theta-low gamma resultant phase differed significantly between groups, as did delta-low gamma phase, suggestive of atypical low frequency-high frequency oscillatory dynamics. These data suggest that group differences (DLD vs TD) in oscillatory encoding of rhythmic speech occur both in the power domain and also when low-frequency phases have to synchronise with high-frequency gamma responses. This is suggestive of a different underlying relationship between low-frequency phase and high-frequency phase during speech listening in the DLD brain, at least when rhythmic speech is the input signal.

In the current EEG study, we measured cortical tracking of low-frequency speech information during a story listening task, computing backward multivariate temporal response functions to assess cortical tracking (mTRFs, see Crosse et al., 2016). On the basis of TS theory,

we predicted impaired decoding of envelope information < 10 Hz (delta and theta bands), H1. We also assessed both power and phase relationships between bands. On the basis of prior TS-driven studies described above (Araújo et al., 2024; Keshavarzi et al., 2024a) and the available resting state oscillatory literature with infants and children (Benasich et al., 2008; Choudhury and Benasich, 2011; Gou et al., 2011; Cantiani et al., 2016, 2019; Meng et al., 2022, Lum et al., 2022), we predicted greater theta and gamma power in DLD (H2), and atypical delta-theta and theta-gamma PAC (H3, Attaheri et al., 2024; Araujo et al., 2024). Finally, given the resultant phase data reported by Keshavarzi et al. (2024a) for rhythmic speech, we also tentatively predicted differences in delta-gamma and theta-gamma PPC for the children with DLD (H4).

## 2. Methods and Material

### *2.1. Participants*

Sixteen typically developing children (TD control group, mean age of 9.1 ± 1.1 years) and sixteen children with DLD (mean age of 9 ± 0.9 years) took part in the study. All participants were taking part in an ongoing study of auditory processing in DLD (Keshavarzi et al., 2024a), and those children with suspected language difficulties were nominated by the special educational needs teachers in their schools. Children in the TD group were nominated by classroom teachers as being typically-developing. All children had English as the main language spoken at home. All participants exhibited normal hearing when tested with an audiometer. In a short hearing test across the frequency range 0.25 – 8 kHz (0.25, 0.5, 1, 2, 4, 8 kHz), all children were sensitive to sounds within the 20 dB HL range. Language status was ascertained by a trained speech and language therapist (the second author), who administered two subtests of CELF-V (Wiig et al., 2017) to all the participants: recalling sentences and formulating sentences. Those children who appeared to have language difficulties then received

(depending on age) two further CELF subtests drawn from word structure, sentence comprehension, word classes and semantic relationships. Children who scored at least 1 S.D. below the mean (7 or less when the mean score is 10) on at least 2 of these 4 subtests were included in the DLD group. Oral language skills in the control children were thus measured using only two CELF tasks, recalling sentences and formulating sentences, and all TD control children scored in the normal range (achieving scores of 8 or above). Due to the Pandemic, although all 16 control children received the recalling sentences task, only 11 also received the formulating sentences task (all children with DLD received 4 CELF tasks). The Picture Completion subtest of the Wechsler Intelligence Scale for Children (WISC IV, Wechsler, 2016) was used to assess non-verbal intelligence (NVIQ) and did not differ significantly between groups. Group performance for the tasks administered to both groups is shown in Table 1. All participants and their parents provided informed consent to participate in the EEG study, in accordance with the Declaration of Helsinki. The study was reviewed by the University of Cambridge, Psychology Research Ethics Committee and received a favourable opinion.

**Table 1.** Details of the participating children, showing Scaled Scores (ScS, population mean = 10) and Standard Scores (SS, population mean = 100).

| | DLD | TD Controls | Significance |
|---|---|---|---|
| N | 16 | 16 | – |
| Age (months) | 108.3 (11.3) | 108.9 (13.3) | 0.585 |
| Recalling Sentences ScS | 5.3 (1.7) | 10.9 (2.3) | 0.0001 |
| Formulating Sentences ScS | 4.4 (1.9) | 10.8 (1.7) | 0.0001 |
| WISC Picture Completion ScS | 7.9 (3.0) | 9.9 (2.8) | 0.075 |

Note. WISC: Wechsler Intelligence Scale for Children.

*2.2. Experimental set-up and stimuli*

The experimental setup and stimuli utilised in the EEG study were identical to those used in a prior TS-driven study of children with DD, please see Keshavarzi et al. (2022a). The

participants listened to a 10-minute story for children, *The Iron Man: A Children's Story in Five Nights* by Ted Hughes. During the experiment, participants were instructed to listen to the speech carefully and to look at a red cross (+) shown on the computer screen. The sampling rate was 44.1 kHz for presenting the auditory stimulus, and EEG data were concurrently collected at a sampling rate of 1 kHz using a 128-channel EEG system (HydroCel Geodesic Sensor Net). To ensure the children attended to the task, they were informed beforehand that they would be asked two simple comprehension questions after the story. We assessed the correct scores on the two comprehension questions administered after the story-listening paradigm. Comprehension was assessed by scoring these two questions, with possible scores ranging from 0 to 2. Mean scores (± SD) were 1.9 ± 0.3 and 1.81 ± 0.4 for TD and DLD groups, respectively. A Wilcoxon rank-sum test revealed no significant difference between the groups ($z = 0.45$, $p = 0.65$), indicating that comprehension performance was comparable.

*2.3. Auditory stimuli and EEG data pre-processing*

We initially obtained the broad-band envelope by computing the absolute value of the analytical signal from the speech stimuli. Subsequently, the broad-band envelope was then band-pass filtered within the frequency range of 0.5–8 Hz. This low-frequency envelope was then utilised for the analyses conducted in this study. The EEG data were referenced to the Cz channel and subsequently band-pass filtered within a frequency range of 0.5–48 Hz. This filtering was accomplished using a zero-phase FIR filter with a low cutoff (-6 dB) at 0.25 Hz and a high cutoff (-6 dB) at 48.25 Hz (EEGLab Toolbox; Delorme and Makeig, 2004). Bad channels were identified manually by visually inspecting both the spectral and temporal characteristics of the channel signals and interpolated through spherical interpolation (EEGLab Toolbox). We also applied the independent component analysis provided in EEGLab Toolbox for each participant. The obtained independent components were then evaluated carefully to remove artefactual components. After preprocessing, EEG data were downsampled to 100 Hz

for subsequent analyses. For PPC and PAC analyses, band-pass filtering was applied using the MNE-Python library to extract delta (0.5–4 Hz), theta (4–8 Hz), and low gamma (25–40 Hz) frequency bands. For decoding-related computations, MATLAB was used to implement filtering, and subsequent downsampling to 50 Hz was carried out to mitigate computational costs only for decoding analyses.

*2.4. Computation of band-power*

To investigate the power of neural response over the entrainment period used for analysis, we calculated the power of EEG responses for each child and group through a four-step process: (1) Individual EEG channel power calculation using the *pspectrum*() function in MATLAB, applying Welch's method (Welch, 1967); (2) Power calculation by averaging across channel power values from step 1; (3) Participant power calculation by averaging across power values from step 2 for each participant; (4) Group power calculation by averaging across power values from step 2 for all children within each group.

*2.5. Computation of cross frequency PAC*

Cross frequency PAC refers to the modulation of the amplitude of the signal in a high frequency band by the phase of a low frequency oscillation. Here we quantified the strength of this type of modulation using the modulation index (*MI*; Tort et al. 2008):

$$MI = \frac{KL\,(U,X)}{logB} \qquad (1)$$

where $B$ (=18) is the number of bins, $U$ refers to the uniform distribution, $X$ is the distribution of the data, and $KL\,(U,X)$ is Kullback–Leibler distance which is calculated as:

$$KL\,(U,X) = logB - H(P) \qquad (2)$$

where $H(.)$ is the Shannon entropy and $P$ is the vector of normalized averaged amplitudes per phase bin which is calculated as:

$$P(j) = \frac{\bar{a}}{\sum_{k=1}^{N} \bar{a}_k} \quad , \quad j = 1, \ldots, N \qquad (3)$$

where $\bar{a}$ is the average amplitude of each bin, $k$ refers to running index for the bins. Note that $P$ is a vector with $N$ elements.

2.6. *Computation of cross frequency PPC*

Cross-frequency PPC refers to the phase synchrony between oscillations in two frequency bands. To quantify the PPC, we employed the phase-locking value (*PLV*; Lachaux et al., 1999), which is calculated as:

$$PLV = \frac{1}{T} \left| \sum_{t=1}^{T} e^{-j\Delta\varphi(t)} \right| \quad (4)$$

where | . | refers to the absolute value operator, $T$ is the number of time samples, and $\Delta\varphi(t)$ is the phase difference, and is calculated as:

$$\Delta\varphi(t) = \varphi_1(t) - \varphi_2(t) \quad (5)$$

where $\varphi_1(t)$ is the instantaneous phase of first signal and $\varphi_2(t)$ is the instantaneous phase of the second signal.

*2.6. Stimulus reconstruction using backward TRF model*

We applied the backward TRF model (Crosse et al., 2016) to reconstruct the stimuli envelopes from the EEG signals at each frequency band of interest (delta, theta, alpha), and to estimate decoding accuracy. The backward TRF model predicts (reconstructs) the stimulus envelope, denoted as $s(t)$, through the following equation:

$$s(t) = g(t,k) * r(t,k) = \sum_{k=1}^{K} \sum_{\tau=-T_{min}}^{T_{max}} g(\tau,k) r(t+\tau,k) \quad (6)$$

where $g(\tau,k)$ is a decoder representing the linear mapping from the neural response to the stimulus envelope for time lag $\tau$ and channel $k$. Parameters $T_{min} = 0\ ms$ and $T_{max} = 400\ ms$ determine the minimum and maximum time lags, respectively, and $r(t,k)$ denotes the neural response at channel $k$. The validation procedure utilised to regularise the backward linear model was the "leave-one-out" cross-validation (using *mTRFcrossval* function from the mTRF Toobox) in which one trial is "left out" or used for testing and the remainder are used to train the model. Each trial was 1 minute in length. This process was repeated across all trials in the

training set. The performance of the model was evaluated on the independent test set using the Pearson correlation between the estimated envelope and the actual envelope, with a higher correlation value indicating more accurate decoding by the model.

*2.7. Between-group backward TRF analysis*

To simulate normative decoding of the speech envelope from the neural responses at each frequency band, we used EEG recorded from the TD control children. For each frequency band of interest, we used a randomly selected subset of control children ($C_{train}$ = 8) for training 8 backward TRF models. A final model was obtained by averaging across all 8 individual trained models. Subsequently, this averaged model was independently tested on the remaining TD control children ($C_{test}$ = 8) as well as on the 16 children with DLD. We then computed the mean correlation values for both the tested TD control children and the children with DLD, resulting in a single correlation value for each group. This procedure was iterated 100 times, employing random permutations across all control children, thereby enabling the use of different combinations of 8 TD control children (for $C_{train}$ and $C_{test}$) for training and testing the model. As a result, 100 normative (averaged) models were generated. Accordingly, 100 correlation values were produced for both the TD control children and the children with DLD, yielding an averaged correlation value for each group. This approach facilitated the assessment of potential differences in speech decoding accuracy at the group level between children with and without DLD.

The rationale behind the between-group backward TRF analysis is to establish a normative decoding model based on TD children, which serves as a reference for assessing neural decoding performance in children with DLD. By averaging TRF models trained on random subsets of TD children, we create a generalised normative model that captures typical neural encoding of speech. Testing this model on DLD children allows us to assess how well their neural responses align with normative patterns, providing insights into potential

deviations in speech-brain coupling. This generalisation of the normative model to DLD data is a key feature of the analysis, as it enables us to evaluate the extent to which DLD children's neural responses conform to or diverge from typical encoding patterns.

*2.8. Within-child backward TRF analysis*

In order to examine the consistency of perceptual experience regarding low-frequency envelope information within the speech signal for individual children, we constructed a single backward TRF model for each child in the study, utilising only the data from that specific child. This within-child approach allowed us to investigate whether the representations of speech developed by individual children with DLD exhibit lower consistency than those developed by individual TD children. To accomplish this, we allocated 80% of the data from each child for training the TRF model, reserving the remaining 20% for testing the model. Subsequently, we computed the Pearson correlation between the estimated speech envelope and the actual speech envelope for each child individually and for each frequency band. This yielded a single correlation score for each band for every child. These scores were then aggregated by group (TD, DLD) for each frequency band and compared between groups. This approach allowed us to assess whether there are differences in the consistency of speech-based representations between children with and without DLD.

*2.9. Computation of chance level for Backward TRF model*

In order to assess the statistical significance of stimulus reconstruction accuracy as estimated by the backward TRF models (both the between-group and within-child models), null models were computed for each frequency band of interest. To generate these null models, eight TD control children were randomly selected, and EEG data were permuted across different story sections for each of these children. Subsequently, a single model was constructed for each child, where 80% of the data were utilised for training the null model, and the remaining data were employed for testing. The Pearson correlation between the estimated speech envelope and the

actual speech envelope was then calculated separately for each TD child and each frequency band within these null models, resulting in a single correlation value for each band and child. Subsequently, the mean reconstruction accuracy was computed by averaging across the accuracy scores obtained for the selected children. This process was repeated 100 times for each frequency band to generate probability density functions, which serve as statistical measures determining the probability distribution of a variable.

# 3. Results

*3.1. Does the accuracy of speech envelope decoding vary between children with and without DLD?*

To investigate the first prediction H1 concerning the expected impaired accuracy of low-frequency speech envelope decoding in children with DLD, the between-group backward TRF analysis method (as detailed in Section 2.7) was independently applied for each frequency band. To assess the statistical significance of the stimulus reconstruction accuracy achieved for each frequency band by group, we first compared decoding accuracy in each band to that of the null models (which represent the chance level for each band, as described in Section 2.9). The between-group analysis revealed that stimulus reconstruction accuracy was significantly higher than chance level in the delta band only, for both groups of children (Figure S1). To compare the decoding accuracy between the TD and DLD groups in the delta band, we conducted a two-sample t-test. The results indicated that the reconstruction accuracy for the TD control group in the delta band (derived from 100 TRF models) did not differ significantly from the reconstruction accuracy for the DLD group (Figure 1, $p = 0.42$).

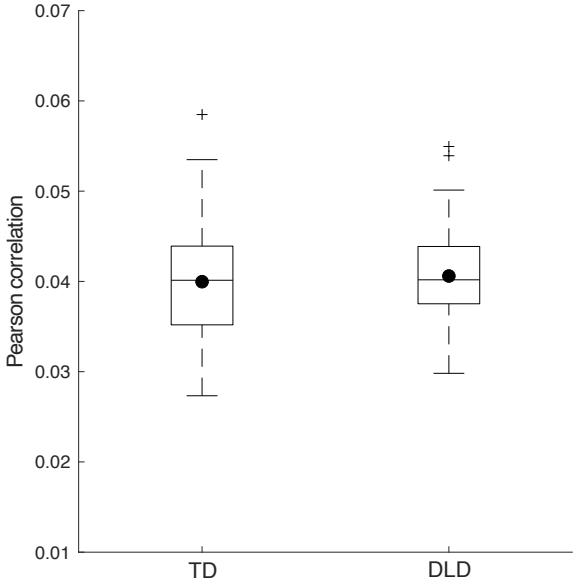


**Figure 1. Stimulus-reconstruction accuracy in the delta band for children in the DLD and TD groups, summarising correlation values from 100 backward TRF models.** The black circles represent the mean accuracy scores. In each box plot, the central line marks the median, while the bottom and top edges represent the 25th and 75th percentiles, respectively. The whiskers extend to the most extreme data points.

*3.2. Do individual children with DLD develop less precise representations of low-frequency information in speech?*

To investigate whether children with DLD exhibit less precise representations of the low-frequency envelope information in the speech signal compared to TD children, the within-child backward TRF analysis method (as described in Section 2.8) was applied independently for each frequency band. Comparisons with the null models revealed that stimulus reconstruction accuracy surpassed chance levels for both groups across all three frequency bands (Figure S2). Figure 2 displays the box plots illustrating stimulus reconstruction accuracies for both the TD and DLD groups, categorised by band, based on the backward TRF models from individual children. To compare the reconstruction accuracy between the two groups, we conducted independent two-sample t-tests. The results revealed no significant difference between the TD

and DLD groups across any band (delta band, Figure 2A, $p = 0.54$; theta band, Figure 2B, $p = 0.33$; alpha band, Figure 2C, $p = 0.55$). Additionally, Bayesian factor analysis was employed to quantify the strength of evidence for the alternative model. The findings indicated greater evidence in favour of the null model for all three bands (Bayesian factor analysis; delta band, *BF10* = 0.31; theta band, *BF10* = 0.39; alpha band, *BF10* = 0.29). Accordingly, H1 was not supported.

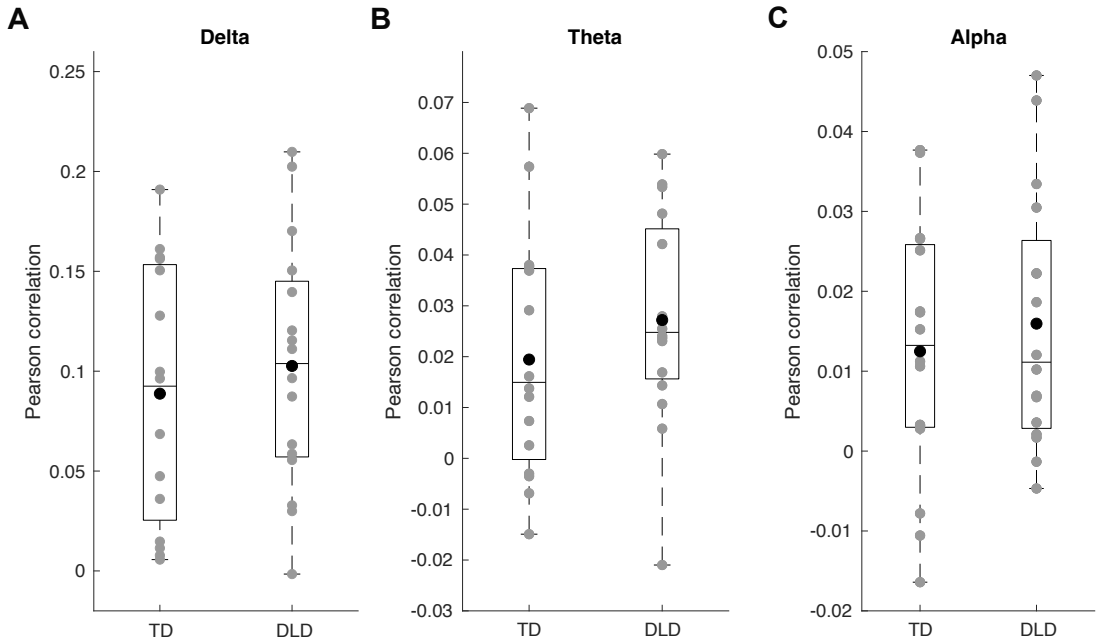


**Figure 2. Stimulus-reconstruction accuracy for children in the DLD and TD groups, in the delta (Panel A), theta (Panel B), and alpha (Panel C) bands, based on the within-child analysis.** Grey circles represent the reconstruction accuracy scores for individual children, while the black circles indicate the mean accuracy scores for each band and group.

*3.3. Comparison of band-power between groups*

To investigate H2, we compared the band-power between groups for the delta, theta and gamma bands. Wilcoxon rank sum tests were applied for each frequency band after removing outliers. A data point was classified as an outlier if its corresponding power value exceeded 1.5 times

the interquartile range above the upper quartile or fell below the lower quartile of the group's population data. Figure 3 shows the average power versus frequency separately for each group and for delta (see Figure 3A), theta (see Figure 3B), and low gamma (see Figure 3C) bands. A significant difference between TD control children and children with DLD was found in all the three bands: delta ($z = -2.07$, $p = 0.04$), theta ($z = -2.68$, $p = 0.007$), low gamma ($z = -2.83$, $p = 0.005$), with the DLD group having significantly greater power.

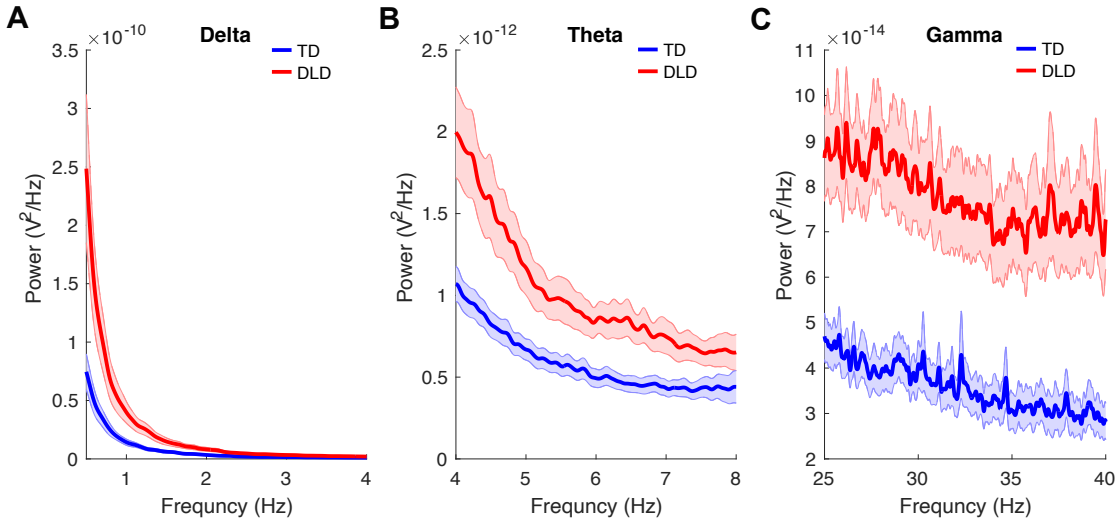


**Figure 3. Mean power for delta-band (Panel A), theta-band (Panel B), and low gamma-band (Panel C).** The blue and red curves represent the power density function for the TD and DLD groups, respectively. The shaded areas show the standard error of the mean for each group.

Given the earlier DLD fMRI literature which indicated atypical left-hemisphere function, similar analyses were also conducted separately for the right and left hemispheres (See Supplementary Figures S3, S4). The only visible difference is that the magnitude of the power increase in the gamma band appeared greater in the right hemisphere. Nevertheless, the pattern of findings were the same for each hemisphere. For the right hemisphere, there were significant differences between the two groups in all three bands: delta ($z = -2.17$, $p = 0.03$), theta ($z = -2.68$, $p = 0.007$), low gamma ($z = -2.93$, $p = 0.003$), with the DLD group having

significantly greater power. For the left hemisphere, there were also significant differences between the two groups in all three bands (See Supplementary Figure S4): delta ($z = –2.17$, $p = 0.03$), theta ($z = –2.68$, $p = 0.007$), low gamma ($z = –2.35$, $p = 0.02$), with the DLD group having significantly greater power.

To assess whether higher power during active speech processing would be related to worse language outcomes, here we calculated Spearman correlations between standard CELF scores and band power values across frequency bands. The results for the whole group of participants showed no significant correlations (see Table S1). Specifically, for Recalling Sentences, the correlation values were as follows: delta ($r = –0.07$), theta ($r = –0.17$), and low gamma ($r = –0.16$). Similarly, for Formulating Sentences, the correlation values were: delta ($r = –0.23$), theta ($r = –0.33$), and low gamma ($r = –0.30$). These findings suggest that when oscillatory mechanisms are actively engaged in speech listening, power is not related to CELF scores (all $p$'s > 0.05). Given that the prior resting state studies showing relations with language involved TD children, the correlational analyses were also run for each group of children separately (DLD, TD, see Tables S2 and S3). The correlations remained non-significant for the DLD group, but the data indicated two significant correlations for the TD group, between Recalling Sentences and delta power ($r = 0.51$, $p = 0.03$) and Recalling Sentences and theta power ($r = 0.54$, $p = 0.04$). This may suggest that when oscillatory mechanisms are actively engaged in speech listening, the relationship between power and higher language scores becomes positive for TD children. However, as shown in the scatterplots (see Supplementary Figure S5), this relationship appears to be driven by a couple of the TD children. All other correlations were nonsignificant ($p > 0.05$).

### *3.4. Comparison of PAC between groups*

To test H3, that delta-theta and theta-gamma PAC may be atypical in children with DLD, we compared the PAC measures between the groups. Wilcoxon rank sum tests were applied for each PAC measure after removing outliers. The results revealed that there was no significant difference between the two groups in delta-theta PAC ($z = -1.4517$, $p = 0.15$), nor in delta-low gamma PAC ($z = -0.02$, $p = 0.98$), nor in theta-low gamma PAC ($z = -0.14$, $p = 0.89$). These PAC values are depicted as bar plots in Figure S6.

*3.5. Comparison of PPC between groups*

To test H4, that PPC may differ between groups, we applied two-sample t-tests to compare PPC after removing outliers. The results showed no significant difference between the two groups neither for delta-theta PPC ($p = 0.65$), nor for delta-low gamma PPC ($p = 0.85$), nor for theta-low gamma PPC ($p = 0.22$). These PPC values are depicted as bar plots in Figure S7.

*3.6. Can the neural responses of children with DLD to natural speech be used to predict group membership?*

Finally, in order to quantify the effectiveness of each neural measure derived above regarding prediction of group membership, we computed receiver-operating-characteristic (ROC) curves utilising two machine learning approaches, SVM and LR, independently (see Figure 4 and Supplementary Figures S8 and S9). ROC curves illustrate the relationship between the true-positive rate (the proportion of children correctly identified as belonging to the DLD group) and the false-positive rate (the proportion of children from the TD group erroneously identified as belonging to the DLD group). The effectiveness of a particular measure is summarised by the area under the curve (AUC), which ranges from 0.5 to 1, with a value of 1 indicating flawless classification performance. The highest AUC values were obtained for the classifiers based on EEG power, as shown in Figure 4. The data for the PAC and PPC classifiers are

provided in the Supplementary Materials. The AUC measures for the PAC analyses did not exceed 0.66 (delta-theta PAC, see Supplementary Figure S8), or 0.62 (theta-gamma PPC, see Supplementary Figure S9). Accordingly, EEG gamma band power was the best predictor of membership of the DLD group.

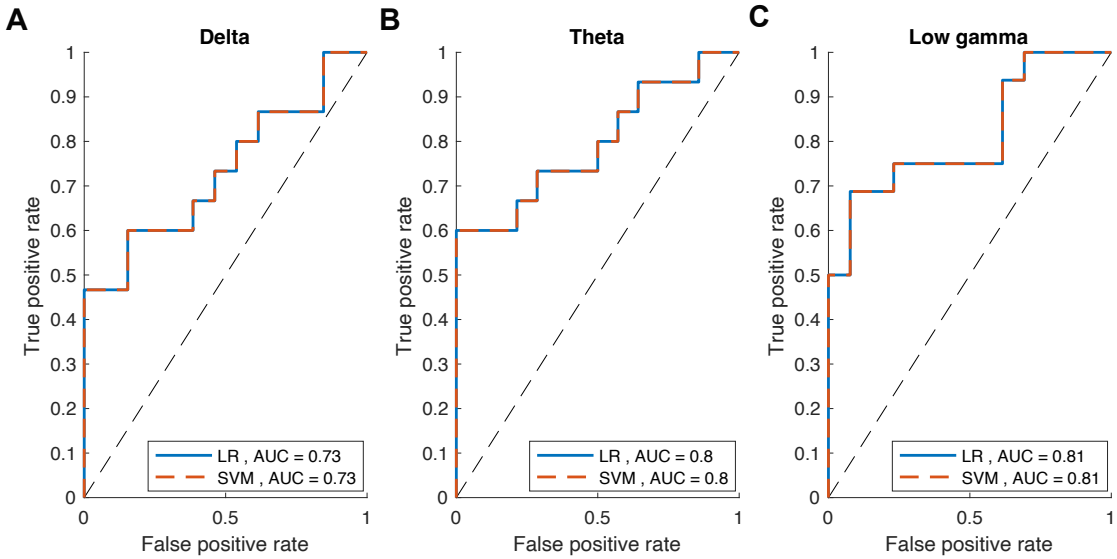


**Figure 4. ROC curves for each band-power measure, showing the true positive rate against the false positive rate.** The diagonal black dashed lines represent where the ROC curves would lie if the measure did not predict group membership.

## 4. Discussion

The current study explored neural processes during continuous speech listening in two groups of children aged on average 9 years, who were classified as either TD or DLD. Given the extensive nature of the language difficulties exhibited by children with DLD (CATALISE, Bishop et al., 2017), we combined TS theory with a broader oscillatory framework, and explored both low-frequency cortical tracking of the speech signal by oscillatory responses in the delta and theta bands, and PSD, PAC and PPC between oscillatory networks responding at different temporal rates (Giraud and Poeppel, 2012; Gross et al., 2013). The EEG data collected here in a continuous speech listening paradigm provided little support for the impairments in

low-frequency cortical tracking predicted by TS theory. Notably, the key prediction (H1) that delta and theta band cortical tracking of the speech signal should be less accurate in children with DLD was not supported. In the within-child mTRF analyses, the children with DLD showed equivalent reconstruction accuracy to the TD children for all frequency bands measured (delta, theta, alpha), indicating stable neural representations. Bayesian analyses of the within-child EEG data suggested that these null results were secure. Accordingly, at least using the mTRF measure of low-frequency cortical tracking employed here, the brains of children with DLD do not seem to exhibit an impairment regarding the reconstruction of low-frequency speech information. Although unexpected, the data are consistent with a prior DLD study using filtered speech (Goswami et al., 2016). When children with either DLD or dyslexia were administered a filtered speech nursery rhyme recognition task, the children with DLD (who had intact reading) showed impairments when the nursery rhymes were passed through a band pass filter, which retained only faster modulation information (centred on ~33Hz). They were as accurate as TD children at recognising nursery rhymes passed through a low pass filter, which retained only the slower modulation information (<4Hz). By contrast, the children with dyslexia showed perceptual impairments only for the low pass filtered nursery rhymes, and were as accurate as the TD control children for band pass filtered nursery rhymes. These data are suggestive of impairments in different modulation bands during speech processing (faster bands for DLD, slower bands for dyslexia).

Regarding the hypothesis about group differences in band power in the theta and gamma bands (H2), both theta power and gamma power were significantly elevated in the DLD group during continuous speech listening. Indeed, delta band power was also significantly elevated in the DLD group (see Figure 3). These power differences persisted when the data were analysed by hemisphere, and suggest that the infant and child resting state data in which both theta and gamma resting state power have been reported to be elevated in either TD

children with poorer language skills or in infants at family risk for DLD also characterise the DLD brain during natural language processing (Benasich et al., 2008; Choudhury and Benasich, 2011; Gou et al., 2011; Cantiani et al., 2016, 2019; Meng et al., 2022, Lum et al., 2022). However, correlational analyses showed that higher power was not related to language outcomes as measured by the CELF in the whole group (N = 32) nor in the DLD group alone. Surprisingly, for the TD sample tested here, higher power in both the delta and theta bands during natural language processing was related to *better* scores in the Recalling Sentences subtest of the CELF (see Table S2 and Figure S5). This is the opposite of the relationship found in resting state TD studies, where higher power relates to worse language scores on the CELF (Meng et al., 2022, Lum et al., 2022). As our TD sample is small, this finding should be treated with caution. Nevertheless, it does suggest that the polarity of relationships found in resting state EEG studies may not be indicative of how the brain behaves during active speech processing.

As noted, the significant increase in band power in the DLD brain during active speech processing was found in both hemispheres (see Supplementary Figures S3, S4) and hence does not point to an impairment in any particular linguistic processing mechanism. However, one interpretation could be that there are system-wide oscillatory differences when the DLD brain is listening to natural speech. Indeed, in the classifier analyses, simple band power measures during linguistic processing performed best at distinguishing between children with and without DLD, notably theta power (AUC = 0.80) and gamma power (AUC = 0.81). These classifier data should be considered as preliminary only, given the sample size.

There was only partial support for the predictions concerning neural dynamics during speech listening that were drawn from a broader oscillatory framework (PAC and PPC). Regarding H3, it had been tentatively predicted that theta-gamma PAC (following Attaheri et al., 2024) and delta-theta PAC (following Araújo et al., 2024) should be atypical in children

with DLD during continuous speech listening. Neither prediction was supported, as the modulation indices were equivalent in the TD and DLD brains. Nevertheless, inspection of Figure S6A shows that the modulation index for delta-theta PAC was numerically greater for the children with DLD compared to the TD children ($p = 0.15$). This numerical difference was significant in Araújo et al. (2024), however that study used a different story and only recorded EEG data from 7 children. Accordingly, a study with greater power may either find that delta-theta PAC is indeed atypical in the DLD brain, or that the current lack of PAC impairment is reliable. H3 was also generated in part by data from the Cambridge BabyRhythm infant study, in which a higher theta-gamma modulation index predicted better language outcomes (Attaheri et al., 2024). This finding led to the prediction that children with DLD may have lower theta-gamma modulation indices. This was not supported either, as Figure S6C shows almost identical modulation indices for theta-gamma PAC at the group level. Finally, H4 was that PPC may differ between groups, at least when a low-frequency phase has to couple with a high-frequency phase (here tested by delta-gamma and theta-gamma PPC). The PPC analyses (Figure S7) did not support this prediction. The TD control children and the children with DLD showed comparable coupling indices.

The current study has a number of limitations. Firstly, the sample size was small, with 16 children with DLD and 16 control children. However, the sample size is representative of the existing neural DLD literature (e.g., Heim et al. 2011 studied 17 children with DLD, Nora et al. 2024 studied 17 children with DLD; Choudhury and Benasich 2011 studied 17 infants at risk for DLD). Secondly, EEG is a relatively noisy neural measure when used with children. More precise data regarding cortical tracking of continuous speech could be gathered by using MEG rather than EEG. If converging evidence regarding the intact fidelity of low-frequency cortical tracking and similar PAC and PPC mechanisms during continuous speech listening were to be found with MEG, this would be important regarding interpretation of the null

findings in the current data. Finally, the mTRF is only one method that can be used for estimating cortical tracking of the speech signal, and different results may have been found if a different method had been utilised. However, in prior TS-driven natural language infant studies, low-frequency cortical tracking has been estimated using 3 different measures, the mTRF measure, mutual information, and convolutional neural networks (Keshavarzi et al., 2024b). For TD infants, the pattern of low-frequency cortical tracking using all 3 measures has been broadly similar across all three measures (see Table 1, Keshavarzi et al., 2024b).

In conclusion, the current data do not provide strong support for the low-frequency cortical entrainment aspect of TS theory as a useful sensory/neural framework for explaining the linguistic processing difficulties that characterise children with DLD. This may be because the TS sensory/neural framework was originally derived from neural data gathered with children with DD (Goswami, 2011). TS theory was expected to be useful regarding the aetiology of DLD because children with DLD share a number of sensory and linguistic features with children with DD, such as shared impairments in processing both speech and non-speech rhythm, impairments in processing speech prosody, and impairments in the discrimination of ARTs (Goswami, 2022; for recent review). However, when measured with EEG, children with DLD do not appear to share the low-frequency cortical tracking impairments found in children with dyslexia (see Power et al., 2016; Di Liberto et al., 2018; Destoky et al., 2020, 2022; Keshavarzi et al., 2022a,b). At least when measured using EEG, the accuracy of low-frequency cortical tracking using a signal reconstruction approach appears neurotypical in children with DLD.

The group differences that were found here between TD children and children with DLD were indicative of elevated neural power during speech processing in all oscillatory bands studied. Elevated gamma band power produced the best classifier data (AUC = 0.81). Further studies, ideally longitudinal, involving larger samples of children, and utilising a range of

methods for estimating cortical tracking, are required for an in-depth assessment of the accuracy of the neural mechanisms involved in the cortical processing of continuous speech by the DLD brain. Meanwhile, the current data suggest that there is enhanced neural power in the DLD brain in many frequency bands during natural speech processing. This may possibly reflect the reduced speech encoding precision in DLD that has been suggested by data gathered using sensory and linguistic tasks (Bishop et al., 2017). At the current time, the cortical mechanisms that generate this enhanced neural power remain to be identified.

## Author contributions

M.K. conceptualisation, methodology, data collection, data analyses, visualisation, writing – original draft; S.R. data collection, writing – review & editing; G.F. data collection, writing – review & editing; L.P. data collection, writing – review & editing; U.G. funding acquisition, project administration, supervision, conceptualisation, methodology, writing – original draft.

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## Conflict of Interest

None of the authors have potential conflicts of interest to be disclosed.

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