Comparing the Neural and Behavioral Outcomes of Fine and Gross Motor Language Intervention in Children with DLD: An Exploratory Study

Bayan Ahmad
Department of Biomedical Engineering
The University of Akron
Akron, OH, USA
ba82@uakron.edu

Rachael Amira Brimm
Department of Biomedical Engineering
The University of Akron
Akron, OH, USA
rab218@uakron.edu

Mary Sill
School of Speech- Language Pathology and Audiology
The University of Akron
Akron, OH, USA
maryisilla1220@gmail.com

Kristen Shepherd Crish
School of Speech- Language Pathology and Audiology
The University of Akron
Akron, OH, USA
kas180@uakron.edu

Buket D. Barkana
Department of Biomedical Engineering
The University of Akron
Akron, OH, USA
bbarkana@uakron.edu

Abstract— **Children with Developmental Language Disorder (DLD) often present with atypical neural responses during language processing when compared with children of typical language development (TLD), yet the influence of therapy style on these patterns remains underexplored. This study examined EEG-based neural signatures and behavioral outcomes associated with fine-motor and gross-motor intervention approaches. DLD (6 participants) and TLD (14 participants) children each completed tasks involving the retrieval of familiar words and the encoding and retrieval of novel words. EEG signals were segmented into four regional groupings and analyzed across delta, theta, alpha, and beta frequency bands. Power spectral density estimates were computed, and mel-frequency cepstral coefficients were extracted to capture spectral-temporal features. Machine learning classifiers, including SVM, KNN, and an ensemble model, were used to assess separability across groups, tasks, and therapy styles. Results revealed distinct spectral patterns between groups, with DLD participants showing elevated delta and theta power and reduced alpha and beta activity across tasks. Classifier performance varied by therapy style and task, with certain models achieving accuracy above 0.80 in discriminating between groups or task conditions.**

Keywords— Developmental language disorders, EEG, language therapy, recall, learning

I. INTRODUCTION

Early childhood is a critical period for language acquisition, during which the brain exhibits heightened plasticity and sensitivity to linguistic input [1]. Speech and language therapy interventions administered during this developmental window can significantly influence communication skills, cognitive development, and academic readiness. Despite their widespread use, the underlying neural mechanisms through which these interventions exert their effects are only beginning to receive increased research attention. A 2016 National Academy of Sciences report estimates that 3–16% of individuals between the ages of 3 and 21 in the United States experience some form of speech or language disorder [2]. The prevalence of speech and language disorders (SLDs) in the U.S. underscores the importance of understanding their neurodevelopmental and clinical characteristics. Children with language disorders often struggle to organize words into meaningful sentences, which frequently coincides with challenges in understanding and following spoken instructions [2].

Language interventions primarily focus on the use of words and sentences, as well as story comprehension skills. SLPs work on the child's vocabulary and exposure to advanced phrases. These sessions typically include reading, writing, and speaking, tailored to the child's individual needs. There are two main therapy approaches: didactic and naturalistic. Didactic approaches are considered effective in delivering therapy focused on the use and comprehension of language, however long-term display of habits acquired through this therapy is considered a shortcoming of the method [3]. Naturalistic approaches include passive-like acquisition of content. The lack of an organized structure and sense of control given to the child makes it a more positive, "fun", and comfortable environment. These factors encourage content retention over memorization. Naturalistic methods are favored for their ease of use and implementation into everyday life.

EEG has emerged as a powerful tool for investigating the neural fundamentals and markers of language processing, as well as identifying atypical brain activity associated with speech and language disorders [4,5]. Its high temporal resolution makes EEG suitable for capturing rapid neural responses to auditory and linguistic stimuli, providing insight into the timing and coordination of language-related brain functions in children with and without language disorders. Language processing involves a distributed network of brain regions, with the left hemisphere playing a dominant role.

EEG studies have shown that these regions contribute to time-locked electrical potentials, known as event-related potentials (ERPs), that reflect the brain's response to different stages of language processing, including lexical access, semantic integration, and phonological encoding [6]. Developmental EEG studies reported that dominant brainwave patterns evolve with age. In general, younger children between 3 and 7 years old exhibit higher theta activity, which transitions to alpha and beta dominance by adolescence, reflecting cognitive maturation [7,8]. A growing body of research in the literature utilizing EEGs to study the neural markers of SLDs has reported that children with developmental language disorder (DLD) often exhibit atypical ERPs to phonological and syntactic stimuli, indicating disruptions in linguistic processing [9].

EEG-based SLD literature highlights the comparison of the disorders and the associated changes in the brain [10,11,12,13] as opposed to the impacts of therapy intervention methods. Our study primarily focuses on how therapy methods support improvements in word encoding, comprehension, retrieval, vocabulary use, and sentence construction, addressing language-related difficulties.

II. Methods

A. Data Collection

DLD participants consisted of those diagnosed with a language disorder by their school district and/or an outpatient therapist. Recruitment was done through the Audiology and Speech Center at The University of Akron (Akron, OH, 44325 USA). Additional participants were recruited from local school districts affiliated with The University of Akron Speech and Audiology Department through flyers. Documentation of the participants' most recent speech therapy evaluation and reports from their treatment therapist (school or outpatient) was provided to ensure their eligibility as a study participant. Inclusion criteria consisted of both male and female participants, aged 3-7 years old, who were able to follow verbal instructions and perform all the programmed tests. Participants were required to have written consent provided by a legal parent or guardian to volunteer in the study. DLD participants needed to have a documented/ diagnosed language disorder (mild to moderate range of Core language scores (CLS) with standard scores spanning from 70 – 85). Exclusion criteria included children who were younger than three years old and older than seven years old. Children with severe cognitive deficits or other serious medical conditions, including epilepsy and seizures, were excluded. The child's legal parents or guardians were asked to follow an informed consent process and complete a basic demographic questionnaire before conducting any experimental tasks. Table I presents the demographic records, including age, sex given at birth, race, and speech and language-related health status.

The first half of the session consisted of one therapy style, and the second half consisted of the other style. Participants completed a language therapy session while wearing a wireless 32-channel EEG cap; the full session lasted between 30 and 45 minutes. Each session was also video recorded for further evaluation. The clinician collected the therapeutic data. The procedural sequence of the study, novel object definition, and baseline periods are outlined in Fig. 1. The novel object names "Tade" and "Koob" were introduced in a previous study by Horton-Ikard et al. [14].

TABLE I. Participant demographics.

		Control Group			DLD Group		
Number of participants		14 (8 M, 6 F)			6 (5 M, 1 F)		
Spoken Language at Home		English			English		
		Range	**Mean**	**STD**	**Range**	**Mean**	**STD**
Age (mo.)	**Overall**	36-84	60.86	17.27	36-85	58.00	17.66
	First Word	6-12	8.38	1.89	11-21	14.80	4.44
	Begin Walking	9-15	10.77	1.71	11-21	12.21	2.99
CLS					70-85	78.60	6.15

Therapy style A was conducted in a stagnant manner. The children participated in a clinician-driven session where they were required to sit at a table and play a game that required fine motor skills. Language concepts were addressed through drills. This session lasted a total of 15-20 minutes. To begin this portion of the therapy, two novel objects with novel names were introduced. Each participant was given the opportunity to test the function of the object and say the newly introduced word. Immediately after object introduction, a "Goliath Pop the Pig" game was set up. The participant was asked to blindly select an object out of a bag. The objects in the bag were of varying categories (e.g., food, animals, transportation). Upon selection, the child was prompted to name the object and its category or function. The participant performed a cycle of playing and familiar object selections. After 5 known objects had been selected, the participant was prompted to name the object and the function of the first novel object. The process continued with object selections and game playing, and was then repeated for the second novel object. After a total of 22 objects, the first sub-session was concluded.

Therapy method B implemented a hybrid approach that consisted of child-led elements with clinician support. The clinician provided the child with activities requiring gross motor movements, incorporating a tunnel ball pit and animal walks. These activities provided the child with proprioception, vestibular input, and tactile stimulation. This style lasted approximately 15-20 minutes. Two additional novel objects with novel names were introduced. The participant was instructed to crawl through the tunnel to the ball pit and throw five balls into the hoop. The same object selection system as the first therapy style was implemented; a series of crawling, object selection, and ball throwing, followed by an intermission to name the novel object and its function. The participant was then instructed to walk across the room in a certain animal walk and rest their hands on the wall for 5 seconds. The purpose of hand resting was to reduce hyperactivity in the brain, which was caused by excessive movement and could potentially cloud the target EEG signals. After hand resting, the clinician asked the participant the name and function of the second novel object.

The EEG system used in this study was the Emotiv FLEX 2.0 (EMOTIV, San Francisco, California, USA), a 32-channel wireless EEG head cap equipped with saline-based silver/silver-chloride (Ag/AgCl) electrodes [15]. EEG data were acquired using EmotivPRO software (version 4.6.1.578) at a sampling rate of F_s =256 Hz, and were automatically stored on the Emotiv cloud and saved in an EDF file format.

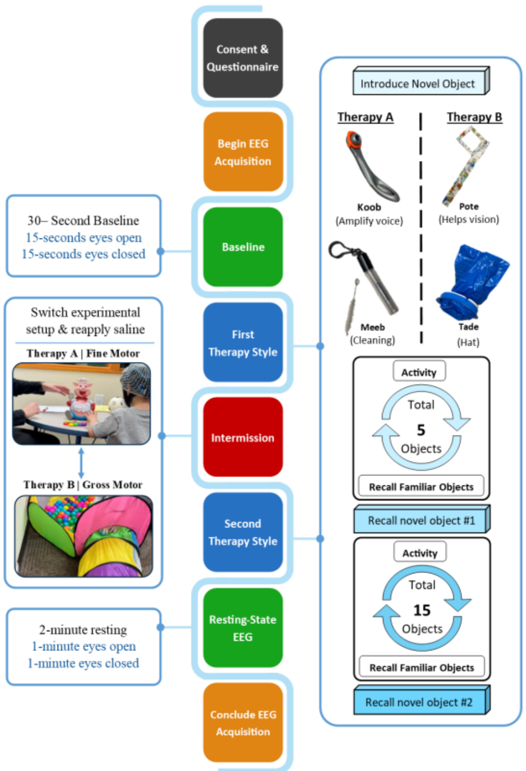

Figure 1. Experimental Timeline, Task Structure, and Therapy-Style Contrast.

Signal connectivity and EEG quality were verified before data collection began. Two research team members monitored the recording in real time, documenting timestamps and noting any potential artifacts. During the transition between therapy styles, saline solution was reapplied to the electrodes to maintain consistent signal quality.

B. EEG Preprocessing

The EDF files were imported into EEGLAB [16]. Fig. 2 shows the stages of the data preparation process. The EEG data were filtered using a band-pass filter (0.1–30 Hz). Channel inspection was guided by time-stamped notes recorded by two researchers during therapy sessions. Noisy channels were identified through visual inspection and removed. These channels were then reconstructed using linear interpolation. A common average reference (CAR) was applied to enhance the spatial resolution of the EEG data and reduce global noise.

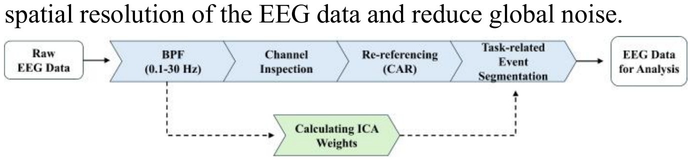

Figure 2. EEG data preparation protocol.

Following the bandpass filtering, independent component analysis (ICA) was performed using EEGLAB to identify and separate artifacts. Infomax ICA was applied to the continuous, pre-processed EEG dataset after filtering and artifact rejection steps. The resulting independent components (ICs) were inspected for artifact-related activity (e.g., eye blinks, muscle noise), and clean components were used to reconstruct the signal.

Faculty Research Council at The University of Akron. FRG.2405

C. Analytical Methods

The channels for each segment were grouped and averaged into brain regions: temporal/fronto-temporal (T7, T8, FT9, FT10), frontal/fronto-central/fronto-parietal (F3, F4, F7, F8, FZ, FC1, FC2, FC5, FC6, FP1, FP2), parietal/central-parietal(P3, P4, P7, P8, PZ, CP1, CP2, CP5, CP6), and occipital/parietal-occipital (O1, O2, OZ, PO9, PO10). The analysis was conducted on a broadband frequency range (1–30 Hz) as well as on the standard EEG sub-bands: delta (1–4 Hz), theta (4–8 Hz), alpha (8–13 Hz), and beta (13–30 Hz). Band power for each frequency range was computed using Equation 1, a Hamming window, and a modified periodogram method to estimate the power spectral density, from which the average power within each band was extracted [17,18].

$$\hat{P}(f) = \frac{\Delta t}{N}\left|\sum_{n=0}^{N-1} h_n x_n e^{-j2\pi f \Delta t\, n}\right|^2, \quad -1/2\Delta t < f \leq 1/2\Delta t \qquad (1)$$

Where Δt is the sampling interval (Δt=1/F_s) and h_n is the Hamming window function with a frame size of 100 (N=100) and 99% overlapping.

Statistical descriptors were computed to extract time-domain features. Specifically, the mean, standard deviation, variance, kurtosis, and skewness were calculated using a sliding window of 100 samples with 50% overlapping.

We calculated 12 MFCCs [19] and the energy coefficient in each band to capture the broad spectral shape of the signal. Lower-order coefficients represent global spectral shape and higher-order coefficients encode fine spectral details. These coefficients are effective in capturing the dynamic temporal-spectral patterns associated with auditory and phonological processing, which are often disrupted in individuals with DLD.

Support vector machines (SVM), K-nearest neighbor (KNN), and an ensemble were designed using three feature sets. A Hamming window with 50 % overlap was used to derive features for each frame. For each brain region, the feature set consisted of statistical descriptors (6), alpha-beta range powers (5), and alpha-beta range MFCCs (65). With four brain regions, a total of 304 features were extracted and used for model training. These features were designed to capture patterns associated with the effects of different therapy styles on the recall and learning of novel objects and their corresponding names in both TLD and DLD groups.

D. Statistical Methods

To identify significance between group means, one-way ANOVA was utilized. The null hypothesis states that group means are equal, while the alternative hypothesis is that the group means are different. The ratio of between-groups to within-group variation is determined using the F-statistic given in Equation 2.

$$F = \frac{SSR/_{k-1}}{SSE/_{B-k}} = \frac{MSR}{MSE} \sim F_{k-1,B-k} \qquad (2)$$

where k is the number of groups, B is the total number of observations, MSR is the mean squared of between-group effects, and MSE is the mean squared error [20]. The null hypothesis was rejected if the F-statistic correlated with a p-value less than 0.05. Effect sizes were assessed using Hedge's g, where values of 0.2, 0.4, and 0.8 represented small, medium, and large effect sizes, respectively.

III. RESULTS

We compared the control group and the DLD group across conditions involving the recall of known objects, the recall of novel words, and both the learning and recall of novel objects, using EEG band power as the primary measure. Additionally, we examined the effects of different therapy styles on neural activity by applying machine learning-based analytical tools.

A. Band Power

The average band power for each trial in four brain regions, occipital, temporal, parietal, and frontal, was calculated. Due to technical issues, subjects excessively touching and adjusting their EEG cap, or study abandonment, data from 9 subjects were excluded from the analysis. As a result, a total of 8 control and 3 DLD participants were included in the band power analysis. Fig. 3 depicts the findings.

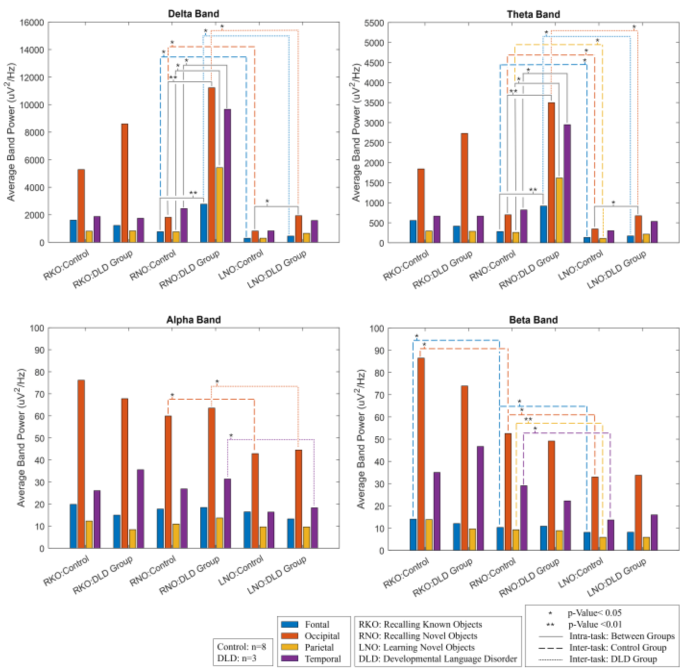

Figure 3. Average band powers in the (a) delta, (b) theta, (c) alpha, and (d) beta of both the control (n=8) and DLD (n=3) group during the recalling of known objects (RKO), recalling of novel objects (RNO), and learning of novel objects (LNO). Significance is determined by one-way ANOVA.

The results show that delta-theta and alpha-beta band powers show similar patterns. The delta displays a much greater average power range than any of the other bands. Although the average theta power range is less than the delta, it is still distinctly greater than the alpha-beta. When comparing the DLD group to the control in the RNO, all regions showed significantly higher delta and theta power ($p<0.05$), especially in the frontal and occipital regions ($p<0.001$). During LNO, only the occipital was significantly higher in the DLD group. However, the effect sizes in all three conditions were found to be small (Hedge's $g<0.2$).

We compared the RKO and RNO tasks, as well as the LNO and RNO tasks in the control group. For RKO-RNO, only the frontal and occipital beta powers were significantly higher in RKO, while the occipital beta power was statistically greater during RNO. For LNO-RNO, all band powers were greater during RNO. However, the frontal delta/theta, parietal theta/beta, temporal beta, and all occipital powers demonstrated significant differences. Although the effect sizes were small (Hedge's $g<0.2$), the beta band in the frontal and parietal regions showed the greatest effect size among the control group, 0.12 and 0.18, respectively.

For DLD group comparisons, none of the brain regions in any of the bands resulted in statistically significant differences between RKO and RNO, while RNO had greater power in all brain regions for every band compared to LNO. This difference was significant in the frontal and occipital delta/theta powers, as well as occipital and temporal alpha powers. All effect sizes were found to be small (Hedge's $g<0.25$).

B. Machine Learning Approach

In this study, we applied an SVM, KNN, and ensemble model to the EEG data. The SVM model employed a Gaussian kernel with a scale parameter of 70. The box constraint was set to 1, controlling the trade-off between maximizing the margin and minimizing classification error. The KNN was configured with 100 neighbors, used a Euclidean distance metric, and applied equal weighting to all neighbors. The ensemble model used the AdaBoost algorithm with decision-tree learners as base classifiers. There was a total of 30 weak learners, each trained with a learning rate of 0.1 to ensure gradual optimization and reduce the risk of overfitting. The decision trees were configured with a maximum of 20 splits to balance model complexity and interpretability. For each model, 10% of the data was set aside for testing, and a 5-fold cross-validation was implemented.

Accuracy alone can be misleading in cases of class imbalance. For this reason, we included the F1-score, which offers a more balanced assessment of a model's performance, especially when evaluating how well it identifies true positives without overpredicting false positives. This is particularly relevant in EEG studies involving clinical populations such as children with DLD, where differences in brain responses may lead to uneven class distributions or subtle signal variations.

The classification results presented in Table II provide insights into how different language therapy styles, Therapy A and Therapy B, affect object recall and learning in children from control and DLD groups.

TABLE II. THERAPY STYLE CLASSIFICATION PERFORMANCE FOR THE DLD (N=3) AND CONTROL (N=8) GROUPS. ACCURACY AND F1 SCORES ARE REPORTED, WITH F1 SCORES SHOWN IN PARENTHESES (0 AND 1 CORRELATE TO 0% AND 100%, RESPECTIVELY).

	Therapy A vs. Therapy B					
	Recall (Known Objects)		**Recall (Novel Objects)**		**Learn (Novel Objects)**	
ML Model	*Control Group*	*DLD Group*	*Control Group*	*DLD Group*	*Control Group*	*DLD Group*
SVM	0.59 *(0.69)*	0.64 *(0.69)*	0.54 *(0.62)*	0.63 *(0.59)*	0.51 *(0.56)*	0.68 *(0.50)*
KNN	0.58 *(0.71)*	0.60 *(0.71)*	0.56 *(0.65)*	0.68 *(0.71)*	0.53 *(0.49)*	0.68 *(0.50)*
Ensemble	0.54 *(0.63)*	0.56 *(0.59)*	0.59 *(0.63)*	0.61 *(0.69)*	0.62 *(0.61)*	0.64 *(0.65)*

Table III evaluates how well the models can distinguish between control and DLD groups under Therapy A and Therapy B for three core cognitive tasks: recall of known objects, recall of novel objects, and learning of novel objects.

TABLE III. CONTROL (N=8) AND DLD (N=3) GROUP CLASSIFICATION PERFORMANCE FOR EACH TASK. ACCURACY AND F1 SCORES ARE REPORTED, WITH F1 SCORES SHOWN IN PARENTHESES. (0 AND 1 CORRELATE TO 0% AND 100%, RESPECTIVELY.)

	Control Group vs. DLD Group					
	Recall (Known Objects)		**Recall (Novel Objects)**		**Learn (Novel Objects)**	
ML Model	*Therapy A*	*Therapy B*	*Therapy A*	*Therapy B*	*Therapy A*	*Therapy B*
SVM	0.79 *(0.88)*	0.79 *(0.88)*	0.78 *(0.88)*	0.79 *(0.88)*	0.77 *(0.87)*	0.74 *(0.85)*
KNN	0.79 *(0.88)*	0.79 *(0.88)*	0.78 *(0.88)*	0.79 *(0.88)*	0.77 *(0.87)*	0.74 *(0.85)*
Ensemble	0.82 *(0.89)*	0.84 *(0.91)*	0.84 *(0.90)*	0.84 *(0.90)*	0.80 *(0.88)*	0.70 *(0.82)*

Table IV assesses whether EEG patterns can differentiate between recall of known objects vs. recall of novel objects and learning of novel objects vs. recall of novel objects. It evaluates the task-level separability of neural responses to investigate how children process familiar vs. unfamiliar linguistic stimuli and how therapy influences these dynamics.

TABLE IV. TASK CLASSIFICATION PERFORMANCE FOR THE DLD (N=3) AND CONTROL (N=8) GROUPS. ACCURACY AND F1 SCORES ARE REPORTED, WITH F1 SCORES SHOWN IN PARENTHESES; (>>) REFERS TO AN F1 SCORE OF INFINITY, (<<) REFERS TO AN F1 SCORE LESS THAN 0.1.

	Recall Known Objects vs. Recall Novel Objects			
	Therapy A		**Therapy B**	
ML Model	*Control*	*DLD*	*Control*	*DLD*
SVM	0.59*(<<)*	0.59*(>>)*	0.64*(0.23)*	0.61*(>>)*
KNN	0.58*(<<)*	0.63*(0.54)*	0.62*(0.12)*	0.71*(0.47)*
Ensemble	0.67*(0.54)*	0.63*(0.64)*	0.68*(0.53)*	0.68*(0.80)*
	Learn Novel Objects vs. Recall Novel Objects			
	Therapy A		**Therapy B**	
ML Model	*Control*	*DLD*	*Control*	*DLD*
SVM	0.57*(0.52)*	0.58*(0.19)*	0.59*(0.53)*	0.67*(0.46)*
KNN	0.60*(0.48)*	0.53*(>>)*	0.59*(0.45)*	0.62*(0.27)*
Ensemble	0.63*(0.63)*	0.45*(0.27)*	0.67*(0.63)*	0.71*(0.57)*

IV. DISCUSSION

A. *Exploratory Findings: Band Power Analysis*

High delta may reflect compensatory cognitive load or immature language processing circuits in DLD children, representing possible underlying differences in how their brains process linguistic information. Delta oscillations are typically dominant during deep sleep or in very young children, and their presence during cognitive tasks in older children may indicate the recruitment of more primitive or compensatory neural circuits. In this context, high delta power may signal increased cognitive load, as the brain exerts greater effort to perform tasks that require less energy in typically developing children. This pattern is consistent with findings in other neurodevelopmental disorders where delta activity remains elevated during task engagement, often correlating with difficulties in attention, memory, and information integration [21].

In the theta band, the DLD group again shows elevated theta power for the RNO task, especially in the occipital and parietal regions. Significant within-group (task-based) and between-group differences are seen. The control group displays a lower and more consistent theta response across tasks. Elevated theta in the DLD group may reflect increased attentional effort or working memory demands during recall and learning.

The alpha band shows clear suppression in control groups, which is consistent with increased cognitive engagement. In contrast, DLD groups show less alpha suppression, especially in the temporal and occipital regions. Furthermore, statistically significant differences were observed, particularly in RNO and LNO tasks. Observed reduced alpha suppression in DLD may be due to less efficient neural inhibition during language tasks. Our study findings in the beta activity were similar to the findings in the alpha band. DLD groups showed significantly reduced beta activity, particularly in the frontal and parietal regions. Often linked to language processing, attention, and motor planning, the reduction of beta power in DLD may signal less robust neural activation or coordination.

For both the control and DLD group, the LNO-RNO had more differences than the RKO-RNO. Therapy tasks (RKO, RNO, LNO) show distinct neural signatures in the DLD group, indicating that therapy style and task type significantly influence brain activity. Control groups show cleaner task separability in alpha and beta, indicating more differentiated and efficient cognitive processing. DLD groups consistently show higher delta and theta, but lower alpha and beta, suggesting: (1) Greater cognitive load and less efficient information processing, and (2) Compensatory activation, possibly reflecting effortful processing.

B. *Exploratory Findings: Machine Learning Approach*

Classification performance is often higher in the DLD group, particularly during learning and recall of novel objects. Given their initial linguistic and cognitive vulnerabilities, therapeutic intervention induces more substantial and structured EEG changes, which classifiers can more readily distinguish. In contrast, TD children show more stable and efficient baseline neural responses, leaving less room for measurable therapy-driven variation. The strongest group and therapy separation emerges during the learning of novel objects. DLD children consistently show clearer differentiation across models, suggesting that therapy amplifies neural processes associated with forming new associations. Conversely, TD children demonstrate lower and more uniform classification performance in learning tasks, consistent with a ceiling effect in which neural efficiency limits observable change. Increased variability in the DLD group likely reflects individualized neural reorganization following therapy, which enhances discriminability.

High accuracy and F1 scores across models in Table III highlight EEG-based separation between DLD and control groups across tasks and therapies, indicating persistent group-specific neural signatures related to language processing. Ensemble models perform best overall, with SVM and KNN showing comparable reliability, reinforcing their ability to capture subtle EEG differences. While Therapy B enhances within-group performance in DLD children, between-group separability during learning is often stronger under Therapy A, suggesting that Therapy A preserves group-specific learning dynamics rather than normalizing them.

Task-based analyses further show that neural differentiation between learning and recall is more pronounced in DLD children, particularly under Therapy B. This is evident in higher classification performance when distinguishing known versus novel recall and learning versus recall tasks. In contrast, TD children exhibit greater neural overlap between learning and recall phases, consistent with more automated processing. Overall, Therapy B appears to enhance neural differentiation during recall in DLD children, while Therapy A better highlights group-specific learning mechanisms.

C. Limitations and Future Directions

While this study provides important insights into therapy-related EEG band power patterns and classification performance in children with DLD, several limitations should be acknowledged. The relatively small sample size may limit generalizability and increase the risk of overfitting. This may also impact the reliability of effect sizes. EEG's limited spatial resolution constrains precise localization of language-related neural activity, and variability in participant engagement or task execution may have influenced outcomes. Additionally, the stimulus set, while controlled, may introduce semantic or perceptual biases. Future work should expand participant diversity and track therapy-induced neural adaptations over time. Extending analyses to temporal–spectral coupling and developing real-time, EEG-informed therapy personalization may further optimize intervention strategies for children with DLD

V. Conclusion

This study investigated the neural and behavioral effects of two distinct language therapy styles in children with and without DLD, focusing on the recall of known and novel words and the learning of novel objects. EEG band power features, regional activity measures, and MFCCs were extracted to characterize neural responses, and multiple machine learning classifiers were applied to distinguish between groups, tasks, and therapy styles. Findings revealed that DLD participants consistently exhibited higher delta and theta power and lower alpha and beta power, patterns suggestive of greater cognitive load, compensatory processing, and less efficient neural inhibition during language tasks. Classification analyses indicated that therapy style influenced both within-group task separability and between-group differences, with Therapy B enhancing recall-related neural distinctions and Therapy A better differentiating group-specific learning dynamics.

Acknowledgment

The authors would like to thank the children participants and their parents/guardians for their time and commitment.

Institutional Review Board Statement

The study was conducted in accordance with the Declaration of Helsinki and approved by the Institutional Review Board (or Ethics Committee) of The University of Akron (Akron, OH, 44325 USA) (IRB-2024-61: approved 09/24/2024).

Informed Consent Statement

Informed consent was obtained from all subjects involved in the study.

References

[1] E. R. Goldenberg, R. L. Repetti, and C. M. Sandhofer, "Contextual variation in language input to children: A naturalistic approach," Developmental Psychology, vol. 58(6), pp. 1051-1065, 2022

[2] M. J. Barry et al., "Screening for Speech and Language Delay and Disorders in Children: US Preventive Services Task Force recommendation statement," JAMA vol. 331(4), pp. 329-334, January 2024

[3] S. Austin, "Didactic Approaches," in Encyclopedia of Autism Spectrum Disorders, Springer International Publishing, pp. 1362-1647, March 2021

[4] R. Sharma and H. K. Meena, " Emerging Trends in EEG Signal Processing: A Systematic Review," SN Computer Science, vol. 5(4), April 2024

[5] I. Gaudet, A. Hüsser, P. Vannasing, and A. Gallagher, " Functional Brain Connectivity of Language Functions in Children Revealed By EEG and MEG: A Systematic Review, " Frontiers in Human Neuroscience, vol. 14, March 2020

[6] L. Y. Ganushchak, I. K. Christoffels, and N. O. Schiller, "The Use of Electroencephalography in Language Production Research: A Review," Frontiers in Psychology, vol. 2, September 2011

[7] K. Konrad, C. Firk, and P. J. Uhlhaas, " Brain Development During Adolescence: Neuroscientific Insights Into This Developmental Period ," Deutsches Ärzteblatt International, vol. 25, June 2013

[8] D. Celllier, J. Riddle, I. Petersen, and K. Hwang, "The Development of Theta and Alpha Neural Oscillations From Ages 3 to 24 Years, "Developmental Cognitive Neuroscience, vol. 50, August 2021

[9] S. A. Kornilov, J. S. Magnuson, N. Rakhlin, N. Landi, and E. L. Grigorenko, " Lexical Processing Deficits in Children With Developmental Language Disorder: An Event-Related Potentials Study, " Development and Psychopathology, vol. 27(2), May 2015

[10] J. Araújo et al., " Atypical Cortical Encoding of Speech Identifies Children With Dyslexia Versus Developmental Language Disorder," BioRxiv, October 2022

[11] M. Keshavarzi, S. Richards, G. Feltham, L. Parves, and U. Goswami, "Neural Processing of Rhythmic Speech By Children With Developmental Language Disorder (DLD): An EEG Study. Imaging Neuroscience, vol.2, December 2024

[12] A. Gul, A. L. Schafer, and Y. Arbel, "Differential Neural Mechanisms of Feedback Processing in Children With Developmental Language Disorder: An Examination of Midfrontal Theta Connectivity, Children, vol. 11(10), October 2024

[13] S. Fatić et al., "Beta Spectral Power during Passive Listening in Preschool Children with Specific Language Impairment," Developmental Neuroscience, vol. 47(2), April 2025

[14] R. Horton-Ikard and S. E. Weismer, "A Preliminary Examination of Vocabulary and Word Learning in African American Toddlers From Middle and Low Socioeconomic Status Homes," American Journal of Speech-Language Pathology, vol. 16(4), 2007

[15] EMOTIV. FLEX 2 Saline - 32 Channel Wireless EEG Head Cap System. [Online] Available: https://www.emotiv.com/products/flex-saline?srsltid=AfmBOory5xRgMPO4NUhXj_W5u5pSZ5TPbgCo_xTaX7zzNui6boagYqTW).

[16] Swartz Center for Computational Neuroscience. What is EEGLAB? [Online] Available online: https://sccn.ucsd.edu/eeglab/

[17] M. H. Hayes, "Statistical Digital Signal Processing and Modeling," John Wiley & Sons, April 1996

[18] F. Auger and P. Flandrin, "Improving the Readability of Time-Frequency and Time-Scale Representations By The Reasssignment Method," IEEE Transactions on Signal Processing, vol. 43(5), May 1995

[19] A. C. Kelly and C. A. Gobl, "Comparison of Mel-Frequency Cepstral Coefficient (MFCC) Calculation Techniques," Journal of Computing, vol. 3(10), October 2011

[20] St L and S. Wold, "Analysis of Variance (ANOVA)," Chemometrics and Intelligent Laboratory Systems, vol. 6(4), November 1989

[21] K. Goodspeed et al., "Electroencephalographic (EEG) Biomarkers in Genetic Neurodevelopmental Disorders," Journal of Child Neurology, vol. 38, pp. 466-477, May 2023