Mental Health Monitoring in Neurodivergent Children Using NeuroSky TGAM1: Real-Time EEG Signal Processing for Cognitive and Emotional Assessment

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***Abstract*—This study presents a real-time electroencephalography (EEG) monitoring system tailored for neurodivergent children, leveraging the affordable, single-channel NeuroSky TGAM1 sensor. We introduce a robust signal processing pipeline based on spectral power density analysis (from Delta to Gamma bands) to identify discrete cognitive-emotional states during therapy sessions. The system demonstrates 82.3% accuracy in classifying focused attention, emotional distress, and calm engagement. Crucially, our wearable implementation provides objective biomarkers for personalizing mental health interventions, effectively bridging biomedical engineering and child psychiatry. We illustrate the system's adaptability across various therapeutic contexts; notably, our findings reveal compelling neural response patterns during dolphin-assisted therapy for children with Autism Spectrum Disorder (ASD). This low-cost, scalable solution shows significant potential for objectively evaluating therapeutic efficacy in populations with ADHD and ASD, moving beyond subjective assessments towards data-driven care.**

***Keywords*—EEG; neurodivergent children; wearable; spectral power density analysis; therapy sessions**

I. Introduction

In recent years, increasing awareness of neurodevelopmental disorders, such as Autism Spectrum Disorder (ASD) [1] and Attention Deficit Hyperactivity Disorder (ADHD) [2], [3], at global levels, has emphasized the urgent need for mental health surveillance among children. Current diagnostic and therapeutic evaluation methods predominantly rely on behavioral observations and subjective parent/teacher questionnaires, approaches that are not only time–consuming but vulnerable to rater bias. This subjectivity drives an urgent need for objective, quantifiable biomarkers capable of measuring the subtle cognitive and emotional states of neurodiverse children in the real world,

Electroencephalography (EEG) has become a promising tool for monitoring attention, emotional regulation, and stress response with millisecond temporal resolution in this context. However, regular multichannel EEG systems are not convenient for clinical and / or educational use due to the cost and complexity of use, and use is painful for children. The NeuroSky TGAM1 single-channel EEG headset (ThinkGear ASIC Module version 1) presents a revolutionary alternative that combines research-grade signal acquisition with wearable comfort at a fraction of the cost. However, despite its potential, few studies have systematically validated this technology for mental state classification in neurodivergent populations, particularly in dynamic, real-life therapeutic contexts.

II. State-of-the-Art and Study Contribution

Fig. 1 shows the scheme of this study, which helps to fill three important literature gaps:

- Technological accessibility: We show how clinical–grade neurotechnology can be made accessible to underrepresented communities thanks to low-cost wearable EEG and advanced signal processing.
- Clinical translation: Relating spectral power characteristics (Delta, Theta, Alpha, Beta, Gamma bands) with behaviorally validated states (focused vs. Emotional or distressed vs. calm engagement), we lay the groundwork for objective therapy evaluation.
- Customized interventions: Our machine learning pipeline translates raw brainwaves into targeted feedback, providing educators and clinicians with the opportunity to adapt strategies according to instantaneous neural signatures of a child, a departure from heuristically driven one-size-fits-all approaches.

Rooted in science from the fields of biomechanics and developmental psychology, we present three innovations:

- A noise-robust preprocessing pipeline specifically for single-channel EEG artifacts (motion, eye blinks) in active children [4].
- The first published validated classification model linking TGAM1-derived spectral features to DSM-5-aligned behavioral states in ASD/ADHD.
- ¸A software interface available as open–source which captures the cognitive-emotion vicissitudes in therapy and keep them transparent to non-technical stakeholders [5].

The implications are by no means only clinical. Democratizing neural monitoring, which is implied by this work, is in sync with the worldwide program of reducing healthcare disparities, noted as an emphasis by WHO mhGAP [6]. Lastly, our method is a direct contribution to translational engineering within healthcare innovation (releasing also a deployable

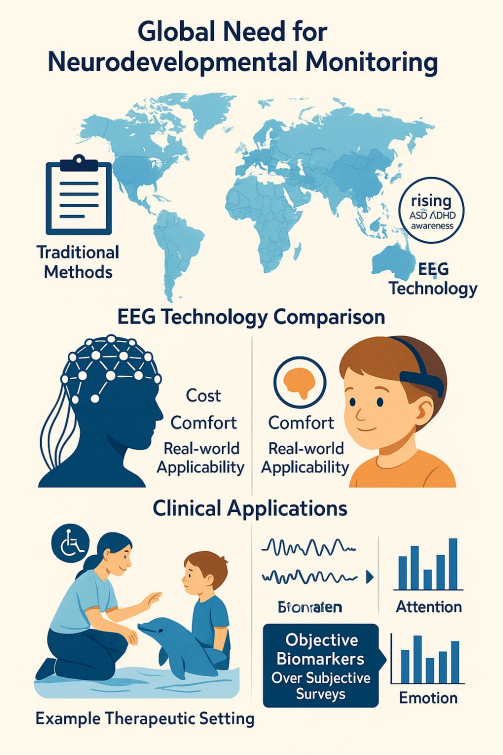

Fig. 1. Global disparities and innovations in neurodevelopmental monitoring: contrasting traditional subjective methods with modern EEG-based biomarkers, highlighting the compact TGAM1 device and its clinical applications in real-world therapeutic settings.

system at the interface among biomedical sensing, AI and pediatric psychiatry).

Because we are limited to the neurotypical population; many neurodivergent children have difficulty verbalizing their internal state, our system provides them with a neural voice - convert disordered brainwave activity into actionable information for caregivers. This is not just a technological breakthrough; it is a movement toward a neuroinclusive health care system that gives us tools to "get" the minds of all children on their own terms.

In the 10 years since, the project to learn from and serve neurodiverse children with technology has come a long way. Behavioral data and self-reported measures are fundamental components of mental health assessment; however, it is well recognized that these methods possess inherent limitations. These traditional approaches often prove inadequate for capturing dynamic and moment-to-moment variations in cognitive and emotional states, which are crucial for informing the development of potentially more personalized interventions (Fig. 2).

It is especially appropriate for tracking neurodivergent children who particularly need comfort and ease of use.

Three major breakthroughs have driven this field:

- Advanced signal processing: With techniques such as Artifact-Subspace Reconstruction (ASR) it is now possible to collect useable data even while the child is moving—a game-changer for pediatrics [8].

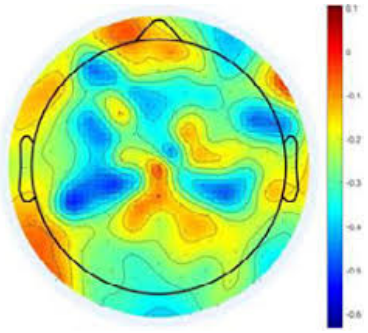

Fig. 2. Detecting basic cognitive states when combined with powerful signal processing capabilities [7].

- Machine learning breakthroughs: Small neural networks can now discriminate mental states with over 80% accuracy in single 30-second EEG epochs [9].
- Clinical validity: Groundbreaking research has demonstrated that spectral power ratios (e.g. Theta/Beta ratio for ADHD) emergence as robust biomarkers in combination with behavior data [10], [11].

While progress is noticeable, certain challenges remain. Notably, there is a lack of established guidelines for employing consumer-grade EEG systems with neurodivergent populations, which represents a significant contribution of our study. Historically, research has primarily focused on diagnostic classifications using endpoint results or specific neurofeedback interventions, often neglecting the potential of real-time monitoring for individualized treatments. Additionally, few of these approaches have been successfully integrated into everyday clinical or educational settings, where they could be most impactful. Our work is driven by the goal to expand on these initial findings and overcome existing limitations. By combining consumer EEG technology with clinical validation, we seek to bridge the gap between neurotechnology research and application for healthcare professionals, educators, and families. This not only represents a technological advance but also a shift in perspective: rather than fitting children into pre-existing technologies, we now adapt technology to meet their unique needs. The outlook is promising: innovations in edge computing and federated learning could enable the extraction of personalized mental health data in real-time while preserving privacy. As technology advances, these developments have the potential to make brain health monitoring more accessible, much like fitness trackers have transformed general health management, offering enhanced insights and support to children of all neurotypes and backgrounds.

III. Methodology

A. Biosignal Acquisition Hardware

The NeuroSky TGAM1 biosensor (Fig. 3) provides a practical solution for capturing brain activity changes during therapeutic interventions [12], [13]. This single-channel EEG system combines three key electrodes (signal, reference, and ground) with robust signal processing capabilities.

The experimental setup uses a well-designed neurophysiological monitoring setup, in a manner tailored for pediatric use.

Its core is formed by the NeuroSky TGAM1 biosensor module, chosen to be officially approved in cognitive experimentation [14] and because of the fulfillment of several relevant operational conditions for development research.

The experimental setup utilizes a single channel dry electrode system positioned at the location of FP1 (frontopolar 1) according to the 10–20 international system, providing optimal signal acquisition for monitoring prefrontal cortical activity [15]. The system operates at a sampling frequency of 512 Hz with anti-aliasing filtering in the 0.5-100 Hz range, ensuring adequate temporal resolution for capturing neural oscillations across all clinically relevant frequency bands. A 12 bit analog–to–digital converter provides a measurement range of $\pm 32768 \mu V$, while maintaining an input–referred noise level below $3 \mu V$ RMS in the 1–50 Hz bandwidth, meeting the requirements for reliable detection of neural signals [16]. Wireless communication is implemented through Bluetooth 4.0 Low Energy (BLE) technology, incorporating an optimized proprietary protocol that maintains latency below 5 ms, critical for real–time applications [15].

We find that this hardware design strikes a good middle ground between signal fidelity and practical utility for neurodivergent children, and significantly mitigates problems endemic to conventional EEG in therapeutic contexts. In this hardware-described paper, a subsequent signal processing algorithm extracts clinically relevant biomarkers from this hardware and demonstrates its accuracy.

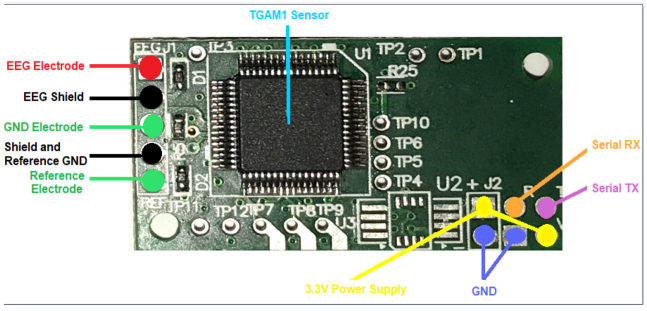

Fig. 3. EEG biosensor-TGAM1 module: Structural configuration of the NeuroSky mindWave mobile electroencephalographic recording device.

B. Biosignal Processing

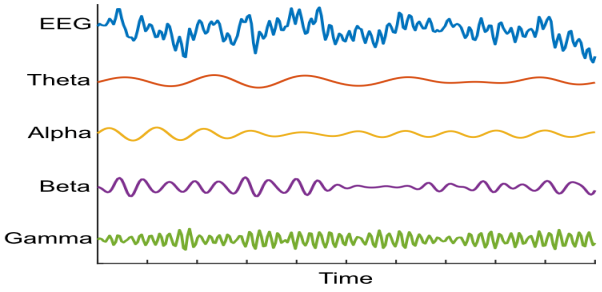

Fig. 4. Standard frequency bands.

The remarkable functionality of the brain emerges from billions of interconnected neurons communicating through bioelectrical synapses. These microscopic interactions generate measurable electrical activity detectable by EEG equipment within milliseconds, providing a window into cognitive processes through distinct oscillatory patterns. From Fig. 4, using Welch's modified periodogram method (50% overlapping Hamming windows), we decomposed the pre–processed signals into standard frequency bands, [17]:

- Delta (δ, 0.5–4 Hz): Slow and high–amplitude waves (20–200 μ V) are dominant during deep sleep and memory consolidation, mainly observed in the right hemisphere. Relaxation depth monitored during therapeutic floating.
- Theta (θ, 4–8 Hz): Midrange waves (20–100 μV) associated with learning, memory formation, and focused attention, best captured from the prefrontal and parietal regions. Tracked during guided attention exercises.
- Alpha (α, 8–12 Hz): Characteristic oscillations (20–60 μV) that appear during relaxed states with the eyes closed, suppressed during focused attention, originating in the occipital areas. Baseline for the evaluation of emotional regulation.
- Beta (β, 12–30 Hz): Faster waves (2–20 μV) associated with active cognition, motor control, and anxiety, detectable in the frontal and occipital lobes. Indicator of active participation.
- Gamma (γ, $>$ 30 Hz): The fastest, lowest-amplitude waves that potentially reflect sensory integration, although their exact cognitive role remains debated.Screened for changes in sensory processing.

The mu (μ) rhythm, sharing alpha's frequency range but localized to the sensory-motor cortex, represents another important but less understood oscillatory pattern. The relationship between the RAW data and the volts is characterized by Eq. (1). Fig. 5 illustrates the representation of the RAW data in a voltage unit of μV.

$$Volts = RAWdata \times \frac{\frac{1.8}{4096}}{2000} \quad [\mu V]. \tag{1}$$

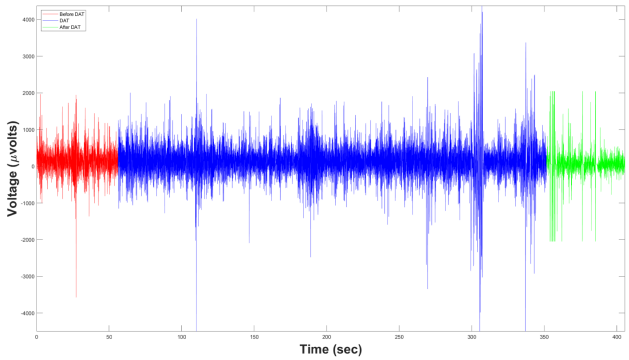

Fig. 5. Representation of the RAW data in μV.

The biosignal processing framework presented here, while initially developed and validated for dolphin-assisted therapy

(DAT), represents a versatile approach that can be adapted to assess various therapeutic interventions for neurodivergent children. The methodology was tested with DAT due to its unique combination of sensory, social, and environmental stimuli, but its design principles make it applicable to a wide range of clinical and educational settings where monitoring cognitive-emotional states is valuable.

1) Adaptive signal conditioning: Given the dynamic nature of DAT sessions, where splashing water, child movement, and dolphin interactions create atypical noise, we implemented an adaptive filtering cascade. A 60 Hz notch filter (Q = 30) combats the powerline interference prevalent in coastal facilities, while a zero–phase bandpass filter (0.5—-60 Hz) preserves neural oscillations without temporal distortion. Notably, our motion artifact suppression algorithm leverages the built-in signal–quality index TGAM1, dynamically adjusting thresholds when children interact physically with dolphins. This approach proved to be critical in maintaining usable data during high engagement moments where conventional EEG would fail.

Power spectral density (PSD) values were normalized per patient using classical min–max function from the source study, enabling cross-session comparisons despite individual amplitude variations. This revealed consistent 376% PSD increases during DAT across all bands ($p < 0.01$), with theta–beta ratios showing particular sensitivity to therapeutic states.

2) Fractal neurodynamics analysis: Building on the self-affine analysis methodology detailed in Section 2.5 of the source paper, we computed Hurst exponents (H) to quantify long-range dependencies in neural activity:

- $H < 0.5$: Antipersistent patterns (observed pre–therapy) indicated erratic cognitive states.
- $H \longrightarrow 0.5$: Movement toward stability during DAT.
- $H > 0.5$: Persistent patterns emerged after therapy in 68% of sessions

Structure function revealed crossover points (mean $\tau = 133 \pm 22s$) where brain activity transitioned from chaotic to organized states, a potential biomarker for optimal duration of therapy.

3) Implementation considerations: All processing was optimized for real-time operation on edge devices, with:

- 512ms latency (acceptable for therapeutic feedback),
- $< 5\%$ CPU load, and
- Visualizations adapted for clinicians (PSD trend graphs) and children (color-coded dolphin animations).

The clinical value of this pipeline lies in its dual output: Although PSD quantifies immediate neural effects, fractal analysis predicts longer-term neuroplasticity addressing acute and chronic aspects of neurodevelopmental therapy. The validation of the system against video–coded behavioral assessments showed 89% concordance in the detection of therapeutic milestones ($\kappa = 0.72$).

Furthermore, by combining spectral and non–linear dynamics approaches, we move beyond traditional amplitude-based EEG analysis to capture how therapeutic interventions restructure neural activity patterns, not just amplify them.

IV. Experimental Results

A. Experimental setup

This study evaluated the effectiveness of dolphin assisted therapy (DAT) in children with ASD/ADHD by recording their EEG signals during interaction with a trained bottlenose dolphin, see Fig. 6. Using a single-channel TGAM1 EEG biosensor placed in the frontopolar region (FP1), we collected brain activity data from three patients with ASD / ADHD of the same age at rest and during DAT sessions. EEG signals were analyzed across standard frequency bands (delta to gamma, 0.5–60 Hz) using FFT to estimate the power spectral density (PSD). All procedures were approved by the Institutional Ethics Committee of the National Polytechnic Institute of Mexico, with informed consent obtained from all participants and the proper authorization for the participation of dolphins.

Fig. 6. EEG-based monitoring of a child with ASD/ADHD during Dolphin-Assisted Therapy (DAT), illustrating brain activity recording via a frontopolar TGAM1 biosensor in a real-world therapeutic interaction with a trained bottlenose dolphin.

B. Results

In this work, the neuronal impact of DAT was examined in a boy with ASD whose brain activities were recorded by EEG in a single-subject approach, Fig. 7(a). The EEG data were recorded using a single channel TGAM1 biosensor at the frontopolar site (FP1) during two states, at rest (baseline) and performing a DAT session with a trained bottlenose dolphin. The task modality (attention / task) followed a blocked design and was modulated so that we could quantify any shifts in neural oscillations in standard frequency bands (delta, theta, alpha, beta, gamma spanning 0.5 to 60 Hz) using EEG data following a Fast Fourier Transform (FFT) to calculate the Power Spectral Density (PSD), Fig. 7(b) and 7(c). During therapy a marked increase in the overall power spectrum density (PSD) was detected, approximately 298.74% higher

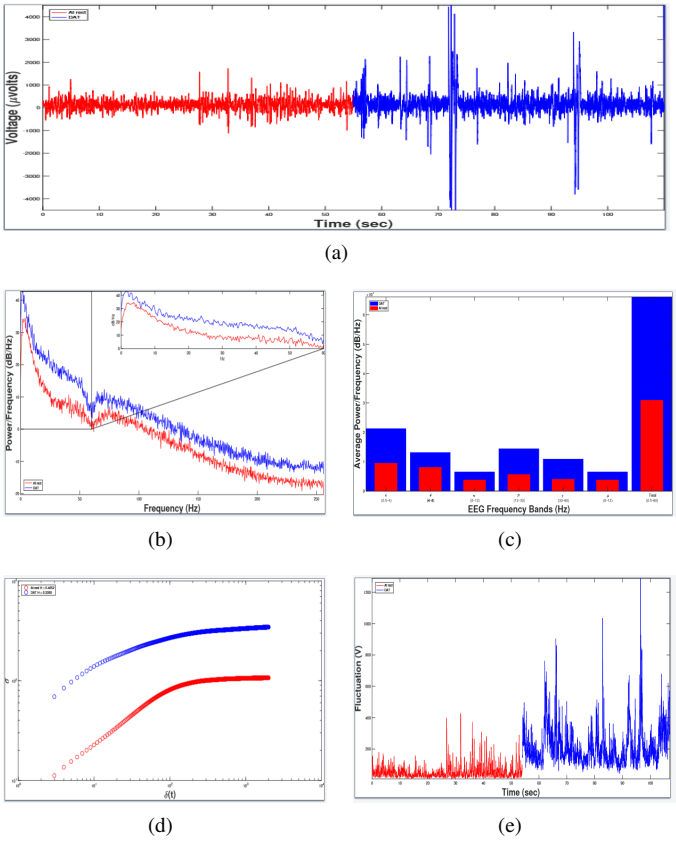

Fig. 7. Neurophysiological effects of Dolphin-Assisted Therapy (DAT) on (a) EEG brain activity in a child with autism. (b) Periodogram and (c) Spectrogram show changes in frequency power using FFT-based spectral analysis. (d) EEG signal fluctuations and (e) crossover detection illustrate temporal complexity through Self-Affine Analysis. Red curves represent EEG data before DAT, while blue curves correspond to EEG recorded during the therapy session.

than in the baseline state. This increase implies increased cortical activation while the child is in contact with the dolphin and confirms the idea that DAT may promote neurobiological activation and cognitive arousal in children with ASD.

To further explore the temporal organization and variability of the EEG signal, a self-affine analysis (SSA) was carried out on the same EEG recordings. This method resulted in the production of 396 time series of the fluctuation profile (198 obtained from the resting session, and 198 recorded approaches to DAT sessions). Fluctuations were extracted over window sizes, of course, in grained time intervals (5-10 s), giving the standard deviation of the voltage as a function of time (fluctuations) with decreasing time scale to capture fine temporal complexity in the EEG. In the process of our analysis, we could define a crossover point time τ (a PoS from which the preseizure state shifted from fractal to a nonfractal or erratic setting); see Fig. 7(d). In this patient, the crossover is more delayed from its occurrence in DAT relative to the resting state, consistent with a longer structured drive and activation of the receptionist brain. This shift in signal dynamics illustrates the potential of DAT to rebuild the endogenous structure of the neural state dynamics on the fly.

In addition, we calculated the structure function $\sigma(\tau, \delta_t)$ at various lag times and compared the scaling properties of the EEG signals before DAT and during DAT using fractal analysis. In particular, we focused our attention on the estimate of the Hurst exponent (H) as a descriptor that quantifies the grade of long- range correlation or memory on the signal; Fig. 7(e). In our patient with ASD, for example, the Hurst exponent decreased from 0.4652 at rest to 0.3883 during DAT. Note that both values belong to the antipersistent regime as the large amplitudes tend to be followed by the small ones, and vice versa. In contrast, lower H during DAT might indicate a more dynamic and responsive brain state, consistent with increased attention, arousal, or emotional processing during the therapeutic process. Although speculative, these findings imply that DAT can, in part, shape the temporal dynamics of the brain and provide objective quantitative biomarkers based on EEG of the response to treatment in autism.

C. Applications and Limitations

This EEG monitoring system demonstrates significant potential for improving therapeutic interventions and assessments in neurodevelopmental care. Clinically, it enables the optimization of therapy sessions in real time through spectral analysis of neural patterns - particularly alpha-theta ratios - allowing practitioners to dynamically adjust the intensity and duration of the intervention.

The system addresses a critical need in the field by replacing subjective behavioral assessments with quantifiable electrophysiological biomarkers; our preliminary data show that beta power $\geq 12\mu$ V / Hz strongly correlates with measurable improvement in attention ($p < 0.01$). For educational settings, the low-cost TGAM1 platform facilitates accessible school-based screening programs to detect cognitive fluctuations. Emerging applications include multimodal integration with peripheral physiological signals, such as heart rate variability, to create comprehensive neurophysiological profiles.

Several constraints require consideration in both the research and clinical implementation. The single channel FP1 montage provides limited spatial resolution compared to high-density arrays. Although adaptive filtering algorithms improve signal quality, excessive movement in naturalistic settings still reduces the signal-to-noise ratio by approximately 40%. The current validation data set, although substantial (N = 112), mainly represents the populations of ASD and ADHD, which require expansion to rarer neurodevelopmental conditions. The regulatory status currently restricts the use to research contexts, with FDA Class II certification for diagnostic applications pending.

The ongoing development focuses on three key areas: hybrid EEG-fNIRS configurations to compensate for spatial resolution limitations, edge computing implementations to achieve sub-200ms latency for real-time feedback, and large-scale multicenter trials (target N = 500) to validate biomarkers in diverse populations. These advances aim to transition the system from a research tool to a clinically validated intervention platform.

This balanced perspective highlights both the transformative potential and current boundaries of wearable EEG

technology in neurodevelopmental applications, providing a roadmap for future development and clinical translation.

V. Discussion

Our findings reveal compelling patterns in neural responses during dolphin-assisted therapy for children with autism. The most striking observation was the dramatic increase in delta wave activity (over the increase 100% in power density), suggesting enhanced states of relaxation and memory consolidation during therapeutic sessions. Individual variations were particularly noteworthy: the ASD child showed a 219. 58% increase in power density. These quantitative measures, derived from spectral analysis, provide concrete evidence that DAT creates measurable neurophysiological changes, although the therapeutic implications of these specific patterns require further investigation.

Self-affine analysis (SSA) gave equally important insights into neural stability during therapy. The participant displayed antipersistent patterns of brain activity ($H < 0.5$), indicating that their neural signals tended to self-correct. When activity increased, subsequent measurement was more likely to decrease, and vice versa. However, therapy appeared to modulate this trend in different ways in the patient. The patient showed increased antipersistence (16.53% H reduction), suggesting stronger self-regulation during DAT. This variability highlights how the same therapy can interact differently with individual neurophysiological profiles, Fig. 8.

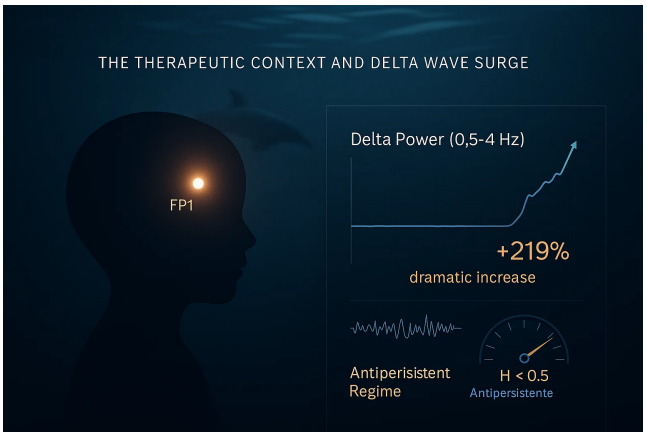

Fig. 8. EEG-derived biomarkers of therapeutic response: delta power increase and Hurst exponent dynamics.

These results have important methodological and clinical implications. Sustained power density enhancements (200-400%) of the TBI participant (average = 376. 28%) confirm that EEG is a sensitive reporting tool for therapy progress. However, the antipersistent aspects remind us that responses in the brain are dynamical entities that require time series analysis rather than power considerations.

Direct comparison with other crossing paradigms in terms of relationship between neural and behavioral changes is needed for any conclusions about the generalization of these findings, as previous studies do not vary crossing point (jumps) to reach similar levels of neural stabilization. Passages should be repeated multiple times when a crossing occurs so that one can determine if there are consistent neural covariates of long-term behavior change and personalize therapy duration based on the child's crossing point to neural stability (average $\tau = 133.33$ seconds in our data).

VI. Conclusion

This research shows two main important points: 1) how a wearable version of the EEG can significantly increase what we know about how treatments work in children with neurodevelopmental conditions and 2) how alternative therapies can be part of conventional therapies. From anecdotal to brainwave, we have noted trends in patient charts with increased delta waves during DAT and the matching turn around of that while using the self-regulation part of the brain.

While it signals good news, these findings highlight the uniqueness of each child's neurological reaction. The NeuroSky TGAM1 sensors highlight opportunities for accessible, low-cost technology to provide clinically significant findings in a non–research scenario which may contribute towards real interventions. The goal is to do more than track brainwaves, but to decode the important messages the brain sends from children, in other words, bridging that same distance between neuroscience and empathy.

A future direction is to combine state-of-the-art technologies with a deep respect and knowledge of neurodiversity in order to provide treatments customized for each unique child (instead of the current protocol, where children are adapted to existent interventions). Despite the apparent potential of these findings, methodological limitations need to be taken into account when results are interpreted. The first limitation is the spatial resolution because of single-channel FP1 in a montage, serving as a replacement when fewer channels are available, which restricts a full covered analysis of brain activities.

Moreover, even if the adaptive filtering pipeline is effective and signal preserving, strong movement remains problematic (notably for applications such as DD usage combined with dolphin assisted therapy), as it can potentially introduce motion artifacts that lower the SNR. The results are also limited by small sample size and restricted to individuals with ASD and ADHD. Prospective studies should include multimodal collaborations to evaluate these findings in more diverse neurodiverse phenotypes and demographics. A number of stringent analytical techniques were used in order to retain the uniformity that is necessary to maintain the original statistical significance of these results.

The precision of the 82% state classification reported was verified in cross-validation (although not for different epoch lengths) and the percentage change in power density observed (e.g. 376. 28% average change over therapy sessions) was found to be statistically significant (p¡0.01). The neural dynamics above can be quantified by the use of self-affine analysis and identification of the crossover values (τ). Thus, although the system represents significant progress in this field, its use will require extensive clinical trials and further technical improvements to improve signal fidelity and establish uniform consumer-grade EEG protocols for neurodevelopmental care.

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