

Article

Short-Latency Changes in Closed-Eye EOG Following Medication Intake in ADHD

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Abstract

Background: Optimising medication for Attention Deficit Hyperactivity Disorder (ADHD) is often hindered by the lack of practical physiological indicators that can inform treatment effects. Electrooculography (EOG) has been suggested as a low-burden marker of neurophysiological processes relevant to ADHD, but its responsiveness to medication within routine clinical settings is not well established. **Methods:** We analysed anonymised clinical records from adults with ADHD receiving stable, ongoing medication who underwent closed-eye EOG recordings immediately before and after taking their scheduled dose during standard consultations. Recordings were obtained using clinical EEG equipment. Heart rate and blood pressure, measured after each EOG session, were included as contextual indices of physiological state. Pre–post changes were assessed using paired t-tests and binomial tests, with effect sizes and confidence intervals reported for the main pre–post comparisons, with Pearson correlations used to evaluate associations between EOG and cardiovascular measures. **Results:** Both mean and peak EOG power showed consistent within-session reductions, with the majority of individuals exhibiting a decrease across measures. Cardiovascular parameters showed no systematic pre–post change, and differences in cardiovascular measures did not correlate with changes in EOG activity. **Conclusions:** Closed-eye EOG showed systematic within-session modulation in adults with ADHD on stable treatment. These preliminary findings suggest that EOG is sensitive to short-latency physiological changes occurring within a clinical timeframe. However, the present design does not establish pharmacological specificity, and further controlled studies are needed to determine whether such changes are specifically medication related and whether they have relevance for treatment monitoring and titration.

Keywords: attention deficit/hyperactivity disorder; electrooculography; neurophysiology; translational psychiatry



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1. Introduction

1.1. Clinical Challenge

Attention Deficit Hyperactivity Disorder (ADHD) is a heterogeneous neurodevelopmental condition that significantly impacts individuals across their lifespan. While contemporary frameworks highlight context-dependent strengths, the functional challenges associated with ADHD remain substantial, as evidenced by significant disparities in employment outcomes and financial stability between affected individuals and their siblings without the condition [1]. Furthermore, the challenges of medication titration complicate treatment adherence, as patients often experience difficulties in managing

their treatment regimens, leading to non-compliance rates ranging from 13% to 64% [2]. This non-adherence is exacerbated during the titration phase, where the need for careful dosage adjustments can discourage patients and their families, ultimately resulting in early discontinuation of treatment [3]. The individual and functional implications of delayed treatment due to titration challenges are significant, not only affecting the individual but also imposing a broader societal impact through increased healthcare costs and lost productivity [4]. Addressing these issues is crucial for improving patient outcomes and optimising healthcare resources.

1.2. Personalised Medication in ADHD

The pursuit of personalised medication in ADHD is increasingly supported by emerging research on biomarkers. ADHD is characterised by considerable heterogeneity in symptom profiles and treatment responses, highlighting the need for approaches that accommodate individual variability. Several potential biomarkers have been identified that may help guide medication titration and improve treatment efficacy. For instance, genetic variants such as single nucleotide polymorphisms (SNPs) in genes including ADRA2A and COMT have been associated with differential responses to methylphenidate, suggesting a genetic basis for individual variation in treatment outcomes [5].

Neuroimaging and electrophysiological measures have also shown promise. Techniques such as electroencephalography (EEG) have revealed neural signatures that may predict stimulant response, offering a more targeted approach to treatment selection [6]. Similarly, stress-related and immune markers measured in saliva have provided insight into physiological processes relevant to ADHD and may help track treatment effects over time [7].

Although these findings point to a growing toolbox of potential biomarkers, their practical value in routine clinical care remains to be established. A central question is whether such markers can deliver reliable, interpretable information that meaningfully supports medication titration in everyday settings. Demonstrating this will require robust validation, standardised protocols, and a clearer understanding of how biomarker signals interact with individual patient characteristics [8,9].

1.3. EOG as a Proxy for Neurocognitive States

Electrooculography (EOG) is a non-invasive technique that measures eye movements by detecting the corneo–retinal standing potential, providing low-burden, high-resolution physiological data well suited to settings where practicality and patient compliance are essential. EOG has been used as a proxy for a range of neurocognitive processes, including emotional responses and sleep stages, and has shown utility in state anxiety monitoring and sleep stage classification [10,11]. Altered EOG patterns have also been described in schizophrenia, reflecting underlying cognitive and emotional processes [12]. In ADHD, several studies indicate that EOG-derived features can distinguish affected individuals from healthy controls. These include eye movement behaviour in virtual reality tasks, which has demonstrated high classification accuracy [13] as well as diagnostic systems based on EOG alone [14]. Differences in EOG signal characteristics, such as complexity measures, further support its relevance to ADHD-related neurophysiology [15].

Importantly, EOG remains informative in closed-eye conditions [11]. Closed-eye movements can be reliably captured and show similarities to REM sleep eye movements in velocity and trajectory when visual input is absent [16,17]. This suggests that closed-eye recordings provide access to intrinsic oculomotor dynamics while minimising external sensory input. Together, these findings highlight EOG as a practical and physiologically

grounded method that can capture meaningful neurophysiological variation relevant to ADHD.

1.4. Hypothesis

Building upon prior evidence linking EOG alterations to ADHD traits, we hypothesise that medication may modulate intrinsic EOG activity in a manner consistent with changes in attentional regulation. Preliminary findings suggest that EOG patterns may change transiently [10], potentially suggesting a short-latency reactivity that could be informative within clinical timeframes. The continuity between REM and closed-eye awake eye movements further supports the use of closed-eye conditions as a stable, low-stimulus recording environment.

Therefore, we hypothesise that closed-eye EOG will be sensitive to medication-related neurophysiological changes within a single clinical session, providing a potential short-latency physiological window into medication-related effects.

1.5. Study Aim

To test this hypothesis, we aim to evaluate the most direct prediction it generates within the constraints of the available clinical data: the EOG of patients with ADHD who receive optimal pharmacological treatment should show a consistent within-session change following medication intake and the intervening clinical procedures. Characterising this initial within-session relationship will allow future research to examine more complex aspects of EOG reactivity in relation to medication efficacy. If our hypothesis is not rejected, it will provide preliminary support for the idea that EOG responses may reflect medication-related neurophysiological changes, forming a basis for future controlled studies to assess their potential relevance for treatment evaluation.

2. Materials and Methods

2.1. Patient Data

This study was based exclusively on anonymised data derived from patient records. The original data were collected as part of standard clinical care for individuals treated for ADHD. As part of routine assessment and treatment, patients were informed about and given the option to undergo EOG recordings before and after medication, to be reviewed alongside other standard clinical measures such as blood pressure, heart rate, body mass index, clinical rating scales, and medication data.

Patients who accepted the option to undergo an EOG recording had been scheduled for their usual consultations in the mornings, with instruction not to take their regular morning medication until immediately after the first measurement. The clinical setting included a consultation room with comfortable seating, where two recording sessions of five minutes each were conducted with the patients' eyes closed and awake. The procedure involved a pre-medication recording session followed by the administration of the medication, after which a normal consultation lasting approximately 30 min took place before the post-medication recording session.

For the present analysis, we included records from patients whose clinical data met the following criteria: a diagnosis of ADHD in accordance with the DSM-5 [18] or ICD-10 [19], with a minimum DIVA score of six elements for inattention and/or six elements for hyperactivity/impulsivity; stable and satisfactory pharmacological treatment; and an age range of 18 to 55 years. Exclusion criteria comprised any diseases affecting eye movements and other significant psychiatric disorders.

2.2. EOG Acquisition

EOG data were recorded using standard clinical EEG equipment with a sampling frequency of 100 Hz. Electrodes were placed at the forehead and at the left and right epicanthus regions. The forehead electrode served as a reference for the two lateral electrodes.

2.3. Cardiovascular Measures

ADHD medications, such as dexamethylphenidate and guanfacine, have been shown to exert significant effects on cardiovascular function, including alterations in heart rate and blood pressure during both acute and long-term treatment phases [20]. In addition, psychological and physical state is likely to vary between measurements. These potentially systematic autonomic and arousal-related changes could influence the EOG measures.

To address this potential source of bias, the blood pressure and heart rate measurements taken directly after each EOG session were interpreted as proxies for general arousal level and included as control parameters in the analysis. These measurements were obtained using a standard automated device.

2.4. Signal Processing

To quantify the frequency characteristics of the EOG signal, spectral analysis was conducted. A minimal processing pipeline was used. Visual quality control was performed to check for obvious technical problems, including missing data and abrupt signal jumps. No such problems were identified, and no recordings, epochs, measurements, or signal segments were rejected, excluded, interpolated, or reconstructed. No digital filtering was applied. The horizontal EOG signal was derived by contrasting the left and right lateral channels. The power spectral density was then computed from the full accepted horizontal EOG signal using Welch's method, which employed a Hanning window with a segment length of 1024 samples.

In this initial analysis, the EOG activity was parameterised by extracting two key features from the recordings. Specifically, mean power defined as the average power spectral density across the full output spectrum, and peak power defined as the maximum power spectral density within it. These features formed the basis for further statistical analysis.

2.5. Statistical Analysis

Prior to statistical testing, both mean and peak EOG power values were normalised by dividing them by the corresponding median group-level pre-medication values. Initially, we conducted paired *t*-tests to assess whether the mean change from pre- to post-medication differed significantly from zero for mean and peak EOG power, as well as the cardiovascular measures, pulse, systolic, and diastolic blood pressure. This approach accounts for the paired nature of the data and quantifies the average magnitude and direction of change across participants, providing a robust measure of within-subject effects; for the main pre-post comparisons, we additionally report paired-sample Cohen's d_z effect sizes, calculated from the mean change divided by the standard deviation of the change scores, and 95% confidence intervals for the mean change. In addition to the paired *t*-tests, we performed binomial (sign) tests to examine the directional consistency of the observed changes. This non-parametric test compares the proportion of participants exhibiting a consistent direction against a 50% chance level, allowing us to determine whether effects were systematically aligned across individuals. Together, these tests offer complementary insights into pre- to post-medication differences with the paired *t*-test focusing on mean magnitude and the binomial test assessing consistency across participants. Given the small sample size, change-score distributions were also inspected descriptively for directionality and possible outlying observations. To further explore the relationship between

EOG and cardiovascular measures, we calculated Pearson correlations between individual differences (Δ = post-medication – pre-medication) in EOG and cardiovascular parameters. For each parameter pair, we reported correlation coefficients (r), two-tailed p -values, and the number of observations (n). All statistical tests were conducted at a standard alpha level of 0.05, which was used to guide the interpretation of statistical significance.

2.6. Analysis Code

The following Python (v. 3.9.5) packages were used for analysis: NumPy (v. 2.0.2) [21], SciPy (v. 1.13.1) [22], pandas (v. 2.3.2) [23], Matplotlib (v. 3.9.4) [24], Seaborn (v. 0.13.2) [25], MNE-Python (v. 1.8.0) [26], Pydantic (v. 2.11.7) [27].

3. Results

3.1. Participant Characteristics

In Table 1, we present the demographic and clinical characteristics of the participants involved in the study. A total of 20 candidates were included, with a mean age of 33 years ($SD = 9$), and a median age of 32 years, ranging from 23 to 53 years. The participants' scores on the Adult ADHD Self-Report Scale (ASRS) [28] at initial assessment averaged 56 ($SD = 6$), with a median score of 55, and scores ranging from 37 to 66. The reduction in ASRS scores (ASRS Δ) showed a mean reduction of 29 ($SD = 7$), with a median reduction of 28, and a range of reductions from 18 to 46. Gender distribution was 70% female ($n = 14$) and 30% male ($n = 6$).

Table 1. Summary of participant characteristics.

Variable	Statistic	Value
Age (years)	Mean (SD)	33 (9)
	Median [IQR]	32 [25 to 37]
	Range	23 to 53
Gender	Female	14 (70%)
	Male	6 (30%)
ASRS (initial)	Mean (SD)	56 (6)
	Median [IQR]	55 [53 to 59]
	Range	37 to 66
ASRS (Δ)	Mean (SD)	−29 (7)
	Median [IQR]	−28 [−31 to −24]
	Range	−46 to −18

IQR: Interquartile range; SD: Standard deviation; ASRS: Adult ADHD Self-Report Scale.

3.2. EOG Change

In our analysis of EOG changes, we observed a consistent reduction in both mean power and peak power following the intervention. Specifically, for mean power, a paired samples t -test indicated that values were significantly lower post-treatment ($M = 0.627$, $SD = 0.653$) compared to pre-treatment ($M = 1.845$, $SD = 2.022$), $t(19) = -2.542$, $p = 0.020$, $\Delta M = -1.218$ a.u., 95% CI for $\Delta M = [-2.221, -0.215]$ a.u., Cohen's $d_z = -0.568$. Similarly, peak power was significantly lower post-treatment ($M = 0.739$, $SD = 1.068$) compared to pre-treatment ($M = 2.403$, $SD = 3.020$), $t(19) = -2.331$, $p = 0.031$, $\Delta M = -1.664$ a.u., 95% CI for $\Delta M = [-3.158, -0.170]$ a.u., Cohen's $d_z = -0.521$. Furthermore, the binomial tests indicated that both EOG measures were aligned with this trend, as 18 out of 20 participants exhibited decreases in mean power and peak power, resulting in a binomial p -value of 0.0004 for both measures. The change scores were therefore strongly directionally consistent,

although the EOG power distributions were right-skewed and the small sample size limits formal assessment of outliers; the two participants showing increases were retained in the paired analyses. These findings are illustrated in Figure 1, which shows the normalised pre- and post-treatment measures together with the corresponding change-score distributions.

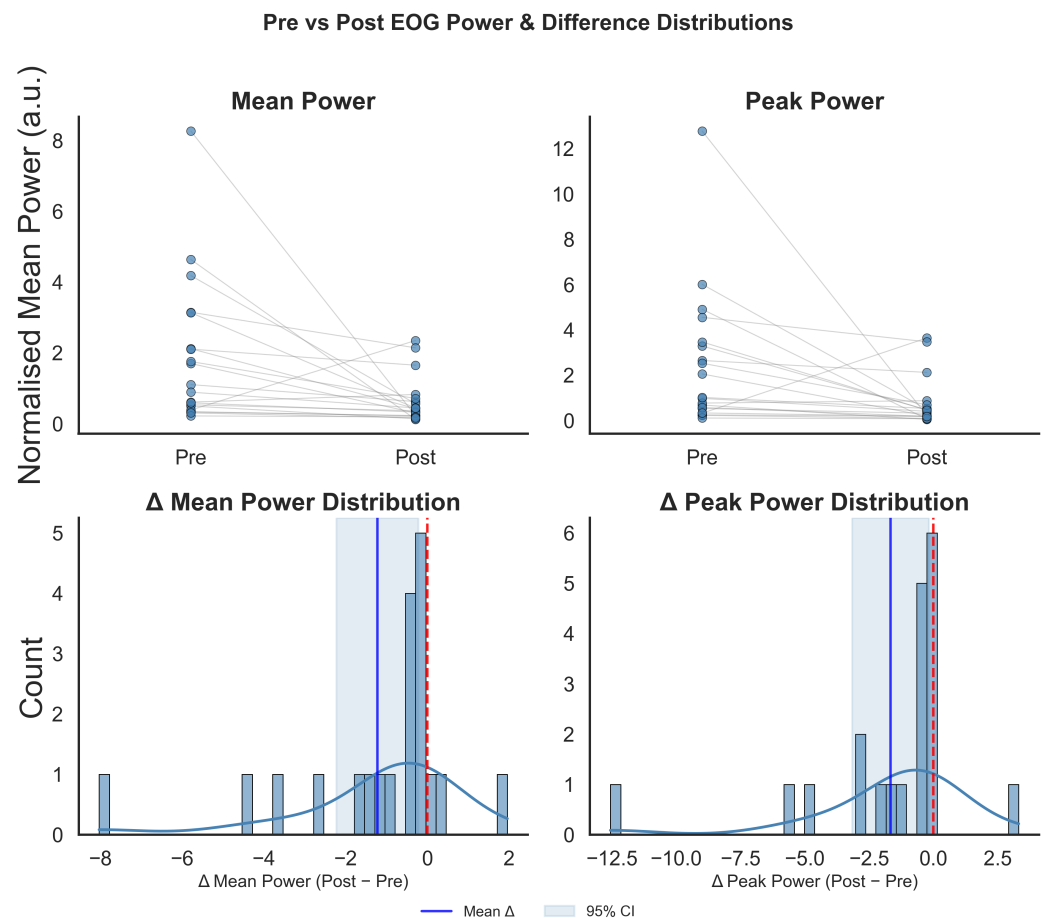


Figure 1. Pre-post changes in EOG power and corresponding change-score distributions. Columns show mean EOG power (left) and peak EOG power (right). **Top row:** normalised pre- and post-medication EOG values. Blue dots represent individual participant values. Gray lines connect the pre- and post-medication values for each participant. **Bottom row:** within-participant change-score distributions (Δ = post-medication minus pre-medication), with the mean change (solid blue line) and 95% confidence interval indicated (shaded area). Blue curve represents a density estimate of the distribution (for illustrative purposes). Red dashed line represent zero change. Values are normalised to the group-level pre-medication median. EOG: electrooculography; a.u.: arbitrary units.

3.3. Cardiovascular Changes

In contrast to the EOG findings, blood pressure showed no systematic change between sessions. This was true for both systolic pressure (post-treatment: $M = 109.20$, $SD = 11.87$; pre-treatment: $M = 108.90$, $SD = 10.84$; $t(19) = 0.188$, $p = 0.853$; $\Delta M = 0.30$ mmHg, 95% CI for $\Delta M = [-3.04, 3.64]$ mmHg, Cohen's $d_z = 0.042$; 13 increases, 7 decreases; binomial $p = 0.263$) and diastolic pressure (post-treatment: $M = 76.90$, $SD = 7.51$; pre-treatment: $M = 75.85$, $SD = 6.05$; $t(19) = 1.038$, $p = 0.312$; $\Delta M = 1.05$ mmHg, 95% CI for $\Delta M = [-1.07, 3.17]$ mmHg, Cohen's $d_z = 0.232$; 12 increases, 8 decreases; binomial $p = 0.503$).

Regarding heart rate, the mean pre-post difference was not statistically significant (post-treatment: $M = 74.05$, $SD = 5.88$; pre-treatment: $M = 72.50$, $SD = 6.84$; $t(19) = 1.651$, $p = 0.115$; $\Delta M = 1.55$ beats/min, 95% CI for $\Delta M = [-0.42, 3.52]$ beats/min, Cohen's $d_z = 0.369$).

However, the binomial test indicated that significantly more participants showed an increase in heart rate ($n = 15$) than a decrease ($n = 5$), binomial $p = 0.041$. Taken together, these results suggest that although average changes were small and non-significant, a majority of participants exhibited an upward shift in heart rate between sessions.

3.4. EOG–Cardiovascular Correlation

In this control analysis, we examined whether changes in cardiovascular measures were associated with changes in the EOG parameters. No significant correlations were found between Δ pulse and either Δ mean EOG power ($r = 0.059$, $p = 0.806$, $n = 20$) or Δ peak EOG power ($r = 0.025$, $p = 0.915$, $n = 20$).

Similarly, the analyses involving blood pressure showed no systematic associations. Δ mean EOG power did not correlate significantly with Δ systolic pressure ($r = 0.042$, $p = 0.860$, $n = 20$) or Δ diastolic pressure ($r = -0.148$, $p = 0.532$, $n = 20$). Δ peak power showed equally negligible relationships with systolic ($r = 0.043$, $p = 0.857$, $n = 20$) and diastolic pressure ($r = -0.179$, $p = 0.449$, $n = 20$).

Overall, these results did not provide evidence that variability in cardiovascular measures was systematically related to changes in the EOG parameters, although the absence of significant correlations in this sample cannot exclude arousal-related or autonomic influences, as illustrated in Figure 2.

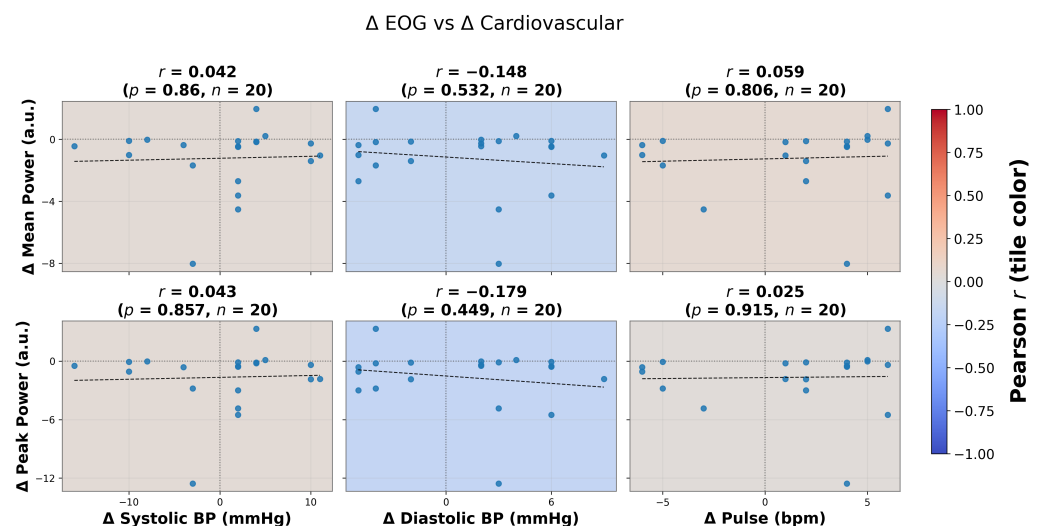


Figure 2. Correlation matrix of Δ EOG and Δ cardiovascular parameters. Scatter plots display the relationship between changes in EOG measures (Δ mean power [top row] and Δ peak power [bottom row]) and cardiovascular parameters (Δ systolic blood pressure [left column], Δ diastolic blood pressure [middle column], and Δ pulse rate [right column]) between sessions ($n = 20$). Each panel represents one parameter pair with individual subject data points (blue circles) and fitted linear regression lines (black dashed lines). Pearson correlation coefficients and corresponding p -values are reported directly in the panels. Background tile colors indicate Pearson correlation coefficient strength (coolwarm colormap: blue = negative correlation, white = near-zero correlation, red = positive correlation). Horizontal and vertical dotted reference lines mark zero change. Normalised EOG values (a.u.). Linear scales on both axes. EOG: electrooculography; BP: blood pressure; Δ : change from pre-medication to post-medication; a.u.: arbitrary units.

3.5. Statistical Summary

Across participants, both mean and peak EOG power showed consistent and statistically significant reductions from pre- to post-medication, with 18 of 20 individuals exhibiting decreases in both measures. The paired-sample effect sizes were moderate in magnitude (Cohen's $d_z = -0.568$ for mean power and $d_z = -0.521$ for peak power), with confidence

intervals for the mean changes excluding zero. These findings indicate a robust within-subject change in EOG activity between sessions, while the skewed EOG distributions and small sample size warrant caution in interpreting individual outlying changes.

In contrast, cardiovascular parameters showed no systematic pre–post change. Systolic and diastolic blood pressure remained stable, and heart rate exhibited no significant mean-level difference despite a directional imbalance favouring increases. Supplementary control analyses did not show significant correlations between changes in cardiovascular measures and changes in EOG parameters. These analyses indicate no detectable association in the present sample, but they cannot rule out arousal-related or autonomic contributions.

4. Discussion

4.1. Main Finding

This study demonstrates that EOG activity exhibits systematic within-session shifts following medication intake and clinical consultation in patients with ADHD receiving stable, ongoing medication. By examining closed-eye, awake EOG recordings across a single clinical session, we show for the first time that this simple measurement setup can detect systematic within-subject changes over a short timeframe. The consistent reductions in EOG power observed across participants support our hypothesis that closed-eye EOG is sensitive to medication-related neurophysiological changes.

Cardiovascular parameters, in contrast, remained largely stable across sessions, and none of the cardiovascular changes correlated with the EOG measures. The absence of significant correlations should not be interpreted as evidence of independence between EOG and cardiovascular dynamics, nor does it control for other factors such as relaxation, fatigue, expectancy, or the psychological impact of the clinical consultation. However, it also prevents us from rejecting the hypothesis.

Together, these findings provide the groundwork for future studies evaluating the clinical applicability and relevance of closed-eye EOG for medication titration in ADHD.

4.2. Comparison to Other Biomarkers

When viewed alongside other proposed biomarkers for ADHD, closed-eye EOG occupies a distinct position in terms of feasibility and potential clinical relevance. Genetic markers, such as single nucleotide polymorphisms (SNPs) in genes including DAT1 and DRD4, have been associated with differential responses to stimulant medication. However, their practical value is limited by modest effect sizes, population-level variability, and the need for specialised laboratory analyses, which restrict their immediate use in routine titration contexts [8,9]. Neuroimaging approaches—particularly functional MRI and task-based or resting-state EEG—provide rich information about neural pathways implicated in ADHD and medication response. Yet their dependence on specialised equipment, technician expertise, and controlled environments poses substantial barriers to their integration into standard appointments [6,29]. Compared to these modalities, EOG requires minimal setup, can be recorded in an ordinary consultation room, and relies on straightforward analytical procedures, positioning it as substantially more accessible for clinical workflows. Other proposed biomarkers, such as circulating microRNAs, remain at an exploratory stage. Although early findings suggest potential diagnostic or mechanistic relevance, the procedures involved—sample collection, laboratory processing, and assay interpretation—are resource intensive and not yet suited for point-of-care use [30]. Taken together, existing biomarker candidates vary widely in promise, maturity, and feasibility. In this landscape, closed-eye EOG stands out not because it is more predictive or better validated—those questions remain open—but because it aligns well with practical constraints of ADHD care. Its simplicity, low burden, and compatibility with routine clinical settings make it a

candidate biomarker with unusual logistical advantages. Future work will be needed to determine how its feasibility translates into clinical utility, particularly in comparison with more technically demanding but mechanistically richer approaches.

4.3. Limitations

A primary limitation of this study is the absence of a negative control or alternative control condition. Because all recordings took place within the natural flow of a clinical consultation, we cannot determine whether the observed EOG changes reflect a medication-specific effect or other factors inherent to the session, such as time, context, or expectancy. This constraint prevents causal inference and limits the strength of conclusions that can be drawn regarding specificity. Relatedly, the present findings do not support any claims regarding prediction of individual medication response. Although systematic EOG changes were observed, the study design does not allow us to establish predictive validity, nor does it address whether the magnitude of EOG change relates to clinical improvement or symptom change. Any such interpretation would exceed the evidence provided here.

The cardiovascular measures included in the analysis served solely as contextual indicators and cannot be regarded as definitive markers of psychological or physiological states. Their variability across participants illustrates the complexity of autonomic processes in this setting and emphasises that the absence of correlation with EOG should not be taken as mechanistic evidence of independence.

Furthermore, as this study was a retrospective analysis of records derived from routine clinical care, certain variables—such as exact medication dosage, treatment duration, and standardised comorbidity screening—were not available for systematic reporting. These factors, alongside the modest sample size ($N = 20$) and the inherent clinical and demographic heterogeneity of the cohort, precluded robust stratified analyses or the inclusion of these variables as statistical covariates. While the 30-min interval between recordings reflects a standard clinical consultation window, the lack of granular timing and dose–response data reinforces that these findings represent naturalistic observations within a real-world clinical context, rather than a controlled pharmacological study.

Taken together, these limitations indicate that the findings should be interpreted cautiously and confined to the within-session physiological effects observed in this specific clinical context.

4.4. Future Directions

Future work should aim to clarify the clinical and scientific relevance of closed-eye EOG by examining its stability, specificity, and potential predictive value in more controlled settings. A key next step will be to conduct longitudinal studies to determine whether within-session EOG changes relate to subsequent clinical outcomes or longer-term patterns of treatment response. Such studies would provide insight into whether the short-latency effects observed here reflect transient physiological modulation or more enduring aspects of medication efficacy. Larger cohorts, ideally across multiple sites, will also be important for assessing generalisability and identifying sources of inter-individual variability. Specifically, future research should be powered to develop a more fine-grained understanding of dose–response relationships both within and between patients. Such work will be essential for determining how demographic and clinical factors, including age, baseline symptom severity, and medication subclass influence EOG dynamics, and is a prerequisite for transitioning the marker from a measure of physiological presence to a functional tool for clinical titration. These studies should incorporate appropriate control conditions or comparison groups to disentangle medication effects from session-related or contextual influences. In addition, integrating independent clinical outcome measures, such as symptom

change, cognitive performance, or functional assessments, will be essential for determining whether EOG metrics contribute unique information beyond established clinical indicators. Together, these steps will help establish whether closed-eye EOG can serve as a meaningful adjunct to existing methods of evaluating medication effects in ADHD and will inform the extent to which it may support more individualised treatment strategies in future work.

5. Conclusions

In conclusion, this study shows that closed-eye EOG activity exhibits systematic within-session shifts following medication intake and clinical consultation in adults with ADHD who are receiving stable, ongoing treatment. The consistent reductions in EOG power suggest that this simple physiological measure is sensitive to shifts occurring within a clinical timeframe. While these preliminary findings do not establish pharmacological specificity, they provide a foundation for exploring how objective markers can assist in personalizing medication and tailoring pharmacological support to the individual's neurodevelopmental profile.

Establishing the clinical relevance of this approach will require controlled designs, longitudinal assessment, and larger, diverse cohorts. As this work progresses, closed-eye EOG could emerge as a low-burden, non-invasive adjunct for providing more individualised and supportive treatment strategies for the neurodivergent population.

6. Patents

S.B. privately owns a patent pending related to the methodology described in this paper (EP3860428A1).

Author Contributions: M.B. conducted data analysis, interpreted the results and drafted the initial manuscript. S.B. performed the clinical and paraclinical assessments, maintained the anonymised clinical database and generated the initial idea and concept of the study. All authors have read and agreed to the published version of the manuscript.

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Institutional Review Board Statement: Ethical review and approval was waived due to Danish legislation. Under the Danish Act on Research Ethics Review of Health Research Projects (Komitéloven) § 14, subs. 2, the requirement to notify and obtain approval from the ethics committee system does not apply to registry-based research projects ("registerforskningsprojekter") that are based on data (such as electronic signals, letters, and numbers) and do not involve human biological samples. As our study utilized non-invasive EOG measurements (digital data) from the clinic's database and involved no biological tissue, it falls strictly within this exclusion. Reference is made to the National Center for Ethics: <https://www.videnskabsetik.dk/ansoegning-til-etisk-komite/overblik-over-anmeldelsespligten/hvad-skal-ikke-anmeldes> (accessed on 6 June 2026).

Informed Consent Statement: Informed consent was not waived because it is a secondary analysis and the study was based exclusively on anonymized registry data. No individual-level patient information, personal identifiers, or sensitive personal data were available to the researchers.

Data Availability Statement: Raw data and the full analysis pipeline are not publicly available due to patient confidentiality and ongoing intellectual property protection. Aggregated anonymized data may be available upon reasonable request.

Conflicts of Interest: S.B. is the inventor of a patent-pending technology (EP3860428A1) related to the measurement and analysis methods described in this study. M.B. declares no conflicts of interest. The funders had no role in the design of the study; in the collection, analyses, or interpretation of data; in the writing of the manuscript; or in the decision to publish the results.

Abbreviations

The following abbreviations are used in this manuscript:

ADHD	Attention deficit/hyperactivity disorder
ASRS	Adult ADHD Self-Report Scale
DSM-5	Diagnostic and Statistical Manual of Mental Disorders, Fifth Edition
EOG	Electrooculography
ICD-10	International Classification of Diseases, Tenth Revision

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