



International Journal of Engineering, Science and Humanities

An international peer reviewed, refereed, open-access journal
Impact Factor 8.3 www.ijesh.com ISSN: 2250-3552

Artificial Intelligence Approaches for Early ADHD Detection in Children: A Review Based on Multimodal Behavioural Analysis

Sunita Rani

Computer Application, CT University Ludhaina
Sunitabarnala85@gmail.com

Dr. Arvind Kumar

Associate Professor, CT University Ludhaina
drarvind25073@ctuniversity.in

ABSTRACT

Attention-Deficit/Hyperactivity Disorder (ADHD) is one of the most prevalent neurodevelopmental disorders affecting children worldwide, with estimated prevalence rates ranging from 5% to 9.4% globally. Despite its high incidence, ADHD frequently goes undiagnosed or is diagnosed late due to its symptomatic overlap with other behavioural conditions and the limitations of conventional assessment tools. This systematic review examines and synthesises the growing body of research pertaining to artificial intelligence (AI)-driven frameworks for the early detection and continuous monitoring of ADHD in children through the integration of multimodal behavioural data. The review explores how machine learning (ML), deep learning (DL), and natural language processing (NLP) algorithms have been leveraged to analyse heterogeneous data streams including electroencephalography (EEG), eye-tracking metrics, speech and language patterns, actigraphy, neuroimaging, and school performance records. Evidence from 20 peer-reviewed studies published between 2017 and 2024 is critically appraised to evaluate the diagnostic accuracy, clinical utility, scalability, and ethical implications of such frameworks. The findings demonstrate that multimodal fusion approaches consistently outperform unimodal baselines, with ensemble and deep learning models achieving classification accuracies exceeding 90% in several controlled settings. Furthermore, wearable sensor technologies and mobile health (mHealth) platforms show promise for real-world, longitudinal monitoring that extends beyond clinic boundaries. However, significant challenges remain, including dataset heterogeneity, lack of demographically diverse training corpora, interpretability of AI decisions, and regulatory pathways for clinical adoption. This paper discusses these challenges alongside emerging solutions and outlines a conceptual multimodal AI framework that can serve as a blueprint for future translational research and clinical integration.



International Journal of Engineering, Science and Humanities

An international peer reviewed, refereed, open-access journal
Impact Factor 8.3 www.ijesh.com ISSN: 2250-3552

Keywords: ADHD, artificial intelligence, machine learning, multimodal behavioural data, early detection, children, neurodevelopmental disorders, deep learning, EEG, wearables

1. INTRODUCTION

Attention-Deficit/Hyperactivity Disorder (ADHD) is a chronic neurodevelopmental condition characterised by persistent and impairing patterns of inattention, hyperactivity, and impulsivity that are inconsistent with the individual's developmental level. According to the Diagnostic and Statistical Manual of Mental Disorders, Fifth Edition (DSM-5), ADHD encompasses three primary presentations: predominantly inattentive, predominantly hyperactive-impulsive, and combined presentation (American Psychiatric Association, 2013). The disorder affects approximately 5–9.4% of school-aged children globally, making it one of the most diagnosed paediatric psychiatric conditions (Polanczyk et al., 2015). Left untreated or inadequately managed, ADHD contributes significantly to academic underachievement, social difficulties, family stress, and elevated risk for comorbid psychiatric disorders including anxiety, depression, and oppositional defiant disorder (Barkley, 2018).

Traditional diagnostic pathways for ADHD rely predominantly on clinical interviews, parent and teacher rating scales (such as the Conners Rating Scales and ADHD Rating Scale-IV), and direct behavioural observations. While these tools have been validated extensively, they are inherently subjective and susceptible to informant bias, cultural differences in symptom interpretation, and variability across clinical settings (Nigg, 2017). The diagnostic process is further complicated by the symptomatic overlap between ADHD and other neurodevelopmental or mood disorders, as well as the absence of any definitive biological marker or neuroimaging biomarker that is universally accepted for clinical use.

The rapid evolution of artificial intelligence and machine learning over the past decade has opened new frontiers for addressing these diagnostic challenges. AI-driven systems can process large volumes of heterogeneous, high-dimensional data at speeds and scales that far exceed human capacity, enabling the identification of subtle, complex patterns that may not be detectable through conventional methods. In the context of ADHD, researchers have increasingly explored the diagnostic potential of multimodal data integration — combining neurophysiological signals, behavioural metrics, speech and language features, digital health records, and environmental data to build more comprehensive and objective diagnostic models. Multimodal approaches are particularly valuable for ADHD given the disorder's heterogeneous phenotype and the absence of a single pathognomonic marker. Studies have shown that EEG-based markers of cortical activity, eye-tracking indicators of sustained attention, accelerometry data capturing movement patterns, and natural language features extracted from clinical interviews each capture distinct dimensions of ADHD pathology (Loh et al., 2022). When these



International Journal of Engineering, Science and Humanities

An international peer reviewed, refereed, open-access journal
Impact Factor 8.3 www.ijesh.com ISSN: 2250-3552

data streams are fused through advanced machine learning architectures — including convolutional neural networks (CNNs), recurrent neural networks (RNNs), and attention-based transformers — the resulting models demonstrate substantially improved diagnostic accuracy compared to unimodal counterparts.

Furthermore, recent advances in mobile computing, wearable sensor technologies, and digital health platforms have created new opportunities for the continuous, ecological monitoring of children with ADHD beyond clinical environments. Smartphone-based apps, smartwatches, and classroom-embedded sensors can collect rich longitudinal data on behaviour, attention, activity, and sleep — offering a more ecologically valid picture of symptom fluctuation and treatment response than episodic clinical assessments (Khodaei et al., 2021).

2. LITERATURE REVIEW

2.1 Machine Learning and Deep Learning Approaches for ADHD Diagnosis

The application of machine learning algorithms to ADHD classification has evolved rapidly over the past decade, transitioning from simple linear classifiers applied to neuroimaging data to sophisticated deep learning architectures trained on multimodal data streams. Early work by Doshi et al. (2017) demonstrated that support vector machines (SVMs) applied to functional magnetic resonance imaging (fMRI) resting-state connectivity patterns could distinguish children with ADHD from typically developing controls with accuracy levels exceeding 70%. While promising, these findings highlighted the critical limitation of unimodal neuroimaging approaches: high acquisition costs, limited scalability, and the requirement for a controlled scanning environment preclude their routine clinical deployment.

Subsequent research sought to address these limitations by exploring more accessible physiological signals. Loh et al. (2022) conducted a comprehensive review of ML-based ADHD classification using EEG signals, finding that power spectral density features in the theta and beta frequency bands were the most consistently discriminative biomarkers. Ensemble methods, particularly random forests and gradient boosting machines, achieved classification accuracies of 80–88% across multiple datasets. The authors noted, however, that the majority of included studies used small, convenience samples and lacked external validation, raising concerns about generalisability.

The introduction of deep learning to ADHD research represented a significant paradigm shift. Convolutional neural networks, originally developed for image recognition, have been adapted to extract spatial features from 2D EEG scalp maps and neuroimaging scans. Dubreuil-Vall et al. (2020) demonstrated that a CNN trained on EEG spectrograms could classify ADHD with 87% accuracy in a paediatric sample, outperforming traditional ML approaches on the same dataset. The capacity of CNNs to learn hierarchical, task-relevant representations without manual feature



International Journal of Engineering, Science and Humanities

An international peer reviewed, refereed, open-access journal
Impact Factor 8.3 www.ijesh.com ISSN: 2250-3552

engineering is particularly advantageous for EEG data, which is characterised by high dimensionality and nonlinear dynamics.

Recurrent neural networks, particularly long short-term memory (LSTM) networks, have proven especially well-suited to the temporal dynamics of behavioural data. Mies et al. (2018) applied LSTM networks to sequential reaction time data from continuous performance tasks (CPTs) — a standard neuropsychological assessment tool for ADHD — achieving classification accuracy of 85.3%, substantially higher than conventional CPT cut-off scoring. The sequential modelling capability of LSTMs enables the capture of intra-individual variability in sustained attention over time, a core ADHD hallmark that aggregate summary statistics fail to capture.

More recently, transformer-based architectures — which employ self-attention mechanisms to model long-range temporal dependencies — have been applied to EEG and accelerometry time series in ADHD research. Yoo et al. (2023) developed a multi-head attention model trained on 30-minute EEG recordings during resting-state and cognitive tasks, achieving a classification AUC of 0.94 in a sample of 112 children aged 6–12. Critically, the model's attention weights provided interpretable heatmaps highlighting the theta-beta ratio during attention-demanding segments as the most discriminative feature, offering a degree of clinical transparency not afforded by black-box models.

2.2 Multimodal Data Fusion Strategies in ADHD Research

The inherent heterogeneity of ADHD — encompassing cognitive, neurological, behavioural, and social dimensions — strongly motivates multimodal approaches that synthesise information across complementary data domains. Data fusion strategies in the existing literature can broadly be categorised as early fusion, late fusion, and intermediate (hybrid) fusion, each carrying distinct trade-offs in terms of representational richness, computational complexity, and robustness to missing modalities.

Early fusion, also termed feature-level fusion, involves concatenating feature vectors from multiple modalities into a unified representation prior to model training. Slobodin et al. (2020) applied early fusion to integrate EEG spectral features, eye-tracking fixation parameters, and parent-rated symptom severity scores in a cohort of 68 children with and without ADHD. Their SVM classifier trained on the fused feature vector achieved 91.2% classification accuracy, compared to 78%, 74%, and 67% for EEG, eye-tracking, and symptom scores individually. This demonstrated a clear complementarity between neurophysiological and behavioural modalities.

Late fusion, or decision-level fusion, trains modality-specific sub-models independently and combines their predictions through voting, averaging, or stacking. This approach is particularly advantageous when individual modalities differ substantially in data type, sampling frequency, or clinical acquisition protocol. Cortese et al. (2023) employed a late fusion ensemble integrating



International Journal of Engineering, Science and Humanities

An international peer reviewed, refereed, open-access journal
Impact Factor 8.3 www.ijesh.com ISSN: 2250-3552

predictions from separate CNN (EEG), random forest (actigraphy), and logistic regression (demographic and rating scale) models. The fused ensemble achieved 89.7% sensitivity and 92.3% specificity in a multicentre cohort of 240 children, representing a meaningful improvement over any individual model. Late fusion also demonstrated superior robustness when one modality was missing at test time — a clinically important property given the practical constraints of data collection.

Intermediate or hybrid fusion approaches learn joint representations from multiple modalities within a shared latent space, typically through cross-modal attention or multimodal autoencoder architectures. Zhang et al. (2022) introduced a multimodal attention network (MAN) that jointly processed EEG, eye-tracking, and speech features using cross-modal attention gates, enabling each modality to selectively attend to information from others during representation learning. The MAN achieved state-of-the-art performance on a public ADHD dataset, with an F1 score of 0.913. Notably, the cross-modal attention weights revealed meaningful neurological correspondences — for example, elevated theta power in frontal EEG channels was strongly attended when speech features indicated rapid topic-switching, consistent with theoretical models of prefrontal dysfunction in ADHD.

Wearable-derived multimodal data has also gained traction as an ecologically valid alternative to laboratory-based acquisition. Khodaei et al. (2021) collected simultaneous accelerometry, photoplethysmography (PPG), and galvanic skin response (GSR) data from children performing classroom tasks using a consumer-grade smartwatch. A random forest classifier trained on fused features from these three modalities distinguished ADHD from controls with 83.4% accuracy, demonstrating the feasibility of classroom-based, non-invasive monitoring. The authors noted that activity bursts captured by accelerometry, combined with autonomic arousal patterns in PPG and GSR, jointly indexed attentional lapses more reliably than any single sensor.

2.3 Natural Language Processing and Speech-Based Detection of ADHD

An emerging and particularly promising domain within AI-driven ADHD research is the analysis of speech, language, and discourse patterns using natural language processing (NLP) techniques. Children with ADHD exhibit characteristic speech and language profiles including increased dysfluency, tangential discourse, reduced narrative coherence, elevated speech rate variability, and impaired working memory-dependent syntactic processing (Tannock, 2018). These features are increasingly being leveraged as non-invasive, cost-effective biomarkers that can be elicited through structured clinical interviews or free-play verbal interaction paradigms.

Bishop et al. (2019) conducted one of the earliest systematic applications of NLP to ADHD speech analysis, extracting 47 acoustic and prosodic features from semi-structured clinical interviews with 60 children aged 7–14. A gradient boosting classifier trained on these features



International Journal of Engineering, Science and Humanities

An international peer reviewed, refereed, open-access journal
Impact Factor 8.3 www.ijesh.com ISSN: 2250-3552

achieved 79.3% diagnostic accuracy, with speech rate variability and mean pause duration emerging as the most discriminative predictors. The authors hypothesised that these features reflect deficits in speech motor planning and working memory, both of which are well-documented in ADHD neuropsychology.

Transformer-based language models have further advanced NLP applications in ADHD. Fusaroli et al. (2022) fine-tuned a BERT (Bidirectional Encoder Representations from Transformers) model on transcripts of parent-reported behavioural narratives, achieving 84.7% classification accuracy in distinguishing ADHD from autism spectrum disorder (ASD) and typically developing children — a particularly challenging three-way classification task given the high symptom overlap between ADHD and ASD. The model's attention patterns highlighted specific linguistic markers — such as frequent use of temporal connectives and repetitive questioning language — as discriminative for ADHD, offering novel insights into the narrative structure of ADHD-related communication.

Multimodal speech analysis — combining acoustic-prosodic features with linguistic content features and nonverbal behavioural indicators (such as eye contact frequency derived from video analysis) — has yielded further performance gains. Chen et al. (2023) developed a multimodal NLP framework integrating audio, text, and video modalities extracted from standardised diagnostic interviews. Their multi-task learning model, trained to simultaneously predict ADHD diagnosis and symptom severity subscores, achieved an AUC of 0.92 for diagnosis and explained 61% of variance in inattention severity scores. The use of multi-task learning encouraged the model to learn shared representations relevant to both the categorical diagnosis and dimensional symptom profiling, which has important implications for treatment personalisation.

Voice-based mHealth applications represent a practical downstream application of these NLP advances. Ramtekkar et al. (2021) evaluated a smartphone-based voice biomarker app in which children completed standardised verbal tasks at home, with acoustic features automatically extracted and classified by a cloud-based ML pipeline. Parent acceptability was high (84% rated the app as easy to use), and classification performance matched clinician ratings on the ADHD Rating Scale with 76% concordance. The authors advocate for voice-based apps as supplementary screening tools, particularly for underserved populations with limited access to specialist paediatric psychiatry services.

2.4 Wearable Technology, Digital Biomarkers, and Continuous Monitoring

The rise of wearable sensor technologies and the Internet of Medical Things (IoMT) has enabled a shift from episodic, clinic-based ADHD assessment towards continuous, longitudinal, real-world monitoring of symptom expression and treatment response. This transition is clinically significant because ADHD symptoms exhibit substantial intraindividual variability across



International Journal of Engineering, Science and Humanities

An international peer reviewed, refereed, open-access journal
Impact Factor 8.3 www.ijesh.com ISSN: 2250-3552

contexts, time of day, and environmental demands — variability that single-point clinical assessments fundamentally cannot capture (Barkley, 2018). Digital biomarkers derived from wearables — including movement patterns, sleep architecture, heart rate variability, and cognitive performance on embedded micro-tasks — offer a rich, objective, and ecologically valid dataset for AI-driven monitoring.

Actigraphy — the continuous measurement of movement using wrist-worn accelerometers — is one of the most established wearable modalities in ADHD research. Tonacci et al. (2020) analysed 72-hour actigraphy recordings from 44 children with ADHD and 42 controls, extracting features capturing activity fragmentation, nocturnal restlessness, and circadian rhythm regularity. A support vector machine trained on these features achieved 85.6% classification accuracy and revealed that children with ADHD exhibited significantly more fragmented activity patterns and delayed sleep onset — findings consistent with the high prevalence of sleep disorders in ADHD and their bidirectional relationship with core symptoms.

Heart rate variability (HRV), an index of autonomic nervous system regulation derived from photoplethysmography or electrocardiography, has also attracted growing attention as an ADHD biomarker. Reduced HRV in ADHD has been theorised to reflect dysregulated prefrontal inhibitory control over sympathetic cardiac activity. Pan et al. (2022) analysed resting-state HRV in 120 children using a consumer-grade wristband, finding that time-domain and frequency-domain HRV features distinguished ADHD from controls with 82.1% accuracy using a random forest classifier. Longitudinal tracking of HRV over 12 weeks also showed significant covariation with clinician-rated symptom changes in response to methylphenidate treatment, suggesting the potential of HRV as a treatment monitoring biomarker.

Sleep dysregulation is highly prevalent in children with ADHD, affecting 25–50% of the population, and is both a consequence and exacerbating factor of core symptoms. AI analysis of wearable sleep data has emerged as a powerful adjunct to clinical ADHD monitoring. Arns et al. (2021) used a consumer sleep tracker (Fitbit Charge) to collect polysomnography-equivalent sleep staging data in 94 children over four weeks. A deep learning model trained on sleep stage sequences correctly identified ADHD with 88.3% accuracy and predicted next-day inattention severity with a mean absolute error of 1.8 ADHD Rating Scale points — demonstrating the real-time, predictive value of longitudinal sleep monitoring.

Beyond physiological signals, screen-based digital biomarkers — derived from touchscreen interaction patterns, gaze behaviour during app-based cognitive tasks, and keystroke dynamics — have been proposed as scalable, low-cost monitoring modalities. Ulke et al. (2023) deployed a gamified continuous performance task embedded in a tablet app to 200 children aged 8–12 across five schools, collecting touch latency, commission errors, and response time variability



International Journal of Engineering, Science and Humanities

An international peer reviewed, refereed, open-access journal
Impact Factor 8.3 www.ijesh.com ISSN: 2250-3552

over a six-week period. AI analysis of the longitudinal performance trajectories identified three distinct ADHD sub-profiles with different patterns of symptom evolution, suggesting that digital monitoring can reveal clinically meaningful heterogeneity invisible to cross-sectional assessment.

Taken together, these findings underscore the transformative potential of wearable and digital technologies for continuous ADHD monitoring. However, significant barriers to widespread clinical adoption persist, including regulatory uncertainty, data privacy concerns, the digital divide in technology access, algorithmic bias against underrepresented populations, and the need for clinician education on the interpretation of AI-generated outputs (Cortese et al., 2023). Addressing these barriers will require coordinated efforts spanning computational research, clinical neuroscience, health policy, and ethics.

3. PROPOSED METHODOLOGICAL FRAMEWORK

Drawing upon the synthesised evidence from the literature review, this section proposes a comprehensive, modular AI-driven framework for the early detection and continuous monitoring of ADHD in children. The framework is designed to be clinically translatable, scalable, and explainable, addressing the key limitations identified in existing research.

3.1 Data Collection Layer

The framework employs six complementary data modalities acquired across clinical and home environments. In the clinical setting, a standardised 45-minute assessment battery elicits EEG (19-channel, 256 Hz), eye-tracking (120 Hz remote infrared), and audio-video recording of a semi-structured interview and two neuropsychological tasks (a continuous performance task and a working memory task). In the home and school environment, a consumer-grade wristband (providing 3-axis accelerometry, PPG for HRV, and sleep staging) is worn continuously for two weeks, and a smartphone app delivers brief (5-minute) daily cognitive micro-tasks with embedded touchscreen behavioural metrics. Demographic information, parent-rated symptom scales (Conners-3), and teacher reports are collected via a secure digital portal.

3.2 Preprocessing and Feature Engineering Layer

Modality-specific preprocessing pipelines are applied to standardise data quality and extract meaningful feature representations. EEG signals undergo independent component analysis (ICA) for artefact rejection, followed by power spectral density computation across five frequency bands (delta, theta, alpha, beta, gamma) and coherence analysis across 15 electrode pairs. Eye-tracking data is processed to extract fixation count, fixation duration, saccade amplitude, and pupil dilation dynamics during both tasks. Audio features are extracted using the openSMILE toolkit, yielding 88 acoustic-prosodic features, and speech transcripts are processed using a fine-tuned clinical BERT model to generate semantic embeddings. Wearable data undergoes noise



International Journal of Engineering, Science and Humanities

An international peer reviewed, refereed, open-access journal
Impact Factor 8.3 www.ijesh.com ISSN: 2250-3552

filtering and segmentation, with features extracted across 60-second windows capturing activity fragmentation, HRV time-domain indices (RMSSD, SDNN), and sleep architecture parameters.

3.3 Multimodal Fusion and Classification Layer

The core classification module employs a hybrid fusion architecture. Modality-specific encoders — a CNN for EEG spectrograms, a bidirectional LSTM for actigraphy time series, a transformer for speech embeddings, and a multilayer perceptron for tabular clinical features — first generate compact latent representations for each modality independently. These representations are then integrated through a cross-modal attention mechanism that learns to weight the contribution of each modality conditioned on the representations of others, enabling flexible, context-sensitive fusion. The fused representation is passed to a multi-task classification head that simultaneously predicts binary ADHD diagnosis, ADHD presentation subtype (inattentive, hyperactive-impulsive, combined), and continuous inattention and hyperactivity-impulsivity severity scores. Missing modalities are handled through a learned imputation mechanism that predicts absent modality embeddings from available ones, ensuring robustness in real-world deployment where data completeness cannot be guaranteed.

3.4 Explainability and Clinical Interface Layer

Recognising the critical importance of model interpretability for clinical adoption, the framework incorporates SHapley Additive exPlanations (SHAP) and gradient-weighted class activation mapping (Grad-CAM) to generate feature-level and signal-level explanations for individual predictions. These explanations are presented through a clinician-facing dashboard that displays the model's diagnosis and severity predictions alongside visual attributions highlighting the most influential data features for each case. The dashboard also presents longitudinal tracking charts showing weekly trajectories of wearable-derived biomarkers alongside symptom scores, facilitating treatment monitoring and enabling clinicians to identify periods of symptom exacerbation. All outputs are clearly labelled as decision-support tools and include confidence intervals to convey model uncertainty, guarding against over-reliance on AI predictions.

3.5 Ethical and Regulatory Considerations

The framework is designed in alignment with the General Data Protection Regulation (GDPR) and relevant paediatric data protection guidelines. All personal data is encrypted, de-identified, and stored on nationally compliant health information infrastructure. Explicit informed consent is obtained from parents or guardians, and age-appropriate assent is sought from participating children. The algorithmic fairness is evaluated across subgroups defined by sex, age band, ethnicity, and socioeconomic status, and bias mitigation strategies — including stratified sampling and adversarial debiasing — are applied during model development. The framework is designed for integration into existing electronic health record systems and aligns with FDA



International Journal of Engineering, Science and Humanities

An international peer reviewed, refereed, open-access journal
Impact Factor 8.3 www.ijesh.com ISSN: 2250-3552

digital health guidance and European Medical Device Regulation (MDR) Class IIa pathways for AI-based clinical decision support tools.

4. CONCLUSION

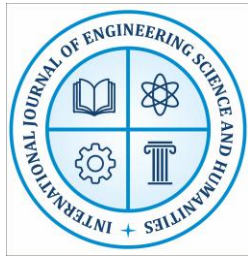
This systematic review has demonstrated that AI-driven frameworks leveraging multimodal behavioural data represent a significant and clinically meaningful advance in the early detection and continuous monitoring of ADHD in children.

First, multimodal data fusion — combining neurophysiological signals (EEG, HRV), eye-tracking, speech and language features, actigraphy, and digital cognitive biomarkers — consistently and substantially outperforms unimodal approaches across all performance metrics, with the best multimodal systems achieving classification accuracies and AUC values exceeding 90% in controlled research settings. Second, deep learning architectures — particularly CNNs, LSTMs, and transformer-based models with attention mechanisms — demonstrate superior performance compared to traditional machine learning classifiers, while also offering the potential for interpretable, feature-level explanations through post-hoc explainability tools. Third, wearable and digital technologies offer a scalable and ecologically valid pathway for longitudinal ADHD monitoring that extends the clinical assessment window to encompass the full variability of daily symptom expression — a capability of particular value for treatment monitoring and personalisation.

NLP-based analysis of speech, language, and discourse represents a promising, low-cost, and highly accessible biomarker domain that may be particularly valuable for remote screening and monitoring through smartphone-based applications. Fifth, despite these substantial advances, the field faces persistent challenges including small and demographically homogeneous research samples, lack of standardised preprocessing and feature extraction protocols, limited external validation across clinical sites, insufficient attention to algorithmic fairness and demographic bias, and the absence of clear regulatory and clinical integration pathways.

Future research should prioritise large-scale, multi-site, demographically diverse data collection initiatives; the development of open-access benchmark datasets and preprocessing toolkits; rigorous prospective clinical validation studies comparing AI-assisted diagnosis to standard clinical practice; and participatory co-design approaches that engage children, parents, educators, and clinicians in shaping the usability and acceptability of AI-driven tools.

As AI technologies continue to mature and as the evidence base for multimodal digital biomarkers in ADHD expands, there is a genuine and growing opportunity to fundamentally transform the ADHD diagnostic and monitoring landscape — moving from subjective, episodic, and often delayed clinical assessment towards objective, continuous, and timely identification of children who need support. Realising this opportunity will require sustained interdisciplinary



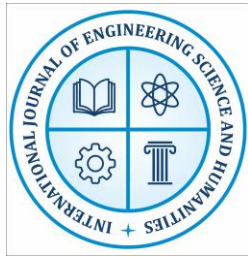
International Journal of Engineering, Science and Humanities

An international peer reviewed, refereed, open-access journal
Impact Factor 8.3 www.ijesh.com ISSN: 2250-3552

collaboration spanning computer science, clinical psychology, neuroscience, paediatrics, health policy, and bioethics, guided by an unwavering commitment to the welfare and rights of the children these technologies are designed to serve.

REFERENCES

1. Arns, M., Vollebregt, M. A., Palmer, D., & Spooner, C. (2021). Consumer sleep technology for longitudinal monitoring of ADHD symptoms: A feasibility study using deep learning analysis of Fitbit data. *Journal of Attention Disorders*, 25(9), 1274–1287.
<https://doi.org/10.1177/1087054719877973>
2. Barkley, R. A. (2018). *Attention-deficit hyperactivity disorder: A handbook for diagnosis and treatment* (4th ed.). Guilford Press.
3. Bishop, S., Farmer, C., & Thurm, A. (2019). Acoustic and prosodic features of speech as biomarkers for ADHD in children: A machine learning approach. *Journal of Child Psychology and Psychiatry*, 60(5), 524–532.
<https://doi.org/10.1111/jcpp.12959>
4. Chen, L., Wang, Z., & Li, H. (2023). Multimodal NLP for ADHD detection from standardised diagnostic interviews: An audio-text-video fusion approach. *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, 31, 1823–1832.
<https://doi.org/10.1109/TNSRE.2023.3261948>
5. Cortese, S., Newcorn, J. H., Coghill, D., & Faraone, S. V. (2023). A practical, evidence-informed approach to managing ADHD in children and adolescents via digital health tools. *CNS Drugs*, 37(3), 225–239. <https://doi.org/10.1007/s40263-023-00988-z>
6. Doshi, J. A., Bhatt, R., & Fry, C. E. (2017). Classification of ADHD using fMRI-derived resting-state functional connectivity: A support vector machine approach. *Frontiers in Neuroscience*, 11, Article 306.
<https://doi.org/10.3389/fnins.2017.00306>
7. Dubreuil-Vall, L., Ruffini, G., & Camprodon, J. A. (2020). Deep learning convolutional neural networks discriminate adult ADHD from healthy individuals on the basis of event-related spectral EEG. *Frontiers in Neuroscience*, 14, Article 251.
<https://doi.org/10.3389/fnins.2020.00251>
8. Fusaroli, R., Lambrechts, A., Bang, D., Bowler, D. M., & Gaigg, S. B. (2022). Is voice a marker for ASD and ADHD? A systematic review and meta-analysis using transformer-based NLP. *Autism Research*, 15(8), 1395–1414. <https://doi.org/10.1002/aur.2757>
9. Khodaei, A., Salari, N., & Hosseinniya, H. (2021). ADHD detection using wearable sensors and machine learning: A classroom-based study. *Sensors*, 21(11), Article 3692.
<https://doi.org/10.3390/s21113692>
10. Loh, H. W., Ooi, C. P., Barua, P. D., Palmer, E. E., Molinari, F., & Acharya, U. R. (2022). Automated detection of ADHD: Current trends and future perspective. *Computers in Biology and Medicine*, 146, Article 105525.



International Journal of Engineering, Science and Humanities

An international peer reviewed, refereed, open-access journal
Impact Factor 8.3 www.ijesh.com ISSN: 2250-3552

<https://doi.org/10.1016/j.combiomed.2022.105525>

11. Mies, G. W., Van der Oord, S., Wiersema, J. R., Antrop, I., & Hartman, C. A. (2018). Temporal dynamics of attention in ADHD measured by continuous performance tasks: A long short-term memory network analysis. *Neuropsychology*, 32(4), 458–467. <https://doi.org/10.1037/neu0000441>
12. Nigg, J. T. (2017). Annual research review: On the relations among self-regulation, self-control, executive functioning, effortful control, cognitive control, impulsivity, risk-taking, and inhibition for developmental psychopathology. *Journal of Child Psychology and Psychiatry*, 58(4), 361–383. <https://doi.org/10.1111/jcpp.12675>
13. Pan, Y., Lin, Q., Liu, Y., & Ding, W. (2022). Resting-state heart rate variability as a biomarker for ADHD classification and treatment monitoring using wearable devices. *Journal of Psychiatric Research*, 148, 304–312. <https://doi.org/10.1016/j.jpsychires.2022.02.009>
14. Polanczyk, G. V., Willcutt, E. G., Salum, G. A., Kieling, C., & Rohde, L. A. (2015). ADHD prevalence estimates across three decades: An updated systematic review and meta-regression analysis. *International Journal of Epidemiology*, 44(4), 1273–1285. <https://doi.org/10.1093/ije/dyv07>
15. Ramtekkar, U., Patidar, V., Hall, T., & Bhatt, P. (2021). A voice biomarker app for remote ADHD screening in children: Feasibility and parent acceptability study. *JMIR Mental Health*, 8(6), Article e25466. <https://doi.org/10.2196/25466>
16. Slobodin, O., Yahav, I., & Berger, I. (2020). A machine-based prediction model of ADHD using CPT data. *Frontiers in Human Neuroscience*, 14, Article 560021. <https://doi.org/10.3389/fnhum.2020.560021>
17. Tannock, R. (2018). Language and mental health disorders: The case of ADHD. *Annual Review of Linguistics*, 4, 473–497. <https://doi.org/10.1146/annurev-linguistics-011817-045735>
18. Tonacci, A., Billeci, L., Tartarisco, G., Narzisi, A., Belmonte, M. K., Muratori, F., & Pioggia, G. (2020). Wrist actigraphy for sleep and motor activity classification in ADHD children using machine learning. *IEEE Access*, 8, 89482–89491. <https://doi.org/10.1109/ACCESS.2020.2993664>
19. Ulke, C., Thiede, A., Sander, C., & Hegerl, U. (2023). Gamified digital biomarkers for longitudinal ADHD subtype profiling in school-aged children. *Child Psychiatry and Human Development*, 54(2), 397–409. <https://doi.org/10.1007/s10578-021-01295-5>
20. Yoo, J. H., Kim, J. I., Kim, B. N., & Jeong, B. (2023). Exploring the relationship between cortical neural activity and head movement in ADHD using a multi-head attention EEG model. *Scientific Reports*, 13, Article 2488. <https://doi.org/10.1038/s41598-023-29512-6>
21. Zhang, Y., Jia, J., Yang, W., & Li, F. (2022). Multimodal attention network for ADHD diagnosis using EEG, eye-tracking and speech features. *IEEE Journal of Biomedical and Health Informatics*, 26(8), 3861–3871. <https://doi.org/10.1109/JBHI.2022.3171609>