ChinaRxiv

AI translation · View original & related papers at
chinarxiv.org/items/chinaxiv-202509.00086

Research Advances in Medical Applications of Artificial Intelligence for Pediatric Attention-Deficit/Hyperactivity Disorder: A Postprint

Authors: Wu Li, Wang Haoyi, Qiu Xiangyang, Yuan Jing, Chen Runan, Chen Runan

Date: 2025-09-15T14:49:16+00:00

Abstract

Attention-deficit/hyperactivity disorder (ADHD) is a neurodevelopmental disorder that severely affects children' s growth and development. Accurate and efficient diagnostic and intervention strategies are essential for promoting the physical and mental health and improving the quality of life of affected children. Currently, clinical diagnosis and treatment of ADHD face numerous challenges, including high diagnostic subjectivity, significant individual variability in treatment efficacy, and complex comorbidities. Artificial intelligence (AI), with its powerful algorithmic analysis and precise feature extraction capabilities, has demonstrated tremendous potential in early diagnosis and treatment efficacy evaluation for children with ADHD. AI technology can provide multi-dimensional clinical decision support and assess prognostic outcomes. This article summarizes recent research advances in AI applications for ADHD disease diagnosis, symptom and medication efficacy prediction, and transdiagnostic studies. It also identifies core common challenges and proposes targeted recommendations to provide a reference for promoting the development and application of AI technology in pediatric ADHD medicine.

Full Text

Progress of Artificial Intelligence in Medical Applications for Children with Attention Deficit Hyperactivity Disorder

WU Li[1], **WANG Haoyi**[2], **QIU Xiangyang**[3], **YUAN Jing**[4], **CHEN Runan**[1*]

[1]Department of Pediatrics, First Affiliated Hospital of Naval Medical University, Shanghai 200433
[2]School of Basic Medical Sciences, Naval Medical University, Shanghai 200433

[3]Institute of Nutrition, Fudan University, Shanghai 200032
[4]Department of Pediatrics, First Affiliated Hospital of Naval Medical University, Shanghai 200433

Corresponding author: CHEN Runan, Lecturer; E-mail: crnsweet@163.com

Abstract

Attention deficit hyperactivity disorder (ADHD) is a neurodevelopmental disorder that significantly impacts children' s growth and development, and accurate, efficient diagnosis and intervention strategies are critical for promoting physical and mental health and improving quality of life. Current clinical diagnosis and treatment of ADHD face numerous challenges, including strong diagnostic subjectivity, substantial individual differences in treatment efficacy, and complex comorbidities. Artificial intelligence (AI), with its powerful algorithmic analysis and precise feature extraction capabilities, has demonstrated tremendous potential in early diagnosis and efficacy evaluation for children with ADHD. AI technology can provide multi-dimensional clinical decision support and assess prognosis. This article summarizes recent research progress on AI applications in ADHD diagnosis, symptom and medication efficacy prediction, and cross-diagnostic studies, while identifying core common challenges and proposing targeted recommendations to provide references for promoting the development and application of AI technology in pediatric ADHD medicine.

Keywords: artificial intelligence; attention deficit hyperactivity disorder; auxiliary diagnosis; disease characteristic prediction; drug efficacy prediction

Funding: Shanghai Municipal Health Commission Research Project (202140010); Naval Medical University Social Science Cultivation Fund (2022SK023)

Citation: WU L, WANG H Y, QIU X Y, et al. Progress of artificial intelligence in children with attention deficit hyperactivity disorder [J]. Chinese General Practice, 2025. DOI: 10.12114/j.issn.1007-9572.2025.0229. [Epub ahead of print].

1 Literature Search Strategy

We conducted computerized searches of CNKI, VIP, Wanfang Data, SinoMed, PubMed, and Web of Science databases for publicly available literature on AI applications in ADHD diagnosis and treatment. Chinese search terms included: artificial intelligence, AI, machine learning, deep learning, attention deficit hyperactivity disorder, ADHD, and their combinations. English search terms included: Artificial Intelligence, AI, Machine Learning, Deep Learning, Attention Deficit Disorder with Hyperactivity, ADHD, and their combinations. The search timeframe was 2015–2025. Inclusion criteria were: (1) study subjects were children with ADHD; (2) basic research, randomized controlled trials, or clinical studies related to the research topic. Exclusion criteria were: duplicate publications, inability to obtain full text or data, irrelevant topics, insufficient information, or poor-quality literature.

---

2 AI Integration with Diagnostic Modalities

2.1 AI and Wearable Devices Wearable devices, as a digital health technology, continuously monitor children' s physiological and behavioral status information—including sleep, activity, and other digital phenotypes—through non-invasive, portable, all-day wear, providing objective data for clinical diagnosis and decision support. When combined with AI technology, wearable devices extract differential diagnostic features from wearable data through various algorithms, offering new pathways for objective ADHD diagnosis. Compared to virtual reality (VR) devices, wearable devices offer advantages of smaller size, greater flexibility, and better continuity of use. KIM et al. [8] utilized wearable device data from the Adolescent Brain Cognitive Development (ABCD) study, combined with Kiddie-Schedule for Affective Disorders and Schizophrenia (K-SADS) diagnostic results, to generate 64 circadian rhythm features including sleep duration, heart rate variability, metabolic equivalent (MET), and activity intensity, developing the first ML model for diagnosing ADHD and sleep problems in children. The results showed AUC values of 0.791 and 0.735 respectively, which did not reach excellent levels (AUC > 0.8), and without validation of calibration or decision curve analysis (DCA), the model had high false-positive potential and uncertain clinical application value. MUÑOZ-ORGANERO et al. [9] collected activity data from 11 ADHD children and 11 healthy controls using triaxial accelerometers worn on the dominant wrist and ankle during school hours. After CNN analysis of ADHD children' s movement acceleration images, the results showed that wearable device-based movement features could effectively distinguish ADHD children from normal children, with classification accuracies of 0.875 for the wrist (sensitivity $= 0.6$, specificity $= 1$) and 0.9375 for the ankle (sensitivity $= 0.8$, specificity $= 1$). Notably, accuracy alone cannot serve as the core metric for model performance evaluation, as it may mask poor sensitivity (0.6). Additionally, neural network models like CNN are recommended for large-volume, dense, and complex datasets, making them suboptimal choices for small sample sizes like this study [10].

Currently, data features collected by wearable devices, particularly behavioral activity data and physiological status information, have opened new objective pathways for AI exploration in ADHD diagnosis. However, AI applications with wearable devices in ADHD diagnosis still face many problems and challenges, such as non-standardized model performance reporting—most studies only report discrimination metrics while lacking calibration and DCA indicators (Table 1). Furthermore, small dataset scales and mismatched algorithms with sample sizes can easily cause overfitting, increased prediction bias, and reduced model reliability, diminishing clinical translation value. Future research should adopt standardized model evaluation systems [11], ensuring comprehensive evaluation using discrimination, calibration, and clinical value metrics; expand sample sizes using a four-step structured framework [12] to scientifically design prediction model study sample sizes and ensure model decision accuracy; and integrate multimodal and cross-scenario data to enhance model generalizability.

2.2 AI and Magnetic Resonance Imaging (MRI) MRI is a non-invasive imaging technology with high resolution for brain tissue that plays an important role in investigating brain structural and functional abnormalities in ADHD [13]. Commonly used MRI modalities in ADHD research include structural MRI (sMRI), diffusion tensor imaging (DTI), and functional MRI (fMRI). AI technologies such as ML and DL have greatly facilitated identification of abnormal characteristics in brain structure, white matter microstructure, and dynamic/static functional connectivity in ADHD children, improving diagnostic accuracy. Deep learning (DL) technology, particularly CNN [14], is advantageous due to its hidden layers' special connection structures that facilitate MRI image feature recognition and learning. ZHU Li et al. [15] explored the application of CNN algorithms combined with coarse segmentation technology for objective classification of ADHD and normal children. By preprocessing and coarsely segmenting Chinese population sMRI images from the ADHD-200 competition dataset, they used a 3-layer CNN for classification, achieving the highest accuracy for the right caudate nucleus feature brain region at 0.7727 (sensitivity = 0.8182, specificity = 0.7273, false positive rate = 0.2727, false negative rate = 0.1818), laying the foundation for AI to move from small-sample validation to clinical case validation in Chinese healthcare. With the deepening of precision medicine concepts, investigating brain structural differences among different ADHD subtypes is significant for accurate diagnosis, treatment, and medication. KE et al. [16] proposed a novel Deep Channel Self-Attention Factorization (Deep CSAF) model for ADHD subtype classification. Leveraging self-attention mechanisms' ability to focus on important features and nonlinear tensor techniques' capacity to extract nonlinear factor matrices from fMRI data, the model significantly improved extraction of nonlinear brain functional connectivity features. Using the ADHD-200 dataset for classification validation, the model achieved AUC 1.0, strongly demonstrating Deep CSAF' s superior performance in distinguishing ADHD subtypes. However, the study should include sufficient clinical samples and improve calibration and DCA metrics to explore practical clinical application value. CHEN Lizhou et al. [17] preprocessed DTI images of white matter microstructure from three groups of children, generating fractional anisotropy (FA) parameter maps, and compared white matter FA values among combined-type ADHD (ADHD-C), inattentive-type ADHD (ADHD-I), and healthy controls, building a classification model using SVM. The results showed that white matter in the right middle frontal gyrus was the distinguishing point between subtypes, with model accuracy of 0.76, sensitivity of 0.885, and specificity of 0.708, filling the gap in imaging biomarkers for Chinese ADHD children.

In MRI diagnosis, DL has advantages over ML, particularly in high recognition and automatic extraction of subtle differences in children' s MRI image features, providing accurate pathways for ADHD diagnosis. However, challenges remain: studies have not identified imaging biomarkers with diagnostic consistency, lack extensive Chinese population datasets, employ insufficiently novel algorithms, and have low model interpretability. Future research should build Chinese ADHD population databases through multi-center collaboration, conduct cross-modal analysis, integrate advanced algorithms to improve model performance, and explore explainable AI (XAI) models in MRI applications to provide transparent and reasonable diagnostic decision-making basis for clinicians, helping improve model credibility.

2.3 AI and Electroencephalogram (EEG) EEG is an electrophysiological technique for evaluating abnormal neural activity and reflecting brain functional status, offering advantages of being non-invasive, easy to implement, and having high temporal resolution, making it one of the most widely used technologies in current ADHD auxiliary diagnosis [18]. With AI development, using AI technology to process and extract EEG characteristic signals has become an important approach to improve diagnostic sensitivity and specificity [19]. To improve accuracy of ML diagnosis for ADHD, GARCÍA-PONSODA et al. [20] applied three preprocessing techniques—filtering (0.5–40 Hz), automatic artifact removal (ASR), and independent component analysis (ICA)—and temporal segmentation to process EEG data, which was important for noise removal and model reliability improvement. The study also identified key parietal channels (P3 and P4) and key features most relevant for ADHD classification, such as kurtosis, Katz fractal dimension, and Delta wave power, achieving high classification accuracy of 0.86 using only three channels (P3/P4/C3), effectively advancing the translation of streamlined EEG data-driven ADHD ML diagnostic models from theory to clinical validation. DL has outstanding advantages in automatically extracting EEG signal features [21]. SANCHIS et al. [22] used the EEG-MHCNet model to automatically extract EEG signals with specific brain regions and channels as diagnostic features to classify ADHD and normally developing children, but the large difference between precision (minimum 0.6019) and recall (all >0.85) suggested imbalanced clinical misdiagnosis/missed diagnosis risk. To improve model interpretability, KHARE et al. [23] first used the Explainable Boosted Machine (EBM) model to analyze 41 EEG signal features extracted by variational mode decomposition (VMD) and Hilbert transform (HT). The results showed highest interpretability of EEG signals in children' s frontal regions, with EBM achieving excellent predictive performance (99.81% accuracy, 99.78% sensitivity, 99.84% specificity, 99.83% F1-score, 99.87% precision, 0.13% false positive rate). However, based on multiple studies [24-25] questioning the authenticity of AUC = 1.0 and lacking sufficient evidence to verify its reliability, possible data leakage risks exist. Independent external validation, calibration curves, and DCA are needed to better indicate clinical applicability of interpretable models.

Current AI-EEG combined ADHD research mainly focuses on exploring diagnostic EEG channels and signal features and the application efficacy of interpretable models, providing reliable theoretical support for translating EEG signals into clinical diagnostic evidence. Notably, data noise greatly interferes with model diagnosis, requiring optimization of model noise filtering algorithms and data preprocessing capabilities to improve prediction performance. Meanwhile, interpretable models not only outperform general models in extracting abnormal EEG signals in ADHD but also provide transparent judgment processes that can offer reasonable basis for clinical decision-making. Future efforts should strengthen medical model supervision, build a global standardized XAI certification system, expand application scenarios, actively conduct performance validation of interpretable models combined with multidimensional data in clinical cases, promote clinical implementation, establish human-machine collaborative diagnosis and treatment, and strengthen XAI technology to develop models with strong traceability, clear decision-making basis, and excellent diagnostic accuracy.

---

3 Current Applications of AI in ADHD Symptom Feature Prediction

Beyond typical features such as attention deficit and impulsivity, children with ADHD often exhibit symptoms like social anxiety and aggressive behavior that affect emotional control and social abilities, hindering their physical and mental development. Based on AI technology development, after investigating relationships between risk factors and ADHD symptoms, AI prediction factors can help clinicians detect and intervene in related symptoms early. Currently, the Continuous Performance Test (CPT) is the prevalent measurement method for assessing attention deficit and impulsivity in childhood ADHD. In SLOBODIN et al.' s study [26], random forest and neural network models were used with CPT indicators and demographic variables to predict childhood ADHD, with the random forest model performing best (accuracy 0.87, sensitivity 0.89, specificity 0.84), suggesting that prediction factors based on CPT have high diagnostic accuracy for typical symptoms, though reliable clinical validation methods are currently lacking. In research on ADHD impulsivity, ELLIOTT et al. [27] used a DTI data-based LASSO regression model to explore differences in dopamine system connectivity structure between ADHD children and normally developing children. The results showed that integrity of the substantia nigra/ventral tegmental area (SN/VTA) and limbic striatum connections, and integrity between executive striatum and SN/VTA regions were the best predictors—increased integrity of the former predicted increased impulsivity, while increased integrity of the latter predicted decreased impulsivity. This model could be clinically translated to build a child impulsivity risk scoring model to directly assist doctors in developing interventions. If a child is predicted to be at high impulsivity risk, clinicians can prioritize intensive behavioral interventions (such as executive function training, cognitive behavioral therapy, etc.), consider combined medication strategies, and strengthen monitoring of dangerous behaviors and emotional fluctuations to improve academic performance, emotional regulation, and reduce aggressive incidents caused by impulse control deficits.

The incidence of social anxiety in children with ADHD is at a medium-high level [28]. ȘIPOȘ et al. [29] used a random forest regression model combining screen time, ADHD severity, and anxiety symptom data to build a prediction model for digital activities' impact on social anxiety in adolescents with ADHD, but the results showed no predictive ability, with social anxiety showing weak negative correlation or no association with screen time. This precisely reveals the complexity of social anxiety and digital behavior in ADHD. Future research should focus on specific analyses of different digital activities and platforms, dividing anxiety dimensions in children and exploring variables such as gender differences that may affect social anxiety. Aggressive behavior in children with ADHD is relatively common and can cause serious adverse effects, but objective methods for tracking and predicting children' s aggressive behavior are currently lacking. PARK et al. [30] used waist-worn ActiGraph GT3X+ sensors to collect physical activity data and built a random forest model to predict aggressive behavior in children with ADHD. The study showed that age, activity vector magnitude, Child Behavior Checklist Scores (CBCL), and height Z-score were the main predictors, with excellent model performance (AUC = 0.893, sensitivity = 0.85, specificity = 0.80). Notably, this model can provide stratified management basis for clinical intervention by generating an "aggressive behavior regulation demand level," enabling intensive comprehensive intervention plans for high-demand children and conventional intervention for medium-low demand children, aiming to reduce aggressive behavior frequency and improve quality of life.

The evolution of ADHD symptoms is also a research priority. SUDRE et al. [31] used multimodal data including genomics, neuroimaging, and cognitive features to track 362 adolescents for an average of 4.8 years, dividing them into four groups based on ADHD symptom course: asymptomatic, stable, improved, and deteriorated. Using conditional random forest models to analyze relationships between baseline genomic, brain structure, and cognitive function with symptom course, the results identified polygenic risk scores (PRS) and cognitive function as the most important features for predicting future symptom trajectories. In clinical translation, this model can generate "personalized symptom development trajectory predictions" for each child. When a child' s trajectory is predicted as "deteriorating," doctors can implement early multidimensional comprehensive intervention strategies to prevent symptom deterioration and overall improvement in quality of life and functional level, achieving proactive health management.

In summary, AI has made certain progress in predicting ADHD symptom features, mainly reflected in exploring influencing factors of various symptoms and symptom evolution, and monitoring and early warning of symptom behaviors through sensor devices, indicating broad research space. However, ADHD symptoms in children are diverse and highly overlapping, with insufficient clinical correlation in symptom prediction. It is recommended to expand multi-center sample sizes and multimodal sensor data, conduct linkage validation of drug treatment or behavioral therapy, and build real-time intervention systems to achieve breakthroughs in clinical translation.

---

4 Current Applications of AI in ADHD Drug Efficacy Prediction

Pharmacotherapy occupies a core position in ADHD intervention methods. First-line treatments include traditional stimulants such as methylphenidate (MPH) and non-stimulants such as atomoxetine (ATX) [32]. However, clinical practice lacks objective tools for assessing drug efficacy. AI, with its exceptional learning capabilities and massive computing power [33], provides personalized medication for children by predicting drug responses across different ADHD subtypes, treatment effects of different medications, and adverse drug reactions, thereby reducing symptom severity and promoting emotional, behavioral, and brain function recovery and development. FENG et al. [34] used Graph Convolutional Network (GCN-BSD) combined with functional network connectivity (FNC) for deep clustering of ADHD-1 and ADHD-2 biological subtypes in the ABCD dataset, finding that heterogeneity in brain functional connectivity across subtypes could reveal differences in MPH and ATX efficacy. The results showed that ADHD-1 children with abnormal default mode network (DMN) and sensorimotor network (SM) connectivity responded better to MPH, while ADHD-2 children with abnormal cerebellum-fusiform gyrus connectivity responded better to ATX, with excellent clustering performance [Calinski-Harabasz index (CHI) = 0.89, Davies-Bouldin index (DBI) = 0.3; theoretical optimal CHI $>$ 0.8, DBI optimal value close to 0]. The value lies in AI-output subtype classification and optimal drug recommendations that can directly assist clinicians in prescription decisions—for example, prioritizing MPH for type 1 children and ATX for type 2 children—thereby enhancing treatment effects and reducing risks of ineffective prescriptions. SU Yi et al. [35] used ML technology to build efficacy prediction models for osmotic-release oral system methylphenidate (OROS MPH) and ATX in treating ADHD children. The study found that baseline symptom severity predicted OROS MPH efficacy, while baseline IQ level and executive function impairment degree were predictive indicators for both OROS MPH and ATX efficacy, with model accuracies reaching 81.3% and 80.7% respectively. However, no specific predictive factors for OROS MPH versus ATX were identified, limiting guidance for future clinical medication decisions. Sleep problems are among the most common adverse reactions in children undergoing MPH treatment. YOO et al. [36] used multimodal data including demographics, clinical questionnaires, environmental factors, neuropsychology, genetics, and neuroimaging, employing three ML methods to predict sleep adverse reactions to MPH treatment. The main predictive factors identified were: CPT reaction time variability, dopamine transporter gene, alpha-2A adrenergic receptor gene, norepinephrine transporter gene, and fronto-striatal circuit structure and other neuropsychological, genetic, and neuroimaging indicators, with model accuracy of 0.861 and AUC = 0.92. The risk scores output by this model can provide direct basis for clinical intervention. If a child is predicted to be at medium or high risk for sleep adverse reactions, it alerts clinicians to choose alternative drugs or strengthen sleep quality monitoring during medication to reduce adverse reaction incidence and ensure treatment safety.

In summary, AI technology shows significant advantages in predicting drug efficacy in children with ADHD, promising to break the current subjective decision-making based solely on physician experience and provide personalized treatment for ADHD children. However, current research limitations include insufficient cross-cultural generalizability of models and limited clinical applicability of predictive factors. Therefore, future research should strengthen specificity of medication indicators for ADHD subtypes, promote transformation from single-modal to multi-modal data input, advance research on adverse drug reaction prediction, and provide precise treatment to reduce caregiver burden and offer accurate prescription decisions for clinicians.

---

5 Current Applications of AI in ADHD Cross-Diagnosis

In mental disorders with significant comorbidity phenomena [37], cross-diagnosis is a reliable method to improve clinical differential diagnosis between ADHD and other mental illnesses. Studies show that single ADHD diagnosis models are unsuitable for complex clinical scenarios with high misdiagnosis risk [38]. Only by combining ML and DL to build cross-diagnostic models covering multiple mental disorders [39] can clinical utility and diagnostic accuracy be improved. ADHD and autism spectrum disorder (ASD) have highly overlapping clinical symptoms and receive considerable attention in ADHD cross-diagnosis research. In WANG Yue et al.' s study [40], support vector machine (SVM) and leave-one-out cross-validation were used to explore the diagnostic value of empathy ability and executive function in distinguishing ADHD, ASD, and typically developing (TD) children. The results showed that ADHD had significant deficits in emotional empathy, response inhibition, and working memory, while ASD showed poor performance in cognitive empathy, executive function shifting, and emotional control. However, classification accuracy for both combined indicators (62.75%) and single indicators (58.82%) was low, facing high risks of misdiagnosis and missed diagnosis, failing to meet standards for model translation from theory to clinical practice.

SCHIRMER et al. [41] introduced a neuroimaging transfer learning challenge based on functional connectomics (rsfMRI) for classifying mental disorders, with two tasks: (1) distinguishing ADHD patients from normal controls (NC); (2) transferring the Task I model to classify patients with comorbid ASD and ADHD to explore generalizability of functional connectivity patterns between ADHD and ASD. Although long short-term memory network (LSTM) ranked highest among multiple competing models, its AUC values for the two tasks were only 0.68 and 0.53, indicating poor ability to distinguish ADHD and ASD and current lack of clinical translation applicability. Conversely, typical symptoms of ADHD and fetal alcohol spectrum disorder (FASD) are also highly similar. In EHRIG et al.' s study [42], six ML models were used to screen six key clinical variables including birth length and head circumference, IQ, social intrusion behavior, poor memory, and sleep disorders. Among them, the random forest model performed best (AUC = 0.92, precision = 0.86, recall = 0.91). Based on this, the FASDetect screening tool integrated with a webpage was developed, which can effectively distinguish ADHD from FASD. By outputting "disorder type probability," the model provides diagnostic support for clinicians to implement specialized treatment interventions for FASD or ADHD, avoiding misdiagnosis and mistreatment, and ultimately improving children' s academic performance and social functioning.

In summary, cross-diagnostic models for ADHD generally show low predictive capability in distinguishing ADHD from ASD or other disorders with highly overlapping symptoms, limited by complex comorbidity, sample heterogeneity, insufficient specific biomarkers, and inadequate application of advanced algorithms. Future cross-diagnostic research should, from a data perspective, strengthen integration of multimodal data (such as neuroimaging and genetics) and design fine large-sample cohorts to improve model prediction capability. From a model optimization perspective, dynamic neural networks and multi-task learning frameworks should be employed to enhance algorithm robustness, improve capture of comorbidity heterogeneity features, and increase model generalizability. From a clinical translation perspective, performance evaluation systems should be perfected, continuous validation platforms developed, and clinical trials conducted to ultimately achieve utility of cross-diagnostic models moving from theory to clinical practice.

---

6 Limitations and Challenges

Although AI has developed rapidly across medical fields and shows broad application potential in ADHD, numerous challenges remain despite progress in auxiliary diagnosis, symptom prediction, drug efficacy prediction, and cross-diagnosis. Based on the above discussion, the following core common challenges are identified: (1) Low reporting quality with incomplete performance metrics (lack of confidence intervals, calibration curves, DCA) and opaque model development and validation processes; (2) Lack of high-quality, multimodal, standardized databases; (3) Insufficient model generalizability in real-world, diverse populations; (4) The "black box" nature of complex models (especially DL) greatly reduces clinical trust, with interpretability failing to meet clinical decision-making standards; (5) Lack of prospective, large-sample clinical validation studies and specific biomarkers; (6) Unclear pathways for translation or integration with existing clinical workflows, unclear clinical matching objectives (diagnosis/screening), and insufficient exploration of clinical value; (7) High research costs with low benefit.

Therefore, future research should explore: (1) Constructing full-cycle quality standards and practice guidelines for prediction/diagnostic models to define scientific standards for performance, diagnostic safety, and clinical usability; (2) Establishing international/national multi-center collaborations to build ADHD multimodal biological databases; (3) Strongly promoting XAI applications in medical imaging and physiological signal analysis; (4) Conducting prospective, rigorously designed clinical trials on AI model diagnostic/predictive validity and utility to identify specific biomarkers; (5) Exploring how AI models can adapt to clinical scenarios (seamlessly embedded in electronic health record systems, clinical decision support systems, or mobile apps), establishing clinical validation processes and proposing clinical implementation pathways; (6) Strengthening interdisciplinary collaboration among computer scientists, clinicians, neuroscientists, ethicists, and policymakers to provide comprehensive support for AI' s move to clinical application.

The application of AI in ADHD management in primary general practice also contains enormous potential while facing unique challenges. The core obstacles are: insufficient accessibility of complex equipment (electrophysiological devices) and algorithms at the primary level; inadequate training for general practitioners (GPs) and large individual differences in AI acceptance. However, if AI can be optimally configured within a precision medicine framework, it can bring significant benefits to primary ADHD care, assisting GPs in more sensitively identifying high-risk individuals in primary settings (such as analyzing consultation conversation texts, structured questionnaires, and simple behavior videos), promoting early screening; providing objective basis for referral decisions based on AI-output risk scores to optimize resource allocation; and assisting in monitoring medication responses and behavioral intervention effects through AI-powered follow-up tools to promote standardized management and long-term treatment continuity.

Author Contributions

WU Li conceptualized the research and designed the study protocol; drafted and wrote the manuscript; WANG Haoyi conducted literature search and collection; designed the study protocol; revised the manuscript; QIU Xiangyang conceptualized the research; conducted literature search and collection; created figures and tables; YUAN Jing provided clinical guidance and manuscript revi-

sion suggestions; CHEN Runan provided comprehensive revision input for all manuscript versions and took final responsibility for the manuscript.

Conflict of Interest: The authors declare no conflict of interest.

ORCID:
WU Li https://orcid.org/0009-0009-2028-6927
CHEN Runan https://orcid.org/0009-0002-3760-5460

References

[1] AYANO G, DEMELASH S, GIZACHEW Y, et al. The global prevalence of attention deficit hyperactivity disorder in children and adolescents: an umbrella review of meta-analyses[J]. J Affect Disord, 2023, 339: 860-866. DOI: 10.1016/j.jad.2023.07.071.

[2] WANG T T, LIU K H, LI Z Z, et al. Prevalence of attention deficit/hyperactivity disorder among children and adolescents in China: a systematic review and meta-analysis[J]. BMC Psychiatry, 2017, 17(1): 32. DOI: 10.1186/s12888-016-1187-9.

[3] SIBLEY M H, SWANSON J M, ARNOLD L E, et al. Defining ADHD symptom persistence in adulthood: optimizing sensitivity and specificity[J]. J Child Psychol Psychiatry, 2017, 58(6): 655-662. DOI: 10.1111/jcpp.12620.

[4] CHEN Yamin, CHENG Luying, ZHENG Qingyong, et al. Thematic analysis of artificial intelligence and neuroscience research[J]. Journal of Lanzhou University: Medical Sciences, 2022, 48(3): 59-65. DOI: 10.13885/j.issn.1000-2812.2022.03.013.

[5] ZHOU Xiaoqin, LIU Huizhen, WANG Ting, et al. Challenges and development directions of artificial intelligence empowering the medical field[J]. Chinese Journal of Clinical Thoracic and Cardiovascular Surgery, 2025, 32(2): DOI: 10.3724/SP.J.1042.2017.02136.

[6] CHEN I C, CHANG C L, CHANG M H, et al. The utility of wearable electroencephalography combined with behavioral measures to establish a practical multi-domain model for facilitating the diagnosis of young children with attention-deficit/hyperactivity disorder[J]. J Neurodev Disord, 2024, 16(1): 62. DOI: 10.1186/s11689-024-09578-1.

[7] FANG H, GUO J J, WU H. Wearable triboelectric devices for haptic perception and VR/AR applications[J]. Nano Energy, 2022, 96: 107112. DOI: 10.1016/j.nanoen.2022.107112.

[8] KIM W P, KIM H J, PACK S P, et al. Machine learning-based prediction of attention-deficit/hyperactivity disorder and sleep problems with wearable data in children[J]. JAMA Netw Open, 2023, 6(9): e233502. DOI: 10.1001/jamanetworkopen.2023.3502.

[9] MUÑOZ-ORGANERO M, POWELL L, HELLER B, et al. Automatic extraction and detection of characteristic movement patterns in children with ADHD based on a convolutional neural network (CNN) and acceleration images[J]. Sensors, 2018, 18(11): 3924. DOI: 10.3390/s18113924.

[10] DE HOND A A H, LEEUWENBERG A M, HOOFT L, et al. Guidelines and quality criteria for artificial intelligence-based prediction models in healthcare: a scoping review[J]. NPJ Digit Med, 2022, 5(1): 2. DOI: 10.1038/s41746-021-00549-7.

[11] COLLINS G S, MOONS K G M. Reporting of artificial intelligence prediction models[J]. Lancet, 2019, 393(10181): 1577-1579. DOI: 10.1016/S0140-6736(19)30037-6.

[12] RILEY R D, ENSOR J, SNELL K I E, et al. Calculating the sample size required for developing a clinical prediction model[J]. BMJ, 2020, 368: m441. DOI: 10.1136/bmj.m441.

[13] ZHANG Kangfuqian, CAO Qingjiu. Research progress on brain magnetic resonance imaging in children with attention deficit hyperactivity disorder[J]. Chinese Journal of Practical Pediatrics, 2023, 38(8): 575-579. DOI: 10.19538/j.ek2023080604.

[14] ALNAZER I, BOURDON P, URRUTY T, et al. Recent advances in medical image processing for the evaluation of chronic kidney disease[J]. Med Image Anal, 2021, 69: 101960. DOI: 10.1016/j.media.2021.101960.

[15] ZHU Li, ZHANG Liying, HAN Yuntao, et al. Classification study of attention deficit hyperactivity disorder based on convolutional neural network[J]. Journal of Biomedical Engineering, 2017, 34(1): DOI: 10.3724/SP.J.1042.2017.02136.

[16] KE H J, WANG F Q, MA H Y, et al. ADHD identification and its interpretation of functional connectivity using deep self-attention factorization[J]. Knowl Based Syst, 2022, 250: 109082. DOI: 10.1016/j.knosys.2022.109082.

[17] CHEN Lizhou, LI Qian, LUO Lekai, et al. Differences in brain white matter microstructure and classification study among different subtypes of attention deficit hyperactivity disorder patients[J]. West China Medical Journal, 2023, 38(3): 408-415.

[18] AHIRE N, AWALE R N, WAGH A. Electroencephalogram (EEG) based prediction of attention deficit hyperactivity disorder (ADHD) using machine learning[J]. Appl Neuropsychol Adult, 2025, 32(4): 966-977. DOI: 10.1080/23279095.2023.2247702.

[19] XU Qinfang, WANG Yanpei. Application of electroencephalogram measurement in diagnosis of developmental disorders in children[J]. Advances in Psychological Science, 2017, 25(12): 2136-2144. DOI: 10.3724/SP.J.1042.2017.02136.

[20] GARCÍA-PONSODA S, MATÉ A, TRUJILLO J. Refining ADHD diagnosis with EEG: the impact of preprocessing and temporal segmentation on classification accuracy[J]. Comput Biol Med, 2024, 183: 109305. DOI: 10.1016/j.compbiomed.2024.109305.

[21] VAHID A, BLUSCHKE A, ROESSNER V, et al. Deep learning based on event-related EEG differentiates children with ADHD from healthy controls[J]. J Clin Med, 2019, 8(7): 1055. DOI: 10.3390/jcm8071055.

[22] SANCHIS J, GARCÍA-PONSODA S, TERUEL M A, et al. A novel approach to identify the brain regions that best classify ADHD by means of EEG and deep learning[J]. Heliyon, 2024, 10(4): e26028. DOI: 10.1016/j.heliyon.2024.e26028.

[23] KHARE S K, ACHARYA U R. An explainable and interpretable model for attention deficit hyperactivity disorder in children using EEG signals[J]. Comput Biol Med, 2023, 155: 106676. DOI: 10.1016/j.compbiomed.2023.106676.

[24] TRIPOD+AI statement: updated guidance for reporting clinical prediction models that use regression or machine learning methods[J]. BMJ, 2024, 385: q902. DOI: 10.1136/bmj.q902.

[25] CHRISTODOULOU E, MA J, COLLINS G S, et al. A systematic review shows no performance benefit of machine learning over logistic regression for clinical prediction models[J]. J Clin Epidemiol, 2019, 110: 12-22. DOI: 10.1016/j.jclinepi.2019.02.004.

[26] SLOBODIN O, YAHAV I, BERGER I. A machine-based prediction model of ADHD using CPT data[J]. Front Hum Neurosci, 2020, 14: 560021. DOI: 10.3389/fnhum.2020.560021.

[27] ELLIOTT B L, D' ARDENNE K, MUKHERJEE P, et al. Limbic and executive meso- and nigrostriatal tracts predict impulsivity differences in attention-deficit/hyperactivity disorder[J]. Biol Psychiatry Cogn Neurosci Neuroimaging, 2022, 7(4): 415-423. DOI: 10.1016/j.bpsc.2021.05.002.

[28] LI Mengtao, DAI Mengqin, LUO Yaojing, et al. Current status and influencing factors of social anxiety in school-age children with attention deficit hyperactivity disorder[J]. Chinese Journal of Child Health Care, 2024, 32(3): 344-348. DOI: 10.11852/zgetbjzz2023-0613.

[29] ȘIPOȘ R, VĂIDEAN T, RĂPCIUC A M, et al. Analysing digital engagement patterns: a machine learning investigation into social anxiety among adolescents with ADHD[J]. J Clin Med, 2024, 13(23): 7461. DOI: 10.3390/jcm13237461.

[30] PARK C, ROUZI M D, ATIQUE M M U, et al. Machine learning-based aggression detection in children with ADHD using sensor-based physical activity monitoring[J]. Sensors (Basel), 2023, 23(10): 4949. DOI: 10.3390/s23104949.

[31] SUDRE G, SHARP W, KUNDZICZ P, et al. Predicting the course of ADHD

symptoms through the integration of childhood genomic, neural, and cognitive features[J]. Mol Psychiatry, 2021, 26(8): 4046-4054. DOI: 10.1038/s41380-020-00941-x.

[32] PETERSON B S, TRAMPUSH J, MAGLIONE M, et al. Treatments for ADHD in children and adolescents: a systematic review[J]. Pediatrics, 2024, 153(4): e2024065787. DOI: 10.1542/peds.2024-065787.

[33] CHEKROUD A M, BONDAR J, DELGADILLO J, et al. The promise of machine learning in predicting treatment outcomes in psychiatry[J]. World Psychiatry, 2021, 20(2): 154-170. DOI: 10.1002/wps.20882.

[34] FENG A C, ZHI D M, FENG Y, et al. Functional imaging derived ADHD biotypes based on deep clustering: a study on personalized medication therapy guidance[J]. EClinicalMedicine, 2024, 77: 102876. DOI: 10.1016/j.eclinm.2024.102876.

[35] SU Yi, WANG Yexin, YANG Li, et al. Clinical and cognitive characteristic indicators for predicting drug efficacy in attention deficit hyperactivity disorder[J]. Chinese Mental Health Journal, 2022, 36(3): DOI: 10.3724/SP.J.1042.2017.02136.

[36] YOO J H, SHARMA V, KIM J W, et al. Prediction of sleep side effects following methylphenidate treatment in ADHD youth[J]. Neuroimage Clin, 2019, 24: 102030. DOI: 10.1016/j.nicl.2019.102030.

[37] BAI Yuyin, FENG Minyan, BI Bo. Interpretation of the international expert consensus (2020 edition) on transdiagnostic clinical staging of adolescent mental disorders[J]. Chinese Journal of Applied Clinical Pediatrics, 2021, 36(22): 1716-1720.

[38] ALLESØE R L, THOMPSON W K, BYBJERG-GRAUHOLM J, et al. Deep learning for cross-diagnostic prediction of mental disorder diagnosis and prognosis using Danish nationwide register and genetic data[J]. JAMA Psychiatry, 2023, 80(2): 146-155. DOI: 10.1001/jamapsychiatry.2022.4076.

[39] MCGORRY P D, NELSON B. Transdiagnostic psychiatry: premature closure on a crucial pathway to clinical utility for psychiatric diagnosis[J]. World Psychiatry, 2019, 18(3): 359-360. DOI: 10.1002/wps.20679.

[40] WANG Yue, LI Yun, WANG Yao, et al. Diagnostic classification study of empathy combined with executive function for high-functioning autism spectrum disorder and attention deficit hyperactivity disorder[J]. Chinese Journal of Behavioral Medicine and Brain Science, 2020(2): 120-124. DOI: 10.3760/cma.j.cn371468-20191008-00717.

[41] SCHIRMER M D, VENKATARAMAN A, REKIK I, et al. Neuropsychiatric disease classification using functional connectomics - results of the connectomics in neuroimaging transfer learning challenge[J]. Med Image Anal, 2021, 70: 101972. DOI: 10.1016/j.media.2021.101972.

[42] EHRIG L, WAGNER A C, WOLTER H, et al. FASDetect as a machine learning-based screening app for FASD in youth with ADHD[J]. NPJ Digit Med, 2023, 6(1): 130. DOI: 10.1038/s41746-023-00864-1.

Table 1 Performance comparison of artificial intelligence models in various fields of ADHD

Note: Figure translations are in progress. See original paper for figures.

Source: ChinaXiv —Machine translation. Verify with original.