

Artificial Intelligence in the Diagnosis and Treatment of ADHD: Opportunities, Evidence, and Challenges

Shivani Bansal

Abstract: *Attention-deficit/hyperactivity disorder (ADHD) is a common neurodevelopmental condition whose diagnosis still rests on clinical interviews and rating scales, and whose treatment is limited by partial response to medication, side effects, and unequal access to behavioural care. Artificial intelligence (AI), and machine learning (ML) in particular, has been proposed as a way to make diagnosis more objective and treatment more personalised and scalable. This review summarises the current state of that evidence. In diagnosis, ML models trained on neuroimaging, electroencephalography (EEG), and behavioural or sensor data frequently report high accuracy, but results vary widely across datasets, are rarely validated externally, and have not yet produced a tool that clinicians can rely on. In treatment, the strongest evidence concerns a prescription digital therapeutic delivered as a video game-like intervention, whereas computerised cognitive training and neurofeedback show limited effects on blinded measures of ADHD symptoms. Key barriers are non-representative training data, algorithmic bias, privacy, weak regulatory and reporting standards, and the risk that predictive accuracy is mistaken for clinical utility. We conclude that AI is best positioned as decision support within a clinician-led, hybrid model of care, and we outline the research needed to move from promising prototypes to validated practice.*

Keywords: ADHD; artificial intelligence; machine learning; diagnosis; digital therapeutics; neurofeedback; algorithmic bias; ethics

1. Introduction

ADHD is characterised by persistent patterns of inattention, hyperactivity, and impulsivity that interfere with functioning. A meta-regression of community and school surveys estimated its worldwide pooled prevalence in children and adolescents at 5.29% (Polanczyk et al., 2007). A later meta-analysis of DSM-IV studies reported 5.9–7.1% in children and adolescents and 5.0% in young adults by self-report (Willcutt, 2012), and the condition is recognised as persisting into adulthood in many cases (Faraone et al., 2015). Untreated or late-recognised ADHD is associated with academic underachievement, relationship difficulties, and higher rates of co-occurring conditions such as anxiety and depression (Barkley, 2015).

Two problems recur throughout the clinical literature. The first is diagnostic. There is no biological test for ADHD; clinicians integrate developmental history, behaviour ratings from parents and teachers, and observation, using criteria such as those of the DSM-5, which require multiple symptoms present for at least six months in more than one setting (American Psychiatric Association, 2013). Each of these inputs is subjective, and symptoms overlap with anxiety, mood disorders, learning difficulties, and sleep problems. The second problem is therapeutic. Medication is effective for many patients (Cortese et al., 2018), but not all respond or tolerate it, and behavioural treatments depend on trained therapists who are scarce in many regions.

AI offers a possible response to both problems. Machine learning methods can find patterns in high-dimensional data, such as brain scans, EEG recordings, or continuous sensor streams, that are difficult for clinicians to assess by eye. Adaptive algorithms can tailor the difficulty and pacing of digital interventions to the individual. At the same time, the field has a history of results that look strong in a single dataset and weaken under independent testing. This review therefore asks not only what AI could do for ADHD care, but what the

evidence currently supports, where it is weak, and what must change before these tools can be used safely.

The paper is organised as follows. Section 2 describes the limits of current diagnostic and treatment practice. Section 3 reviews AI approaches to diagnosis, Section 4 reviews AI-enabled treatment, Section 5 discusses ethical and implementation challenges, and Section 6 considers future directions before the conclusion.

1.1 Scope and Approach

This is a narrative review, not a systematic one. It draws on published systematic reviews, meta-analyses, and randomised trials, prioritising those that evaluate clinical validity or clinical outcomes over technical proofs of concept. Where a claim rests on a single study or on an unpublished thesis, this is stated.

2. The Limits of Current Practice

2.1 Diagnosis

Clinical diagnosis of ADHD is only as reliable as the information it is built on. Parent and teacher reports reflect each informant's expectations, cultural context, and opportunity to observe the child, and obtaining reports from several informants takes time that overstretched services often lack. Clinicians may also weigh the same information differently, which produces variability in who is diagnosed.

There are also known disparities in who is recognised. ADHD is diagnosed more often in boys than in girls, with ratios of roughly two to four boys per girl reported in imaging-based studies (Ashraf et al., 2024), and reviewers have raised concern about under-diagnosis in girls and women (Zhang-James et al., 2023). Any AI system trained on existing diagnostic records inherits these patterns, a point we return to in Section 5.

Finally, the symptoms that define ADHD overlap with those of other conditions, and data-driven studies suggest that diagnostic categories do not map cleanly onto biological or behavioural clusters. In a clustering analysis of 226 children with autism, ADHD, or obsessive-compulsive disorder, data-driven groups built from cortical thickness and symptom measures showed little agreement with the diagnostic labels (normalised mutual information below 0.20; Kushki et al., 2019). The sample was small, so the finding is suggestive rather than definitive. This heterogeneity limits how well any classifier trained to reproduce current labels can perform, because the labels themselves are imperfect targets.

2.2 Treatment

Stimulant and non-stimulant medications reduce core symptoms in many patients, and a network meta-analysis of randomised trials found them effective in the short term, with differences between drugs and between age groups (Cortese et al., 2018). Even so, side effects such as sleep disturbance and reduced appetite affect adherence, and response is variable. Behavioural interventions, including parent training and cognitive-behavioural therapy, are valuable, but access is uneven and sustained participation is demanding for families. These gaps motivate interest in treatments that are cheaper to deliver at scale and can adapt to the individual.

3. AI in the Diagnosis of ADHD

3.1 Neuroimaging-based models

The largest body of work applies ML to structural and functional MRI. A 2024 systematic review of 85 studies published between 2010 and 2023 found that functional MRI was the dominant modality, that support vector machines were the most widely used classifier, and that most studies relied on the public ADHD-200 dataset (Ashraf et al., 2024). More recent work increasingly uses deep learning to extract features directly from the images.

Reported performance is striking but inconsistent. Within the studies summarised by Ashraf et al. (2024), accuracies range from the mid-40s to above 99%, depending on the dataset, the acquisition site, the features used, and the validation scheme. The same review concludes that the models are not generalisable and that performance depends on the locality of the data used. Several features of this literature explain why very high figures should be treated cautiously:

- Accuracy estimated by cross-validation tends to be inflated compared with accuracy on a held-out test set, which compromises generalisability (Zhang-James et al., 2023);
- The ADHD-200 data were collected at multiple sites with different scanners and protocols, and models trained at one site often perform worse at others;
- Phenotypic variables such as age, sex, and IQ can carry much of the predictive signal, so a model may be learning demographic differences rather than ADHD-specific brain patterns (Ashraf et al., 2024);
- Most studies classify ADHD against typically developing controls, which is an easier task than the clinically relevant one of distinguishing ADHD from other conditions in a referred population.

A systematic review of MRI-based classifiers found that studies differed widely in imaging modalities, models, validation methods, and sample sizes, that cross-validation inflated performance estimates relative to held-out tests, and that test accuracy was not associated with training sample size. Its authors concluded that large multimodal datasets will be needed to reach clinically useful tools (Zhang-James et al., 2023). Our reading of the evidence is that neuroimaging classifiers are valuable research tools for studying the neurobiology of ADHD, but there is not yet evidence that they improve diagnosis in routine clinical care. Brain imaging is also expensive and, for young children, difficult to obtain, which limits its practicality as a screening tool.

3.2 EEG-based Models

EEG is cheaper and more portable than MRI and has also attracted ML research. A systematic review of 57 studies using EEG and ML to classify ADHD found numerous reports of high accuracy, but many of the included studies did not meet quality-assessment standards, and the author advised caution in generalising the findings (Rasi, 2024; unpublished thesis). A broader review of machine- and deep-learning studies of ADHD diagnosis noted that the disorder's heterogeneity, its comorbidities, and a global shortage of diagnostic clinicians often delay diagnosis (Loh et al., 2022). As with MRI, the central issue is not whether a classifier can separate groups in a research sample but whether it adds reliable information to a real diagnostic work-up.

3.3 Behavioural, task-based, and sensor data

A third family of approaches uses data that are easier to collect: performance on computerised attention tasks, movement measured by actigraphy or wearables, eye-movement recordings, and digital questionnaires. The potential advantage is that such data can be collected over days or weeks in natural settings, giving a richer picture than a single clinic visit. A review of automated ADHD diagnosis identifies as research gaps the lack of public datasets for modalities other than MRI and the limited attention paid to wearable-device data such as ECG, PPG, and motion signals (Loh et al., 2022).

The closest the field has come to a controlled clinical test is a single-blind randomised trial of a computerised test of attention and activity (QbTest) used as an objective adjunct in diagnostic assessment. The trial examined how adding objective data affected clinicians' decision-making; clinicians with the report reached diagnostic decisions faster, with consultations about 15% shorter and no difference in diagnostic accuracy (Hollis et al., 2018). It is worth noting that this tool provides objective measurement rather than machine-learning prediction, and that it illustrates how the realistic value of such technology may lie in supporting clinicians rather than replacing them.

3.4 Potential benefits

If the technical and validation problems can be solved, diagnostic AI could offer three benefits. First, objective data may reduce reliance on subjective reports and improve consistency between clinicians. Second, data from several

sources could be combined into a single profile that supports earlier and more precise identification. Third, automated screening could help prioritise referrals in services with long waiting lists. None of these benefits has yet been demonstrated in prospective clinical trials of ML-based diagnostic tools, and it should not be assumed that an algorithm is less biased than a clinician simply because it is quantitative (see Section 5.1).

3.5 Limitations

Beyond the points above, three limitations deserve emphasis. Data are limited: large, well-characterised, demographically diverse datasets with expert diagnoses and long-term follow-up are scarce. Interpretability is limited: deep models in particular rarely explain their outputs in terms clinicians can check against their own judgement. And the reference standard is imperfect: a model trained to reproduce a clinical diagnosis cannot be more valid than that diagnosis, so high agreement with labels does not prove that the model has identified ADHD as a biological or functional entity.

4. AI in the Treatment of ADHD

4.1 Digital Therapeutics

The most rigorously tested digital treatment for ADHD is AKL-T01 (EndeavorRx), a game-like intervention designed to target attention and cognitive control. In a randomised controlled trial of 348 children, those who played the game for about 25 minutes a day, five days a week, for four weeks showed greater improvement on a computerised attention measure than children given an education-style control game (Kollins et al., 2020). On the basis of this and related trials, the US Food and Drug Administration authorised the product in 2020 as a prescription digital therapeutic for children, the first video game cleared for this purpose.

Three points of context are important. The primary outcome was a performance-based attention test, and the improvements in everyday functioning reported by parents were secondary findings, so the size of the benefit in daily life is less certain. In addition, the trial describes AKL-T01 as a video game-like digital therapeutic, not as a machine-learning system, so calling it AI is a stretch; any personalisation it offers is far simpler than the deep-learning systems discussed in Section 3. Finally, the trial's authors included people involved in developing the product, so independent replication matters.

4.2 Computerised cognitive training

Adaptive cognitive training programmes, which raise or lower task difficulty according to performance, were among the earliest technology-based approaches. An influential randomised trial of computerised working memory training in children with ADHD reported improvements in working

memory and in parent-rated symptoms (Klingberg et al., 2005). Later syntheses have been less favourable. A meta-analysis of randomised trials found that cognitive training improved working memory performance but had limited effects on ADHD symptoms when assessed by blinded raters, and no effect of working memory training specifically on symptoms (Cortese et al., 2015). Another meta-analysis of 25 studies concluded that claims of academic, behavioural, and cognitive benefits for existing programmes were unsupported (Rapport et al., 2013). The practical lesson is that adaptive training reliably improves performance on the practised tasks, but that transfer to real-world functioning has not been shown. Results from unblinded raters, who know the child is in the training group, should be interpreted accordingly.

4.3 Neurofeedback

Neurofeedback trains people to modify features of their own brain activity using real-time visual or auditory feedback. It involves signal processing and, increasingly, ML-based feature extraction, but it is not inherently an AI intervention and should not be described as one without qualification. The evidence base is mixed. A meta-analysis of 13 randomised trials (520 participants) found significant effects on ADHD symptoms when rated by the assessors closest to the treatment, who were the least blinded, but no significant effects when probably-blinded ratings were used or when trials had active or sham controls. The authors concluded that evidence from well-controlled trials did not support neurofeedback as an effective ADHD treatment (Cortese et al., 2016). Further adequately controlled trials, with standardised protocols and checks that learning actually occurred, are needed before conclusions change.

4.4 Continuous monitoring and personalisation

A frequently proposed advantage of AI is continuous monitoring: wearables and smartphones could track activity, sleep, and attention-related behaviour, allowing treatment to be adjusted between clinic visits and giving clinicians objective data on medication response. This is plausible and attractive, but the supporting evidence is currently limited to feasibility and pilot studies. Evidence that monitoring-driven treatment adjustment improves outcomes, compared with usual care, is still needed.

4.5 Remote delivery and access

Digital interventions can be delivered at home, which could reduce geographical and financial barriers in areas with few specialists. Access to the technology is itself unequal, however: families need devices, connectivity, digital literacy, and in the case of prescription products, a clinician able to prescribe and follow up. Remote tools may therefore widen rather than narrow disparities unless they are designed and funded with equity in mind.

4.6 Summary of treatment evidence

Approach	Strongest evidence	Main caveat
Digital therapeutic (AKL-T01)	Randomised trial of 348 children showing greater improvement on a computerised attention measure than control (Kollins et al., 2020)	Primary outcome was a performance test; daily-life benefit less certain; not a deep-learning system
Computerised cognitive training	Improves practised working memory tasks (Klingberg et al., 2005; Cortese et al., 2015)	Limited effect on ADHD symptoms by blinded raters (Cortese et al., 2015; Rapport et al., 2013)
Neurofeedback	Effects on least-blinded ratings (Cortese et al., 2016)	No significant effect on probably-blinded ratings or in sham-controlled trials
Sensor-based monitoring	Feasibility and pilot data	No trials showing improved outcomes

5. Ethical, Social, and Implementation Challenges

5.1 Bias and fairness

A machine-learning model learns whatever regularities are present in its training data, including those that reflect unequal care. If boys, majority-group children, or children from well-resourced settings are over-represented among diagnosed cases, a model may perform best for those groups and miss ADHD in others. The risk is not hypothetical in healthcare more broadly: a widely cited study of a commercial algorithm used to allocate care resources in the United States found substantial racial bias, arising because the algorithm used healthcare costs as a proxy for health need (Obermeyer et al., 2019). The lesson for ADHD is that performance must be reported separately by sex, age, ethnicity, language, and socioeconomic setting, and that the choice of the target variable, such as a diagnostic label that is itself unevenly applied, deserves as much scrutiny as the algorithm.

5.2 Privacy and data governance

ADHD tools can involve some of the most sensitive categories of data: brain imaging, genetic information, continuous behavioural and location data, and information about children. Regulation differs by jurisdiction. In the United States, health data in clinical settings fall under HIPAA; the European Union's General Data Protection Regulation and its AI Act, which treats AI-enabled medical devices that need third-party conformity assessment as high-risk (with obligations for AI embedded in regulated medical devices now due to apply from August 2028), impose obligations on data processing and on system validation; and India's Digital Personal Data Protection Act, 2023 requires verifiable parental consent before a child's personal data are processed and restricts tracking or behavioural monitoring of children, subject to prescribed exemptions, which any sensor-based monitoring tool for children would need to take into account. Developers and clinicians need to ensure meaningful consent, which for children involves both parents and the child where appropriate, data minimisation, secure storage, and transparency about secondary use of data.

5.3 Validation, transparency, and reporting

The evidence reviewed in Section 3 shows how easily optimistic accuracy figures arise from small samples, data leakage, and lack of external validation. Prediction-model studies should follow reporting guidance such as TRIPOD+AI (Collins et al., 2024), be tested prospectively in the settings where they will be used, and be evaluated on patient-relevant outcomes rather than on accuracy alone.

Tools should also provide outputs that clinicians can interpret and challenge.

5.4 Clinical judgement and over-reliance

A diagnostic score can acquire an authority that exceeds its evidence, particularly when it appears objective. Clinicians may defer to an algorithm in ambiguous cases, and families may interpret a score as definitive. The appropriate role is decision support: the algorithm informs, and the clinician, who can take account of history, context, and comorbidity, decides. Training for clinicians in the strengths and limits of such tools is part of safe implementation.

5.5 Overdiagnosis and commercialisation

Cheap, scalable screening tools, particularly direct-to-consumer ones, could increase false-positive identification and encourage unnecessary treatment, while the commercial incentives around digital health products can run ahead of the evidence. Independent trials, transparent reporting of conflicts of interest, and regulatory review proportionate to risk are therefore important safeguards.

6. Future Directions

- Better data and external validation:** Progress depends on large, multi-site, demographically diverse datasets with standardised protocols, expert diagnoses, and follow-up, together with routine testing of models on data from sites and populations that were not used in training. Federated learning, in which models are trained across institutions without pooling raw data, may help with both scale and privacy, although it remains largely experimental in this field.
- Moving beyond case-control classification:** The more useful clinical questions are prospective and differential: which children will persist in having impairing symptoms, which referred patients have ADHD rather than another condition, and which treatment is likely to work for whom. Data-driven approaches that identify biologically or behaviourally coherent subgroups may eventually refine or complement current diagnostic categories (Kushki et al., 2019).
- Predicting treatment response:** Precision treatment, in which genetic, neurobiological, behavioural, and environmental data are combined to select a medication or behavioural programme, is an appealing goal. Realising it will require prospective trials that compare AI-guided selection with standard care; at present there is no strong evidence that such guidance improves outcomes.

- 4) **Immersive and multimodal interventions:** Virtual and augmented reality could allow practice of attention and self-regulation skills in realistic yet controlled scenarios, and generative AI could support coaching, psychoeducation, and organisational skills. These applications are promising but largely untested in randomised trials, and they raise their own safety and privacy questions, especially for children.
- 5) **Co-design and equity:** Tools are more likely to be useful and acceptable if people with ADHD, families, teachers, and clinicians help design them, and if their evaluation includes cultural adaptation, language access, and attention to the families least able to reach conventional services.

7. Conclusion

AI has real potential in ADHD care, but the strength of the evidence differs sharply between its proposed uses. In diagnosis, machine-learning classifiers using imaging, EEG, and sensor data show that group differences can be detected in research samples, yet inconsistent accuracy, lack of external validation, and imperfect reference labels mean that none is ready to replace or reliably improve routine clinical assessment. In treatment, the best-supported digital intervention has shown benefit on an attention measure in a randomised trial, whereas computerised cognitive training and neurofeedback have limited effects on blinded outcomes. Ethical risks, in particular bias, privacy, and over-reliance, are as important as technical performance.

The most defensible near-term model is a hybrid one in which AI supports, rather than substitutes for, clinical judgement: providing additional objective data, easing access to evidence-based interventions, and monitoring outcomes, all under human oversight. Getting there requires prospective trials with patient-relevant outcomes, transparent reporting, evaluation across diverse populations, and sustained collaboration between clinicians, researchers, patients, and regulators.

References

- [1] American Psychiatric Association. (2013). *Diagnostic and statistical manual of mental disorders* (5th ed.). American Psychiatric Publishing.
- [2] Ashraf, I., Jung, S., Hur, S., & Park, Y. (2024). A systematic literature review of neuroimaging coupled with machine learning approaches for diagnosis of attention deficit hyperactivity disorder. *Journal of Big Data*, 11, Article 140. <https://doi.org/10.1186/s40537-024-00998-3>
- [3] Barkley, R. A. (Ed.). (2015). *Attention-deficit hyperactivity disorder: A handbook for diagnosis and treatment* (4th ed.). Guilford Press.
- [4] Collins, G. S., Moons, K. G. M., Dhiman, P., et al. (2024). TRIPOD+AI statement: Updated guidance for reporting clinical prediction models that use regression or machine learning methods. *BMJ*, 385, e078378. <https://doi.org/10.1136/bmj-2023-078378>
- [5] Cortese, S., Ferrin, M., Brandeis, D., Buitelaar, J., Daley, D., Dittmann, R. W., et al. (2015). Cognitive training for attention-deficit/hyperactivity disorder: Meta-analysis of clinical and neuropsychological outcomes from randomized controlled trials. *Journal of the American Academy of Child and Adolescent Psychiatry*, 54(3), 164–174. <https://doi.org/10.1016/j.jaac.2014.12.010>
- [6] Cortese, S., Ferrin, M., Brandeis, D., Holtmann, M., Aggensteiner, P., Daley, D., et al. (2016). Neurofeedback for attention-deficit/hyperactivity disorder: Meta-analysis of clinical and neuropsychological outcomes from randomized controlled trials. *Journal of the American Academy of Child and Adolescent Psychiatry*, 55(6), 444–455. <https://doi.org/10.1016/j.jaac.2016.03.007>
- [7] Cortese, S., Adamo, N., Del Giovane, C., et al. (2018). Comparative efficacy and tolerability of medications for attention-deficit hyperactivity disorder in children, adolescents, and adults: A systematic review and network meta-analysis. *The Lancet Psychiatry*, 5(9), 727–738. [https://doi.org/10.1016/S2215-0366\(18\)30269-4](https://doi.org/10.1016/S2215-0366(18)30269-4)
- [8] Faraone, S. V., Asherson, P., Banaschewski, T., Biederman, J., Buitelaar, J. K., Ramos-Quiroga, J. A., et al. (2015). Attention-deficit/hyperactivity disorder. *Nature Reviews Disease Primers*, 1, 15020. <https://doi.org/10.1038/nrdp.2015.20>
- [9] Hollis, C., Hall, C. L., Guo, B., James, M., Boadu, J., Groom, M. J., et al. (2018). The impact of a computerised test of attention and activity (QbTest) on diagnostic decision-making in children and young people with suspected attention deficit hyperactivity disorder: Single-blind randomised controlled trial. *Journal of Child Psychology and Psychiatry*, 59(12), 1298–1308. <https://doi.org/10.1111/jcpp.12921>
- [10] Klingberg, T., Fernell, E., Olesen, P. J., Johnson, M., Gustafsson, P., Dahlström, K., et al. (2005). Computerized training of working memory in children with ADHD: A randomized, controlled trial. *Journal of the American Academy of Child and Adolescent Psychiatry*, 44(2), 177–186.
- [11] Kollins, S. H., DeLoss, D. J., Cañadas, E., Lutz, J., Findling, R. L., Keefe, R. S. E., Epstein, J. N., Cutler, A. J., & Faraone, S. V. (2020). A novel digital intervention for actively reducing severity of paediatric ADHD (STARS-ADHD): A randomised controlled trial. *The Lancet Digital Health*, 2(4), e168–e178. [https://doi.org/10.1016/S2589-7500\(20\)30017-0](https://doi.org/10.1016/S2589-7500(20)30017-0)
- [12] Kushki, A., Anagnostou, E., Hammill, C., Duez, P., Brian, J., Iaboni, A., et al. (2019). Examining overlap and homogeneity in ASD, ADHD, and OCD: A data-driven, diagnosis-agnostic approach. *Translational Psychiatry*, 9, 318. <https://doi.org/10.1038/s41398-019-0631-2>
- [13] 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, 105525. <https://doi.org/10.1016/j.compbimed.2022.105525>
- [14] Obermeyer, Z., Powers, B., Vogeli, C., & Mullainathan, S. (2019). Dissecting racial bias in an algorithm used to manage the health of populations. *Science*, 366(6464), 447–453. <https://doi.org/10.1126/science.aax2342>

- [15] Polanczyk, G., Silva de Lima, M., Horta, B. L., Biederman, J., & Rohde, L. A. (2007). The worldwide prevalence of ADHD: A systematic review and metaregression analysis. *American Journal of Psychiatry*, 164(6), 942–948. <https://doi.org/10.1176/ajp.2007.164.6.942>
- [16] Rapport, M. D., Orban, S. A., Kofler, M. J., & Friedman, L. M. (2013). Do programs designed to train working memory, other executive functions, and attention benefit children with ADHD? A meta-analytic review of cognitive, academic, and behavioral outcomes. *Clinical Psychology Review*, 33(8), 1237–1252. <https://doi.org/10.1016/j.cpr.2013.08.005>
- [17] Rasi, A. (2024). *The classification of ADHD using machine learning and EEG data: A systematic review* [Unpublished thesis]. University of Tasmania.
- [18] Willcutt, E. G. (2012). The prevalence of DSM-IV attention-deficit/hyperactivity disorder: A meta-analytic review. *Neurotherapeutics*, 9(3), 490–499. <https://doi.org/10.1007/s13311-012-0135-8>
- [19] Zhang-James, Y., Razavi, A. S., Hoogman, M., Franke, B., & Faraone, S. V. (2023). Machine learning and MRI-based diagnostic models for ADHD: Are we there yet? *Journal of Attention Disorders*, 27(4), 335–353.