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Review Article

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Machine Learning Approaches to Identify and Classify ADHD: What We Know and What Still Needs Work

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ABSTRACT

Attention-Deficit/Hyperactivity Disorder (ADHD) is a highly prevalent neurodevelopmental disorder, affecting an estimated 5–10% of children globally, with symptoms frequently persisting into adulthood for approximately 60% of those individuals [1-6]. ADHD is characterized by a persistent pattern of inattention, hyperactivity, and impulsivity, leading to significant functional impairment across scholastic, social, and occupational domains.

The official diagnosis of ADHD relies on phenomenological criteria, observable behavioral manifestations of symptoms, as specified by the latest edition of the Diagnostic and Statistical Manual of Mental Disorders [7]. However, this diagnostic process is frequently complex, costly, and time-consuming, often complicated further by the heterogeneity of ADHD presentations and frequent comorbidity with other psychiatric disorders. These factors can contribute to misdiagnosis or treatment delays [2,8,9]. In response, machine learning (ML) approaches have emerged as promising tools for the healthcare industry, aiming to expedite the diagnosis, identify risk factors, and improve accuracy and timeliness of ADHD detection [2,10].

In this narrative review, we use a metaphor to bridge clinical expertise and technological tools to frame the discussion. We first outline evidence-based ADHD assessment workflows, then present a synthesis of ten recent ML studies, emphasizing methodologies, predictive features, and distinction between phenotype- and genotype-based approaches. Through the metaphor, we highlight potential points of integration and conclude with practical, ethical, and systemic considerations for ML in ADHD assessment, allowing you to evaluate the implications for clinical practice.

Abbreviations

ADHD-RS	:	ADHD Rating Scale-IV
ASRS	:	Adult ADHD Self-Report Scale
CBCL	:	Child Behavior Checklist
Conners	:	Conners' Rating Scales, Short and Comprehensive Forms
SWAN	:	Strengths and Weaknesses of ADHD Symptoms and Normal Behavior
Vanderbilt	:	Vanderbilt ADHD Diagnostic Rating Scales [27-32].

Background

Before considering how ML might alter ADHD assessment practices, it is important to clarify the foundation that guides contemporary clinical decision-making. This approach matters for discussions of ML because it establishes the reference standard against which new technologies must be evaluated. The proceeding key principles are covered: (a) core principles of evidence-based ADHD assessment, (b) ML approaches applied to ADHD, and (c) observed implementation patterns and regulatory considerations.

Evidence-Based Assessment: Core Concepts and Rationale

Evidence-based assessment provides a structured, hypothesis-driven approach that emphasizes reliability, incremental validity,

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and the integration of information across multiple sources [11]. Rather than relying on any single test or informant, evidence-based assessment views diagnosis as an iterative process in which clinicians generate, test, and refine hypotheses using empirically supported tools and interpretive frameworks [12,13].

Key principles include transparency, replicability, multi-method assessment, and the coordination of subjective and objective data [14-16]. Clinicians synthesize behavioral history, multi-informant reports, and functional observations to develop an integrative diagnostic formulation that guides treatment planning. Understanding these principles establishes the baseline against which ML approaches can be evaluated for clinical utility and fidelity to evidence-based practice.

Machine Learning in ADHD Assessment

Conceptual Overview

Building on the foundation of evidence-based assessment, ML has become increasingly prominent in psychiatry and behavioral health as a means of analyzing complex, multidimensional data and identifying latent patterns associated with clinical conditions [17,18]. In ADHD research specifically, ML has been applied to behavioral ratings, electronic health records (EHR), neuroimaging, and genetic information, reflecting the disorder's cognitive, behavioral, and biological heterogeneity [3,6,9,19].

These applications align with broader trends in precision psychiatry, where models are increasingly used to support risk estimation, stratification, and population-level prediction [1,8]. In ADHD research, ML has been explored as a tool for improving early identification, highlighting predictive symptom patterns, and modeling potential biological signatures of the disorder [20,21].

At the same time, the literature underscores several limitations that constrain the immediate clinical utility of ML tools. Others depend on limited or homogeneous samples, or rely on single data modalities, which may reduce generalizability [9]. Implementation studies note that clinical uptake depends not only on accuracy, but also on transparency, workflow fit, and practitioner trust [22,23].

Observed Implementation and Regulatory Patterns

Finally, research highlights practical and regulatory patterns that shape the adoption of ML in ADHD assessment. Many ML models are complex, limiting transparency and accountability, and may reinforce systemic biases or inequities [18,24]. Regulatory protections such as HIPAA do not always cover AI tools developed outside traditional clinical institutions, raising concerns about data governance and compliance [17]. Proper implementation requires the workforce utilizing AI to undergo AI literacy and technology training [25,26].

Evidence-Based Assessment Workflow

Having established the foundational principles of evidence-based assessment, the current landscape of ML applications in ADHD, and the observed implementation and regulatory patterns, it is now possible to examine how these concepts translate into clinical practice. The structured, evidence-based workflow provides a reference point for understanding where ML tools can be integrated, how they may augment or alter existing procedures, and what challenges might arise when algorithmic predictions intersect with clinical judgment. By mapping ML approaches onto each stage of the ADHD assessment process, practitioners can see both opportunities and limitations in real-world application.

Screening

Screening instruments are the initial, low-burden phase of evaluation designed to detect the possible presence or absence of a psychological condition, screening methods have high utility for triaging clinical concerns [11,14,16]. Screening does not measure severity, chronicity, or diagnostic thresholds, serving instead as a hypothesis-generation step. Consequently, clinical interviews or assessments should follow screening, using the results to identify preliminarily relevant symptom clusters [16].

Clinical Interview

Following screening, a structured, semi-structured, or unstructured clinical interview refines the preliminary hypotheses. Clinicians interpret screening results, assess symptom context and cross-situational impairment, identify relevant informants, and determine appropriate psychometric assessments [11,12]. This step clarifies symptom onset, developmental trajectory, functional impact, and situational variability, providing a foundation for selecting reliable and valid quantifiable assessment instruments [13].

Clinical Assessment Measures

Clinical assessment uses standardized instruments to measure symptom severity, frequency, chronicity, functional impairment, and alignment with diagnostic thresholds [14,16]. It integrates patient self-report, multi-informant ratings, objective performance measures, and contextual information, substantiating or ruling out concerns raised during earlier phases.

Differential Diagnosis

Differential diagnosis occurs after assessment but prior to the final diagnostic decision. It involves systematic consideration of alternative explanations, ruling out comorbid or mimicking conditions, and determining the most parsimonious interpretation of the data [15]. For disorders such as ADHD, differential diagnosis is particularly critical given the high comorbidity and symptom overlap with other neurodevelopmental and psychiatric conditions [13].

Integrative Formulation

The final phase is integrative formulation, which synthesizes data from screening, interview, assessment, and multiple informants into a coherent diagnostic interpretation [11,12].

Table 1 outlines this evidence-based ADHD-specific assessment workflow including standardized screening and assessment batteries.

With this practitioner's workflow as a guide, we can examine how recent ML studies map onto these diagnostic stages. By comparing study designs, data sources, ML models, and performance metrics, the following synthesis illustrates both the promise of ML to enhance ADHD identification and the ongoing challenges for integration into clinician-led practice. Figures and tables (Figure 2, Tables 2–4) provide visual and tabular results of this review.

Table 1: Evidence-Based ADHD-Specific Assessment Workflow

Step	Purpose / Description	ADHD-Specific or Methodological Enhancements
Screening	Identify the possible presence or absence of a condition; serve as a triage mechanism for further evaluation.	**Children/Adolescents:** Conners 3–Short Form (parent/teacher), Vanderbilt ADHD Diagnostic Short Forms (parent/teacher), SWAN Short Form, CBCL Attention Problems subscale, ADHD Rating Scale-IV short form. **Adults:** Adult ADHD Self-Report Scale (ASRS). Incorporate multiple informants (parent, teacher, self-report); flag potential concerns without quantifying severity.
Clinical Interview	Refine hypotheses generated from screening; gather context, symptom onset, course, functional impact, and identify relevant informants.	Structured or semi-structured ADHD interviews; clarify cross-situationality of symptoms; integrate information from parents, teachers, and the patient.
Clinical Assessment	Measure severity, frequency, chronicity, functional impact, and diagnostic thresholds; substantiate or rule out concerns flagged in screening and interview.	Administer ADHD-specific full psychometric instruments (e.g., Conners Comprehensive, ADHD-RS full assessment, Vanderbilt full assessment); use clinical cutoffs, normative comparisons, and multi-informant scoring to quantify severity.
Differential Diagnosis	Systematically evaluate alternative explanations, comorbidities, and overlapping conditions; rule out non-ADHD causes.	Apply ADHD-specific differential rules; consider developmental and comorbid conditions; clarify which symptoms are attributable to ADHD versus other disorders.
Integrative Formulation	Synthesize all data into a coherent diagnostic interpretation, severity classification, functional summary, risk assessment, and treatment planning.	Combine screening, interview, and assessment data; summarize functional impact; provide diagnostic impression, treatment recommendations, and prognosis.

Sources

Screening tools flag potential ADHD symptoms [11,12,13,16]. Clinical interviews refine hypotheses and integrate multi-informant data [11,12]. Clinical assessment instruments quantify severity and functional impact using standardized cutoffs [11,14,16,]. Differential diagnosis precedes integrative formulation to rule out alternative explanations and comorbidities [13,15]. Integrative formulation synthesizes all information into diagnostic impression, severity classification, functional summary, treatment recommendations, and prognosis [11,12].

Synthesis of Machine Learning Studies

These advanced technologies are undeniably complex, demanding that we be not only informed consumers who choose models wisely but also skilled users who apply them effectively with little training. Consequently, we share a metaphor to inform providers in our field about the development process of ML models alongside the life cycle of a sunflower. Figure 1 and Text box 1 comprise the metaphor both visually and narratively.

Figure 1 provides a conceptual metaphor to support clinician understanding of how diverse ML approaches contribute to ADHD assessment without requiring technical expertise. Rather than detailing specific algorithms or performance metrics, the figure illustrates how ML models function as tools that vary in scope, influence, and proximity to clinical judgment across the diagnostic process. This metaphor-based framing is intended to orient readers to the synthesis that follows by highlighting shared functional roles across otherwise heterogeneous studies.

Text Box 1

GMO lab

Visualize a group of machine learning (ML) technologists applying this technology to predicting ADHD. All they need are the variables evidenced as most significant in identifying and classifying this diagnosis. In our metaphor, we have a group of software engineers that are using AI to generate a sunflower seed that is reproducible, meaning the seeds are harvestable and legitimate. The engineers enter code rather than biological sources to compose the seed's DNA.

A sun-kissed seedling

The technologists take their model and feed it with these significant variables. Their methods of construction pertain to their particular design choice, which varies from one tech to another. For the AI-generated sunflower seed, the software engineer hands it off to the developer, who plants the seed in their garden. The sun shines down on the seed, developing into a seedling, a tiny plant and a few leaves.

Growth spurt

The technologists test their individual models on their curated datasets, applying the model's predictive ability to a population (real or fabricated). This is when the seedling gets the assorted nutrients it needs to become a budding, reproductive plant.

Leaving the nursery for the new home

Now that the technologists have used their model in prediction, it is ready for service. They offer it up as a diagnostic tool to various healthcare organizations, who make the final purchase and pass it down to their individual clinicians. Similarly, the budding plant is ready for use and purchased by different nurseries. Gardeners come and take their budding plant home as caretaking responsibilities are passed down to them from the developers.

Full bloom

The ML tool is in the hands of the clinicians now. When a clinician deems the tool worthwhile and necessary for a client, they utilize it in the diagnostic process. Correspondingly, the budding plant is in the hands of the individual gardeners, and continues growing in this new location. The sunflower blooms into vibrance. The bud is open, and the flower fully reveals itself in radiating grandeur. Butterflies drink the nectar, while bees pollinate and fertilize the seeds. Finally, the gardener gets to see their hope and care realized, enjoying the beauty of this very real flower.

Looking out the window

It takes time to see the effectiveness of a procedure or tool, so both gardeners and diagnosticians are patient and observant throughout the waiting period. For clinicians, this is when we discover the accuracy of the ML tool's prediction; client behavior should consistently reflect the results in order to prove

the tool to be truly accurate, reliable, and valid. Over time, if both the client and diagnostician agree with the outcome of the model, then the diagnostic functionality of the tool was a precise measurement of their ADHD risk. Likewise, the gardeners test the original engineer's hypothesis: if these harvested seeds can germinate and become a seedling, they prove that an AI-generated sunflower seed is indeed reproducible. The once blooming flowers begin to wilt as their leaves and petals fall to the ground, their deathbed. Once the plant enters the harvesting stage, their seeds are ripe for use. Gardeners replant these newly produced seeds, and wait for their growth. If they develop into seedlings, then the AI-generated seed is reproductively viable.

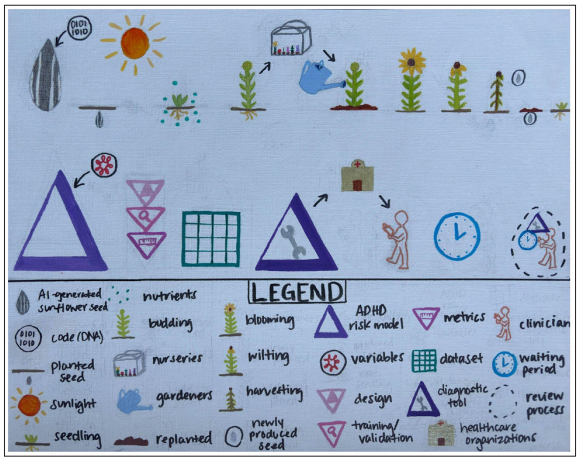

Figure 1: Metaphorical Representation of the Machine Learning Development-to-Clinical Use Pipeline

Note: This figure uses a genetically engineered seed metaphor to represent stages of machine-learning model development, deployment, and clinician-mediated use in ADHD assessment. The metaphor aids conceptual understanding without implying automation or replacement of clinical judgment.

Building on the evidence-based ADHD workflow described above, we synthesize ten recent ML studies to illustrate how algorithmic approaches are currently applied across different phases of assessment, where they align with clinical practices, and where gaps remain. These studies vary widely in research design, sample characteristics, data modalities, ML models, and reported performance metrics. Together, they provide a landscape of current methods, achievements, and ongoing challenges for integrating ML into clinical practice.

Human–AI Diagnostic Workflow

Figure 2 presents a human–AI diagnostic workflow that situates ML applications at varying stages of ADHD assessment. Some models primarily assist in the screening phase, identifying children or adolescents at risk based on behavioral ratings or administrative data. Others aim to augment clinical assessment or differential diagnosis, using neuroimaging, genetic, or multimodal datasets to refine predictions. Due to their design and feature variations, each individual model may utilize different routes to get to the same outcome. Clinician engagement with the model is also irregular given their discrete discernment in adjudicating when the application is needed. Therefore, this figure depicts a foundational level of ML applications to demonstrate their core similarities while providing room for their isolated differences. By mapping studies to workflow stages, the figure clarifies where ML currently complements evidence-based assessment and where it attempts a more ambitious automation.

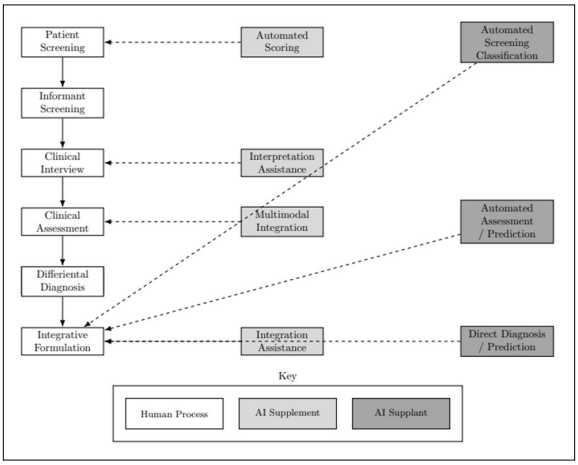

Figure 2: Human–AI Diagnostic Workflow

Comparison of Study Characteristics

Table 2 compares the research design, analysis approach, sample sizes, and data modalities across the ten studies. The table presents studies based on population type (e.g., children, youth, adults), data source (e.g., behavioral surveys, EHR, neuroimaging, genetics), and classification focus (phenotype vs. genotype). This diversity demonstrates both the promise of ML for multi-dimensional prediction and the challenges of synthesizing findings across heterogeneous populations and data types. Notably, most studies rely on convenience or clinical samples, which may limit generalizability to broader populations.

Table 2 : Research Design and Analysis, and Sample Characteristics Across 10 ADHD Studies [2, 3, 6, 8, 9,10,19,20,21,33]

Variable	Maniruzzaman et al. (2022)	Ter-Minassian et al. (2022)	Morrow et al. (2020)	Goh et al. (2023)	Garcia-Argibay et al. (2022)	Kautzky et al. (2020)	Cao et al. (2023)	Mikolas et al. (2022)	Cervantes-Henríquez et al. (2021)	Yasumura et al. (2017)
Research Design / Analysis	Quantitative, empirical	Quantitative, empirical, retrospective	Quantitative, empirical	Quantitative, longitudinal, predictive-modeling	Quantitative, longitudinal, population-based	Quantitative, empirical	Narrative review	Quantitative, empirical, retrospective	Quantitative, empirical, predictive	Quantitative, empirical
Sample Size	45,779	56,258	6630	399	238,696	38	N/A	299	408 individuals	315 children
Sample Composition	Youth (0-17 yrs)	School pupils ages 6-7	Youth (3-17 yrs)	Youth (7-18 yrs)	Swedish individuals (1995-1999 births)	Adults	N/A	Children, help-seeking psychiatric	120 families (ages 6-60)	Children (elementary/ junior high)

Data Modality	Behavioral survey	Linked education and EHR data	Parent-reported questionnaire	Behavioral / symptom report, performance measures	6 national Swedish registers	Multimodal (PET imaging + genetics)	Multiple modalities reviewed	EHR data	Genetic SNP data, demographics, clinical symptoms	NIRS signals (prefrontal cortex)
Class	phenotype	phenotype	phenotype	phenotype	genotype	genotype	genotype	phenotype	genotype	phenotype

Note: This table presents key study characteristics. Sample sizes are approximate for some studies. N/A indicates the data was not applicable to a single sample description (e.g., in a review paper). PET = Positron Emission Tomography; NIRS = Near-Infrared spectroscopy; SNP = Single Nucleotide Polymorphism

Machine Learning Models and Performance

Table 3 details the ML models employed and their reported performance metrics, including accuracy, sensitivity, specificity, area under the curve (AUC), and balanced accuracy. Across studies, behavioral data often yields the most consistent predictive performance, while single-modality neuroimaging or genetic models show greater variability. Ensemble and multimodal approaches appear promising, but remain limited by sample size and methodological heterogeneity. These findings suggest that ML can replicate or enhance some aspects of traditional assessment (e.g., identifying symptom clusters), but is not yet sufficient to replace clinician judgment.

Table 3: Machine Learning Models and Performance Metrics Across 10 ADHD Studies [2,3,6,8-10,19-21,33]

Variable	Maniruzzaman et al. (2022)	Ter-Minassian et al. (2022)	Morrow et al. (2020)	Goh et al. (2023)	Garcia-Argibay et al. (2022)	Kautzky et al. (2020)	Cao et al. (2023)	Mikolas et al. (2022)	Cervantes-Henríquez et al. (2021)	Yasumura et al. (2017)
ML Model(s) Used	RF, NB, DT, XGBoost, KNN, MLP, SVM, 1D CNN	LR, RF, SVM, GNB, MLP	CART, RF, DNN, LR	RF	LR, RF, GB, XGBoost, NB, L1L2, DNN, Ensemble	RF	Review of various ML models	Linear SVM	LR, CART, RF, SVM, GBM, SVM-Poly, LDA	SVM
Performance Metrics Reported	Acc range: 69.8-85.5%; AUC range: 0.78-0.94	AUC: 0.86 (pop samples); Accuracies robust after bias reduction	AUC: 0.68 (CART) to 0.72 (DNN)	Acc: 81-93%; Sens: 0.89-0.97; Spec: 0.86-0.95	AUC: 0.75 (DNN); Bal Acc: ~0.68	Acc: ~0.82; Sens: ~0.75; Spec: ~0.86	Acc range: ~60% to ~90% in surveyed studies	Acc: 66.1%; Sens: 66.9%; Spec: 65.4%; AUC: 0.66	Acc range: ~70-82%; Sens: 0.756; Spec: 0.771	Acc: 86.25%; Sens: 88.71%; Spec: 83.78%; AUC: 0.898

Note: This table presents the machine learning models utilized and the primary performance metric values reported across the studies. Acc = Accuracy; AUC = Area Under the ROC Curve; Bal Acc = Balanced Accuracy; CART = Classification and Regression Tree; DT = Decision Tree; DNN = Deep Neural Network; FDR = False Discovery Rate; FPR = False Positive Rate; GB = Gradient Boosting; GBM = Gradient Boosting Machine; GNB = Gaussian Naive Bayes; KNN = k-nearest neighbor; LDA = Linear Discriminant Analysis; LR = Logistic Regression; MLP = multilayer perceptron; NB = Naïve Bayes; NPV = Negative Predictive Value; PPV = Positive Predictive Value; RF = Random Forest; Sens = Sensitivity; Spec = Specificity; SVM = Support Vector Machine; XGB = XGBoost; 1D CNN = 1-dimensional convolution network.

Methodological Limitations and Feature Categories

Table 4 outlines common methodological limitations and the types of features incorporated. Limitations include small or homogeneous samples, reliance on single-source data, inconsistent cross-validation, and limited transparency in model interpretability. Feature categories span demographic, clinical/symptom, biological/neuroimaging, and educational/administrative data. This highlights the multidimensional nature of ADHD prediction and the ongoing need to optimize ML inputs for both clinical relevance and ethical implementation.

Table 4: Common Methodological Limitations and Feature Categories for ADHD Prediction Studies [8-10,19-21,33]

Category	Description and Relevant Studies
Limitations	
Sample Size	Marginal or small samples can limit generalizability; noted in Kautzky et al. (2020), Mikolas et al. (2022).
Generalizability	Lack of external validation across different populations (e.g., primarily White samples, community-recruited); a key limitation for Goh et al. (2023), Morrow et al. (2023), Kautzky et al. (2020), Cervantes-Henríquez et al. (2021).
Data Source Bias	Reliance on parent-reported data or clinically referred cases may introduce bias (e.g., self-report bias, cases not seeking treatment); noted in Maniruzzaman et al. (2022), Garcia-Argibay et al. (2022).
Method Variance	Using the same source for predictor and outcome variables can inflate correlations (e.g., parent-reported data for both); noted in Morrow et al. (2020).
Feature Categories	
Demographic Data	Common predictors include age, sex, race, parental education, and family structure.
Clinical / Symptom Data	Comorbid conditions, ADHD symptom counts/severity, speech/learning disabilities are widely used features.

Biological / Neuroimaging Data	Genetic SNPs (e.g., DRD4, SNAP25, ADGRL3), brain activity (NIRS, fMRI), and serotonergic data (PET) are utilized in genotype-based models.
Educational / Administrative Data	School performance indicators, attendance, and healthcare records are used in large population studies.

Note: This table highlights recurring methodological challenges and commonly used feature types in the selected ADHD prediction research. The patterns indicate that small or homogeneous samples, reliance on single-source data, and variability in feature types are pervasive, contributing to inconsistent and often weak predictive performance across studies. ML approaches for ADHD identification and classification are highly variable and remain exploratory.

Synthesis Across Studies

Taken together, the figure and tables illustrate both the promise and the challenges of applying ML for assessment and prediction. Key findings can be organized into strengths and benefits, weaknesses and concerns, and emerging opportunities, reflecting the current state of the field and areas for future development.

Strengths and Benefits. ML applications for ADHD assessment show potential to support aspects of clinical practice, particularly in screening and early identification. Behavioral and multi-informant data consistently emerge as useful predictors, suggesting that ML can complement evidence-based assessment by integrating multiple data sources. Large-scale educational and healthcare records may facilitate rapid data processing, offering the possibility of identifying at-risk individuals more efficiently than manual review alone. Some studies demonstrate innovative approaches to combining demographic, clinical, and biological features, which could inform hypothesis-generation or secondary decision support in complex cases. These strengths are resultant when ML is used as an adjunctive tool.

Weaknesses and Concerns. Despite these potential benefits, significant limitations constrain the clinical utility of ML in ADHD assessment. Most models lack transparency, limiting interpretability, and practitioner trust. Many studies rely on convenience or clinical samples, reducing generalizability to broader, more diverse populations. Sample sizes and methodological rigor vary, and single-source or single-modality data often produce inconsistent predictive performance. Furthermore, some ML models are not evaluated against reference standards such as DSM-5-TR criteria and evidence-based assessment protocols, which rely on iterative clinical judgment, multi-informant reporting, and structured hypothesis testing. Because ML cannot yet replicate these processes, misclassification and bias remain concerns. Practical implementation is also constrained by regulatory gaps, data governance challenges, and the need for clinician training in specific ML models or general AI literacy.

Emerging Opportunities. The reviewed studies suggest cautious avenues for future research. Multi-modal integration of behavioral, clinical, and biological data may improve predictive consistency, but such integration must align with clinical standards and ethical principles. Genetic and neurobiological features could eventually support more individualized risk stratification, yet these approaches are experimental and must be evaluated against established diagnostic frameworks. Implementation research highlights that adoption depends not only on predictive performance but also on workflow fit, transparency, and trust. Future efforts should prioritize models that are interpretable, replicable, and compatible with evidence-based clinical assessment, while ensuring compliance with regulatory requirements and addressing systemic biases.

Discussion

This narrative review synthesizes evidence from 10 recent ML studies (2017–2023) on ADHD identification and classification, highlighting methodologies (e.g., random forests [RF], support vector machines [SVM], deep neural networks [DNN]), data modalities (e.g., behavioral ratings, EHR, neuroimaging, genetics), and performance (accuracy: 66–93%; AUC: 0.66–0.94). By mapping these approaches onto an evidence-based ADHD assessment workflow (Table 1), we identify promising integration points while underscoring persistent gaps. Phenotype-based models (e.g., behavioral surveys in Maniruzzaman et al., 2022; Goh et al., 2023) excel in screening and hypothesis-generation, often achieving higher accuracy (up to 93%) in large samples (N=238,696 in Garcia-Argibay et al., 2023) but struggle with real-world generalizability due to homogeneous datasets. Genotype-based models (e.g., neuroimaging in Yasumura et al., 2017; genetics in Cervantes-Henríquez et al., 2021) offer insights into biological mechanisms but yield lower performance (AUC ~0.70) and raise ethical concerns about accessibility in diverse populations [6,8,10,19,20].

Key findings reveal ML's potential to augment traditional diagnostics by expediting multi-informant data synthesis and risk stratification, aligning with precision psychiatry trends [1]. For instance, multi-modal approaches (e.g., combining EHR and behavioral data in Mikolas et al., 2022) improve predictive consistency, supporting early detection in screening phases where tools like the Vanderbilt or ASRS could be enhanced with algorithmic triage [9]. However, limitations persist: small samples (N=38–500 in 60% of studies), single-modality reliance (70% of models), and inconsistent cross-validation reduce external validity, often leading to overestimation of performance in non-clinical settings [9]. These gaps contribute to misdiagnosis risks, particularly in comorbid cases or partial remission, where ML fails to capture contextual factors mandated by DSM-5-TR [13].

Practical implications for clinical practice include adjunctive ML use to streamline workflows (e.g., automating initial screening to flag high-risk cases), while preserving clinician judgment in differential diagnosis and integrative formulation. Ethical considerations demand transparency (e.g., interpretable models to mitigate "black box" issues; Wadden, 2022; Zednik, 2021) and bias mitigation, as homogeneous training data may perpetuate inequities in underrepresented groups (e.g., racial/socioeconomic biases in Ter-Minassian et al., 2022) [2,18,24].

Systemic barriers, such as HIPAA gaps for non-clinical AI tools and clinician AI literacy needs, must be addressed through training programs and regulatory updates to ensure equitable adoption [17,25].

Future research should prioritize interpretable, multi-modal models validated in diverse, real-world cohorts (e.g., longitudinal studies tracking developmental trajectories). Implementation trials could evaluate ML's fit within evidence-based frameworks, measuring outcomes like diagnostic timeliness and error rates. Using the sunflower metaphor, ML "seeds" must be nurtured through clinician-technologist collaboration to yield robust tools that complement, rather than supplant, human expertise.

In conclusion, while ML holds promise for enhancing ADHD assessment efficiency and accuracy, its current limitations necessitate cautious integration. By bridging clinical workflows with technological advancements, practitioners can harness these tools to improve patient outcomes while upholding ethical standards and diagnostic fidelity.

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Compliance & Ethics

Author Contributions
E.N.S.L. conceived the study, designed the research, and curated the data. B.C.B. conducted the data analysis with input from E.N.S.L. E.N.S.L and B.C.B. prepared the visualizations. B.C.B. wrote the original manuscript draft, while E.N.S.L. provided critical revisions. E.N.S.L. supervised the project and secured funding. All authors reviewed and approved the final manuscript.

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Data Availability
This narrative review summarizes information from previously published studies. No raw data were generated. Extracted summary tables used in the preparation of this review are available from the corresponding author upon reasonable request.

Conflicts of Interest
E.N.S.L. serves as the founding clinical director of Easy Does It Counseling, p.c. B.C.B. conducted this work as a research intern at the same organization, and the project contributed to her internship requirements.

E.N.S.L. has participated in commercial software development since 1999, with some projects covered by nondisclosure agreements; however, no proprietary software or data were accessed or used in this study. E.N.S.L. is the author of "Expertise in AI and clinical publishing exposes peer review gaps: A perspective" in Artificial Intelligence in Health, written in his capacity as an AI/ML and clinical expert who also reviewed similar studies for methodological quality. These prior publications and peer-review activities did not influence the design or conclusions of the present study.

The authors declare no additional financial or non-financial conflicts of interest.

AI and Computational Tool Use
This research employed conventional computational tools and reference management software, to organize, sort, and annotate research materials. These tools performed preprogrammed administrative functions such as citation metadata extraction, keyword searching, and data sorting, without generating, interpreting, or synthesizing content.

No generative AI systems were used for analysis, synthesis, drafting, or interpretation. All conceptual reasoning, analytical judgments, narrative synthesis, and framework development were conducted independently by the authors.

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