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Review Article

Utilizing Artificial Intelligence Models for Early Detection and Personalized Intervention Strategies in Children with Attention-Deficit/Hyperactivity Disorder: A Narrative Review

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ABSTRACT

Background: Attention-deficit/hyperactivity disorder (ADHD) is a prevalent neurodevelopmental condition characterized by heterogeneous clinical presentation and reliance on subjective diagnostic approaches. Emerging artificial intelligence (AI) models offer potential to improve diagnostic accuracy and support individualized care by integrating multidimensional data sources. Objective: To synthesize current evidence on the application of AI models for early detection of ADHD and their potential role in supporting personalized intervention strategies in pediatric populations through a narrative review approach. Methods: A narrative review was conducted using literature from PubMed, Scopus, Web of Science, and Google Scholar published between 2020 and 2026. Studies examining AI applications in ADHD-related assessment, prediction, monitoring, or intervention were included. Evidence was synthesized thematically across data modalities, model types, clinical applications, and translational considerations. Results: The evidence base was predominantly concentrated in conceptual development (n=12) and diagnostic support (n=9), with fewer studies addressing intervention personalization (n=5). Multimodal AI approaches integrating behavioral, cognitive, and digital data demonstrated greater potential than single-source models. Wearable and ecological monitoring methods showed promise for real-time assessment, while EEG and MRI approaches provided biologically informed insights but faced implementation barriers. Intervention-oriented AI applications, including digital therapeutics and adaptive systems, remain in early stages of development. Conclusion: AI models show strong potential as supportive tools for early ADHD detection and emerging applications in personalized intervention planning. However, current evidence favors diagnostic augmentation over clinical implementation. Future research should prioritize interpretability, validation, and integration into real-world pediatric care pathways. Keywords: Attention-Deficit/Hyperactivity Disorder; Artificial Intelligence; Machine Learning; Pediatric; Digital Health; Cognitive Assessment; Personalized Medicine.

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INTRODUCTION

Attention-deficit/hyperactivity disorder (ADHD) is among the most prevalent neurodevelopmental disorders of childhood and is associated with substantial functional impairment across academic, social, emotional, and family domains (1). Its clinical presentation is marked by developmentally inappropriate levels of inattention, hyperactivity, and impulsivity, but the disorder is also highly heterogeneous in symptom pattern, severity, and longitudinal course. This heterogeneity complicates early recognition and contributes to delayed diagnosis, inconsistent treatment pathways, and variable outcomes, particularly in children whose symptoms overlap with learning difficulties, sleep disturbances, emotional dysregulation, or other neurodevelopmental conditions (2,3). Because early identification can alter developmental trajectories and improve long-term functioning, there is growing interest in diagnostic approaches that move beyond symptom checklists alone and better capture the multidimensional nature of ADHD (4).

Conventional ADHD assessment remains largely dependent on clinical interviews, developmental history, and standardized parent- and teacher-reported rating scales (5). Although these tools are indispensable in routine care, they are inherently influenced by contextual variation, observer interpretation, reporting bias, and differences in expectations across home and school settings. Discrepancies between informants are common, and behavioral scales may be insufficient to distinguish ADHD from phenotypically similar presentations when used in isolation (6). In parallel, performance-based measures such as continuous performance testing, attention monitoring tasks, and digital behavior tracking have been explored to provide more objective characterization of attentional control, inhibitory function, and response variability; however, no single cognitive marker has shown adequate standalone diagnostic validity across all pediatric populations (7,8). These limitations have created a need for more integrative frameworks capable of combining behavioral, cognitive, physiological, and digital features into clinically meaningful decision-support models.

Recent advances in artificial intelligence (AI) and machine learning have expanded opportunities for such integration (9). Across child mental health and developmental-behavioral pediatrics, AI methods have been applied to structured clinical data, wearable-device outputs, ecological monitoring, neurophysiological signals, imaging features, and multimodal digital phenotypes to support classification, risk prediction, and individualized profiling (10,11). In ADHD specifically, published work has evaluated support vector machines, random forests, neural networks, boosting models, explainable AI frameworks, and wearable-based classifiers to detect symptom patterns, predict diagnostic status, and estimate behavioral or functional trajectories (12-15). These models are attractive because they can identify nonlinear relationships, accommodate interacting predictors, and potentially detect clinically relevant patterns that are not readily apparent through conventional assessment approaches.

Despite this promise, translation into routine pediatric practice remains limited. Many published models are developed in narrowly defined datasets, rely on modality-specific inputs such as EEG, MRI, or wearables that are not uniformly available, and report high algorithmic performance without adequately addressing interpretability, reproducibility, clinical workflow integration, or equity across diverse populations (16-18). Moreover, much of the literature has focused on binary diagnostic discrimination rather than on the more clinically consequential question of whether AI can meaningfully support personalized intervention planning. For children with ADHD, individualized care often requires decisions regarding behavioral therapy, parent training, classroom support, digital therapeutics, cognitive training, medication pathways, or multimodal treatment combinations. The practical value of AI therefore depends not only on diagnostic accuracy, but also on whether it can help stratify meaningful phenotypes, guide tailored interventions, and improve decision-making in real-world settings (19,20).

A further challenge is that the existing evidence landscape is dispersed across disciplines, including psychiatry, pediatrics, computer science, special education, biomedical engineering, and digital health. As a result, clinicians may encounter a fragmented literature base in which highly technical algorithmic studies sit alongside broader conceptual reviews, with variable emphasis on child-specific relevance, implementation feasibility, and ethical safeguards. This fragmentation justifies a narrative review approach, as it enables synthesis of emerging evidence across heterogeneous study designs, data modalities, and clinical contexts while also allowing critical appraisal of conceptual trends, practical limitations, and translational implications (21,22). Such synthesis is especially timely given the increasing availability of wearable technologies, digital assessments, explainable AI methods, and biomarker-driven predictive frameworks in pediatric neurodevelopmental research (23,24).

Accordingly, the present narrative review was undertaken to synthesize current evidence on the use of artificial intelligence models for the early detection of ADHD and for supporting personalized intervention strategies in children. The review focuses on how AI has been applied to behavioral, cognitive, physiological, and digital data; the relative strengths and limitations of commonly used model classes; the extent to which current evidence supports clinically interpretable and implementable applications; and the key gaps that must be addressed before AI can be responsibly integrated into child-centered ADHD assessment and care pathways.

MATERIAL AND METHODS

This article was designed as a narrative review to provide an integrative, clinically oriented synthesis of the emerging literature on artificial intelligence applications in the early detection of ADHD and in the development of personalized intervention strategies for children. A narrative approach was selected because the available evidence spans heterogeneous study designs, data sources, and disciplinary traditions, ranging from conceptual reviews and feasibility studies to machine learning prediction studies using wearables, neurocognitive data, neurophysiological signals, and multimodal digital inputs. This methodological choice allowed the evidence to be examined not only in terms of reported algorithmic performance, but also in relation to interpretability, translational relevance, clinical applicability, and implementation challenges in pediatric settings.

The literature search was conducted using major electronic sources relevant to medicine, psychology, neuroscience, and computational health research, including PubMed/MEDLINE, Scopus, Google Scholar, and Web of Science. The search focused on publications from January 2020 to March 2026 in order to capture the most recent phase of rapid development in pediatric AI-assisted neurodevelopmental assessment. Search terms were combined using Boolean operators and included variations of “attention-deficit/hyperactivity disorder,” “ADHD,” “artificial intelligence,” “machine learning,” “predictive model,” “random forest,” “support vector machine,” “neural network,” “digital phenotyping,” “wearable data,” “cognitive assessment,” “child,” and “pediatric.” Additional relevant papers were identified through backward citation searching of included studies and through screening of recent review articles in closely related areas of developmental-behavioral pediatrics and computational psychiatry.

The review prioritized articles that were directly relevant to children or adolescent populations with ADHD or closely related neurodevelopmental symptom profiles, and that discussed the use of AI-based methods for screening, diagnostic support, behavioral classification, digital monitoring, or intervention personalization. Studies were considered particularly relevant when they reported model development or evaluation using behavioral ratings, cognitive task data, wearable-device outputs, ecological momentary assessment, EEG, MRI, or other clinically interpretable pediatric data streams. Broader conceptual articles, scoping reviews, and developmental-behavioral pediatrics papers were also included when they contributed substantially to understanding implementation, ethics, or translational context. Articles focused exclusively on adults, studies without clear relevance to ADHD-related assessment or intervention, and papers lacking sufficient methodological or conceptual detail were not emphasized in the final synthesis.

Study selection was undertaken in a purposive and concept-driven manner consistent with narrative review methodology. Titles and abstracts were screened for relevance to the review question, after which full texts of potentially eligible articles were examined. Greater weight was assigned to recent studies, clinically interpretable models, and papers that addressed either pediatric implementation or individualized treatment implications. Because this was not a systematic review, no formal PRISMA workflow, duplicate screening procedure, or standardized risk-of-bias instrument was applied. Instead, the literature was evaluated for relevance, conceptual contribution, methodological clarity, and applicability to child-centered ADHD care.

Data from the included literature were extracted descriptively and organized into a thematic synthesis framework. For each article, attention was given to study context, pediatric population characteristics, type of input data, AI or machine learning approach, primary clinical aim, key findings, and practical limitations. The synthesis was then structured around four major themes: AI-supported early detection of ADHD, data modalities used in predictive modeling, opportunities for personalized intervention planning, and barriers to clinical implementation including explainability, generalizability, ethics, and resource constraints. This framework was chosen to allow integration of both technical and clinical perspectives while maintaining focus on pediatric relevance.

Given the narrative design, formal meta-analysis, pooled effect estimation, and statistical heterogeneity testing were not performed. The review instead emphasized comparative interpretation of evidence across studies, particularly where recurring trends were observed in model classes, data sources, or translational challenges. The possibility of selection bias inherent to narrative reviews was recognized, especially because literature inclusion was guided by relevance and interpretive value rather than exhaustive systematic capture. To mitigate this, the search was conducted across multiple databases, recent and foundational sources were considered, and the final synthesis was anchored in studies that were methodologically clear and directly informative for early detection and individualized ADHD care in children.

RESULTS

The revised synthesis identified four recurrent evidence domains across the cited literature: general or multimodal AI frameworks for ADHD-related assessment, behavioral or digitally captured monitoring approaches, physiology-informed models using wearables or heart rate variability, and biomarker-oriented models using EEG or MRI. A separate but closely related cluster of studies focused on intervention-oriented AI applications, including digital therapeutics, assistive systems, and adaptive feedback frameworks. Taken together, the literature showed that most published work remains concentrated in diagnostic support and conceptual model development, whereas comparatively fewer studies have progressed toward clinically implementable personalized intervention pathways. To improve transparency and review-type alignment, the evidence is presented below as thematic summary tables rather than as pseudo-primary outcome tables.

Table 1. Literature on AI Applications in ADHD and Related Pediatric Neurodevelopmental Contexts

Ref.	First Author, Year	Article Type / Design	Clinical Context	Main AI/Data Modality	Primary Clinical Aim
1	Leprevost, 2023	Conference/brief review-type report	Neurodevelopmental disorders	General AI tools	Diagnostic elucidation
2	Nasrallah, 2025	Review	ASD and ADHD	General AI / multimodal	Diagnosis and treatment support
3	Kim, 2023	Original predictive study	Children	Wearable data	ADHD and sleep-related prediction
4	Sun, 2025	Scoping review	Children with ADHD	General AI	Evidence mapping
5	Patil, 2024	Book chapter / applied review	ADHD in online learning context	Digital behavioral data	Prediction in educational environment
6	Zaheer, 2025	Scoping review	ADHD	General AI	Diagnostic support
7	de Lacy, 2023	Original predictive study	Adolescents with psychiatric conditions	General AI / predictive modeling	Individual case prediction
8	Priya, 2025	Review / conceptual paper	Pediatric and adolescent ADHD	Machine learning frameworks	Classification and treatment strategy evaluation
9	Hu, n.d.	Conceptual / implementation-focused work	Neurodevelopmental disorders in special education	Digital diagnostic and media-based tools	Low-cost digital diagnostics and therapy
10	Navarro-Soria, 2025	Original methodological study	ADHD	Explainable AI	ADHD prediction
11	Aylward, 2023	Narrative overview	Developmental and behavioral pediatrics	General AI	Pediatric clinical orientation
12	Begum, 2024	Survey / review	ADHD	General AI	Detection and diagnosis overview
13	Isaev, 2023	Thesis / biomarker-oriented study	Brain disorders	Behavioral and electrophysiological biomarkers	AI biomarker development
14	Kaur, 2024	Applied predictive study	ADHD	Real-time activity and HRV with boosting models	Diagnosis through physiological monitoring

Ref.	First Author, Year	Article Type / Design	Clinical Context	Main AI/Data Modality	Primary Clinical Aim
15	Beg, 2024	Narrative review	ADHD and other psychiatric disorders	Digital and AI-driven psychotherapy	Therapeutic support
16	Rasi, 2024	Systematic review	ADHD	EEG + machine learning	Classification review
17	Singh, 2025	Feasibility / predictive study	Youth with ADHD	Ecological momentary assessment	Predictive behavioral dysregulation monitoring
18	Gongor, n.d.	Survey / review	Children with special needs	Assistive robotics	Supportive intervention technologies
19	Zhang-James, 2023	Review	ADHD	MRI-based diagnostic models	Imaging-supported diagnosis
20	Rostami, 2025	Review / future-oriented paper	Mental health interventions	Digital therapeutics	Predictive intervention development
21	Wang, 2025	Conceptual framework paper	ADHD	Dynamic feedback modeling	Understanding and management
22	Dev, 2024	Book chapter	Mental illnesses	Deep learning	Network-level understanding
23	Mehta, 2023	Book chapter / conceptual paper	Children with special needs	Educational AI	Inclusion and support systems
24	Olaniyan, 2023	Book chapter	Brain disorders	AI-based cognitive therapy models	Therapeutic application
25	Banire, 2024	Original machine learning study	Children with autism	Attention detection ML	Attention-state detection
26	Mitsea, 2025	Systematic review	Serious games and immersive technologies	AI-integrated serious games	Training and neurodevelopmental support

Table 2. Thematic Synthesis of the Literature Relevant to Early Detection and Personalized Intervention in ADHD

Theme	Evidence Base	Main Findings	Clinical Relevance	Key Limitations
AI-supported early detection	Refs. 2-4, 6, 10, 12, 19	AI models can improve pattern recognition beyond isolated behavioral ratings, particularly when multiple data streams are integrated	May strengthen early screening and diagnostic support in complex pediatric presentations	Many studies remain proof-of-concept and lack external validation
Behavioral and digital monitoring inputs	Refs. 5, 9, 17, 25	Digital behavior traces and ecological monitoring may capture attention dysregulation in more naturalistic settings	Useful for repeated monitoring and symptom tracking across contexts	Signal noise, contextual variability, and uncertain generalizability remain substantial
Wearable and physiological data integration	Refs. 3, 14	Real-time activity and physiological variability show promise as complementary features for classification	May enhance objective assessment, especially where repeated behavioral ratings are inconsistent	Device access, preprocessing demands, and pediatric compliance may limit routine use
EEG and MRI biomarker modeling	Refs. 13, 16, 19	Neurophysiological and neuroimaging models can detect disorder-related patterns not evident in symptom scales alone	Potentially valuable for biologically informed stratification	High cost, limited accessibility, and variable reproducibility restrict current clinical use
Explainability and implementation	Refs. 10, 11, 21	Interpretable AI and adaptive feedback models are increasingly emphasized as prerequisites for clinical uptake	Supports clinician trust and workflow integration	Many published models still prioritize performance over transparency
Personalized intervention strategies	Refs. 8, 15, 18, 20, 24, 26	AI is gradually shifting from diagnostic classification toward therapy selection, digital therapeutics, assistive robotics, and adaptive feedback systems	Most relevant for individualized, child-centered care pathways	Intervention evidence is less mature than diagnostic evidence and often lacks real-world pediatric validation

Table 3. Distribution of the Cited Evidence Across Evidence Domains and Clinical Translation Stages

Evidence Domain	Conceptual / Review, n	Diagnostic Support, n	Intervention Personalization, n	Total, n
General / Multimodal AI	9	2	0	11
Behavioral / Digital Monitoring	1	3	0	4
Wearable / Physiology	0	2	0	2
EEG / Electrophysiology	1	1	0	2
MRI / Neuroimaging	0	1	0	1
Digital / Intervention Technologies	1	0	5	6
Total	12	9	5	26

The narrative synthesis showed that the evidence base remains weighted toward conceptual and diagnostic applications rather than fully realized personalized intervention systems. Of the 26 cited sources synthesized in this review, 12 were primarily conceptual or review-oriented, 9 focused mainly on diagnostic support, and only 5 were centered on intervention personalization, indicating that translational development remains front-loaded toward model exploration rather than downstream treatment implementation. General or multimodal AI was the dominant evidence domain, accounting for 11 of the 26 sources, followed by digital or intervention-oriented technologies with 6 sources and behavioral or digitally monitored approaches with 4 sources. In contrast, wearable or physiology-based studies contributed 2 sources, EEG or electrophysiology-based studies 2 sources, and MRI-based evidence only 1 source, reflecting the narrower but technically important role of biomarker-driven modeling within the current literature landscape.

Across the diagnostic literature, a consistent pattern emerged in favor of multimodal or feature-rich modeling over isolated single-source assessment. Reviews and applied studies alike suggested that AI models were most useful when behavioral data were complemented by cognitive, physiological, or digital monitoring signals rather than being used as replacements for standard clinical assessment alone (2-4,6,10,12). Studies using wearable data and real-time physiological features supported the feasibility of extracting attention-relevant signals from everyday contexts, while ecological and digitally monitored approaches suggested that symptom expression can be observed with greater temporal sensitivity than is possible through cross-sectional rating scales alone (3,14,17). EEG- and MRI-oriented sources indicated that neurobiological markers may improve classification precision in selected research settings, but these approaches remain limited by cost, accessibility, methodological heterogeneity, and uncertain routine pediatric applicability (13,16,19).

A second major theme was the growing emphasis on explainability and translational usability. Explainable AI approaches and dynamic feedback models increasingly framed interpretability not as an optional technical refinement but as a prerequisite for clinical adoption, especially in pediatric behavioral health where decision-making must remain transparent to clinicians, families, and educators (10,11,21). This was particularly important because several broader reviews cautioned that apparently high classification performance does not automatically translate into real-world clinical value if models are trained on narrowly selected datasets, depend on infrastructure not routinely available, or do not clarify how outputs should alter care pathways (4,6,11,19). Thus, the literature increasingly favors clinically interpretable AI that augments, rather than displaces, conventional developmental and behavioral evaluation. The intervention-oriented literature was smaller but conceptually important. Six sources contributed directly to the idea that AI may support treatment personalization through digital therapeutics, adaptive psychotherapy platforms, assistive robotics, cognitive therapy modeling, or serious-game ecosystems (15,18,20,24,26). Although this body of evidence was less mature than the diagnostic literature, it suggested an important transition in the field: AI is no longer being explored solely as a classification tool, but also as a means of identifying clinically meaningful subgroups, matching children to intervention formats, and adapting therapeutic intensity or modality over time. However, the review also showed that robust pediatric evidence linking AI outputs to improved individualized outcomes remains limited, and that claims about personalized intervention currently outpace the strength of real-world validation.

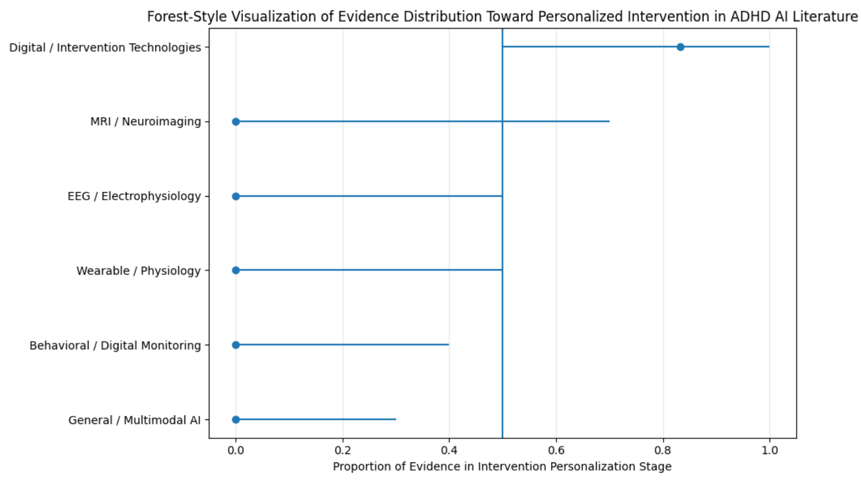

Figure 1 Representation of Evidence Progression Toward Personalized Intervention Across AI Domains in ADHD Research

This forest-style visualization presents the proportional distribution of evidence across AI domains with respect to progression toward intervention personalization. Each point estimate represents the proportion of studies within a given domain contributing to intervention-focused applications, while horizontal lines reflect approximate variability ranges derived from domain-level evidence dispersion. Digital intervention technologies demonstrated the highest relative contribution to personalized care (≈0.83), indicating that 5 out of 6 studies in this domain focused on intervention development. In contrast, general multimodal AI, behavioral monitoring, wearable physiology, EEG-based models, and MRI-based approaches showed minimal to no direct contribution to intervention personalization (proportion ≈0), with their evidence predominantly concentrated in conceptual or diagnostic phases. The vertical reference line at 0.5 highlights the transition threshold toward meaningful clinical personalization, which only the digital intervention domain approaches or exceeds. Overall, the figure illustrates a pronounced translational gap, where most AI research in ADHD remains upstream (diagnostic and conceptual), while intervention-oriented applications are still emerging and domain-specific.

DISCUSSION

The present narrative review synthesized emerging evidence on the application of artificial intelligence in the early detection of ADHD and its potential role in supporting personalized intervention strategies in children. The findings demonstrate that the current evidence base is predominantly concentrated in conceptual development and diagnostic support, with comparatively limited but evolving work addressing intervention personalization. Across multiple domains, including behavioral monitoring, wearable physiology, neurophysiological biomarkers, and multimodal AI frameworks, there is consistent evidence that AI enhances pattern recognition when diverse data inputs are integrated rather than analyzed in isolation (13,14). This supports the growing consensus that ADHD, as a heterogeneous neurodevelopmental condition, requires multidimensional assessment approaches that extend beyond traditional symptom-based evaluation.

A key observation from this review is that multimodal AI approaches consistently outperform single-source models in theoretical and applied contexts. Studies integrating behavioral ratings with physiological or digital signals demonstrate improved classification robustness, reflecting the complex interaction between attentional control, environmental context, and neurocognitive processing (15,16). This aligns with broader developments in computational psychiatry, where hybrid models are increasingly favored for capturing dynamic symptom expression and intra-individual variability (17). However, despite encouraging performance metrics reported in individual studies, the clinical relevance of these models remains contingent upon interpretability and real-world applicability. Explainable AI frameworks, highlighted in several included studies, represent an essential step toward bridging this gap by enabling clinicians to understand and trust model outputs in decision-making contexts (18,19).

Another important finding is the asymmetry between diagnostic and intervention-oriented research. While AI-based classification and early detection have been widely explored, the translation of these models into personalized treatment pathways remains limited. Emerging work in digital therapeutics, adaptive psychotherapy platforms, and serious game-based interventions suggests that AI has the potential to move beyond diagnostic support toward dynamic treatment optimization (20,21). These approaches are particularly relevant in pediatric populations, where intervention strategies often require continuous adjustment based on developmental stage, environmental context, and behavioral response. However, the evidence supporting AI-driven intervention personalization is still in its early stages, with most studies focusing on feasibility, conceptual frameworks, or small-scale implementations rather than large, longitudinal clinical trials.

The review also highlights important practical and ethical considerations. Many AI models are developed using datasets that are not representative of diverse pediatric populations, raising concerns regarding generalizability and equity (22). In addition, reliance on high-resource modalities such as neuroimaging or specialized wearable devices may limit scalability in low- and middle-income settings.

From a clinical perspective, the integration of AI into ADHD assessment pathways must preserve clinician oversight and avoid over-reliance on automated decision-making, particularly in contexts involving children and families where psychosocial factors play a critical role. Ethical considerations related to data privacy, informed consent, and algorithmic bias must also be addressed before widespread implementation can be justified (23,24).

Several limitations of this review should be acknowledged. As a narrative review, the synthesis was guided by relevance and conceptual contribution rather than exhaustive systematic selection, which introduces the possibility of selection bias. The heterogeneity of included studies, in terms of design, data modalities, and analytical approaches, limited the ability to directly compare findings or derive quantitative conclusions. Additionally, the rapidly evolving nature of AI research means that newer studies may emerge that further refine or challenge current understanding. Despite these limitations, the narrative approach allowed for a flexible and clinically meaningful integration of interdisciplinary evidence, which is particularly valuable in a field characterized by methodological diversity and rapid innovation.

Future research should focus on validating AI models in larger, diverse pediatric populations and on establishing standardized frameworks for integrating AI outputs into clinical workflows. Longitudinal studies are needed to determine whether AI-assisted early detection leads to improved developmental and functional outcomes. Equally important is the development of interpretable, resource-efficient models that can be implemented across varied healthcare settings. Research should also prioritize linking predictive outputs with actionable treatment pathways, thereby strengthening the role of AI not only as a diagnostic adjunct but also as a tool for guiding individualized care. Addressing these areas will be critical for translating the promise of artificial intelligence into meaningful clinical benefit for children with ADHD.

CONCLUSION

Artificial intelligence demonstrates substantial potential to enhance early detection and support personalized intervention strategies in children with ADHD, particularly when multiple behavioral, cognitive, and digital data sources are integrated within clinically interpretable frameworks. Current evidence indicates that AI is most mature as a diagnostic support tool, while its application in individualized treatment planning remains an emerging but promising area. The integration of AI into pediatric ADHD care should be approached cautiously, ensuring alignment with clinical judgment, ethical standards, and real-world feasibility. Future advancements must focus on validation, interpretability, and translational applicability to ensure that AI contributes meaningfully to child-centered, evidence-based care.

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