Information Fusion 124 (2025) 103441

Contents lists available at ScienceDirect

Information Fusion

journal homepage: www.elsevier.com/locate/inffus

A systematic review for artificial intelligence-driven assistive technologies to support children with neurodevelopmental disorders

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ARTICLE INFO

Keywords:
Artificial intelligence
Neurodevelopmental disorders
Assistive technology
Machine learning
Deep learning
Pediatric care

ABSTRACT

This systematic review examines AI-powered assistive technologies for children with neurodevelopmental disorders, with a focus on dyslexia (DYS), attention-deficit hyperactivity disorder (ADHD), and autism spectrum disorder (ASD). Our analysis of 84 studies from 2018 to 2024 provides the first thorough cross-disorder comparison of AI implementation patterns. According to our data, each condition has different success rates and technological preferences. AI applications are expanding quickly, especially in research on ASD (56 % of studies), followed by ADHD (36 %), and DYS (8 %). In almost half of the reviewed studies, computer-assisted technologies, which have demonstrated encouraging results in terms of treatment support and diagnostic accuracy, became the main mode of intervention. Despite high accuracy in controlled settings, the implementation of these technologies in clinical practice faces significant challenges. While human oversight remains essential in clinical applications, future advancements should prioritize privacy protection and the ability to assess tools longitudinally. Notably, multimodal approaches that integrate various data types have improved diagnostic accuracy; recent research has shown that they can detect ASD with up to 99.8 % accuracy and ADHD with up to 97.4 % accuracy. A promising trend is the combination of mobile applications and wearable technology, especially for real-time monitoring and intervention. This review highlights the potential and current limitations of AI-driven tools in supporting children with neurodevelopmental disorders. Future development should focus not on replacing clinical expertise, but on augmenting it. Research efforts should aim at creating tools that enhance professional judgment while preserving the essential human components of assessment and intervention.

1. Introduction

Childhood-onset neurodevelopmental disorders (NDDs), which coincide with critical periods of nervous system development [1], typically manifest before formal schooling and often persist into adulthood [2]. They affect approximately 10-20 % of young people globally [3], contributing to significant morbidity that also impacts family members and the broader society.

NDDs stem from complex interactions between genetic predisposition and environmental factors [4], including socioeconomic status. Children from disadvantaged backgrounds often face challenges in their education, which potentially limit their developmental trajectory. There is therefore a need for enhanced support strategies to diagnose NDDs and to aid students who are diagnosed with NDDs in their educational

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https://doi.org/10.1016/j.inffus.2025.103441
Received 11 February 2025; Received in revised form 21 May 2025; Accepted 17 June 2025
Available online 17 June 2025

endeavors within traditional educational settings [5].

This study aims to examine emerging technological assistive tools for diagnosing and supporting the education of concerned children, with a focus on three prevalent NDDs: attention deficit hyperactivity disorder (ADHD), autism spectrum disorders (ASD), and dyslexia (DYS). Affecting three to five percent of school-aged children [6], individuals with ADHD exhibit difficulty in sustained attention, hyperactive behavior, and impulsivity, particularly evident in social interactions and turn-taking scenarios [7,8]. Neuroimaging reveals structural differences in brain volumes between children with ADHD and their peers [9], providing some biological bases for the observed behavioral manifestations [10,11]. The integration of affected students into mainstream classrooms requires educators to adapt their pedagogical methods. Institutions must develop and implement effective support strategies while maintaining inclusive learning environments. This necessitates innovative approaches to accommodate diverse learning needs without compromising the educational quality for any student [12]. ASD, a complex neurodevelopmental condition, encompasses a broad spectrum of manifestations of varying severity, with initial signs typically emerging during the first three years of life [13,14]. ASD adversely impacts multiple domains of daily functioning, including social communication, speech and language development, and non-verbal communication [15]. Additionally, individuals often demonstrate specific behavioral patterns, including resistance to environmental changes and engagement in repetitive activities [16,17]. The heterogeneous nature of learning profiles among individuals with ASD necessitates personalized educational approaches. DYS affects reading ability and is frequently encountered in educational settings: in primary school populations, 5 % to 17 % of students are affected, albeit with varying degrees of severity [18]. Dyslexic students have difficulties in reading and word recognition, which impact academic progress across multiple subjects [19]. The dyslexic brain processes repeated information differently than normal, which may underpin the clinical manifestation [20,21]. Additionally, DYS can adversely impact broader issues beyond academic challenges, including poor emotional well-being and self-confidence, as well as increased rates of anxiety and depression [22].

Growing awareness of the personal and societal burdens of NDDs has instigated governmental policy changes: Australia now formally recognizes ADHD, ASD, and DYS as disabilities [23], ensuring students receive necessary educational support. ADHS/ASD/DYS students are prone to poor academic performance in traditional teaching environments. With teachers struggling to balance their individual needs within large class settings, teacher-student relationships in NDD cases are often fraught with increased conflict and reduced emotional connection. Further, the varying severity of these conditions and frequent mental health comorbidities demand personalized approaches to diagnosis as well as educational support. Toward this end, artificial intelligence (AI)-based tools, their rapid growth being driven by increased data availability, enhanced computing power, and rapid algorithm development [24–26]—have shown promise in improving diagnostic accuracy as well as learning outcomes among affected students with NDDs. In this study, we have performed a systematic review of AI-enabled assistive tools for ADHD/ASD/DYS diagnosis and educational support, as well as discussed their benefits and limitations.

2. Motivation for our study

Several researchers have recently reviewed different aspects of AI applications in NDDs. Saleh et al. [27] analyzed 166 studies on the use of robots for autism treatment. Barua et al. [5] reviewed AI-enabled tools to enhance the education of children with NDDs, and demonstrated that they could improve social skills and learning. Ribas et al. [28] reviewed technologies for the diagnosis and treatment of NDDs, concentrating more on the clinical outcomes rather than the AI methods. Thapliyal et al. [29] reviewed assistive technology in teaching strategies, focusing on learning disabilities without much discussion on the AI applications. Welch et al. [30] specifically reviewed the use of AI-enabled mobile and wearable devices in child psychiatry. These studies, while helpful, are limited to specific, selective areas of focus within the wide framework of assistive educational technology in NDDs (Fig. 1).

Taking a different approach, we aimed to perform an up-to-date systematic review of AI applications across the three prevalent NDDs of interest (ADHD, ASD, and DYS), focusing on both diagnosis and educational support, with a deep dive into the technical methods and their performance in practice. AI-based diagnostic tools play a vital role in educational support for children with NDDs by enabling personalized learning plans, timely interventions, and adaptive strategies. Specifically, AI technologies help diagnose NDDs by identifying patterns in data that may not be immediately visible to clinicians, which then informs tailored educational interventions. Once a diagnosis is made, AI allows for dynamic adaptation of teaching methods, adjusting learning plans based on real-time data, such as progress monitoring and behavioral feedback. Moreover, AI facilitates continuous progress monitoring, dynamically adjusting educational support based on real-time feedback, thus enabling more effective and personalized educational experiences for children with NDDs.

3. Literature search method

We searched Web of Science, IEEE Xplore, and Scopus for articles related to assistive educational AI tools for ASD, ADHD, and DYS published between 01 January 2018 and 31 October 2024 using Boolean search strings containing pre-specified keywords (Table 1). The initial search yielded 869 articles, which were reduced to 84 articles after removing duplicates and manual screening by investigators (A.S., A.P.K) according to pre-defined eligibility criteria: (1) disease focus, ASD, ADHD, or DYS; (2) focus, AI approaches; (3) application, educational or assistive tools; (4) target population, students or children; (5) language, English; and (6) publication period, 2018 to 2024.

In this review, we applied basic quality assessment criteria to evaluate the included studies. Studies were primarily assessed based on: (1) clarity of research objectives and methodology; (2) appropriate description of the study population and sample characteristics; (3) transparency in reporting algorithm performance metrics; and (4)

Fig. 1. Comparison of our paper with recent review articles. PISC: Problem Manifestation, Underpinned Implication, Instructional Strategy and Cognitive Strength Developed.

Table 1
Boolean search strings and results for AI-based methods in neurodevelopmental disorders across scientific repositories (2018-2024).

Scientific repository	Disease	Boolean string	No. of articles
Web of Science	ADHD	(((AB = attention deficit hyperactivity disorder) OR (AB = ADHD)) AND (AB = Machine Learning) AND ((AB= Students) OR (AB = Children)) AND ((AB = Assistive Tools) OR (AB = Learning)))	202
	ASD	(((AB = autism spectrum disorder) OR (AB = ASD)) AND (AB = Machine Learning) AND ((AB= Students) OR (AB = Children)) AND ((AB = Assistive Tools) OR (AB = Learning)))	511
	DYS	((AB = Dyslexia) AND (AB = Machine Learning) AND ((AB= Students) OR (AB = Children)) AND ((AB = Assistive Tools) OR (AB = Learning)))	70
IEEE Xplore	ADHD	((("Abstract": Attention Deficit Hyperactivity Disorder) OR ("Abstract": ADHD)) AND ("Abstract": Machine Learning) AND (("Abstract": Students) OR ("Abstract": Children)) AND (("Abstract": Assistive Tools) OR ("Abstract": Learning)))	14
	ASD	((("Abstract": Autism Spectrum Disorder) OR ("Abstract": ASD)) AND ("Abstract": Machine Learning) AND (("Abstract": Students) OR ("Abstract": Children)) AND (("Abstract": Assistive Tools) OR ("Abstract": Learning)))	21
	DYS	(("Abstract": Dyslexia) AND ("Abstract": Machine Learning) AND (("Abstract": Students) OR ("Abstract": Children)) AND (("Abstract": Assistive Tools) OR ("Abstract": Learning)))	1
Scopus	ADHD	(ADHD OR Attention Deficit Hyperactivity Disorder) AND (Machine Learning) AND (Students OR Children) AND (Assistive Tools OR Learning)	4
	ASD	(Autism Spectrum Disorder OR ASD) AND (Machine Learning) AND (Students OR Children) AND (Assistive Tools OR Learning)	39
	DYS	Dyslexia AND (Machine Learning) AND (Students OR Children) AND (Assistive Tools OR Learning)	7

discussion of study limitations. We noted significant variability in reporting quality across the reviewed literature, particularly regarding sample size adequacy and validation procedures.

For AI-specific assessment, we examined whether studies reported appropriate validation methods (e.g., cross-validation, independent test sets), comprehensive performance metrics beyond accuracy (e.g., sensitivity, specificity, AUC), and sufficient details about model architecture and training procedures. Fig. 2 illustrates the PRISMA flow diagram.

4. Results

Our systematic review identified 84 eligible papers for analysis. 47 papers (56 %) were focused on ASD; 30 (36 %) on ADHD, and 7 (8 %) on DYS. The number of publications has steadily increased from 2018 to 2024, driven initially by articles on ASD, and latterly by ADHD-related articles (Fig. 3). A detailed breakdown of the reviewed studies for each condition is provided in Appendix Table A1 (ADHD), Table A2 (ASD), and Table A3 (DYS).

AI assistive tools in the reviewed studies can be grouped into seven categories: computer assistance, mobile application, physical activity, robot assistance, therapy training, virtual reality, and wearable device (Fig. 4). Computer assistance encompasses tools that primarily leverage desktop or laptop systems to deliver support, including software for cognitive training, educational programs, and behavior tracking [31, 32]. Mobile apps make AI tools portable and accessible. They are often used for real-time monitoring, self-management, and gamified interventions tailored to individual needs [33]. Physical activity tools incorporate movement-based therapeutic games and exercises designed to improve motor skills, attention, and social interaction [34]. These interventions recognize the crucial role of physical engagement in

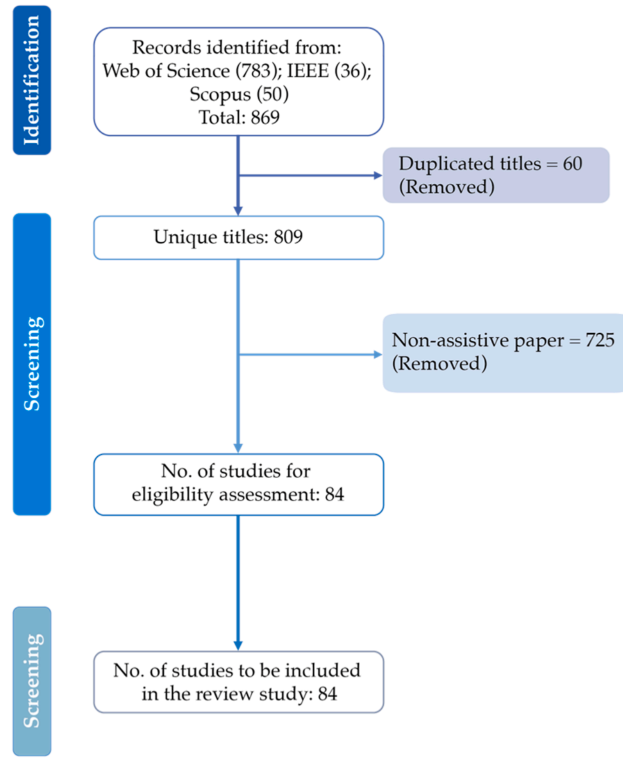

Fig. 2. PRISMA flow diagram of the literature review process.

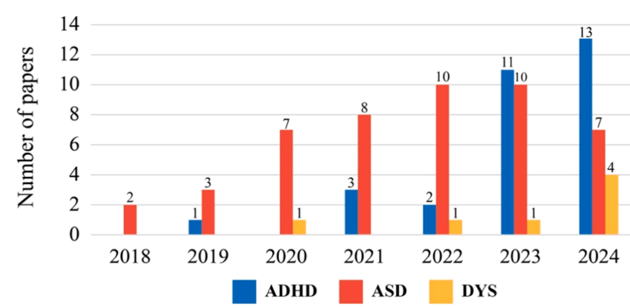

Fig. 3. Secular trend (2018-2024) of publications on AI assistive tools by disorder.

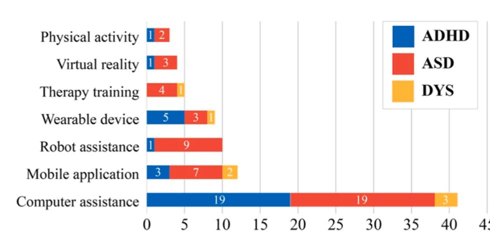

Fig. 4. Distribution of articles stratified by major categories of AI assistive tools by condition.

neurodevelopmental therapy. Social and assistive robots provide engaging, interactive therapy by mimicking human behavior or acting as companions [35–37]. This category represents AI tools designed for face-to-face interaction, which can be particularly effective in developing social and communication skills. VR tools immerse users in simulated environments for safe, controlled practice of real-world scenarios [38–40]. Wearable AI devices like smartwatches or headbands monitor physiological signals (e.g., heart rate, brain activity) to provide real-time feedback [41,42].

The distribution of studies across these categories (Fig. 4) reveals that computer assistance dominates, reaching 48.8 % of all tools, with particular focus on diagnosis and recognition of ASD (19 studies), ADHD (19 studies), and DYS (3 studies). 12 papers follow mobile application-based assistance tools . ASD predominates across all types of assistance provided, except for wearable devices, which appear most suitable for studying hyperactive behavior in ADHD.

5. Discussion

The current research landscape demonstrates promising advancements in the integration of AI assistive tools. Unlike previous reviews that focused on single disorders or specific technologies, our analysis provides the first comparison of AI implementation strategies across multiple disorders, revealing how different neurodevelopmental conditions benefit from distinct technological approaches. AI technology has the potential to significantly improve communication, interaction, and social engagement for individuals with NDDs, offering a glimpse into a future where AI plays a central role in supporting neurodiversity.

5.1. Artificial intelligence techniques

Of the 84 reviewed studies, 49 used machine learning (ML), 29 deep learning (DL), and 6 used ML and DL. While ML applications have dominated up to 2023, several studies involving DL overtook ML in the last year (Fig. 5). For both ML and DL categories, studies on ASD dominated (Fig. 6).

55 studies used ML techniques, including six that utilized both ML and DL. These 55 studies collectively examined 60 ML models based on 11 techniques, among which random forest (RF) and support vector machine (SVM) dominated, being used in 14 and 13 studies, respectively (Fig. 7a). RF was applied most to ADHD research (10 studies). For example, Lindhiem et al. [43], attained 89 % accuracy for ADHD detection using body sensor signals and behavioral data. SVM was applied most to ASD research (8 studies). For example, Zhang et al. [44] reported 96.67 % accuracy in distinguishing ASD from neurotypical children using video game performance data.

35 studies used DL techniques (including six that used both ML and DL). These studies collectively examined 35 DL models based on 3 distinguished major techniques. Convolutional neural networks (CNNs) dominate, followed by general deep neural networks (DNNs), and then long short-term memory (LSTM) or recurrent neural networks (RNNs),

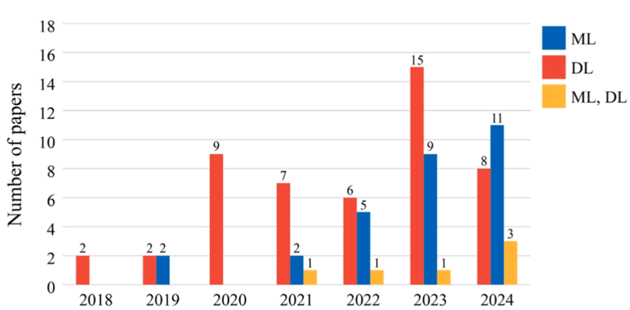

Fig. 5. Secular trend (2018-2024) of publications on AI assistive tools by use of machine learning (ML), deep learning (DL), or ML plus DL.

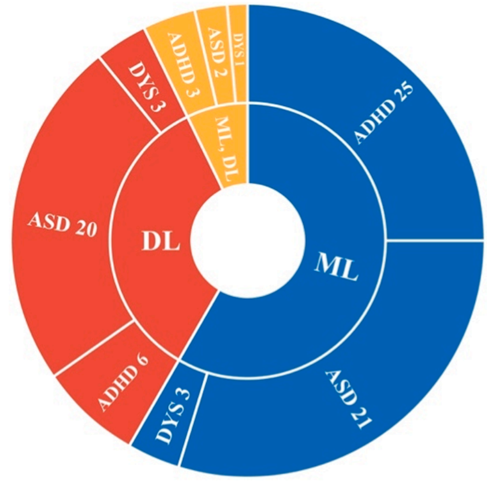

Fig. 6. Distribution of publications on AI assistive tools using machine learning (ML), deep learning (DL), or ML plus DL.

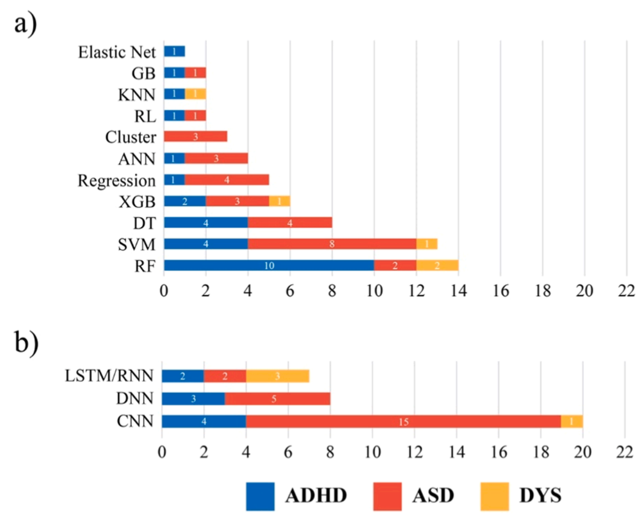

Fig. 7. Distribution of ML (a) and DL models (b) by disorder. The number of either ML or DL models exceeds the number of ML or DL studies, respectively, as individual studies may examine more than one model.

being used in 20, 8, and 7 studies, respectively (Fig. 7b). In the broader category of CNNs, an article implementing a Transformer architecture [45] and an article using a Graph Convolutional Network (GCN) [25] were included, as the former is a hybrid CNN-Transformer architecture, and the latter generalizes the convolutional operation to graph-structured data. CNN and DNN were applied most to ASD research, with 15 and 5 papers, respectively. For example, Castellanos et al. [46] attained 99.8 % accuracy in 2 epochs of training with their mobile application for linguistic therapy in ASD. Accuracy assessed how well the system could match the generated output (from Text-to-Speech and Image Classification) with human input (Speech-to-Text). In another study, Subah et al. [47] attained 88 % accuracy for DNN-based ASD detection using functional magnetic resonance imaging signal readouts. The remaining ASD studies (2 papers) utilized LSTM or RNN approaches. For example, Varma et al. [48] employed LSTM for analyzing gaze patterns for ASD diagnosis. ASD research accounts for over 60 % of all DL applications (22 papers), suggesting a particular suitability of DL approaches for autism-related challenges.

5.2. Monomodal vs. multimodal analysis in neurodevelopmental disorders

Given the complexity of NDDs, integrating diverse data from various sources may yield better model performance [49–51]. To examine this, we categorize the reviewed studies into monomodal (single-mode) approach (69 %) versus multimodal approach (31 %), where information from multiple data types is used (Fig. 8).

For ASD, research typically favors monomodal methods. For example, Nogay et al. [52] achieved 100 % accuracy using brain magnetic resonance imaging (MRI) data alone, and Derbali et al. [53] achieved 92.3 % accuracy using facial image analysis. Chen et al. [25] developed a GCN method for ASD diagnosis using multimodal data, achieving an accuracy of 88.09 %. In contrast, for ADHD, the numbers of monomodal and multimodal studies were more balanced:14 monomodal versus 16 multimodal studies. For instance, Chen et al. [54] achieved 97.4 % accuracy for ADHD using electroencephalography (EEG) data combined with diagnostic behavioral features, while Yoo et al. [7] integrated eye-tracking with demographic, behavioral, and clinical data, reporting 76.3 % accuracy for ADHD diagnosis. Among the seven DYS studies, only one employed a multimodal approach. Zhong et al. [45] studied both reading and writing using eye-tracking data and reported 81.14 % for DYS detection accuracy with a hybrid CNN-Transformer architecture, indicating that multimodal methods could be beneficial even in less explored domains, such as DYS.

Fig. 9 depicts the distribution of studies employing monomodal and multimodal approaches by data type and disorder. We categorized the data types as administrative and public data, behavioral and psychosocial data, clinical data, and digital and technology data (which include audio, video, and sensor data from wearable devices). Among the 58 monomodal studies, 30 used digital and technology data (Fig. 9a). ASD studies particularly favored these methods (23 studies), as did nearly all DYS research (4 studies), which relied on this approach. Clinical data–primarily from EEG, functional magnetic resonance imaging, and magnetic resonance imaging, which provided crucial neurological information–were used in 8 ADHD, 9 ASD, and 9 studies, 1 DYS study. Behavioral and psychological data–encompassing questionnaires, interviews, self-reports, and diagnostic indicators, which enable researchers to understand subjects' psychological and emotional states–proved especially valuable in ADHD research (20 studies). Administrative data played a minor role, appearing only in one ADHD monomodal study that drew data from national surveys [55]. Among the 26 multimodal studies, the most prevalent data combinations were behavioral-digital and behavioral-clinical, with 11 and 10 studies, respectively, suggesting that behavioral and psychosocial data serve as a crucial foundation for multimodal approaches. The behavioral-clinical combination was predominantly used in ADHD studies, likely due to the importance of combining clinical observations with behavioral assessments for accurate ADHD diagnosis [56,57]. The behavioral-digital combination was used in six ASD and four ADHD studies, reflecting the value of digital monitoring tools in assessing behavioral patterns [45,58,59]. Of note, ADHD studies used the most data combinations, perhaps reflecting the complex nature of ADHD assessment, which may benefit from diverse data sources.

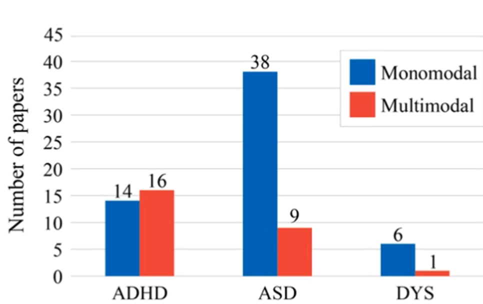

Fig. 8. Distribution of studies employing monomodal and multimodal approaches by disorder.

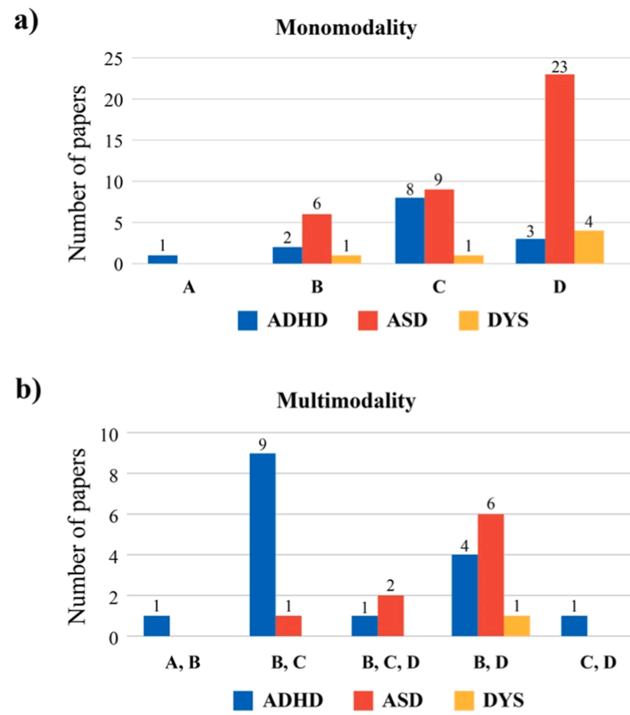

Fig. 9. Distribution of studies employing monomodal (a) and multimodal approaches (b) by data type and disorder. A: administrative and public data; B: behavioral and psychosocial data; C: clinical data; and D: digital and technology data.

5.3. Data fusion approaches in NDD assessment

Different data types capture complementary aspects of brain structure, function, and behavior, enabling more comprehensive assessment of conditions like ADHD. According to recent research, there are three primary categories of multimodal data in NDD studies: image data, physiological signals, and clinical data. Image data includes both structural and functional neuroimaging, which records brain anatomy and activity patterns. EEG, eye movements, and physical activity tracking are examples of physiological signals that offer additional information about behavior and brain activity. Diagnostic tests, demographic data, and other behavioral metrics that put the biological results in context are all examples of clinical and behavioral data. Clinical data includes diagnostic tests, demographic data, and other behavioral metrics that put the biological results in context.

The fusion of these heterogeneous data types requires advanced approaches to handle their different dimensionalities, scales, and temporal characteristics. Multiple kernel learning (MKL) has shown promise for neuroimaging data fusion. Zhou et al. [60] used modality-specific kernels to combine structural and diffusion MRI features, achieving 64.3 % accuracy in ADHD classification. The distinct features of various imaging modalities can be preserved by processing them separately before integrating them, thanks to this kernel-level fusion technique. Yu et al. [61] integrated four complementary ADHD datasets. To harmonize these heterogeneous sources, they applied unified preprocessing pipelines such as score normalization and median imputation for questionnaire and demographic data, time-series alignment and categorical encoding for longitudinal measures, skull-stripping, spatial normalization, and smoothing for MRI, and artifact filtering, epoch segmentation, and baseline correction for EEG. Such techniques guarantee data consistency within individual datasets, not extending the concept between them. However, this study showed the potential of integrating neuroimaging data with physical activity monitoring, achieving accuracy rates of 93.94 % to 98.21 % in detecting ADHD.

The integration of physiological signals with clinical data has also proven effective. Chen et al. [54] highlighted the absence of signal fusion in this field. They used an ensemble model that leveraged the complementary nature of neurophysiological (EEG) and clinical data (diagnostic measures). EEG data were acquired during two cognitive functioning and attention tests, filtered, and cleaned using Independent Component Analysis (ICA) to remove electrical, muscular, or eye artifacts. They achieved 97.4 % accuracy in ADHD detection, outperforming the classification performance of individual models. Using a similar approach, Kim et al. [59] developed a fusion strategy that integrates data from wearable devices (sleep, heart rate, physical activity) with clinical assessments through an ensemble of ML models, achieving an AUC of 0.798 in predicting ADHD.

These studies reveal that successful multimodal fusion strategies must consider the nature of each data type and its relationships. While early fusion approaches concatenate features, more sophisticated intermediate and late fusion strategies that preserve modality-specific characteristics often yield better results [54]. However, challenges remain in harmonizing data collected through different protocols and maintaining model interpretability as the number of data sources increases [60].

5.4. Current challenges and future research directions

Our systematic review reveals fundamental challenges in translating AI advances for NDDs from laboratory settings to clinical practice. The existing research landscape, while technically impressive, exposes critical gaps between theoretical capabilities and practical implementation.

The majority of validation studies have controlled acquisition settings, which represent a persistent methodological limitation. Although multimodal systems and other tools show impressive accuracy in controlled settings [54,62,63], these outcomes are rarely applicable in dynamic clinical settings where data collection is subject to numerous practical limitations. For instance, Mandal et al. [64] achieved 92.4 % accuracy with their EEG-based ADHD detection system in laboratory conditions, but acknowledged significant challenges in real-world implementations. Similarly, Zhang et al. [26] reported 91.72 % accuracy in ASD trait classification using video analysis, but noted substantial performance variations in uncontrolled environments.

Due to this discrepancy, research procedures must specifically take into consideration the unpredictability present in clinical settings and real-world environments. Several reviewed studies using mobile applications or wearable devices adopted controlled laboratory settings to manage confounding factors and ensure data reliability [33,42]. To advance real-time applicability in noisy, uncontrolled environments, future research [48] should emphasize data preconditioning and robustness. Signal preprocessing techniques, such as filtering, denoising and artifact removal, are essential [54,65,66]. Temporal smoothing and sliding window-based aggregation can stabilize short-term fluctuations, particularly in mobile data [42]. Multi-sensor redundancy, using sensor fusion to cross-validate events across modalities, may improve reliability by detecting and compensating for individual sensor failures or signal corruption. System design should balance model complexity with explainability and noise resilience, ensuring that AI-generated insights remain trustworthy when deployed in varied and uncontrolled home, school, or community settings. DL can handle noisy data through its feature learning and generalization capabilities, reducing the need for explicit artifact removal 64], but their robustness depends heavily on training data that includes representative noise. In real-world settings, relying solely on implicit noise handling may be insufficient. Combining minimal preprocessing with DL models remains a more reliable approach for maintaining data fidelity in uncontrolled environments. Future systems should also integrate mechanisms for estimating prediction confidence and model uncertainty, especially when operating under conditions where noise, sensor degradation, or unexpected inputs are common. Techniques such as Bayesian deep learning, Monte Carlo dropout, or ensemble modeling can provide uncertainty metrics, enabling the detection of unreliable predictions or out-of-distribution (OOD) inputs.

The standardized assessment frameworks widely used in the reviewed studies conflict with the inherently heterogeneous nature of these conditions. Current diagnostic tools attempt to fit diverse symptom presentations into rigid categorical systems, fundamentally limiting their clinical utility. Recent implementations show how adaptive approaches can enhance effectiveness. For example, Shi et al. [67] developed a personalized robotic system that adapts to individual ASD children's cognitive-affective needs, outperforming non-personalized approaches. Similarly, Castellanos et al. [46] created a mobile application achieving 99.8 % accuracy that allows ASD patients to perform therapy anywhere while transmitting information to medical specialists, demonstrating how technology can extend therapeutic support beyond clinical settings.

Moreover, capabilities for longitudinal assessment are still noticeably lacking. Because NDDs are progressive, monitoring systems that can detect minor alterations over long periods of time are necessary. Some researchers have begun addressing the longitudinal monitoring challenge. Yu et al. [61] conducted a comprehensive study combining physical activity monitoring with neuroimaging data, achieving accuracy between 93.94 % and 98.21 % in tracking the cognitive and behavioral changes over time in individuals with ADHD. In the ASD domain, Wang et al. [68] developed a tool achieving 82.4 % AUC in recognizing training states during interventions, enabling continuous assessment of therapeutic progress. However, this research field lacks strong frameworks for analyzing developmental trajectories and determining significant intervention points, despite recent wearable technology advancements showing promise.

For effective longitudinal follow-up and continuous refinement of AI-based interventions, we recommend several approaches. First, implementing structured A/B testing frameworks in real classrooms and clinical environments would allow systematic comparison of intervention variants to identify optimal configurations for different user profiles [69]. Second, developing hybrid evaluation systems that integrate quantitative metrics (such as academic performance indicators and symptom severity scales) with qualitative feedback from various stakeholders (including children, caregivers, educators, and clinicians) would offer a more holistic understanding of the intervention effectiveness [70]. This could be facilitated through user-friendly feedback interfaces embedded within the technology that periodically prompt for inputs using age-appropriate formats [71].

Future research should consider the integration of generative AI techniques, such as generative adversarial networks (GANs) and large language models (LLMs). These technologies may have the potential to be relevant to NDD support [72]. GANs can help improve model generalization, generating synthetic yet realistic data, particularly in scenarios where datasets are small, imbalanced, or ethically constrained. LLMs can enable personalized interactions in real-time, adjusting therapeutic or educational responses based on contextual cues, historical behavior, or developmental goals. This opens avenues for precision medicine in behavioral support, where interventions are dynamically adapted to the child's cognitive and emotional profile. Moreover, the integration of LLMs introduces new possibilities for natural-language interfaces in assistive technologies. These models can potentially enhance engagement for children, parents, and educators. Despite this promise, careful evaluation of reliability, safety, and explainability remains essential, particularly in pediatric applications. Indeed, generative systems must align with developmental appropriateness, privacy requirements, and clinical oversight.

Data privacy considerations pose significant implementation barriers. The comprehensive monitoring required for effective intervention conflicts with legitimate concerns about data protection, particularly for pediatric populations. Federated learning represents a promising solution by enabling model training across multiple institutions without sharing raw patient data [73]. In this approach, each clinical site trains models locally on their data, and only model parameters—not the sensitive data itself—are exchanged. This architecture could enable large-scale collaborative research while maintaining regulatory compliance with privacy frameworks like HIPAA and GDPR.

Beyond federated learning, additional privacy-preserving techniques could further enhance data utility while protecting confidentiality. Differential privacy frameworks can provide mathematical guarantees against individual identification by controlling the amount of noise added to aggregate statistics. Secure multi-party computation allows multiple clinical entities to jointly compute results without revealing their inputs to other parties [74]. Homomorphic encryption [75] enables computations on encrypted data without decryption, allowing sensitive information to remain protected throughout analysis pipelines.

The implementation of these approaches requires careful consideration of the trade-off between privacy protection and clinical outcome utility. Wearable devices, frequently employed in NDD monitoring [59] and intervention [41], present heightened privacy challenges due to their continuous collection of sensitive physiological and behavioral data across uncontrolled environments, often with limited computational resources for robust encryption. In pediatric applications, frameworks for obtaining parental consent must establish transparent governance structures that clearly outline data usage and offer meaningful opt-out mechanisms. Future research should focus on establishing field-specific privacy protocols that balance these competing demands, potentially through privacy-by-design approaches that incorporate protection mechanisms at the earliest stages of system development.

Finally, future research should also focus not just on increasing the quantity of data collected but on improving the quality of data fusion methods to provide clinicians with actionable, real-time insights. The future development of AI-based tools should shift towards augmenting clinical expertise rather than replacing it. Researchers should focus on designing tools that enhance professional judgment and decision-making, allowing clinicians to leverage AI insights while maintaining crucial human components of assessment and intervention. To ensure these tools complement rather than displace human judgment, future efforts must prioritize co-design methodologies by actively involving clinicians, educators, and caregivers throughout the development pipeline. This participatory approach helps to align AI systems with clinical workflows, ethical considerations, and interpretability requirements. Interfaces should prioritize transparency and explainability, enabling users to scrutinize model outputs and confidently integrate them into their professional reasoning. Collaborative human-AI decision-making frameworks are essential to ensure these technologies serve as trusted assistants.

6. Conclusion

Our comprehensive review highlights the promise of AI applications in neurodevelopmental disorders as well as their present limitations. By reviewing studies conducted between 2018 and 2024, we have found important trends in diagnosis, care, and technology use that should be considered by researchers and medical professionals. Our analysis of deep learning and machine learning approaches shows positive advances in treatment optimization and diagnostic precision. These developments in technology must be evaluated in relation to practical clinical applications, though. Although statistical performance metrics show remarkable outcomes in controlled environments, it remains challenging to translate these findings into real-world clinical applications. AI tools should be seen as facilitators, filling in the gaps between various support systems and therapeutic modalities. The integration of AI systems with established clinical methods offers a synergistic approach that strengthens diagnostic accuracy and treatment effectiveness while preserving essential human judgment.

Funding statement

This research received no external funding.

CRediT authorship contribution statement

Alen Shahini: Writing – original draft, Visualization, Formal analysis. **Aditya Prabhakara Kamath:** Writing – review & editing, Methodology, Formal analysis. **Ekta Sharma:** Writing – original draft. **Massimo Salvi:** Writing – review & editing, Supervision. **Ru-San Tan:** Writing – review & editing. **Siuly Siuly:** Writing – review & editing, Methodology. **Silvia Seoni:** Writing – review & editing, Visualization. **Rahul Ganguly:** Writing – review & editing, Investigation, Conceptualization. **Aruna Devi:** Writing – review & editing, Methodology, Investigation. **Ravinesh Deo:** Writing – review & editing, Methodology. **Prabal Datta Barua:** Writing – review & editing. **U. Rajendra Acharya:** Writing – review & editing, Supervision, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix

Table A1
Summary of studies that implements AI-based assistive tools for ADHD.

Author, year	Assistance & Data	Dataset (#subjects)	Technique	Results & Findings
Itani et al., 2019 [32]	Computer Assistance: phenotipic features, diagnostic features, fMRI	n = 105	ML: DT	Accuracy: 73.2 %. This study identified the limbic system as relevant for diagnosis and provided interpretable explanations for model predictions.
Lai et al., 2021 [50]	Robot Assistance: sensor readings, thermal images	CrowdHuman Training: 15k images Validation: 4k images Test: 5k images WIDER FACE Training: 32,203 images and labels, 393,703 faces	ML: RL	Thermal image sensing data presents a higher F1-score than image-based cognitive emotion recognition. Fear F1-score: 84 %. Thermal images perform better than optical images in intense emotions recognition. Robotic aids can effectively reduce the number of emotional occurrences.

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Table A1 (*continued*)

Author, year	Assistance & Data	Dataset (#subjects)	Technique	Results & Findings
Kim et al., 2021 [8]	Computer Assistance: questionnaire, MMPI-2, ASRS	n = 5726	ML: KNN, LDA, RF	Accuracy: 93.1 % (KNN); 91.2 % (LDA); 93.6 % (RF). ML using the MMPI-2 in a large group could provide reliable accuracy in screening for adult ADHD.
Zhou et al., 2021 [60]	Computer Assistance: MRI, DTI	n = 11,878	ML: SVM	Accuracy: 64.3 %. The abnormal functional connectivity predictors and the anatomical regions in basal ganglia are found to encode the most discriminative information.
Ardulov et al., 2021 [14]	Computer Assistance: diagnostic and phenotipic features	n = 119	ML: RL	F1-score: 56.20 %. Reinforcement learning frameworks can be utilized to train more robust classifiers by jointly learning to maximize diagnostic accuracy while minimizing the amount of information required.
Lindhiem et al., 2022 [43]	Mobile Application: Body sensors, report, interview, questionnaire	n = 30 (15 ADHD, 15 TD)	ML: RF	Accuracy: 89 %; Sensitivity: 93 %; Specificity: 86 %. Accuracy improved significantly when contextual information and activity labels were added to the models.
Chen et al., 2023 [31]	Computer Assistance: electronic health records, interviews	n = 501	ML: DT	Accuracy: 75.03 % (DT); 93.61 % (hybrid model). The results are encouraging and suggest that the AI algorithm can be used in clinical practice.
Garcia-Argibay et al., 2023 [76]	Computer Assistance: surveys, phenotipic, diagnostic and demographic features	n = 238,696	DL: DNN	Accuracy: 69 %. This model could be used to alert clinicians to individuals who ought to be screened for ADHD and to aid clinicians' decision-making with the goal of decreasing misdiagnoses.
Goh et al., 2023 [56]	Computer Assistance: diagnostic and phenotipic features, global impairment, academic performance, and social skills	n = 399 (222 ADHD, 177 TD)	ML: RF	Accuracy: 93 %. Results suggested eight symptoms as most important in predicting impairment outcomes five years later.
Haque et al., 2023 [55]	Computer Assistance: surveys	n = 1011	ML: RF	Accuracy: 91 %; Precision: 94 %; Specificity: 99 %. The application will assist parents/guardians and school officials in detecting mental illnesses early in their children and adolescents using signs and symptoms to start the treatment at the earliest convenience.
Kim et al., 2023 [59]	Wearable Device: sensor readings, diagnostic and phenotipic features	n = 1090 (79 ADHD, 1011 TD)	ML: GB	AUC: 79.8 %; Sensitivity: 71.8 %; Specificity: 71.6 %. The findings of this diagnostic study suggest that wearable data have the potential to detect ADHD.
Lin et al., 2023 [77]	Computer Assistance: fMRI, diagnostic and phenotipic features	n = 7,805 (1,798 ADHD, 6,007 TD)	ML: SVM	AUC: 61.3 %. This study highlights the neurobiological implication of frontal lobe cortex and associate white matter tracts in pathogenesis of childhood ADHD.
Lin et al., 2023 [57]	Computer Assistance: diagnostic and phenotipic features, Online test	n = 328 (97 ADHD-I, 194 ADHD-C, 37 TD)	ML: ANN	Accuracy: ADHD-I vs. ADHD-C: 89.46 %; ADHD-I vs. ADHD-C, and TD: 77.43 %. The ML model helps clinicians identify patients with ADHD in a timely manner.
Liu et al., 2023 [78]	Computer Assistance: Questionnaires, Diagnostic features	n = 955 (432 ADHD, 523 TD)	ML: Elastic Net model	Accuracy: 78.8 %. The proposed tool can inform clinicians the risk of ADHD.
Lohani et al., 2023 [10]	Computer Assistance: MRI, diagnostic and phenotipic features	n = 632 (316 ADHD, 316 TD)	ML: SVM	Accuracy: 75 %. An increase in gray matter volume in fifteen brain regions and loss of cortical thickness in twenty-seven brain regions were observed.
Park et al., 2023 [79]	Wearable device: sensor readings, aggression episodes, demographic and clinical data	n = 39 (with and without ADHD)	ML: RF	Precision: 80.2 %; Accuracy: 82.0 %; Recall: 85.0 %; F1 score: 82.4 %; AUC: 89.3 %. ML is a practical and efficient solution for detecting aggressive incidents.
Weigard et al., 2023 [80]	Computer Assistance: diagnostic, phenotipic, demographic features	n = 11,878	ML: Linear Regression	Features from multiple domains contributed meaningfully to prediction, including neurocognition, sex, self-reported impulsivity, parental monitoring, and screen time. This work quantifies the information value of neurocognitive abilities and other child characteristics for predicting ADHD symptoms.
Misgar et al., 2024 [63]	Wearable device: sensor readings	n = 85	ML: RF	Accuracy: 98.3. This work contributed to advancing the understanding of ADHD through objective, data-driven methodologies.
Lee et al., 2022 [33]	Mobile application: skeleton data, Azure Kinect device	n = 50 (25 ADHD, 25 TD)	DL: LSTM	Accuracy: 97 %. This system makes possible to judge children's situation by ADHD scrrening results.
Grazioli et al., 2024 [81]	Computer Assistance: questionnaires	n = 342	ML: DT	Accuracy: 82 %. ASD symptoms were a confounding factor when ADHD severity had to be established (accuracy: 74 %).
Chen et al., 2024 [54]	Wearable Device: EEG, diagnostic features	n = 78 (43 ADHD, 35 TD)	ML, DL (Ensemble): DT, RF, LSTM	Accuracy: 97.4 %. This system can facilitate the clinical diagnosis of ADHD in preschool young children.
Cura et al., 2024 [82]	Computer Assistance: EEG	n = 33 (15 ADHD, 18 TD)	ML, DL: SVM, CNN	Accuracies between 96.6 % and 99.9 %. Experimental results indicate that the use of EEG-FM-based images as input to DarkNet19 architecture gives significant advantages in the detection of ADHD.
Feng et al., 2024 [83]	Computer Assistance: EEG	n = 121 (61 ADHD, 60 TD)	DL: DCNN	Accuracy: 94.52 %. These outcomes demonstrate the potential of ConvMixer-ECA as a valuable tool to assist clinicians in the early diagnosis and intervention of ADHD in children.
Firouzi et al., 2024 [11]	Computer Assistance: fMRI	n = 220 (44 ADHD-I, 77 ADHD-C, 99 TD)	DL: CNN	Accuracy: ADHD, C (balanced): 97 %; ADHD, C (unbalanced): 97.7 %,; ADHD-I, ADHD-C: 99.4 %; ADHD-I, ADHD-C, C: 98.86 %. Effective diagnostic tool for identifying ADHD subtypes and distinguishing ADHD.
Jahani et al., 2024 [84]	Computer Assistance: EEG	n = 121 (61 ADHD, 60 TD)	DL: ResNet	Accuracy: 98.6 %. The model's exceptional accuracy, exceeding conventional methods, showcases its potential as a biologically inspired tool.

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Table A1 (*continued*)

Author, year	Assistance & Data	Dataset (#subjects)	Technique	Results & Findings
Mandal et al., 2024 [64]	Mobile application: EEG	Dataset 1: n = 121 (61 ADHD, 60 TD) Dataset 2: n = 9 (4 ADHD, 5 TD)	DL: DCNN	Accuracy: 92.4 %. The DL model outperforms other benchmark methods.
Oh et al., 2024 [39]	Virtual Reality: videogames	n = 20 (15 ADHD, 5 TD)	ML	Accuracy: 89.3 %. AttnKare-D can be a useful tool for diagnosing ADHD in children.
Ouyang et al., 2024 [85]	Computer Assistance: videos, skeleton data	n = 96 (48 ADHD, 48 TD)	ML: XGB	Accuracy: 91.20 %. The single feature descriptor “thigh angle” achieved the best result. This tool can assist physicians in diagnosing ADHD.
Yoo et al., 2024 [7]	Wearable device: eye tracking	n = 137 (58 ADHD, 79 TD)	ML: RF	Accuracy: 76.3 %. Combining demographic, behavioral, and clinical data with eye-tracking features improved accuracy. Eye-tracking features could be reliable indicators of impaired neurobiological functioning in individuals with ADHD.
Yu et al., 2024 [61]	Physical Activity: diagnostic and phenotipic features, fMRI, EEG	D1: n = +7400 D2: n = 1500 D3 (fMRI): n = 776 (285 ADHD, 491 TD) D4 (EEG): n= 121 (61ADHD, 60 TD)	ML, DL: RF, CNN	Accuracy: from 93.94 %, to 98.21 % This study reveals the immediate effects of physical interventions on the cognition and behavior of ADHD patients.
Zamanzadeh et al., 2024 [86]	Computer Assistance: fMRI	n = 116 (53 ADHD, 63 TD)	ML: RF, XGB	Accuracy: 74.3 %. These results contri.bute to understanding ADHD’s neural underpinnings.

ADHD: Attention Deficit Hyperactivity Disorder; ADHD-I: inattentive-type ADHD; ADHD-C: combined-type ADHD; ANN: Artificial Neural Network; ASRS: ADHD Self-Report Scale; CNN: Convolutional Neural Network; DCNN: Deep Convolutional Neural Network; DL: Deep Learning; DNN: Deep Neural Network; DT: Decicion Tree; DTI: Diffusion Tensor Images; GB: Gradient Boosting; KNN: K-Nearest Neighbors; LDA: Linear Discriminant Analysis; LSTM: Long Short-Term Memory; ML: Machine Learning; MMPI-2: Minnesota Multiphasic Personality Inventory-2; RF: Random Forest; RL: Reinforcement Learning; SVM: Support Vector Machine; TD: Typically Developing; XGB: Extreme Gradient Boosting.

Table A2
Summary of studies that implements AI-based assistive tools for ASD.

Author, year	Assistance & Data	Dataset (#subjects)	Technique	Results & Findings
Daniels et al., 2018 [87]	Wearable Device: SRS-2, EGG, reports	n =14	ML	Significant decrease in SRS-2; improvement on EGG task; positive parent reports of increased eye contact and social acuity. This feasibility study supports using mobile technologies for potential therapeutic purposes.
Xavier et al., 2018 [88]	Robot Assistance: sensor readings	Dataset 1: Human-robot posture imitation Dataset 2: n = 85 (29 ASD, 39 TD, 17 DCD)	ML: ANN	ASD children show differences in interpersonal synchronization, motor coordination, and control compared to TD and DCD children. ASD children behave during motor tasks expresses a specific behavioral signature.
Dapogny et al., 2019 [89]	Mobile application: facial images	n = 157; 3,768 videos	ML: RF	Accuracy: 81.9 %. Achieved high accuracy in both classifying and assessing the quality of children’s facial expressions.
Ramirez-Duque et al., 2019 [90]	Robot Assistance: sensor readings, facial images	Training CNN: 6975 images Case study: n = 6 (3 ASD, 3 TD)	DL: CNN	Effectiveness and accuracy of the robot-assisted diagnosis system not presented in current search results. Improvement over the traditional tools used in ASD diagnosis.
Xiao et al., 2019 [91]	Computer Assistance: fMRI	n = 198 (117 ASD, 81 TD)	DL: SAE	Accuracy: 96.26 %; Sensitivity: 98.03 %; Specificity: 93.62 %. Results demonstrate the potential clinical application of ASD diagnostic tools.
Alcaniz Raya et al., 2020 [40]	Virtual Reality: sensor readings	n = 49 (24 ASD, 25 TD)	ML: SVM	Accuracy: 82.98 %. This outperforms previous studies using limited frequency bands.
Alivar et al., 2020 [92]	Computer Assistance: BCG	n = 2	ML: SVM, ANN	Accuracy above 78 % for daytime behavior and sleep quality prediction. Restlessness feature improves the prediction performance.
Fu et al., 2020 [93]	Therapy training: video recordings	n = 70	ML: SVM	R2: 0.75; RMSE: 0.59. Play-based communication and behavior intervention is beneficial for ASD children.
Jain et al., 2020 [94]	Robot Assistance: audios, videos, robot actions, and touch interactions	n = 7	ML: SVM	AUROC: 90 %. Feasibility of real-time detection and potential for intervention adjustments.
Leblanc et al., 2020 [95]	Computer Assistance: electronic health records, videos	n = 140	ML: LR, DT	AUROC: 91.09 % (LR); 90.83 % (DT). General and dynamic feature replacement methods outperform classic methods in maintaining model performance despite missing data, supporting the feasibility of video-based autism detection with readily available home videos.
Nag et al., 2020 [41]	Wearable Device: videos	n = 33 (16 ASD, 17 TD)	ML: Regression	Accuracy: 71 %. Gaze and emotion recognition patterns allowed classification of ASD and TD groups.

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Table A2 (*continued*)

Author, year	Assistance & Data	Dataset (#subjects)	Technique	Results & Findings
Silleresi et al., 2020 [17]	Therapy training: audios	n = 37	ML: Cluster Analysis	Identified four distinct language and cognitive profiles in children with ASD. Hypothesis of the existence of a separate language module in the brain is reinforced.
Ardulov et al., 2021 [14]	Computer Assistance: diagnostic and phenotipic features	n =119	ML: RL	F1 score: 56.20 %. Reinforcement learning frameworks can be utilized to train more robust classifiers by jointly learning to maximize diagnostic accuracy while minimizing the amount of information required.
Banire et al., 2021 [96]	Computer Assistance: facial images	n = 46 (20 ASD, 26 control)	ML: SVM; DL: CNN	Accuracy: 91 % (SVM), 76.31 % (CNN). Attention detection is more generalizable within typically developing children than within ASD groups and within low-attention tasks than within high-attention tasks.
Ghiglino et al., 2021 [35]	Robot Assistance, therapy training: diagnostic and phenotipic features	24 ASD	-	Results showed that the combination of robot-assisted training with standard therapy was more effective than the standard therapy alone. ASD improved in their ability to generate and respond to behavioral requests and to maintain social interaction with the adult.
Mertz et al., 2021 [97]	Robot Assistance, virtual Reality: questionnaires, videos	-	ML	Canvas Dx by Cognoa helps streamline diagnosis by providing an initial assessment (positive, negative, or inconclusive for ASD) and reducing diagnosis time.
Romero-Garcia et al., 2021 [98]	Robot Assistance: questionnaires	1054 responses	ML: DT	Accuracy: 91.94 %. Q-CHAT-NAO can lead to a red flag for autism risk.
Subah et al., 2021 [47]	Computer Assistance: fMRI	n = 866 (402 ASD, 464 TD)	DL: DNN	Accuracy: 88 %. The proposed model outperforms state-of-the-art methods in terms of accuracy.
Tawhid et al., 2021 [99]	Computer Assistance: EEG	n = 16 (12 ASD, 4 TD)	DL: CNN	Accuracy: 99.15 %. The DL model can be used fot the automatic diagnosis of ASD.
Washington et al., 2021 [100]	Computer Assistance: videos, annotations	n = 50	ML: Logistic Regression	Accuracy: 88 %. Analysis of short home videos can help enable rapid and mobile ML detection of developmental delays in children.
Alam et al., 2022 [101]	Computer Assistance: facial images	50 % ASD, 50 % control; 2940 images	DL: ResNet	Accuracy: 94 %. This model can be employed to assist doctors and practitioners in validating their initial screening to detect children with ASD disease.
Balaji et al., 2022 [24]	Computer Assistance: fMRI, MRI	n = 1112	ML, DL: DNN (training), K-means (clustering) SGD (optimization)	Accuracy: 99.54 %. The paper highlights studies where CNN-based models achieved high accuracy (over 96 %) for ASD screening using datasets with various sizes.
Castellanos et al., 2022 [46]	Mobile application: images, videos, sentences	TensorFlow for Image Classification, ArKit for Text-to-Speech, Cloud Database, Binary Search, NLP, Datasets of Sentences and Images	DL: CNN	Accuracy: 99.8 %. This system allows ASD patient to perform the therapy anytime and everywhere, as well as transmitting information to a medical specialist.
Deng et al., 2022 [12]	Mobile application: sensor readings	n = 35	ML: XGB	Accuracy: 86.67 % (attention), 98.50 % (stress). This system aids ASD children in class by offering strategy recommendations based on real-time environmental data.
Katsanis et al., 2022 [36]	Robot Assistance: facial images, questionnaires	n = 15	DL: CNN	Accuracy: 88.08 %. Pilot study with educators showed promising results, indicating the robot's design and potential of machine learning for child-robot interaction in ASD interventions.
Lytridis et al., 2022 [37]	Robot Assistance: facial images	6846 frames	ML: Lattice Computing models in conjunction with ML techniques	Identifying effective robot actions and their corresponding child behavioral states to improve intervention design. This system can give psychologists studying the data the opportunity to make observations regarding behaviors either at the individual or the scenario level.
Shi et al., 2022 [67]	Robot Assistance: visual, audio and game performance features	n = 4	ML: XGB	XGB outperformed two non-personalized individualized and generic model baselines. This work paves the way for the development of personalized autonomous SAR systems tailored toward individuals with atypical cognitive-affective and socio-emotional needs.
Sun et al., 2022 [16]	Physical Activity: clinical information, behavioral factors, and potentially brain structural indicators	n = 26	ML: SVM	Social communication: 83 % variance. Repetitive behaviors: 85.9 % variance. ML models achieved high accuracy in predicting post-treatment improvements in social communication (83 % variance) and repetitive behaviors (85.9 % variance) compared to traditional statistical models.
Varma et al., 2022 [48]	Mobile application: videos	n = 95 (47 ASD, 48 TD)	DL: LSTM	Identified 1 statistically significant region of fixation and 1 significant gaze transition pattern differing between ASD and neurotypical groups. LSTM model showed mild predictive power for identifying ASD based on gaze fixations. Heterogeneous video data

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Table A2 (*continued*)

Author, year	Assistance & Data	Dataset (#subjects)	Technique	Results & Findings
				sets collected from mobile devices hold potential for quantifying visual patterns and providing insights into ASD.
Zhang et al., 2022 [102]	Computer Assistance: fMRI	n = 1035 (505 ASD, 530 TD)	DL: CNN	Accuracy: 64.53 %. The altered brain network may provide insight into the underlying pathology of ASD, and the functional connectivity features may serve as biomarkers.
Chawla et al., 2023 [103]	Computer Assistance: EEG	n = 16 (12 ASD, 4 TD)	DL: CNN	Accuracy: 99.19 %; Sensitivity 99.34 %; Specificity: 99.21 %; AUC: 99.97 %. CNN architecture would be extremely helpful during diagnostic process of autism disease for neurologists.
Derbali et al., 2023 [53]	Mobile application: facial images	2,536 facial images of children (ASD and TD)	DL: CNN	Accuracy: 92.3 %. Accurate prediction outcomes generated by the CNN model.
Grazioli et al., 2023 [81]	Computer Assistance: questionnaires	n = 342	ML: DT	Accuracy: 82 %. ASD symptoms were a confounding factor when ADHD severity had to be established (accuracy: 74 %).
Haoues et al., 2023 [65]	Mobile Application: reviews	97,051 reviews, 13 ASD apps	DL: RNN, LSTM	Accuracy: 96.58 %; AUC: 99.41 %. Good performance. App users complain about their quality issues especially usability, reliability, etc.
Nogay et al., 2023 [52]	Computer Assistance: MRI	n = 2248 (1072 ASD, 1176 TD)	DL: DCNN	Accuracy: 100 %. Excellent performance.
Polireddi et al., 2023 [104]	Computer Assistance: questionnaires	-	ML: DT	Individualized replies based on user mood. Ability to offer empathetic conversational style. Weekly charts outlining mental condition.
Singh et al., 2023 [105]	Robot Assistance: audios	-	DL: CNN	Increased efficacy of therapy and improved learning outcomes for children with ASD
Ullah et al., 2023 [42]	Wearable Device: sensor readings	200 samples	ML: ANN	Accuracy: 96.2 %. Good performance.
Wang et al., 2023 [68]	Therapy training: Videos	n = 61	DL: CNN	AUC: 82.4 %. The proposed tool can effectively recognize the training states in ASD intervention.
Zhang et al., 2023 [44]	Computer Assistance: videogames	n = 60 (30 ASD, 30 TD)	ML: SVM	Accuracy: 96.67 %; Sensitivity: 93.33 %; Specificity: 96 %. Children with ASD showed significant differences in performance compared to TD children on various visual motor integration measures.
Zhang et al., 2023 [26]	Computer Assistance: videos	n = 33	DL: DCNN	Accuracy: 91.72 %. It is shown that certain interview scenes carry more discriminative information for ASD trait classification than others.
Alsaidi et al., 2024 [106]	Computer Assistance: eye tracking	n = 59 (29 ASD, 30 TD)	DL: CNN	Accuracy: 95.59 %. The proposed model demonstrated superior performance when compared to the findings reported in previous studies.
Chen et al., 2024	Computer Assistance: Diagnostic, phenotipic, demographic features, fMRI	D1: n = 871 (403 ASD, 468 TD) D2: n = 949 (419 ASD, 530 TD)	DL: CNN	Accuracy: 87.38 % (D1), 88.09 % (D2). Improvement of 13.25 % in accuracy.
Konishi et al., 2024 [58]	Robot Assistance: questionnaires, audios, videos, eye tracking	n = 25 (ASD)	ML: GB	AUC: 87 %. AUC values of arousal, valence, and engagement were improved by including self-administered questionnaire data in the classification.
Srivathsan et al., 2024 [38]	Virtual Reality: videogames	-	ML: Linear Regression	MAE: 0.0394. The VR games led to improved memory in children. The linear regression model could predict future memory performance based on VR game data.
Talaat et al., 2024 [107]	Mobile application: facial images	830 images (758 for training, 72 for testing)	DL: DCNN	Accuracy 95.23 %. This application can help medical experts and families improving the quality of life for individuals with ASD.
Varghese et al., 2024 [108]	Computer Assistance: videos	n = 39 (19 ASD, 20 TD)	DL: CNN	Accuracy: 98 %. This method opens the door to developing real-time attention recognition systems.
Xu et al., 2024 [34]	Physical Activity: diagnostic features, MRI	n = 90 (ASD)	ML: XGB, RF, SVM, DT	Accuracy: 77.9 % (XGB); 72.4 % (RF); 71.9 % (SVM); 66.9 % (DT). SHAP analysis revealed that muscular strength and thalamic GMV significantly influenced the decision-making process of the XGB model.

ANN: Artificial Neural Network; ASD: Autism Spectrum Disorder; BCG: Ballistocardiogram; CNN: Convolutional Neural Network; DL: Deep Learning; DNN: Deep Neural Network; DCD: Developmental Coordination Disorder; DCNN: Deep Convolutional Neural Network; DT: Decision Tree; EGG: facial affect recognition task; GB: Gradient Boosting; LSTM: Long Short-Term Memory; ML: Machine Learning; RF: Random Forest; RL: Reinforcement Learning; SAE: Stacked Autoencoders; SGD: Stochastic Gradient Descent; SRS-2: Social Responsiveness Scale; SVM: Support Vector Machine; TD: Typically Developing; XGB: Extreme Gradient Boosting; LR: Logistic Regression.

Table A3
Summary of studies that implements AI-based assistive tools for DYS.

Author, year	Assistance & Data	Dataset (#subjects)	Technique	Results & Findings
Atkar G. et al., 2020 [109]	Computer Assistance: audios	n = 35	ML: Least Square	Accuracy from 90 % to 100 % if system is tested with same user. Accuracy of 30 % accuracy if system is tested with new user. Assistive system for dyslexic children.
Rauschenberger et al., 2022 [110]	Mobile Application: videogames	n = 313 (116 DYS, 197 HC)	ML: RF	Accuracy: 0.74 (German) / 0.69 (Spanish). Universal screening with language-independent content can be used for the screening of prereaders who do not have any language skills, facilitating a potential early intervention.
Zhong et al., 2023 [45]	Mobile Application: reading, writing tests, eye tracking	n = 207 (39 DYS, 168 HC)	ML, DL: XGB, CNN	Accuracy: 81.14 %; Sensitivity: 74.27 %; Specificity: 82.71 %. Results prove the efficacy of the multilevel Chinese handwriting analysis framework.
Gallego-Molina et al., 2024 [21]	Computer Assistance: EEG	n = 48 (15 DYS, 33 HC)	DL: LSTM	Accuracy: 83 %. Link between cross-frequency phase synchronisation patterns with regions that are attributed to normal reading and those corresponding to compensatory mechanisms found in DYS.
Gomolka et al., 2024 [66]	Wearable Device: eye tracking	n = 145	DL: LSTM	Accuracy: 97.7 %. The ease of implementation of this approach in school settings and its non-stressful nature make it suitable for use with children of different ages and developmental stages, and for effective educational and emotional support for children with DYS.
Liu et al., 2024 [19]	Computer Assistance: writing images	n = 1064 (483 DYS, 581 HC)	DL: LSTM	Accuracy: 85 %. These findings suggest the potential of utilizing machine learning technology to identify children at risk for dyslexia at an early age.
Zingoni et al., 2024 [111]	Therapy training: questionnaires	n = +1200 students	ML: KNN, RF, SVM	Average accuracy > 94 %. This study aims at modifying teaching activities toward students' needs, instead of simply reducing their study load or duties.

CNN: Convolutional Neural Network; DL: Deep Learning; DYS: Dyslexia; HC: healthy control; KNN: K-Nearest Neighbors; LSTM: Long Short-Term Memory; ML: Machine Learning; RF: Random Forest; SVM: Support Vector Machine; XGB: Extreme Gradient Boosting.

Data availability

Data will be made available on request.

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