Journal of Evidence-Based Psychotherapies,
Vol. 25, No. 2, September 2025, 71-102.

10.24193/jebp.2025.2.12

THE IMPACT OF AI-MEDIATED THERAPY ON TREATMENT OUTCOMES IN AUTISM SPECTRUM DISORDER: A SYSTEMATIC REVIEW

Sultan M. Alshahrani[1,2] *

[1] College of Pharmacy, King Khalid University, Abha 61441, Saudi Arabia.
2 King Salman Center for Disability Research, Riyadh 11614, Saudi Arabia.

Abstract

Autism Spectrum Disorder (ASD) is a neurodevelopmental condition characterized by deficits in communication, cognition, and social behavior. This review evaluates the effectiveness of AI-mediated therapies in improving treatment outcomes for individuals with ASD.

A systematic search was conducted in Google Scholar and PubMed for studies published between 2015 and 2025, following PRISMA guidelines. Twenty-two studies met the inclusion criteria. Data screening, quality assessment using the Joanna Briggs Institute checklist, and statistical evaluation were performed.

AI-based interventions showed positive impacts on social interaction, adaptive behavior, and learning in individuals with ASD. Humanoid robots such as NAO and MARIA T21 improved emotional recognition, imitation skills, and motor coordination. AI-enabled mobile apps like Superpower Glass enhanced facial recognition and social engagement. IoT-integrated ABA therapy facilitated personalized interventions by tracking physiological and environmental parameters.

AI-mediated therapies significantly enhance treatment outcomes in ASD, particularly in social, cognitive, and behavioral domains. These technologies provide scalable, individualized approaches that may complement traditional therapy and support long-term development.

Keywords: Autism Spectrum Disorder, Artificial Intelligence, Social Interaction, Applied Behavior Analysis, Treatment outcomes, Motor Skills Disorder, Cognitive Skills, Robotics.

* Correspondence concerning this article should be addressed to Associate professor Dr. Sultan M. Alshahrani, Department of Clinical Pharmacy, College of Pharmacy, King Khalid University, Asir, Abha-AlFara, 62223, Saudi Arabia.
ORCID ID: 0000-0002-6194-7092
Mobile: +966508747473
Email: Shahrani@kku.edu.sa

Autism spectrum disorder (ASD), accounting for almost 1 in 54 children globally, is a neurodevelopmental condition that manifests as ineffective communication, lack of cognition and restricted social behaviors (Chowdhury et al., 2024; Zhang et al., 2022). The variation in clinical manifestations of the disease makes its diagnosis challenging (Klaiman et al., 2024). Traditionally, ASD was diagnosed by observing patients' behaviors and using subjective observational tools which led to diagnostic delays (Qin et al., 2024). Moreover, the treatment of ASD requires a comprehensive approach that targets patients' behaviors, learning skills, education as well as disease pathophysiology (Shi et al., 2021). The need for a comprehensive treatment plan for ASD creates difficulties for psychiatrists in developing personalized treatment plans for autistic children, negatively impacting the effectiveness of therapy and reducing the productivity of treatment in terms of behavioral outcomes (Shi et al., 2021).

Since the advent of artificial intelligence (AI) globally, the field of neurosciences has been revolutionized through the widespread use of AI in the diagnosis and treatment of neurodevelopmental disorders such as ASD (Moridian et al., 2022). Artificial intelligence-based diagnostic instruments have transformed early identification through examination of multimodal information, such as neuroimaging (fMRI, EEG), behavioral routines, and genetic signs. Machine learning algorithms attain a 90% success rate in differentiating ASD from neurotypical development by identifying biomarkers in patterns of brain connectivity and eye tracking (Jia et al., 2023; Wankhede et al., 2024). For example, deep learning algorithms used with functional MRI scans may identify unusual neural signatures in infants as early as 6 months, allowing interventions within key windows of neuroplasticity (Chowdhury et al., 2024; Jia et al., 2023). Such technologies bypass subjectivity and timeliness of traditional diagnosis tests like the Autism Diagnostic Observation Schedule (ADOS) (Chowdhury et al., 2024).

Clinical uses of AI are most promising in social skills development. Humanoid robots like Kaspar have been shown to be effective in enhancing communication and emotion detection by utilizing interactive scenarios that promote social reciprocity (Wankhede et al., 2024; Zhang et al., 2022). Augmented reality (AR) devices combined with AI algorithms feedback in real time while facilitating social interactions decreases anxiety and increase adaptive responses in clinical trials (Doulah et al., 2023; Zhang et al., 2022). Physiological sensor wearables and machine learning classifiers are now enabling real-time monitoring of stress indicators such that caregivers may foresee meltdowns through predictive modeling (Vignapiano et al., 2024; Zhang et al., 2022). New studies highlight how AI-powered virtual reality environments advance theory of mind skill by 40% above conventional therapy in adolescents with ASD (Doulah et al., 2023; Wankhede et al., 2024).

AI has made customizable treatment planning possible by the capability of AI to combine heterogeneous data streams. Master Data Plan (MDP) architecture integrates genomic profiles, sensor readings from IoT, clinical histories and develops dynamic intervention models which continuously update themselves based on the personalized symptom severity of a patient as well as learning styles of choice (Vignapiano et al., 2024). This method has minimized treatment outcome variability in multicenter trials, especially among nonverbal participants who are helped by visual communication systems created by AI (Chowdhury et al., 2024; Vignapiano et al., 2024). Neuro-GPT EEG and other multimodal interfaces now integrate neural data with behavioral outputs to tailor therapy timing and content presentation (Vignapiano et al., 2024).

International research collaboration has hastened such innovations, with the United States (164 studies), China (90 studies), and India (65 studies) being top producers of AI-ASD research (Chowdhury et al., 2024). Stanford University and McGill University have been at the forefront of machine learning techniques for use in finding biomarkers for ASD, while new technologies such as brain-computer interfaces have exhibited promising potential in improving cognitive flexibility (Chowdhury et al., 2024; Jia et al., 2023). Yet, challenges still exist around algorithmic bias against diverse populations as well as clinician translation of research prototypes (Jia et al., 2023; Wankhede et al., 2024). AI diagnostic models remain prospectively validated in real-world environments only by 12%, highlighting the lack of strong multiethnic datasets as well as frameworks for clinician-AI collaboration (Jia et al., 2023; Vignapiano et al., 2024).

Multiple AI technologies have been developed and utilized till now which have shown effectiveness in early diagnosis of disease, predicting the disease course and affecting the treatment outcomes of autism with variable results targeting variety of personal skills in children with autism. This systematic review aimed to summarize the literature describing use of AI technology in improving treatment outcomes in ASD in recent decade.

Methodology

Study Registration

The Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines were followed in reporting this systematic review and meta-analysis, which was carried out in accordance with a protocol created in advance and registered with the Prospective Register of Systematic Reviews (PROSPERO) (http://www.crd.york.ac.uk/PROSPERO/) under registration number: CRD42025644815.

Search Strategy

The literature was searched from January 2015 to January 2025 by using Google Scholar and Pubmed as search engines. "Artificial intelligence", "machine learning", "deep learning", "autism spectrum disorder" and "treatment outcomes" were used as keywords while using MeSh terms and Boolean operators (AND/OR). All the articles describing effect of AI technology on treatment outcomes in autism and published in English language were included in this study. Studies describing the role of AI in diagnosing autism or predicting treatment outcomes were not included in this review. Moreover, we excluded animal studies, all types of reviews, documentaries, editorials, letter to editors, non-English language literature and studies without free access. Duplicates from search literature were removed manually. Snowballing method was applied to references of recruited articles to expand our research.

Data Screening

The screening of recruited data was done in accordance to PRISMA (Institute, 2020). A total of 2774 searches were obtained by using defined search strategy. After removal of duplicates, 2706 studies were included in data screening. Search strategy is summarized in Figure 1.

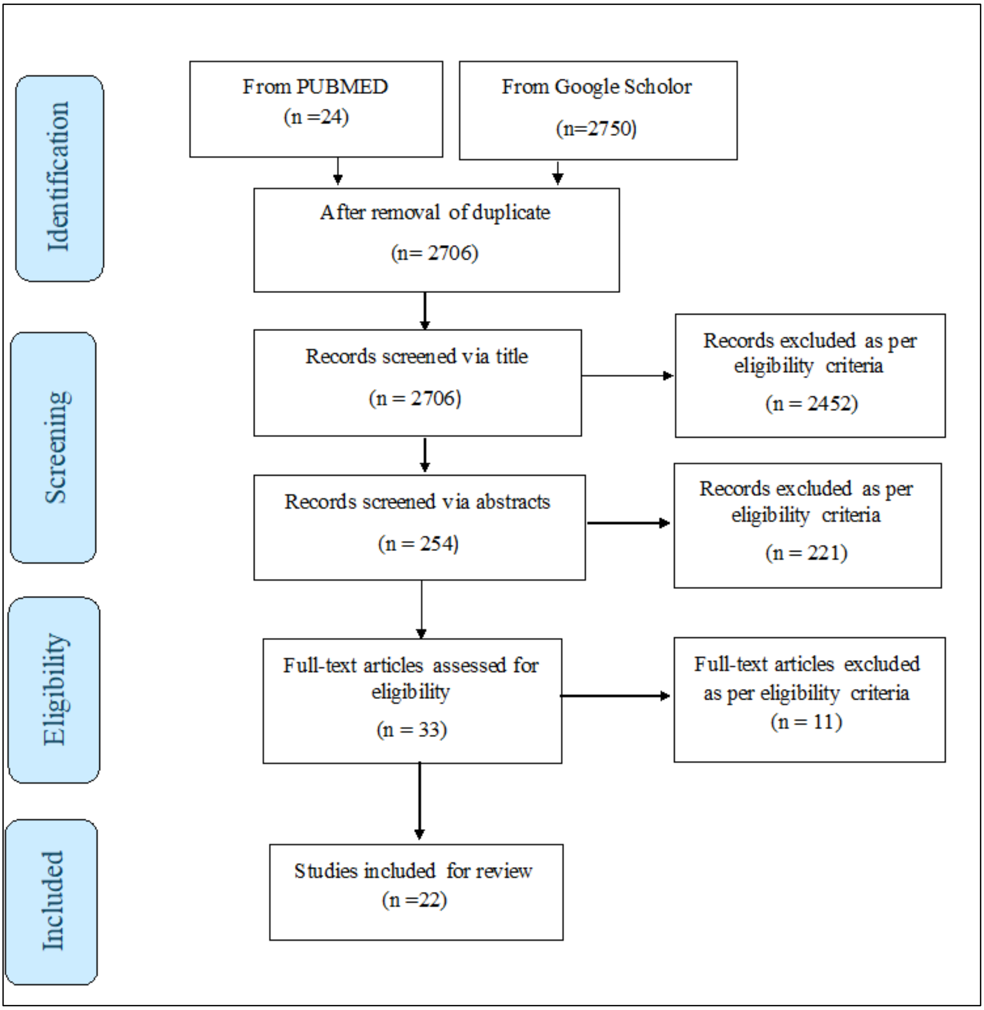

Figure 1. Schematic Presentation of Search Strategy

Quality Assessment

The quality assessment of the articles included was done using Joanna Briggs Institute (JBI) checklist of critical appraisal. The results of critical appraisal were classified as selection bias, performance bias, attrition bias, detection bias and reporting bias. The overall risk of bias was low in majority of the studies included. The results of critical appraisal of included studies are shown in Figure 2.

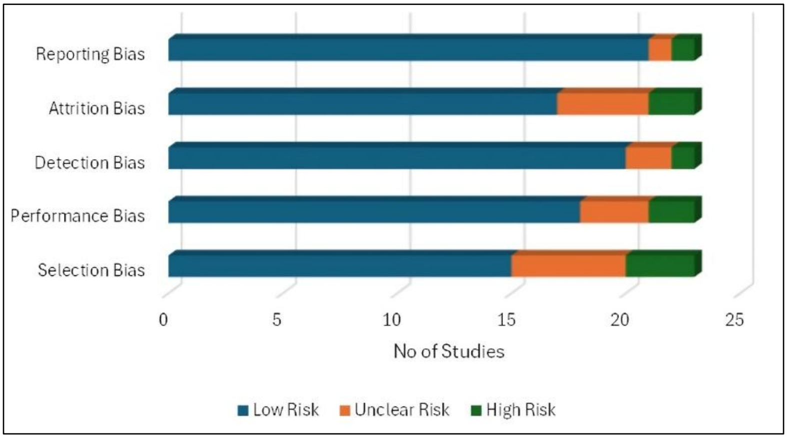

Figure 2. Quality Assessment of Included Studies

To ensure a more robust evaluation, we further examined each study's methodological rigor, noting that randomized controlled trials (RCTs) comprised 41% of included studies, providing stronger internal validity. However, several studies utilized mixed-method or qualitative designs, which, while valuable for contextual insights, lacked blinding or standardized outcome metrics, potentially introducing bias.

Additionally, we performed a cross-sectional comparative analysis of the methodologies applied across different AI modalities. Robotics-based interventions, particularly those using humanoid robots like NAO, generally incorporated structured protocols and objective behavioral measures. In contrast, mobile app-based interventions such as Superpower Glass employed digital tracking and wearable sensors, offering real-time quantitative data but were often conducted over shorter durations. IoT-enhanced ABA therapies, although innovative in integrating physiological monitoring, relied heavily on environmental variables and lacked uniformity in intervention duration and intensity.

Data Extraction and Analysis

A total of 22 articles were included in our systematic review after data screening. The cumulative sample size was 487. Most of the study participants were males accounting for almost 52% of sample size whereas gender was not discussed in almost 32% of included studies. The gender distribution of study participants is provided below in figure 3.

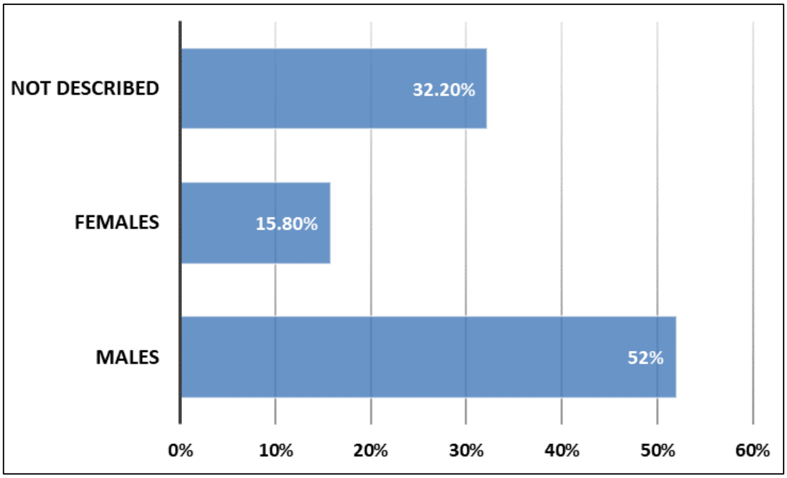

Figure 3. Gender Distribution of Study Participants

The author's name, year of publication, type of research, sample size, age (mean/ranges), type of intervention done and duration of intervention was recorded in Table 1. Additionally, study outcomes, assessment tools, and findings were recorded in Table 2.

Table 1. Summary of Included Studies

Author	Year	Type of study	Sample Size	Mean Age/ Range	Intervention	Duration of Intervention
(So et al., 2018)	2018	RCT	45	4-6	Robot-based gestural training sessions (NAO)	9 weeks
(Yun et al., 2017)	2017	RCT	15	4-7 5.75±0.89 (TG) 6.32±1.23 (CG)	Robotic behavioral intervention programs (iRobiQ and CARO)	8 session, 30-40 min each
(Conti et al., 2021)	2018	Mixed-method	6 Only males	104.3±18.6 months	Robot-assisted imitation training (NAO)	3 months
(Srinivasan et al., 2015)	2016	Pilot RCT	36 32 females 4 males	5-12	Rhythm and Robotic Interventions (NAO and Rovio)	8 weeks (4 session/week)
(Costescu et al., 2017)	2017	RCT	27 20 males 9 females	6-12 8.7±1.8	Robot-Enhanced Cognitive behavior therapy (Keepon)	6 weeks (2-hourly session)
(Lyu et al., 2024)	2024	Pilot Mixed-method	24 21 males 3 females	6.0±2.3	social-emotional game (EMooly)	40 mins

Author	Year	Type of study	Sample Size	Mean Age/ Range	Intervention	Duration of Intervention
(Wong et al., 2021)	2021	User Study with IoT-Enhanced ABA	15 11 males 4 females	7-16	ABA therapy via 3i learning system	10 week
(Clabaugh et al., 2019)	2019	Single-case study model	17 15 males 2 females	3-8	Socially Assistive Robots (SPRITE)	30 days
(Chung, 2021)	2020	Quasi-experimental time-series design	15	5-11	Robotic educational programme (NAO)	12 weeks
(Voss et al., 2019)	2019	RCT	71 63 males 8 females	8.38±2.46	Superpower Glass intervention	6 weeks
(Herrero-Martín et al., 2024)	2024	Mixed-method pilot study	11	5-13	Interactive Robotic intervention (NAO)	-
(Ali et al., 2020)	2020	Preliminary longitudinal study	8	3-10	Standardized multi-robot therapy (NAO)	10 Weeks
(Telisheva et al., 2022)	2022	Case-by-case analysis	34 32 males 2 females	3-12	Robot-Assisted Therapy (NAO)	10 Days
(Ilijoski et al., 2022)	2022	Quantitative Evaluation	20	23-76 M	Robot-Assisted therapy (Kaspar) robot, complemented by a web and mobile application	-
(Fachantidis et al., 2020)	2020	robot-mediated intervention study	22 14 males 8 females	9.9	3D LEGO robot bicycle model	5 Months
(Urdanivia Alarcon et al., 2021)	2021	**qualitative study**	3	9-13	Robot-Assisted Therapy (NAO)	**3–4 sessions**, with each session lasting **2–5 minutes**.
(Feng et al., 2022)	2022	Pilot Study	16	11.73 & 10.22	Robot-Assisted Therapy (NAO).	8 Months

Author	Year	Type of study	Sample Size	Mean Age/ Range	Intervention	Duration of Intervention
(Silva et al., 2019)	2019	Preliminary comparative study	23 21 males 2 females	5-10 >20	Robotic dog (Zoomer dog from SpinaMaster)	three test sessions) one per experimental condition) separated by a one-week "wash-out" period
(Alnafjan et al., 2024)	2025	Experimental study	7 6 males 1 female	5 to 9	Deep learning-based imitation detection system (NAO robot)	3 weeks (30 sessions)
(Panceri et al., 2021)	2021	Pilot study	6 5 males 1 female	4 to 12	social robot integrated with the concept of Serious Games (MARIA T21)	-
(Zhang et al., 2019)	2019	RCT	40 5 females 35 males	ASD:5.08-8.83 (6.79±0.93) CG: 5.24–7.32 (6.35±0.56)	Robot-Assisted Therapy (Distrust and deception games played by NAO)	25 min
(Bharatharaj et al., 2017)	2017	RCT	24	6-16 9.71±3.24	Robot-Assisted therapy (KiliRo)	49 days

Table 2. Treatment Outcomes in Included Studies

References	Outcomes	Assessment Tool	Findings
(So et al., 2018)	Accuracy of gestural production Verbal imitation	Gesture recognition tests	Improved Gestural production and verbal imitation
(Yun et al., 2017)	Eye contact, Facial emotional recognition	Eye contact tracker	Improved eye contact; similar facial emotion recognition
(Conti et al., 2021)	Gross motor skills	TEACCH assessment	Improved Gross Motor Imitation skills
(Srinivasan et al., 2015)	Gross motor skills, imitation, praxis, interpersonal synchrony	BOT-2 (Bruininks-Oseretsky Test of Motor Proficiency), imitation error score, custom-developed test activities	Enhanced body coordination and facilitated interpersonal synchrony. Fine motor skills showed improvement within the control group.
(Costescu et al., 2017)	Social knowledge, Beliefs (Rational, Irrational), Emotional intensity, Adaptive behaviors	frequency of correct strategies to be used in a social situation, frequency of used	Enhancements in rational beliefs and a decrease in emotional intensity; however, no notable differences in adaptive

References	Outcomes	Assessment Tool	Findings
		rational beliefs or irrational beliefs, emotional intensity rating scale, frequency of using adaptive and dezadaptive behaviors	behavior or social knowledge
(Lyu et al., 2024)	Social emotional involvement	Self-structured questionnaire and interview	Improved social-emotional involvement
(Wong et al., 2021)	Task mastery, Teacher reception	Behavior Interventions Rating Scale (BIRS)	IoT-ABA system is effective in improving task mastery and have good teacher reception.
(Clabaugh et al., 2019)	Participant engagement, numerical operations, mathematical learning	Wechsler Individual Achievement Test (WIAT II)	Significant cognitive gains in intervention group
(Chung, 2021)	Eye contact, verbal initiation	Eye contact during communication, verbal initiation frequency	Improved eye contact (in frequency and duration) and verbal initiation
(Voss et al., 2019)	Adaptive functioning, facial engagement, emotional recognition	Vineland Adaptive Behaviours Scale socialization subscale, Developmental Neuropsychological Assessment, Second edition (NEPSY-II), Emotion Guessing Game (EGG)	improve social behavior, facial engagement and emotion engagement
(Herrero-Martín et al., 2024)	Language, social skills	Educator's assessment	Improved motivation level, social interaction and engagement
(Ali et al., 2020)	Improvement in multi-human interaction skills	human-human interaction (HHI),Childhood Autism Rating Scale (CARS)	Improved in social communication
(Telisheva et al., 2022)	Engagement, valence, smiling, affection, curiosity, aggression, stereotyped behaviors, and word count.	ELAN software for behavior coding. Likert scale for engagement and valence.	Improved engagement and socio-emotional outcomes.
(Ilijoski et al., 2022)	Personification of therapy and patient improvement	Multiple self-structured questionnaires	developmental evaluation showed positive changes in children's behavior and skills in less than half of included patients.

References	Outcomes	Assessment Tool	Findings
(Fachantidis et al., 2020)	Development of social, communicational, and emotional skills, along with a reduction in challenging behaviors	Sociometric tests	Improved social and communication skills, Reduced challenging behaviours
(Urdanivia Alarcon et al., 2021)	Improvement in motor control, turn-taking skills, and emotional arousal detection, Expressivity reactions	instrument designed to evaluate facial, verbal, and body expressions, scored on a Likert scale (0–4).	Facilitated emotional expressiveness and imitation skills. However, the level of progress varied among participants, depending on their emotional state and familiarity with the robot.
(Feng et al., 2022)	Social interaction, Social communication	EDA signal analysis, video annotations, and a custom scoring system	Improved motor control and turn-taking skills, Results in Emotional arousal
(Silva et al., 2019)	Social communication behavior, parasympathetic activity	percentage of appropriate responses, emotional ratings, Time domains, frequency domains	Living dogs are particularly effective in promoting suitable social interactions and improving emotional regulation. robotic dogs do not provide the autonomic advantages.
(Alnafjan et al., 2024)	Imitation skills	Verbal Behavior Milestones Assessment and Placement Program (VB-MAPP) assessment tool	Enhanced imitation skills
(Panceri et al., 2021)	Social interaction	Goal Attainment Scale	Enhanced the interaction between the mind and body, thereby fostering improved adherence to therapy
(Zhang et al., 2019)	Distrust, deception, Anthropomorphic thinking, social learning	Performance scores, anthropomorphic thinking questions	Facilitated learning of social rules and showed that children’s perception of the robot plays an important role in their social learning,
(Bharatharaj et al., 2017)	Social interaction, learning, physiological effects	Social network density, letter and number recognition score, Mean protein and amylase levels, blood pressure, Heart rate, and SPO2	improved learning and social interaction abilities, and reduced stress levels, no physiological change

To better understand relative effectiveness, we compared the three major categories of AI tools used:

- **Humanoid Robots (e.g., NAO, MARIA T21):** These demonstrated strong improvements in imitation, emotional expression, and motor coordination across diverse cultural settings. Most robot-based studies had medium-to-high quality scores and employed standardized assessments such as BOT-2 and Vineland Scales.
- **Mobile Applications (e.g., Superpower Glass, Emooly):** These interventions were more accessible and cost-effective but often showed variability in adherence and limited long-term follow-up. Their strengths lay in portability and personalization, although some studies lacked control groups.
- **IoT-based ABA Systems (e.g., 3i Learning System):** These integrated real-time monitoring with behavioral feedback, enhancing ecological validity. However, they were constrained by the need for technical infrastructure and showed mixed methodological consistency across studies.

In addition to categorizing the AI modalities, we noted that several robotic interventions particularly those involving the NAO robot (Ali et al., 2020; Conti et al., 2021; So et al., 2018) utilized Wizard-of-Oz (WoZ) technology. In these setups, human operators controlled the robot behind the scenes to simulate autonomy, which may influence the intervention's perceived effectiveness and ecological validity. Differentiating WoZ-based designs from fully autonomous systems is important for interpreting outcomes and scalability.

Results

The AI interventions utilized in included studies is categorized into IOT-Enhanced Applied Behavioral Analysis (3i-Learning system, AI-mediated smartphone based therapy and robotics-assisted interventions). The distribution of type of AI-mediated autism therapy used and percentage of studies is provided in Figure 4.

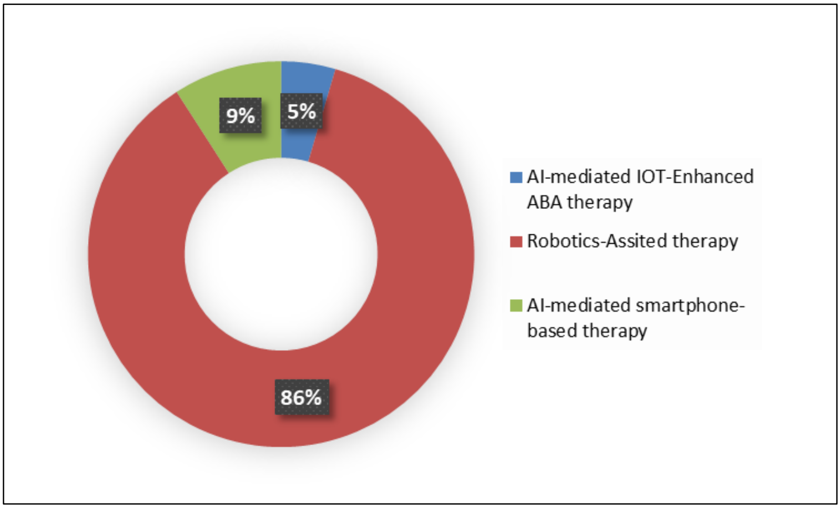

Figure 4. Types of AI-mediated Autism Therapy in Included Studies

Social and communication development was the most commonly observed treatment outcome in included studies followed by motor and physiological development, cognitive and behavioral adaptations and learning or academic performance as shown in Figure 5.

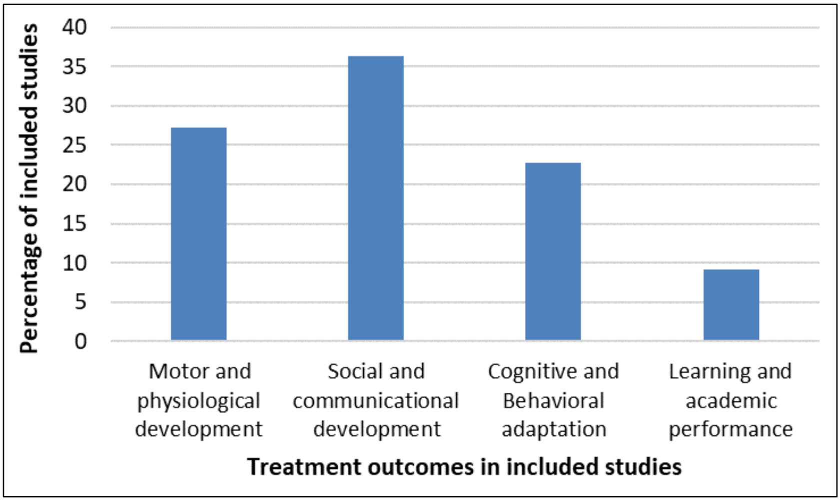

Figure 5. Distribution of Treatment Outcomes in Included Studies

IOT-Enhanced Applied Behavioral Analysis (3i-Learning system)

The integrated Intelligent Intervention- learning system (3i-learning system) is developed through synchronization of traditional Applied Behavioral therapy (ABA therapy) with the AI technology. It comprises of two-level integration with the first level targeting integration of parents and caregivers to the personalized educational plans for their children followed by second level integration focusing over AI and Internet-Of things (IoT) measurements (Clabaugh et al., 2019). It enables the parents and caregivers of children with ASD to monitor the progress of IOT-Enhanced ABA therapy in terms of task performance, environmental factors and physiological factors that may impact child learning performance. Moreover, it serves as an effective assistant of parents and caregivers with regards to developing personalized therapy plans to improve development and progress of system (Clabaugh et al., 2019). The 3i-learning system comprises of three core functional components including student-centered learning environment (SCLE) (Contexts, Tools, Resources and Scaffolds). Modularized learning object (physical or digital) and an emotion recognizer (IoT-based data collection device and an AI-device to detect emotions by detecting physiological factors) (Clabaugh et al., 2019).

A summary of the main studies evaluating IoT-Enhanced ABA interventions, their samples, tools used, and effect sizes is presented in Table 3.

Table 3. Summary of IoT-Enhanced ABA studies

Study	Sample	Tool Used	Effect Size / Outcome
(Wong et al., 2021).	15 students (7–16 yrs)	IoT-based sensors, task mastery assessments	86.7% task mastery; ~2 hrs per task; mean gain +5 points per session
(Clabaugh et al., 2019).	17 children (3–8 yrs)	Emotion recognizer (IoT, AI)	Personalized therapy; improved engagement and cognitive performance

In a study conducted with 15 students by Wong et al. (2021), it was found that 86.7% achieved mastery in at least one training task, while 59.6% of the tasks fulfilled the mastery criteria after an average of 3.86 sessions, equating to approximately 2 hours per task (Wong et al., 2021). The interventions resulted in stable gains in learning, with tasks showing a mean increase of 5 points per session. Additionally, AI-driven IoT-sensors monitored physiological and environmental variables, uncovering findings such as the detrimental effects of CO_2 levels on learning performance, as well as correlations between classroom temperature, Galvanic Skin Response (GSR), and skin temperature. This monitoring facilitated customized interventions, enhancing the learning environment for improved results. Even the teachers highlighted that the AI-enhanced therapy is effective in enhancing students' attention and ability to follow directions (Wong et al., 2021).

Robotics-assisted Interventions

Children with ASD often have difficulty interpreting nonverbal cues, making eye contact, expressing their emotions, and understanding others' feelings. They also struggle with imitation skills, using these behaviours less frequently than their typically developing peers. Imitation includes body movements, whispering, and facial expressions, which are essential for interaction with parents. Robots have played a supportive role in numerous human activities, including the rehabilitation of individuals with ASD. The integration of social or interactive robots into clinical settings shows potential for enhancing the social abilities of children diagnosed with ASD (Alnafjan et al., 2024; Bharatharaj et al., 2017; Feng et al., 2022; Zhang et al., 2019). A total of 11 types of robots have been used in included studies for robot-assisted therapy with NAO being the most frequently utilized humanoid robot i.e., used in approximately 52% of included studies. The percentage distribution of types of robots in included studies is provided below in Figure 6, and a structured summary of the main findings is presented in Table 4.

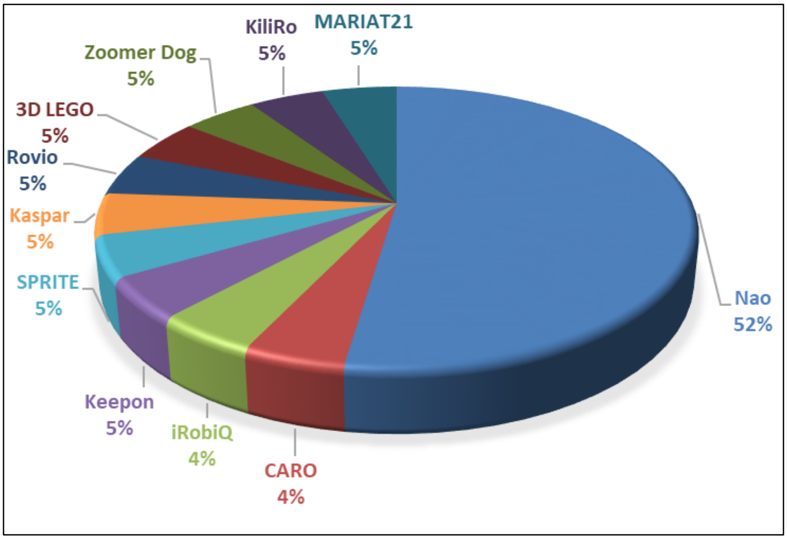

Figure 6. Percentage Distribution of Robots Used in Included Studies

Alnafjan et al. assessed the efficacy of robot-assisted intervention by NAO in improving imitation skills among children with ASD in relation to conventional therapy methods (Alnafjan et al., 2024). The Softbank Robotics NAO is a humanoid robot from SoftBank Group Corporation, featuring 25 degrees of freedom for diverse human-like movements. Its microphones have a sensitivity of 20 mV/Pa ± 3 dB at 1 kHz, with an input frequency range of 150 Hz to 12 kHz. The group that underwent robot-assisted therapy demonstrated an average enhancement in imitation skills of

17.14%, in contrast to the non-robotic group, which achieved a mere 2.86% improvement, despite numerous children encountering difficulties. The results for the robot-assisted group were consistently more favorable, as children in this cohort demonstrated greater accuracy in tasks such as imitating clapping. In addition, experts gave feedback that the children showed increased excitement, interest, and concentration in the robot-mediated sessions. The feedback included statements such as "the children look excited and cannot wait to see the robot following each session" and "we have not seen such enjoyment during previous sessions" (Alnafjan et al., 2024).

Various researches covered by this review have examined the influence of a humanoid robot, NAO, a robotic assisted treatment in ASD and reported high flexibility in terms of meeting needs of children with ASD (Ali et al., 2020; Bharatharaj et al., 2017; Costescu et al., 2017; Feng et al., 2022; Ilijoski et al., 2022; Panceri et al., 2021; Silva et al., 2019; Srinivasan et al., 2015; Telisheva et al., 2022; Voss et al., 2019; Yun et al., 2017). NAO, with the size-weight measurement of about 58 cm and 5 kg and 25 degrees of freedom, is a humanoid robot that ensures stability and nimble movements through the utilization of inertial navigation system. In addition, it can detect and navigate obstacles in the surrounding environment accurately (Bharatharaj et al., 2017).

Feng et al. (2022) stable turn-taking skills and motor task accuracy in almost 67% and 70% of study participants in 50 sessions respectively by using NAO-based music therapy as well as a significant improvement in emotional arousal when detected by electrodermal activity signals (Feng et al., 2022). Similarly, Alarcon et al. have put emphasis over the impact of NAO-assisted video-based interventions on enhancing the expressiveness of children (body, verbal and facial) while using pre-recorded video sessions (Urdanivia Alarcon et al., 2021). Zhang et al. (2019) assessed the mechanism of acquiring complex social skills by using robot-assisted game therapy designed on the principles of distrust and deception in children with ASD and found that autistic children skills to distrust and deceive social robots in comparison to control group yet these children exhibited exceptional performance in learning to distrust a robot compared to a real person, especially during the initial stages of the distrust task. These finding support the nuances in acquiring social skills among children with and without autism (Zhang et al., 2019). Similarly, So et al. (2018) noted a significant improvement in gesture performance score in children suffering from ASD while using robot-assisted therapy by NAO i.e., 41% improvement with $p < 0.001$ (So et al., 2018).

MARIA T21 is a socially assistive robot, with a height of about 1.40 m, widely recognized in research due to the capabilities it carries in assisting effective adaptation to the needs of an autistic child. Its capacity for customization based on the therapeutic attitude allows it to function as a friend or a mentor. In addition, it is able to project visual stimuli on several surfaces while at the same time interacting with children and providing instructions and motivation to children with ASD through music therapy and pre-recorded audio messages (Zhang et al., 2019). Panceri et al. tested the efficiency of the MARIA T21-based game therapy in enhancing therapeutic results for ASD children with Goal Attainment Scaling (GAS) of 8 to 10 with outstanding scores in some activities such as clapping verbal response. In addition, it enhanced therapists-children interaction by inducing a dynamic mind-body (Panceri et al., 2021).

The findings from Silva et al. (2019) reported that live dogs outperformed robotic dogs and no-stimulus condition in eliciting social communication behavior and cardiac autonomic activity among children (Silva et al., 2019). On the other hand, robotic dogs were as effective as live dogs in adults. Remarkably, children demonstrated a significantly higher percentage of correct responses when there were live dogs (68.65 ± 11.26) than when there were robotic dogs (48.00 ± 16.21; $p = 0.011$) or when there were no stimuli (34.38 ± 12.73; $p < 0.001$). In adults, the live dog (54.69 ± 13.94) and robotic dog (63.56 ± 13.19) conditions each elicited significantly better responses than the no-stimulus condition (32.38 ± 7.50; $p < 0.003$), and no significant difference was found between the live dog and robotic dog conditions (Silva et al., 2019). In terms of heart rate variability (HRV), the condition involving dogs demonstrated a greater level of parasympathetic activity, evidenced by notable enhancements in LnRR (dog: -0.47 compared to no stimulus: 0.16; $p = 0.043$), LnSDNN (dog: 0.228 versus no stimulus: -0.91; $p = 0.030$), and LnRMSSD (dog: 0.372 against robot: -0.099; $p < 0.001$). Additionally, there were significant increases in LnHFnu within the dog condition (5.668), which markedly surpassed the robot condition (-10.372; $p < 0.001$) and the no-stimulus condition (-7.824; $p = 0.005$). These results highlight the enhanced therapeutic advantages of live dogs in fostering social interaction and emotional regulation, especially among children, while robotic dogs present a viable, though less effective alternative (Silva et al., 2019).

Bharatraj et al. (2017) researched the benefit of KiliRo in improving learning and social interaction abilities, reducing levels of stress, and enhancing the physiological status in a group of 24 children with autism for a period of 49 days (Bharatharaj et al., 2017). KiliRo is a two degree of freedom social interactive robot divided into three segments classified as upper (head, eyes), middle (body, wings and tail), and lower (legs). KiliRo has two wireless cameras and a USB camera that provide a practically 270-degree field of vision, real time video streaming, and letter/number recognition utilizing QR codes.

Srinivasan et al. (2015) examined the effects of robotic and rhythmic interventions on ASD children's motor ability, imitation, and interpersonal synchrony. An 8-week randomized controlled trial was performed where a humanoid robot supported the robotic group in performing gross and fine motor imitation training (Srinivasan et al., 2015). The robot group performed significantly better than the standard-of-care group in both praxis skill ($p < 0.01$) and imitation ($p < 0.05$) based on outcomes, improved their gross motor coordination by 18.3%, and interpersonal synchrony by 21.7%. Based on therapists' assessments, 86% of children showed sustained attention and enthusiasm when participating in the activities, where the children are shown to have been excited about the robotic training (Srinivasan et al., 2015).

The effectiveness of Robot-Enhanced Cognitive Behavioral Therapy (RET) in the treatment of children with ASD with dysfunctional emotional responses was measured by Costescu et al. through the use of Keepon (Costescu et al., 2017). Keepon is a rubber body snow-man like robot that sits on a dark cylinder containing motors and circuit boards. It allows four degrees of freedom of movement and assists in teaching adaptive behaviors in emotionally demanding social interactions and modifying irrational beliefs. There was an improvement in 78% of RET group children for better emotion regulation, and a statistically significant reduction in emotional intensity was seen (p = 0.02). Further, there was an appreciable enhancement in rational beliefs of RET group during Keepon use i.e., 13.46±8.88 vs 4.33±8.49, p=0.007).

To enhance social skills, a robotic behavioral intervention system that places priority on facial emotion recognition and eye contact was developed by Yun et al. (2017). 15 children aged 4 to 7 took part (Yun et al., 2017). Eye contact and facial emotion recognition were significantly improved in both groups; the robotic group's eye contact frequency increased by 32% (p < 0.01). Better social communication results were made possible using humanoid robots, which offered regular, predictable interactions that suited the children's preferences. To overcome accessibility and resource availability constraints, Ilijoski et al. (2022) extended robot therapy via web and mobile applications (Ilijoski et al., 2022). Their hybrid approach improved social skills and engagement by enabling remote, individualized therapy sessions for kids with ASD. The study found that when these digital tools were added to therapy, 92% of children demonstrated improved interaction, and therapists reported a significant decrease in scheduling conflicts.

Table 4: Summary of Robotics-assisted intervention studies

Study	Sample	Tool Used	Effect Size / Outcome
(Alnafjan et al., 2024).	7 children (5–9 yrs)	NAO humanoid robot	17.14% improvement in imitation vs 2.86% in controls
(Feng et al., 2022).	16 children	NAO robot (music therapy)	67% turn-taking, 70% motor accuracy, improved emotional arousal
(So et al., 2018).	45 preschoolers	NAO robot	41% improvement in gesture performance (p < 0.001)
(Panceri et al., 2021)	6 children (4–12 yrs)	MARIA T21	Goal Attainment Scale: 8–10 (high performance)

AI-mediated Mobile Device-based Therapies

Superpower Glass intervention is one effective AI-mediated mobile device-based autism therapy which improved facial recognition and facial engagement (Voss et al., 2019). In this therapy, smart glasses are synced with a smartphone application capable of classifying emotion via machine learning. According to Voss et al. there is a significant improvement in Vineland Adaptive Behaviours Scale socialization subscale score i.e., mean treatment impact of 4.58±1.62, p = 0.005 (Voss et al., 2019). Similarly, Lyu et al. (2024) utilized, a tablet based game, titled as Emooly (an integrated setup of GenAI and augmented reality) in autism therapy and observed significant improvement in social-emotional development of autistic children (Lyu et al., 2024). The details of these mobile device-based interventions are summarized in Table 5.

Table 5. Summary of Mobile Device-based intervention studies

Study	Sample	Tool Used	Effect Size / Outcome
(Voss et al., 2019)	71 children (8.4 ± 2.5 yrs)	Superpower Glass + Smartphone ML app	+4.58 ± 1.62 improvement in Vineland socialization (p = 0.005)
(Lyu et al., 2024)	24 children (6.0 ± 2.3 yrs)	Emooly (GenAI + AR) tablet game	Significant improvement in social-emotional development

Discussion

This systematic review demonstrates that AI technology can effectively enhance ASD treatment results for social interaction while also boosting learning behaviors and stress management together with motor coordination and enhancing cognitive skills. Implementation of AI in learning settings for children with Autism provides better personalized learning opportunities to students through individualized learning strategies. The programming capability based on algorithms of AI creates individualized learning programs which enhances children's engagement and understanding. Smith et al (2023) explained how implementation of AI technology in therapy sessions offers individualized therapeutic strategies which gets adjusted automatically as students exhibit varying learning styles (Smith et al., 2023).

Four of these studies in this systematic review proved that AI-based interventions were able to improve motor coordination and imitation skills in autism. This is supported in literature by Anum et al. (2024) who observed a significant improvement in motor skills learning outcomes of Elementary School Teacher Education (PGSD) by using AI (Anam et al., 2024).

One study in this review demonstrated the role of an AI-driven wearable digital intervention for improving social skills in children suffering from autism in terms of facial engagement and emotion recognition. These findings are consistent to that of a study conducted by Özcan et al (2016) who proposed the effectiveness of transitional wearable companions in improving social skills in children with ASD. While explaining the logical reasoning behind this effectiveness, he stated that robots are controlled by an on-board computer (such as an Arduino board, which responds to the child's actions by emitting lights, sounds, and vibrations when the child acts on its touch or interactive sensors (Özcan et al., 2016).

However, a persistent gap in the current literature is the limited evidence supporting long-term effectiveness of AI-mediated interventions. While many studies demonstrate short-term gains (typically ≤ 12 weeks), few assess whether these improvements persist. For instance, Rakhymbayeva et al. (2021) conducted a month-long, in-home study with 11 children, demonstrating sustained engagement and maintained behavioral improvements over four weeks, but did not include follow-up assessments beyond the intervention period (Rakhymbayeva et al., 2021).

Complementing this, the work by Pakkar et al. (2020) and Clabaugh et al. (2019) involved month-long in-home engagements, revealing that robotic systems could personalize interactions and sustain attention across multiple weeks, yet both concluded with no long-term post-intervention follow-up (Clabaugh et al., 2019; Pakkar et al., 2019).

In addition to clinical efficacy and short-term feasibility, it is vital to assess the cost-effectiveness and accessibility of AI-based therapies for broader clinical adoption. AI-driven therapies have shown promising cost-effectiveness across various domains of healthcare. For example, AI-based mental health chatbots and digital therapeutics reduce costs by automating screening, triage, and support, enabling broader outreach with lower marginal expenditure per patient compared to conventional methods (Fulmer et al., 2018; Rollwage et al., 2022; Sapanel et al., 2023; Yadav, 2021). Economic evaluations demonstrate that AI-supported interventions in mental health, dermatology, dentistry, ophthalmology, and primary care generally outperform standard care or are at least cost-comparable, largely by optimizing resource utilization, minimizing unnecessary interventions, and streamlining workflows (Chang et al., 2021; Gomez Rossi et al., 2022; Khanna et al., 2022; Olawade et al., 2024). Decision-analytic studies in China show that hierarchical, AI-driven screening for cataracts is more cost-effective than both telescreening and conventional approaches in both urban and rural settings (Wu et al., 2024). Similar models in tuberculosis screening, cancer diagnostics, and clinical decision support consistently report improved outcomes and reduced per-patient costs, especially at scale (Olugbami & Ogundeko, 2025; Rao et al., 2025; Zhao & Yuan, 2025).

Scaling AI-driven therapies in resource-limited settings presents both promising opportunities and significant challenges. Notable success stories, such as AI-based tuberculosis detection in rural India and telemedicine initiatives in sub-Saharan Africa, demonstrate that cost-effective deployment is achievable when cloud infrastructure, mobile technology, and community involvement are emphasized (Murrillo, 2024; Olugbami & Ogundeko, 2025). Key enablers of scalability include the use of cloud-based platforms that minimize local computing demands (Olugbami & Ogundeko, 2025), task-shifting and automation to reduce dependency on scarce specialized personnel (Wang et al., 2024), and targeted training programs that empower local healthcare workers to effectively use and interpret AI tools (Hafeez et al., 2024; Pillai, 2023). Nevertheless, barriers such as inadequate infrastructure, workforce shortages, inconsistent data quality, diverse regulatory frameworks, and the need for upfront investment persist (Chomutare et al., 2022; Pillai, 2023; Zhao & Yuan, 2025). To address these challenges, collaborative funding efforts from international donors and government bodies are essential to support initial implementation and ensure long-term sustainability (Murrillo, 2024; Olugbami & Ogundeko, 2025).

AI technologies can be adapted and implemented across diverse healthcare systems, but this process requires careful integration with local clinical workflows and electronic health record systems (Chomutare et al., 2022). Successful implementation depends on the clear identification of clinical objectives to ensure measurable outcomes, active engagement of stakeholders including clinicians, IT teams, and policymakers to address resistance and maintain relevance (Ahluwalia et al., 2025; Olugbami & Ogundeko, 2025), and continuous monitoring and validation to assess real-world performance and detect potential biases (Ahluwalia et al., 2025; Elvidge & Dawoud, 2024). Additionally, variations in legal frameworks, technology adoption rates, and standards of care can influence the speed and scope of AI integration across different healthcare settings (Pillai, 2023; Zhao & Yuan, 2025).

AI-driven therapy solutions offer promising opportunities to enhance healthcare equity and improve access for diverse populations; however, they may also risk reinforcing existing disparities if inclusivity is not intentionally embedded into their design. Key challenges include algorithmic bias, where systems trained on non-representative datasets may perform inequitably for underrepresented groups (Ahluwalia et al., 2025; Ferebee, 2025); the digital divide, which limits access for marginalized communities due to insufficient internet connectivity or device availability (Pillai, 2023; Zhao & Yuan, 2025); and the lack of cultural and linguistic sensitivity, which can hinder effectiveness if interventions are not adapted to local beliefs, languages, and health literacy levels (Ahluwalia et al., 2025; Olugbami & Ogundeko, 2025). To mitigate these issues, best practices recommend strategies such as diverse data collection, federated learning, culturally-aware design, and continuous algorithmic auditing (Ahluwalia et al., 2025; Ferebee, 2025). When such approaches are implemented, AI can play a transformative role in improving accessibility for individuals with disabilities and traditionally underserved communities (Atturu & Naraganti, 2024; Ferebee, 2025). Ultimately, while AI-driven therapies can reduce costs and offer scalable interventions, ensuring equitable access particularly in resource-limited or culturally varied contexts requires careful and inclusive planning (Ahluwalia et al., 2025; Murrillo, 2024; Olugbami & Ogundeko, 2025; Wu et al., 2024).

However, ethical considerations surrounding AI use in ASD therapy warrant critical reflection. Given that the target population children with autism is especially vulnerable, issues like emotional impact, data privacy, and the risk of replacing human therapists must be carefully evaluated. Children with ASD may form attachments to robots or AI tools, leading to possible confusion between real human emotions and programmed responses (Sharkey, 2016). Such emotional dependence could hinder natural social development if not guided appropriately by human clinicians.

Another significant limitation observed in the reviewed studies is the lack of ethnic and cultural diversity among the participant samples. Most of the included studies did not specify the racial or ethnic composition of their cohorts, making it difficult to generalize findings across diverse populations. This homogeneity raises concerns about the cultural applicability of AI interventions, as effectiveness may vary due to sociocultural norms, linguistic differences, or varying levels of technological accessibility. Future research should prioritize the inclusion of multi-ethnic and cross-cultural populations to ensure that AI-mediated therapies are both effective and equitable across demographic boundaries.

Additionally, the use of AI requires extensive data collection, often including sensitive biometric, behavioral, and psychological information. Inadequate data protection practices pose significant privacy risks (Floridi et al., 2018). Many AI systems lack transparency and explainability, making it difficult for caregivers to understand how decisions are made. This black-box nature of AI increases the chances of algorithmic bias, which could exacerbate disparities in therapy access or outcomes across different socioeconomic or ethnic groups (Challen et al., 2019; Char et al., 2018).

Moreover, concerns have been raised about the potential overreliance on AI replacing qualified therapists. Critics emphasize that, although AI may simulate empathic responses, it "lacks the emotional depth and empathy necessary for effective psychotherapy", which are foundational to the therapeutic alliance (Salil et al., 2024). While AI can assist with screening or augmenting treatments, it cannot fully replicate genuine human empathy, intuition, and emotional responsiveness, and thus should be viewed as a support tool rather than a substitute for clinicians.

Consequently, ethical guidelines recommend human-AI collaboration, where AI enhances therapist efficiency but final decisions and emotional care remain under clinician oversight. Moreover, frameworks such as the Belmont Report and contemporary scoping reviews assert the necessity of informed consent protocols, ongoing clinician training, and robust regulatory structures to ensure data privacy, patient agency, and safety in AI-assisted mental health interventions (Cilar Budler & Stiglic, 2025).

The robot-assisted interventions in ASD by NAO, a humanoid robot, have been discussed in four studies included in this review. The findings of these studies confirm previous assessments by Kouroupa et al. (2022) who established that NAO-like robots produce better language development and interaction enhancements along with increased participation than traditional practices for autistic children (Kouroupa et al., 2022). NAO demonstrates its ability to teach children social skills using avatars according to Batool et al. (2024) through instruction in emotional understanding and sharing and eye contact. The system operates as a therapeutic device since its adaptable design lets therapists conduct developmental-supportive sessions for children with individualized targets (Batool et al., 2024)

Another study in this review found that real dogs delivered better results than robotic dogs when it came to boosting the parasympathetic system and emotional management in children. It is evident from literature that AI-driven interventions supply helpful resources to humans yet they do not replicate all advantages which occur when individuals interact with animals directly (Thakkar et al., 2024). According to Haladjian and Montemayor (2016) AI imitates attention processes yet fails to replicate both human emotional capacity and empathetic abilities (Haladjian & Montemayor, 2016). The utilization of physiological markers as stress evaluation tools represented a new approach in two studies performed included in this review. They proved robot-aided therapy generated important α-amylase enzyme activity reductions in saliva of children confirming their decreased state of stress. Moreover, they investigated external influences on the execution of a task such as CO_2 conditions within their study and proposed enhancements for therapy. The present findings augment those found previously by Thakkar et al. demonstrating how AI neurofeedback and biofeedback systems form individual abilities in order to control and observe biological reaction. By providing instantaneous feedback of heart rate and brain activity as well as other physiological signs, such systems allow a person to acquire self-regulatory skills for stress response control (Thakkar et al., 2024).

Conclusion

This systematic review presents the evidence of AI-supported interventions to improve therapy outcomes in ASD children, particularly motor skills, social communication, cognition, and tolerance to stress. AI-mediated interventions such as robotics-assisted therapy, Internet of Things-enhanced ABA, and AI-assisted mobile applications have reflected noteworthy improvements in social interaction, motor skills, and emotional interpretation. The application of tailored approaches facilitated by AI has the potential to personalize therapies to suit the particular needs of the individual, ultimately giving rise to improved motivation and learning. Though challenges exist with standardization and validation, the potential for benefit through AI-facilitated interventions points toward a positive direction for future implementation and research in ASD treatment.

Limitations and Future Implications

Limitation exists within this research review method. Studied methodologies varied within the selected research including randomized controlled trials as well as case studies. The various experimental methods make it difficult to make direct comparisons and conduct meaningful statistical analyses which in turn lowers the findings' applicability to other situations. Future studies should emphasize on large-scale, longitudinal designs to confirm AI-mediated therapies for ASD. Future research must also emphasize on developing standardized protocols and sampling participants from diverse backgrounds at longer intervention lengths to monitor AI-based therapy development success. Moreover, the current body of literature reviewed suffers from a notable lack of demographic diversity, particularly in terms of ethnicity and cultural background. This limitation restricts the generalizability of findings across diverse populations. To enhance the inclusivity and relevance of AI-based interventions in ASD therapy, future studies must incorporate participants from varied ethnic, cultural, and socio-economic backgrounds. Ensuring demographic diversity is essential for understanding how AI tools perform in real-world, multicultural settings. Furthermore, incorporating real-time monitoring and feedback mechanisms could also further tailor treatment, enhancing outcomes. Moreover, ethical considerations, algorithmic bias, and accessibility is also important to ensure the equitable utilization of AI in ASD therapy.

Authors' Notes

Data Availability: The data presented in this study is available upon request from the corresponding author.

Ethical Approval: Not applicable.

Acknowledgments: The authors are grateful to the King Salman Center for Disability Research for supporting this work under Research Group no. KSRG-2024-259.

Funding: This work was supported by the King Salman Center for Disability Research through Research Group no. KSRG-2024-259.

Conflicts of Interest: The authors declare that there is no conflict of interest to disclose.

References

Ahluwalia, M., Sehgal, S., Lee, G., Agu, E., & Kpodonu, J. (2025). Disparities in Artificial Intelligence-Based Tools Among Diverse Minority Populations: Biases, Barriers, and Solutions. *JACC Adv*, *4*(5), 101742. https://doi.org/10.1016/j.jacadv.2025.101742

Ali, S., Mehmood, F., Khan, M. J., Ayaz, Y., Asgher, U., Sadia, H., Edifor, E., & Nawaz, R. (2020). A preliminary study on effectiveness of a standardized multi-robot therapy for improvement in collaborative multi-human interaction of children with ASD. *IEEE Access*, *8*, 109466-109474.

Alnafjan, A., Alghamdi, M., Alhakbani, N., & Al-Ohali, Y. (2024). Improving Imitation Skills in Children with Autism Spectrum Disorder Using the NAO Robot and a Human Action Recognition. *Diagnostics*, *15*(1), 60.

Anam, K., Sadli, M., & Wijaya, H. (2024). Analysis of artificial intelligence (AI) utilization for improving motor skills learning outcomes among elementary school teacher education (PGSD) students. *DIAJAR: Jurnal Pendidikan dan Pembelajaran*, *3*(2), 202-209.

Atturu, H., & Naraganti, S. (2024). Effectiveness of AI-driven Individualized Learning Approach for Children with Autism Spectrum Disorder (ASD). *European Psychiatry*, *67*(S1), S77-S77.

Batool, S., Akhtar, M. N., Anjum, S. A., Kousar, R., Zahid, A., & Nawaz, M. (2024). Enhancing Scientific Writing with AI: Evaluating Tools, Practices and Future Implications. *Dialogue Social Science Review (DSSR)*, *2*(3 (October)), 281-323.

Bharatharaj, J., Huang, L., Al-Jumaily, A., Mohan, R. E., & Krägeloh, C. (2017). Sociopsychological and physiological effects of a robot-assisted therapy for children with autism. *International Journal of Advanced Robotic Systems*, *14*(5), 1729881417736895.

Challen, R., Denny, J., Pitt, M., Gompels, L., Edwards, T., & Tsaneva-Atanasova, K. (2019). Artificial intelligence, bias and clinical safety. *BMJ quality & safety*, *28*(3), 231-237.

Chang, L., Wu, J., Moustafa, N., Bashir, A. K., & Yu, K. (2021). AI-driven synthetic biology for non-small cell lung cancer drug effectiveness-cost analysis in intelligent assisted medical systems. *IEEE Journal of Biomedical and Health Informatics*, *26*(10), 5055-5066.

Char, D. S., Shah, N. H., & Magnus, D. (2018). Implementing machine learning in health care—addressing ethical challenges. *The New England journal of medicine*, *378*(11), 981.

Chomutare, T., Tejedor, M., Svenning, T. O., Marco-Ruiz, L., Tayefi, M., Lind, K., Godtliebsen, F., Moen, A., Ismail, L., Makhlysheva, A., & Ngo, P. D. (2022).

Artificial Intelligence Implementation in Healthcare: A Theory-Based Scoping Review of Barriers and Facilitators. *Int J Environ Res Public Health*, *19*(23). https://doi.org/10.3390/ijerph192316359

Chowdhury, M., Gould, M., & Ganti, L. (2024). Advances in Autism: a bibliometric analysis. *Health Psychol Res*, *12*, 125844. https://doi.org/10.52965/001c.125844

Chung, E. Y.-h. (2021). Robot-mediated social skill intervention programme for children with autism spectrum disorder: An ABA time-series study. *International Journal of Social Robotics*, *13*(5), 1095-1107.

Cilar Budler, L., & Stiglic, G. (2025). Ethical approval and informed consent in mental health research: a scoping review. *AI & SOCIETY*, 1-18.

Clabaugh, C., Mahajan, K., Jain, S., Pakkar, R., Becerra, D., Shi, Z., Deng, E., Lee, R., Ragusa, G., & Matarić, M. (2019). Long-term personalization of an in-home socially assistive robot for children with autism spectrum disorders. *Frontiers in Robotics and AI*, *6*, 110.

Conti, D., Trubia, G., Buono, S., Di Nuovo, S., & Di Nuovo, A. (2021). An empirical study on integrating a small humanoid robot to support the therapy of children with Autism Spectrum Disorder and Intellectual Disability. *Interaction Studies*, *22*(2), 177-211.

Costescu, C. A., Vanderborght, B., & David, D. O. (2017). ROBOT-ENHANCED CBT FOR DYSFUNCTIONAL EMOTIONS IN SOCIAL SITUATIONS FOR CHILDREN WITH ASD. *Journal of Evidence-Based Psychotherapies*, *17*(2).

Doulah, A. B. M. S. U., Rasheduzzaman, M., Arnob, F. A., Sarker, F., Roy, N., Ullah, M. A., & Mamun, K. A. (2023). Application of augmented reality interventions for children with autism spectrum disorder (ASD): A systematic review. *Computers*, *12*(10), 215.

Elvidge, J., & Dawoud, D. (2024). Reporting standards to support cost-effectiveness evaluations of AI-driven health care. *The Lancet Digital Health*, *6*(9), e602-e603.

Fachantidis, N., Syriopoulou-Delli, C. K., Vezyrtzis, I., & Zygopoulou, M. (2020). Beneficial effects of robot-mediated class activities on a child with ASD and his typical classmates. *International Journal of Developmental Disabilities*, *66*(3), 245-253.

Feng, H., Mahoor, M. H., & Dino, F. (2022). A music-therapy robotic platform for children with autism: A pilot study. *Frontiers in Robotics and AI*, *9*, 855819.

Ferebee, S. (2025). AI and Accessibility: Breaking Barriers for People with Disabilities. *Premier Journal of Artificial Intelligence*, *2*, 100012.

Floridi, L., Cowls, J., Beltrametti, M., Chatila, R., Chazerand, P., Dignum, V., Luetge, C., Madelin, R., Pagallo, U., & Rossi, F. (2018). AI4People—An ethical framework for a good AI society: Opportunities, risks, principles, and recommendations. *Minds and machines*, *28*(4), 689-707.

Fulmer, R., Joerin, A., Gentile, B., Lakerink, L., & Rauws, M. (2018). Using Psychological Artificial Intelligence (Tess) to Relieve Symptoms of Depression and Anxiety: Randomized Controlled Trial. *JMIR Ment Health*, *5*(4), e64. https://doi.org/10.2196/mental.9782

Gomez Rossi, J., Rojas-Perilla, N., Krois, J., & Schwendicke, F. (2022). Cost-effectiveness of Artificial Intelligence as a Decision-Support System Applied to the Detection and Grading of Melanoma, Dental Caries, and Diabetic Retinopathy. *JAMA Netw Open*, *5*(3), e220269. https://doi.org/10.1001/jamanetworkopen.2022.0269

Hafeez, M., Haq, M. Z. U., Tahzeem, Z., Rahim, S., & Rao, N. (2024). AI ASSOCIATED CHALLENGES TO PHYSICAL THERAPY PROFESSION. *Insights-Journal of Health and Rehabilitation*, *2*(2 (Health & Allied)), 531-538.

Haladjian, H. H., & Montemayor, C. (2016). Artificial consciousness and the consciousness-attention dissociation. *Consciousness and Cognition*, *45*, 210-225.

Herrero-Martín, J., Fonseca, D., Caro-Via, S., & Canaleta, X. (2024). Development of personalized profiles of students with autism spectrum disorder for interactive interventions with robots to enhance language and social skills. *Frontiers in Psychiatry*, *15*, 1455627.

Ilijoski, B., Ackovska, N., Zorcec, T., & Popeska, Z. (2022). Extending robot therapy for children with autism using mobile and web application. *Sensors*, *22*(16), 5965.

Institute, J. B. (2020). Critical appraisal tools [Internet]. *Adelaide: JBI*.

Jia, Q., Wang, X., Zhou, R., Ma, B., Fei, F., & Han, H. (2023). Systematic bibliometric and visualized analysis of research hotspots and trends in artificial intelligence in autism spectrum disorder. *Frontiers in Neuroinformatics*, *17*, 1310400.

Khanna, N. N., Maindarkar, M. A., Viswanathan, V., Fernandes, J. F. E., Paul, S., Bhagawati, M., Ahluwalia, P., Ruzsa, Z., Sharma, A., Kolluri, R., Singh, I. M., Laird, J. R., Fatemi, M., Alizad, A., Saba, L., Agarwal, V., Sharma, A., Teji, J. S., Al-Maini, M., ... Suri, J. S. (2022). Economics of Artificial Intelligence in Healthcare: Diagnosis vs. Treatment. *Healthcare (Basel)*, *10*(12). https://doi.org/10.3390/healthcare10122493

Klaiman, C., White, S., Richardson, S., McQueen, E., Walum, H., Aoki, C., Smith, C., Minjarez, M., Bernier, R., & Pedapati, E. (2024). Expert clinician certainty in diagnosing autism spectrum disorder in 16–30-month-olds: A multi-site trial secondary analysis. *Journal of autism and developmental disorders*, *54*(2), 393-408.

Kouroupa, A., Laws, K. R., Irvine, K., Mengoni, S. E., Baird, A., & Sharma, S. (2022). The use of social robots with children and young people on the autism spectrum: A systematic review and meta-analysis. *Plos one*, *17*(6), e0269800.

Lyu, Y., Liu, D., An, P., Tong, X., Zhang, H., Katsuragawa, K., & Zhao, J. (2024). EMooly: Supporting Autistic Children in Collaborative Social-Emotional Learning with Caregiver Participation through Interactive AI-infused and AR Activities. *Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies*, *8*(4), 1-36.

Moridian, P., Ghassemi, N., Jafari, M., Salloum-Asfar, S., Sadeghi, D., Khodatars, M., Shoeibi, A., Khosravi, A., Ling, S. H., & Subasi, A. (2022). Automatic autism spectrum disorder detection using artificial intelligence methods with MRI neuroimaging: A review. *Frontiers in Molecular Neuroscience*, *15*, 999605.

Murrillo, M. (2024). On Utilizing Artificial Intelligence to Impact Healthcare in Low-Income Countries. *International Journal of Translational Medical Research and Public Health*, *8*.

Olawade, D. B., Wada, O. Z., Odetayo, A., David-Olawade, A. C., Asaolu, F., & Eberhardt, J. (2024). Enhancing mental health with Artificial Intelligence: Current trends and future prospects. *Journal of medicine, surgery, and public health*, *3*, 100099.

Olugbami, O. O., & Ogundeko, O. (2025). AI-enhanced predictive analytics systems combatting health disparities while driving equity in US healthcare delivery. *World Journal of Advanced Research and Reviews*, *25*(1), 2067-2084.

Özcan, B., Caligiore, D., Sperati, V., Moretta, T., & Baldassarre, G. (2016). Transitional wearable companions: a novel concept of soft interactive social robots to improve social skills in children with autism spectrum disorder. *International Journal of Social Robotics*, *8*, 471-481.

Pakkar, R., Clabaugh, C., Lee, R., Deng, E., & Mataricć, M. J. (2019). Designing a socially assistive robot for long-term in-home use for children with autism spectrum disorders. 2019 28th IEEE international conference on robot and human interactive communication (RO-MAN),

Panceri, J. A. C., Freitas, É., de Souza, J. C., da Luz Schreider, S., Caldeira, E., & Bastos, T. F. (2021). A new socially assistive robot with integrated serious games for therapies with children with autism spectrum disorder and down syndrome: a pilot study. *Sensors*, *21*(24), 8414.

Pillai, A. (2023). Artificial Intelligence in Healthcare Systems of low-and Middle-Income countries: requirements, gaps, challenges, and potential strategies. *International Journal of Applied Health Care Analytics*, *8*(3), 19-33.

Qin, L., Wang, H., Ning, W., Cui, M., & Wang, Q. (2024). New advances in the diagnosis and treatment of autism spectrum disorders. *European Journal of Medical Research*, *29*(1), 322.

Rakhymbayeva, N., Amirova, A., & Sandygulova, A. (2021). A Long-Term Engagement with a Social Robot for Autism Therapy. *Front Robot AI*, *8*, 669972. https://doi.org/10.3389/frobt.2021.669972

Rao, S. K., Gupta, P., Mohammed, A., Zakhmi, K., Mohanty, M. R., & Jalaja, P. P. (2025). The Impact of Artificial Intelligence on Financial Systems in Healthcare: A Systematic Review of Economic Evaluation Studies. *Cureus*, *17*(6).

Rollwage, M., Juchems, K., Habicht, J., Carrington, B., Hauser, T., & Harper, R. (2022). Conversational AI facilitates mental health assessments and is associated with improved recovery rates. *medRxiv*, 2022.2011. 2003.22281887.

Salil, R., Jose, B., Cherian, J., R, S. P., & Vikraman, N. (2024). Digitalized therapy and the unresolved gap between artificial and human empathy. *Front Psychiatry*, *15*, 1522915. https://doi.org/10.3389/fpsyt.2024.1522915

Sapanel, Y., Tadeo, X., Brenna, C. T. A., Remus, A., Koerber, F., Cloutier, L. M., Tremblay, G., Blasiak, A., Hardesty, C. L., Yoong, J., & Ho, D. (2023). Economic Evaluation Associated With Clinical-Grade Mobile App-Based Digital Therapeutic Interventions: Systematic Review. *J Med Internet Res*, *25*, e47094. https://doi.org/10.2196/47094

Sharkey, A. J. (2016). Should we welcome robot teachers? *Ethics and Information Technology*, *18*(4), 283-297.

Shi, B., Wu, W., Dai, M., Zeng, J., Luo, J., Cai, L., Wan, B., & Jing, J. (2021). Cognitive, language, and behavioral outcomes in children with autism spectrum disorders exposed to early comprehensive treatment models: a meta-analysis and meta-regression. *Frontiers in Psychiatry*, *12*, 691148.

Silva, K., Lima, M., Santos-Magalhães, A., Fafiães, C., & de Sousa, L. (2019). Living and robotic dogs as elicitors of social communication behavior and regulated emotional responding in individuals with autism and severe language delay: a preliminary comparative study. *Anthrozoös*, *32*(1), 23-33.

Smith, E. M., Graham, D., Morgan, C., & MacLachlan, M. (2023). Artificial intelligence and assistive technology: risks, rewards, challenges, and opportunities. *Assistive Technology*, *35*(5), 375-377.

So, W.-C., Wong, M. K.-Y., Lam, W.-Y., Cheng, C.-H., Yang, J.-H., Huang, Y., Ng, P., Wong, W.-L., Ho, C.-L., & Yeung, K.-L. (2018). Robot-based intervention may reduce delay in the production of intransitive gestures in Chinese-speaking preschoolers with autism spectrum disorder. *Molecular autism*, *9*, 1-16.

Srinivasan, S. M., Kaur, M., Park, I. K., Gifford, T. D., Marsh, K. L., & Bhat, A. N. (2015). The effects of rhythm and robotic interventions on the imitation/praxis, interpersonal synchrony, and motor performance of children with autism spectrum disorder (ASD): a pilot randomized controlled trial. *Autism research and treatment*, *2015*(1), 736516.

Telisheva, Z., Amirova, A., Rakhymbayeva, N., Zhanatkyzy, A., & Sandygulova, A. (2022). The quantitative case-by-case analyses of the socio-emotional outcomes of children with ASD in robot-assisted autism therapy. *Multimodal Technologies and Interaction*, *6*(6), 46.

Thakkar, A., Gupta, A., & De Sousa, A. (2024). Artificial intelligence in positive mental health: a narrative review. *Frontiers in digital health*, *6*, 1280235.

Urdanivia Alarcon, D. A., Cano, S., Paucar, F. H. R., Quispe, R. F. P., Talavera-Mendoza, F., & Zegarra, M. E. R. (2021). Exploring the effect of robot-based video interventions for children with autism spectrum disorder as an alternative to remote education. *Electronics*, *10*(21), 2577.

Vignapiano, A., Monaco, F., Landi, S., Steardo, L., Jr., Mancuso, C., Pagano, C., Petrillo, G., Marenna, A., Piacente, M., Leo, S., Ingenito, C. M., Bonifacio, R., Di Gruttola, B., Solmi, M., Pontillo, M., Di Lorenzo, G., Fasano, A., & Corrivetti, G. (2024). Proximity-based solutions for optimizing autism spectrum disorder treatment: integrating clinical and process data for personalized care. *Front Psychiatry*, *15*, 1512818. https://doi.org/10.3389/fpsyt.2024.1512818

Voss, C., Schwartz, J., Daniels, J., Kline, A., Haber, N., Washington, P., Tariq, Q., Robinson, T. N., Desai, M., & Phillips, J. M. (2019). Effect of wearable digital intervention for improving socialization in children with autism spectrum disorder: a randomized clinical trial. *JAMA pediatrics*, *173*(5), 446-454.

Wang, Y., Liu, C., Hu, W., Luo, L., Shi, D., Zhang, J., Yin, Q., Zhang, L., Han, X., & He, M. (2024). Economic evaluation for medical artificial intelligence: accuracy vs. cost-effectiveness in a diabetic retinopathy screening case. *NPJ Digital Medicine*, *7*(1), 43.

Wankhede, N., Kale, M., Shukla, M., Nathiya, D., R, R., Kaur, P., Goyanka, B., Rahangdale, S., Taksande, B., Upaganlawar, A., Khalid, M., Chigurupati, S., Umekar, M., Kopalli, S. R., & Koppula, S. (2024). Leveraging AI for the diagnosis and treatment of autism spectrum disorder: Current trends and future prospects. *Asian J Psychiatr*, *101*, 104241. https://doi.org/10.1016/j.ajp.2024.104241

Wong, C. M. V., Chan, R. Y.-Y., Yum, Y. N., & Wang, K. (2021). Internet of Things (IoT)-enhanced applied behavior analysis (ABA) for special education needs. *Sensors*, *21*(19), 6693.

Wu, X., Wu, Y., Tu, Z., Cao, Z., Xu, M., Xiang, Y., Lin, D., Jin, L., Zhao, L., & Zhang, Y. (2024). Cost-effectiveness and cost-utility of a digital technology-driven hierarchical healthcare screening pattern in China. *Nature communications*, *15*(1), 3650.

Yadav, V. (2021). AI and economics of mental health: analyzing how AI can be used to improve the cost-effectiveness of mental health treatments and interventions. *J Sci Eng Res*, *8*(7), 274-284.

Yun, S. S., Choi, J., Park, S. K., Bong, G. Y., & Yoo, H. (2017). Social skills training for children with autism spectrum disorder using a robotic behavioral intervention system. *Autism Research*, *10*(7), 1306-1323.

Zhang, S., Wang, S., Liu, R., Dong, H., Zhang, X., & Tai, X. (2022). A bibliometric analysis of research trends of artificial intelligence in the treatment of autistic spectrum disorders. *Front Psychiatry*, *13*, 967074. https://doi.org/10.3389/fpsyt.2022.967074

Zhang, Y., Song, W., Tan, Z., Zhu, H., Wang, Y., Lam, C. M., Weng, Y., Hoi, S. P., Lu, H., & Chan, B. S. M. (2019). Could social robots facilitate children with autism spectrum disorders in learning distrust and deception? *Computers in Human Behavior*, *98*, 140-149.

Zhao, R. C., & Yuan, X. (2025). AI in Healthcare for Resource Limited Settings: An Exploration and Ethical Evaluation. Companion Proceedings of the ACM on Web Conference 2025,