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SYSTEMATIC REVIEW

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# The role of artificial intelligence interventions to improve eye contact for children with autism spectrum disorder: a systematic review

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## Abstract

**Background** Children with autism spectrum disorder (ASD) often struggle with eye contact during social interactions, a key aspect of effective communication. In recent years, various artificial intelligence (AI)-based interventions have been developed to support children with ASD. This study aims to systematically review the published literature on the AI-based interventions for improving eye contact.

**Methods** The review adhered to the 2020 Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines. Two researchers searched six databases: Scopus, Web of Science, PubMed, APA PsycInfo, Education Source, and IEEE Xplore, which initially yielded 1663 records. After screening and eligibility assessment, 16 studies met all inclusion criteria. Data were extracted through a narrative synthesis focusing on key variables, including study characteristics (author, year, region, sample, design, setting, and duration), definitions and measurements of eye contact, AI tool, and technological modalities, findings including reported effectiveness, generalization and maintenance outcomes, as well as whether social validity was assessed in each study. Two researchers independently conducted data extraction, quality assessment, and risk-of-bias evaluation using the Joanna Briggs Institute (JBI) checklists and the Single-Case Experimental Design (SCED) scale.

**Results** Included studies used a variety of AI-based tools. The most frequently used intervention modality was robotic systems, which were used in 12 studies, followed by wearable technologies (two studies), virtual reality (one), and game-based software (one). Preliminary findings suggest that AI technologies are often associated with increases in the frequency and duration of eye contact. Six studies (38%) assessed generalization of treatment effects, generally reporting positive outcomes, while seven studies (44%) assessed social validity. The research mostly utilized quantitative designs, including randomized controlled trials, repeated measure designs, single-subject research designs, and quasi-experimental designs. One qualitative case study and one case report were also identified. Methodological quality ratings ranged from moderate to high across study designs.


Note:*Studies included in the systematic review

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**Conclusion** This systematic review revealed that AI-based interventions are developing technology for improving eye contact behavior in children with ASD. Particularly, robotic systems provide promising evidence for improving eye-contact behaviors in children with ASD. However, the current evidence base remains limited due to small sample sizes and variations in the operational definitions of eye contact, measurement methods, and levels of AI sophistication. Data on generalization and social validity were also limited, highlighting the need for larger, methodologically rigorous studies to confirm these findings and assess their broader applicability.

**Clinical trial number** This study did not involve clinical trials, and as such, there is no clinical trial number to report.

**Keywords** Eye contact, Artificial intelligence, Interventions, Autism, Systematic review

## Introduction

Autism spectrum disorder (ASD) is a neurodevelopmental condition characterized by social communication difficulties, repetitive behaviors, and restricted interests [1]. Challenges include initiating and maintaining eye contact [2, 3], which can be defined as the behavior of looking into another person's eyes [4]. A number of studies have shown that children with autism engage in less eye contact than their typically developing peers [1, 5, 6]. Instead, they frequently focus on the mouth [7, 8] or other parts of the face [5, 6, 9, 10]. In this context, eye contact is viewed as one of the key behavioral indicators for diagnosing children with autism [1].

### The role of eye contact in social communication and learning

Eye contact plays a central role in social communication and learning, serving as a key behavior through which individuals connect, exchange information, and engage with others. It supports both the initiation and maintenance of interpersonal interactions [3, 11, 12]. It enables individuals to interpret others' thoughts, emotions, and intentions [13, 14] and plays a critical role in early development by regulating social exchanges and enhancing language acquisition [15–17]. Beyond its role in communication, sustained eye contact also contributes to greater attention and learning outcomes, as students who engage visually with instructors tend to process information more effectively [18, 19]. Therefore, well-designed eye contact interventions may promote both social and academic engagement in children with ASD.

### Neurodiversity-informed perspectives on eye contact interventions

Traditional eye contact interventions for individuals with autism have largely focused on increasing the frequency or duration of gaze through behavioral interventions (e.g. [4, 18, 20–27]). These interventions have generally conceptualized limited eye contact as a skill to be taught and used reinforcement-based strategies to increase gaze behaviors. Although these studies have shown to enhance eye contact in some individuals, concerns have been raised that they may emphasize adaptation to neurotypical social norms over considerations of comfort, consent, and emotional well-being for autistic individuals. The neurodiversity paradigm, in contrast, views autism and other neurodevelopmental conditions as natural variations of human cognition rather than deficits to be corrected [28].

From the neurodiversity paradigm, interventions should not aim to normalize neurotypical behaviors but instead respect individual differences and promote well-being. In the context of eye contact, this means recognizing that gaze experiences are not universally positive [29, 30] and that efforts to increase eye contact should not override an individual's comfort or autonomy. Although some individuals with autism avoid eye contact for several reasons, including discomfort, anxiety, or even physical distress [29, 30], others may wish to improve their ability to tolerate or manage eye contact in social situations despite discomfort [31]. Neurodiversity-informed approaches, therefore, emphasize flexibility and personal choice [32].

Cultural norms further complicate expectations around gaze behavior, as mutual gaze is interpreted differently across societies and prolonged eye contact is not always considered appropriate [33]. As a result, it is important to ensure that interventions aimed at increasing eye contact in children with autism are responsive to their individual needs and preferences. From an ethical standpoint, obtaining informed consent from participants or their caregivers before participation, providing detailed information about the purpose and process of the intervention, and allowing the option to withdraw at any time are essential to ensure autonomy and respect within neurodiversity-informed practices. In line with this perspective, technology-aided instruction and intervention (TAII) can serve as an ethically responsive approach in autism interventions, as adaptive AI-based systems enable the tailoring of interventions to each learner's comfort level, engagement, and affective state.

### TAII for eye contact

TAII is an evidence-based practice that uses technology to enhance learning and skill performance [34]. Studies have shown that TAII can improve eye contact (e.g.

[35, 36]). In most households, at least one technological device is available, making technology-based interventions widely available [37]. With TAII, families and individuals with autism can learn various skills, reducing the need for professional assistance [38]. Through TAII, teaching algorithms can also be tailored to each child's abilities and preferences [39], making them more effective for some children [40]. Consequently, TAII enables students to learn at their convenience [41], highlighting the need to integrate it into educational practices [42].

#### Artificial intelligence in autism research

Artificial intelligence (AI) is one way in which technology can be effectively incorporated into education [42]. AI is a computer system that can perform tasks that normally require human intelligence, such as solving problems, making decisions, and comprehending language [43, 44]. There are various types of AI systems. It includes a variety of models ranging from rule-based models based on predefined symbolic rules, machine learning approaches that learn patterns from data, and deep learning architectures that represent the most advanced, adaptive forms of AI [44].

AI plays an important role in autism research by detecting behavioral and neuroimaging patterns early with machine learning and deep learning [45, 46] and enabling intervention strategies with tools such as social robots to enhance social interaction [47, 48]. With AI-based interventions, it is possible to customize learning, enhance the effectiveness of the learning environment, assist teachers and students in teaching and learning activities, and increase interactive experiences [49]. By combining machine learning with real-time data analysis, these interventions provide customized solutions that increase effectiveness and meet individual needs [50]. Tailored systems can respond to the unique characteristics of students and meet their educational needs [51, 52]. AI in teaching and learning practices can therefore leverage outcomes. In this context, several AI-based interventions have been used for children with autism. These include robots, virtual reality (VR) technology, and augmented reality (AR) [50].

#### AI-Based intervention modalities

Various modalities of AI-based interventions have emerged to support social and communication skills in children with ASD, utilizing technologies such as robotics, virtual reality, wearable technologies, and game-based software. Among these, AI-based robots serve as interactive companions and therapeutic aids for children with ASD, using advanced sensor technology and machine learning algorithms to identify and respond to user behavior. Using reinforcement learning algorithms, they adapt their behaviors and communication strategies according to individual preferences and therapeutic goals [53]. As a result of these customized interventions, children with autism are able to enhance their social interactions and improve their overall quality of life [54]. A humanoid robot, with a body structure similar to that of a human, can provide individuals with ASD with easy and less stressful opportunities for social interaction. However, it is difficult to implement nonverbal behaviors such as eye contact [55]. Alternatively, socially assistive robotics (SARs) are commonly used in interventions, available in various forms such as humanoid, animal-like/zoomorphic robots, and machine-like/non-biomimetic designs [56]. The SARs such as Pepper and Kaspar can improve the interaction and learning of children with ASD by mimicking behavior and providing a stable, predictable environment [57]. Robots are effective at various skills, including eye contact, joint attention, imitation, communication, turn-taking, and triadic interactions [58–60].

Virtual reality (VR) technology is highly beneficial for children with autism. Virtual reality provides children with the opportunity to interact in a 360-degree environment that mimics real-world scenarios, providing a safe and controlled learning environment. This immersive experience helps them to better understand social cues and engage in social interactions, which are often challenging for them. VR's multisensory capabilities allow multiple senses, such as sight, sound, and movement, to be stimulated at the same time. It facilitates a more comprehensive learning experience for children with ASD. VR's immersive nature and its ability to track and adapt to the user's gaze provide a significant advantage for auxiliary ASD intervention [61].

VR technology with an eye tracker has been increasingly applied in interventions for children with autism [62]. A VR headset equipped with an eye tracker could be used as a control device, replacing the need for a regular joystick and thereby increasing user interaction [61]. Despite the fact that VR-based interventions cannot replace professional therapy interventions, they have the potential to provide a secure and immersive virtual environment [63]. A structured environment within VR is another important aspect that contributes to learning for children with ASD. In a controlled environment, learning objectives can be introduced in a systematic manner and complexity can be gradually introduced, accommodating a child's pace and ability to learn [61]. A virtual environment can also be used to teach certain high-risk skills, such as crossing the road. Moreover, VR interventions can be customized to address the sensory sensitivities commonly observed in individuals with autism, resulting in a more comfortable learning environment for these individuals [61]. In addition, through deepfake technology, children can hear and respond to a familiar voice, promoting positive interactions in the VR environment

[64]. A number of skills can be improved through VR, including social skills, everyday living skills, and emotional regulation skills [65].

AI-based augmentative communication systems utilize advanced natural language processing (NLP) algorithms to interpret user inputs and create context-relevant speech and text outputs [66]. By using deep learning techniques, these systems analyze linguistic patterns and user preferences, allowing them to be customized in real time [50]. The use of this technology has been shown to be highly effective in improving communication skills [67].

#### Rationale for the present systematic review

Given the growing interest in AI-based interventions, a systematic review of research on AI applications targeting eye contact in children with ASD can provide a comprehensive synthesis of existing evidence. Since impaired eye contact is a core difficulty in autism [1, 30], such a review is needed to identify which AI technologies have been employed, summarize their reported outcomes, and highlight current gaps to guide future research [42, 68].

Recent systematic reviews have examined broader outcome domains, including general adaptive functioning and social communication, or focused on specific technologies used in interventions (e.g., robotics, virtual reality). For example, Perry et al. [69] conducted a systematic review of AI-based assistive technologies aimed at supporting adaptive functioning in individuals with neurodevelopmental conditions. Similarly, Yang et al. [70] examined virtual reality interventions designed to improve social skills in children with ASD. Altın et al. [71] also explored VR interventions targeting social skill development in individuals with ASD. Furthermore, Kotsi et al. [72] conducted a systematic review to examine research trends in the design and development of AI-based teaching interventions in special education, with a particular focus on students with ASD. While these reviews have examined AI applications and related technologies to support social communication in children with autism, to the best of our knowledge, no systematic review has been conducted to date on AI-based interventions specifically targeting eye contact improvement, which is a fundamental component of social communication and a core challenge for children with ASD.

The present review addresses this gap by systematically synthesizing studies focused exclusively on AI-based interventions designed to improve eye contact in children with ASD. By narrowing the scope in this way, our review provides a practical, time-saving resource for researchers and practitioners seeking targeted AI-based interventions to improve eye contact in children with ASD. Moreover, rather than focusing on specific technologies (e.g., robotics or virtual reality), we adopt a comprehensive approach that includes a broad range of AI-based tools. Therefore, the scope of this review is to examine AI-based interventions that range from rule-based models to advanced deep learning architectures, specifically targeting eye contact in children with autism. AI-based technologies are examined based on their computational complexity and level of advancement, ranging from rule-based systems to machine learning and deep learning models. In this context, this study aims to systematically review and synthesize the published literature on AI-based interventions for improving eye contact in children with ASD.

#### Research questions

The following research questions were investigated in this review:

1. Which types of AI-based technologies have been used to enhance eye contact in children with ASD in the included studies?
2. What are the methodological characteristics of the included studies, such as region, sample, design, setting, duration of intervention, and approaches to defining and measuring eye contact?
3. What evidence has been reported on the effectiveness of AI-based interventions in improving eye contact among children with ASD?
4. What evidence has been reported on the generalization of eye-contact improvements in the included studies?
5. What evidence has been reported on the maintenance of treatment effects in the included studies?
6. What evidence has been reported on the assessment of social validity in the included studies?

## Methods

This systematic review adhered to the 2020 Preferred Reporting Items for Systematic Review and Meta-Analyses (PRISMA) checklists [73]. The completed checklists are provided in Supplementary Materials S7–S8. The review protocol was registered with the Open Science Framework (OSF; reference number: 5FKM3) and is available at https://osf.io/5fkm3. The protocol was registered retrospectively after the screening stage had begun.

#### Eligibility criteria

We applied specific inclusion and exclusion criteria to the systematic review. Articles were included in this review if they met the following criteria: (a) focused on AI-based interventions including rule-based, machine learning, or deep learning models, (b) included children with ASD, (c) targeted eye contact as a dependent variable, (d) were published in peer-reviewed journals, (e) were designed with qualitative, quantitative, or mixed-method research designs, and (f) were written in English. This rationale was chosen to capture the current range of AI-driven approaches applied to addressing eye contact in ASD while excluding digital tools without AI capabilities.

The following criteria were used to exclude studies: (a) did not involve an AI-based intervention evaluating its effectiveness, (b) did not include participants diagnosed with ASD, (c) did not target eye contact as a primary or secondary dependent variable, (d) were not published in peer-reviewed journals (e.g., dissertations, conference abstracts, or unpublished manuscripts), (e) were literature reviews, opinion pieces, or editorials), and (f) were not written in English.

### Search strategy

The first author, with a PhD in special education, and the second author, with a PhD in instructional technology, independently conducted systematic searches. The searches were performed in six scientific databases: Scopus, Web of Science (all editions), PubMed, APA PsycInfo, Education Source, and IEEE Xplore until 29 January 2025. These databases were selected to ensure comprehensive coverage of relevant literature across the interdisciplinary fields of healthcare, psychology, education, and computer science. The search terms were developed based on the existing literature (e.g. [74, 75]) and the researchers' areas of expertise, which included three categories: autism-related terms (e.g., "autism", "autistic", "ASD"), AI-related terms (e.g., "artificial intelligence", "machine learning", "generative AI", "deep learning", "intelligent system", "natural language processing", "adaptive learning", "neural network", "chatbot", "virtual agent", "humanoid robot", "socially assistive robot", "image recognition", "speech recognition"), and eye contact-related terms (e.g., "eye contact", "gaze", "gazing"). The search queries were tailored to each database's specific rules. There were no restrictions on publication dates. The researchers examined the articles' abstracts, titles, and keywords. The complete search strategy terms are provided in Supplementary Materials S6.

### Study selection

The first and second authors independently reviewed the titles and/or abstracts of the original articles to identify eligible studies. The authors also manually reviewed reference lists and imported all retrieved records into EndNote Online (Clarivate Analytics). Duplicate entries were initially removed via EndNote's automated deduplication function, which identifies matches based on author, year, title, and reference type. Following this, all records were manually verified to ensure the removal of any duplicates not detected by the automated process. Once the list of potentially eligible articles was finalized, two authors independently conducted full-text screening to determine eligibility. Interrater agreement was 91% for title and abstract screening and 96% for full-text screening. Discrepancies were reviewed in joint meetings until consensus was reached. Consensus was facilitated by the complementary expertise of the reviewers: the first author, with expertise in autism and eye contact interventions, evaluated the relevance of each study to the inclusion criteria, while the second author, with expertise in artificial intelligence, assessed whether the technological components met the criteria for AI modalities. This combination of perspectives reduced ambiguity and facilitated consensus, ensuring accurate and transparent inclusion decisions.

### Data extraction

We collaboratively developed an Excel form for charting data and extracted the data using a pre-prepared and piloted table. The following data were extracted from each study: (a) characteristics of the study, including author(s)/year, study region, sample, design, and setting, eye contact definition and measurement; (b) summary of the studies, including AI tool/technology, reported outcome, duration of intervention, statistics/effect size, generalization, maintenance and social validity. Two researchers independently extracted data from the 16 included studies using predefined variables. An agreement was reached on 93% of the extracted items. Any disagreements were discussed item by item in joint meetings until a consensus was achieved. Joint discussions allowed each reviewer to present reasoned arguments from their disciplinary perspective, reducing ambiguity and facilitating consensus.

### Quality assessment

The methodological quality of each study was assessed using the Joanna Briggs Institute (JBI) Critical Appraisal Tools for Quasi-Experimental Studies [76], Randomised Controlled Trials [77], Qualitative Research [78], and Case Reports [79]). For single-case designs, the Single-Case Experimental Design (SCED) Scale [80], an 11-item checklist evaluating design, measurement, and analysis, was used. The first and second authors independently assessed the methodological quality of all included studies. Where discrepancies occurred, the reviewers discussed each item with their rationales until agreement was reached. Consensus was achieved through open discussion and cross-checking of scoring decisions. Studies were categorized as high ($>70\%$), moderate (50–69%), or low ($<50\%$) quality, following the JBI Manual for Evidence Synthesis [81]. As the SCED scale does not provide explicit quality thresholds, we applied a $\geq 70\%$ score criterion to identify moderate- to high-quality studies. No studies were excluded based on methodological quality; instead, the quality assessments are reported in the results section.

## Synthesis of results

We employed a narrative synthesis to analyze and present the review findings. The findings were organized based on the research question and the study's objectives. Each study was reviewed using predefined variables to ensure consistency in data management. Given the variability of interventions (e.g., robotic systems, virtual reality, wearable devices, and game-based software), studies were categorized and synthesized according to the type of AI technology used, study design, and outcome measurement. This approach allowed us to integrate findings within each intervention type and then identify broader patterns across different technologies. When direct comparisons were not feasible due to heterogeneity in intervention design or outcome definitions, the results were synthesized descriptively to ensure methodological rigor.

## Search outcome

The PRISMA flow diagram is presented in Fig. 1. A comprehensive literature search was conducted across six databases: Web of Science, Scopus, Education Source, APA PsycInfo, PubMed, and IEEE Xplore. The search initially identified 1,663 publications, of which 653 duplicates were removed. The remaining 1,010 records were screened for eligibility, and 937 were excluded for not addressing either children with ASD or AI-based eye contact interventions. The full texts of 73 articles were retrieved and assessed for eligibility. Of these, 57 studies were excluded because they did not meet the inclusion criteria (e.g., eye contact and AI were not a central or explicit part of the aim or research question; eye contact was not assessed; AI was not used). Ultimately, 16 studies met all the inclusion criteria and were included in this review (see Fig. 1 for further details).

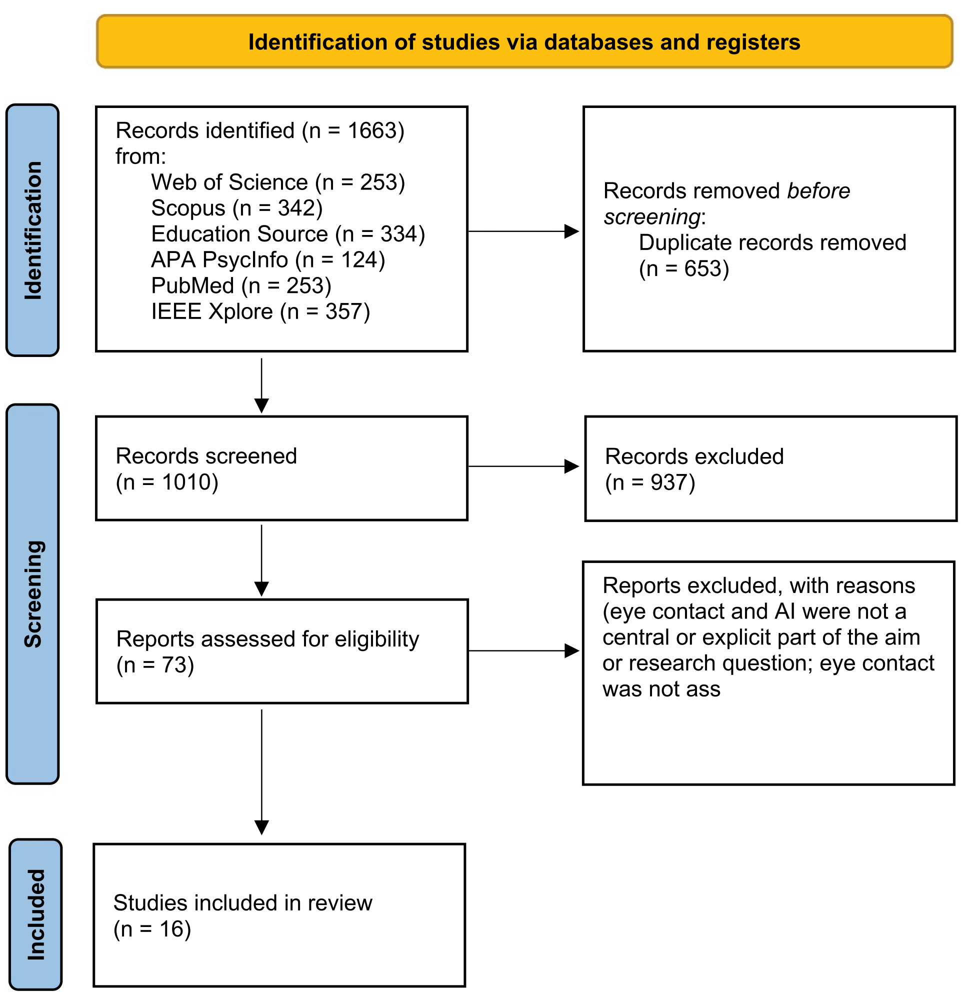


**Fig. 1** PRISMA flow diagram [73] of the selection process for evidence sources

## Results

### Study characteristics

#### Study region, sample, research design, setting, and duration of intervention

Table 1 below lists the characteristics of the studies that reviewed the use of artificial intelligence in eye contact interventions for children with ASD across various regions and settings. The geographical distribution of the studies reveals a global interest in exploring AI-based interventions for children with ASD. Several studies have been conducted in the USA [84, 88, 90]. Greece is another country with multiple studies focusing on this topic [85–87]. Additionally, research has been carried out in China, Japan, and Pakistan. However, some studies did not report the region specifically [35, 83, 93, 94].

The study samples vary in size, age, and gender distribution across the studies. The sample sizes ranged from two to 54 participants with ASD, with a total of 306

**Table 1** Study characteristics

| Author(s)/Year | Study Region | Study Sample | Study Design | Setting | Duration/Frequency | Eye Contact Definition/Measurement |
|---|---|---|---|---|---|---|
| Ali et al. [82] | Pakistan | 12 (11 M, 1 F) children with ASD, ages 3 to 10 | Quasi-Experimental design | Clinical | 6 months/12 sessions | Frequency and duration of eye contact with the robot/Robot eye tracker |
| Chung [83] | NR | 14 (14 M, 0 F) children with ASD, ages 9 to 11 | Repeated measures design | School | 12 weeks/12 sessions | Frequency and duration of eye contact during communication/Direct observation |
| Chung [35] | NR | 15 (13 M, 2 F) children with ASD, ages 5 to 11 | Single-subject research design | School | 12 weeks/12 sessions | Frequency and duration of eye contact during communication/Direct observation |
| Daniels et al. [84] | USA | 14 (11 M, 3 F) children (11 ASD and 3 Asperger's), ages 3 to 17 (mean: 9.57) | Repeated measures design | Home | 10.29 weeks/three sessions per week | Eye contact during social interaction/Indirectly through parent reports |
| Fachantidis et al. [85] | Greece | 4 (4 M, 0 F) children with ASD, ages 7 to 12 | Single-subject research design | Special Education Center | 5 months/eight sessions | Frequency of eye contact with the teacher and robot/Direct observation |
| Gkiolnta et al. [86] | Greece | 2 (1 M, 1 F) children (1 with ASD and 1 with typical development), both ages 8 | Case study | School | 2 months/eight sessions | Frequency of eye contact with the other child/Direct observation |
| Holeva et al. [87] | Greece | 51 (41 M, 10 F) children with ASD, ages 6 to 12 (mean: 9.43) | Randomized controlled trial | Clinical and learning disabilities center | 3 months/21 sessions | Maintaining eye contact and duration of eye contact/Direct observation and a robot eye tracker |
| Liu et al. [88] | USA | 2 (2 M, 0 F) children with ASD, ages 8 and 9 | Case Report | Clinical | 1 day/one session | Direct gaze at another person's face/SmartGlass eye tracker and indirectly through parent reports |
| Mutawa et al. [89] | Kuwait | 34 (2 M, 0 F) children with ASD, ages 3 to 6 | Quasi-Experimental design | School | 8 weeks/36 sessions | Frequency of eye contact with the teacher/Direct observation |
| Scassellati et al. [90] | USA | 12 (7 M, 5 F) children with ASD, ages 6 to 12 (mean: 9.02) | Single-subject research design | Home | 1 month/30 sessions | Frequency and duration of eye contact with the robot/Robot eye tracker and indirectly through parent reports |
| So et al. [91] | China | 23 (20 M, 3 F) children with ASD, ages 6 to 12 | Randomized controlled trial | School | 9 weeks/Ten sessions | Frequency and duration of eye contact with parents and robot/Direct observation |
| Sosnowski et al. [92] | USA | 54 (47 M, 7 F) children with ASD, ages 4 to 14 (mean: 8.56) | Randomized controlled trial | School, Clinical, Home | 6 weeks/Three to five sessions per week | Gaze directed at the eye and mouth regions of game characters/Tobii 4C eye tracker device |
| Yoshikawa et al. [55] | Japan | 10 (10 M, 0 F), 4 children with ASD and 6 without ASD, ages 15 to 18 | Quasi-Experimental design | School | 1 day/five sessions | Duration of fixation on face and eye region/Tobii, X2-60 eye-tracker device |
| Yu et al. [61] | China | 36 (gender NR) children with ASD, ages NR | Repeated measures design | Clinical | 1 week/five sessions | Gaze fixation/A built-in 7Invensun eye tracker in the VR headset |
| Yun et al. [93] | NR | 8 (gender NR) children with ASD, ages 3 to 5 | Repeated measures design | Clinical | 8 weeks/eight sessions | A binary assessment (either the child is making eye contact or not)/Robot eye tracker |
| Yun et al. [94] | NR | 15 (15 M, 0 F) children with ASD, ages 4 to 7 | Randomized controlled trial | Clinical | 8 weeks/eight sessions | Frequency and duration of eye contact with facilitators and robot/Direct observation and robot eye tracker |

*ASD: Autism spectrum disorder; M: Male; F: Female; NR: Not reported participants across studies. The age ranges vary across studies, spanning 3 to 18 years, with some focusing on younger children (e.g. [89, 94]) and others including adolescents [55, 84]. Most studies include a predominantly male sample (M: 245, F: 42). While some studies included only male participants (e.g. [83, 85, 88]), others did not report the gender of the participants [61, 93]. Yoshikawa et al. [55] included participants with and without ASD. Daniels et al. [84] included participants with both ASD and Asperger's (diagnosed according to DSM-IV criteria). Overall, the study samples reflect a range of ages and developmental stages within the ASD population.

The study designs include a variety of approaches to investigate the effectiveness of AI-based interventions for children with ASD. Researchers have almost exclusively utilized quantitative designs ($n=14$ of 16), including randomized controlled trials ($n=4$) [87, 91, 92, 94], repeated measure designs ($n=4$) [61, 83, 84, 93], single-subject research designs ($n=3$) [35, 85, 90], and quasi-experimental designs ($n=3$) [55, 82, 89]. However, only two studies used a qualitative research approach using a case study design [86], and another used a case report design [88].

The intervention settings of the studies also varied. Specifically, six studies were conducted within school settings [35, 55, 83, 86, 89, 91], whereas five were conducted in clinical environments [61, 82, 88, 93, 94]. Home environments were utilized in two studies [84, 90]. One study was carried out in both a special education center and a clinical context [87]. Another study incorporated a combination of school, clinical, and home settings within its research design [92].

The duration of interventions varied considerably across the studies reviewed, ranging from single, brief sessions to programs spanning several months. The shortest interventions included feasibility assessments conducted within 1 day. For example, Yoshikawa et al. [55] utilized five conversational trials, while Liu et al. [88] evaluated a single behavioral coaching session. Slightly longer programs were exemplified by Yu et al. [61], in which participants engaged in daily 10-minute virtual reality sessions across 5 consecutive days within 7-day period. Medium-term programs typically lasted between 1 and 3 months. For instance, Gkiolnta et al. [86] conducted eight 20-minute sessions over 2 months, whereas Sosnowski et al. [92] implemented video gameplay sessions over approximately 6 weeks, requiring three to five 15-minute sessions per week. Similarly, Yun et al. [93, 94] administered eight sessions of 30–40 minutes over an 8-week period, So et al. [91] conducted 10 training sessions over 9 weeks, Scassellati et al. [90] implemented a 1-month home-based intervention in which children completed daily 30-minute sessions, and Mutawa et al. [89] conducted an 8 week intervention consisting of a total of 36 sessions.

Several studies employed 12-week (3-month) interventions. For example, both Chung [83] and Chung [35] involved 12 weekly 30-minute sessions, while Holeva et al. [87] conducted a 3-month program consisting of 21 sessions lasting 35–45 minutes each, administered twice weekly. Daniels et al. [84] reported an average intervention length of 10.29 weeks (72 days), with participants completing three 20-minute sessions per week. The longest structured interventions were reported by Fachantidis et al. [85] and Ali et al. [82]. Fachantidis et al. [85] implemented a 5-month program consisting of 8 weekly 30-minute sessions, whereas Ali et al. [82] conducted a 6-month therapy in which the core experimentation and monitoring occurred over 4 months. The latter study tested two intervention types, each comprising eight sessions lasting 20–45 minutes.

#### *Eye contact definition and measurement*

The studies demonstrated a variety of approaches to defining and measuring eye contact. For most studies ($n=7$), eye contact was defined as the frequency and duration of eye contact during communication or interaction with robots, teachers, facilitators, or peers [35, 82, 83, 87, 90, 91, 94]. Four studies investigated only the frequency of eye contact during interventions [84–86, 89]. Several studies have focused on gaze as a measure of eye contact and defined it in terms of visual attention directed toward specific facial regions, such as the eyes or mouth, or the face as a whole. For instance, Sosnowski et al. [92] and Yoshikawa et al. [55] defined eye contact as gaze directed at the eye and mouth regions or the duration of fixation on the face and eye regions, respectively. Similarly, Yu et al. [61] defined eye contact as gaze fixation on the face area, while Liu et al. [88] described it as direct gaze to another person's face. In contrast, Yun et al. [93] adopted broader or binary definitions of gaze-related eye contact. They used a robotic eye tracker to measure eye contact through a binary assessment, determining whether eye contact was made by the child. The studies employed a variety of tools to measure eye contact, using both traditional observational methods and advanced technological systems. Most studies ($n=6$) employed direct measurement systems involving direct observation for assessing eye contact with teachers, peers, or facilitators, and researchers manually recorded the frequency and duration of eye contact during interactions [35, 83, 85, 86, 89, 91]. Some studies also supplemented observational data with parent-reported measures, which provided additional context for eye contact behaviors during social interactions [84, 90].

In contrast to direct observation, many studies have utilized advanced technologies to increase the precision and objectivity of eye contact measurements. Robotic systems with integrated eye trackers have been widely used to measure both the frequency and duration of eye contact during interactions with robots [82, 87, 90, 93, 94]. Eye-tracking devices, such as Tobii trackers, SmartGlass systems, and VR headsets, were also frequently employed to measure eye contact. For instance, Sosnowski et al. [92] and Yoshikawa et al. [55] used Tobii trackers to capture detailed gaze data, while Liu et al. [88] employed SmartGlass eye trackers to measure direct gaze to another person's face. Yu et al. [61] used a built-in 7Invensun eye tracker in a VR headset to measure gaze fixation.

#### *Overview of AI tools, outcomes, generalization/maintenance, and social validity*

Table 2 below shows an overview of the AI tools/technologies, study outcomes, generalization, and social validity of the studies reviewed on the use of AI in eye contact interventions for children with ASD.

**Artificial intelligence tool/technology** Studies have highlighted that AI tools have emerged as effective solutions in interventions aimed at improving eye contact in children with ASD. These tools can be broadly categorized as robotic systems, wearable technology, virtual reality (VR) systems, and game-based software with AI capabilities.

**Robotic systems** Robotic systems were the most frequently employed AI tool ($n = 12$) in the studies, with a variety of robots employed to enhance eye contact in children with ASD. These robotic systems can be further expanded into three subcategories: humanoid robots, socially assistive robots, and android robots. Each type of robotic system was employed with specific features and purposes to enhance eye contact.

Humanoid robots were the most frequently ($n = 8$) employed AI tools across the studies [35, 82, 83, 87, 89, 91, 93, 94]. These robots were employed in various interventions to improve eye contact. Among these humanoid robots, the NAO robot was used to facilitate training in most ($n = 6$) studies [35, 82, 83, 87, 89, 91]. These robots were often equipped with AI features such as adaptive reinforcement learning [82], structured activities (e.g., games, storytelling, singing, and dancing) [35, 83], machine vision and speech recognition algorithms [87, 89], and pre-programmed activities [91] to enhance interaction and engagement of children with ASD. Other humanoid robots, such as iRobiQ and CARO, were also used in studies [93, 94]. These robots were equipped with AI technologies, including eye contact detection and tracking, adaptive response, and behavior execution.

Socially assistive robots were another robotic system utilized in eye contact interventions for children with ASD. Fachantidis et al. [85] utilized a socially assistive, non-humanoid robot named Daisy, which looks like a flower and features pre-programmed speech and expression capabilities, including an embedded tablet serving as an expressive face. Its actions and expressions were controlled remotely by a researcher using a wirelessly connected tablet, who gave instructions for appropriate words, sentences, and expressions. Gkiolnta et al. [86] utilized a fully autonomous, socially assistive robot enhanced with AI technology that was adapted to each child's strengths and weaknesses by adjusting task difficulty based on their preferences and performance, showcasing the application of adaptive learning.

The Android robot emerged as another robotic system employed in the reviewed studies. Yoshikawa et al. [55] utilized an Android robot called Actroid-F. The robot closely mimicked human appearance and behavior and was explored as a potential training partner to facilitate face-to-face communication skills in children with ASD. It was controlled by human operators using the "Wizard of Oz" technique, rather than being fully autonomous. The system utilized pneumatic actuators to enable silent and rapid skin movements, offering 11 degrees of freedom across key facial and neck regions, including the neck, eyeballs, eyelids, cheeks, lips, and eyebrows.

**Wearable technologies** Wearable technologies also emerged as an AI-based intervention ($n = 2$) in the reviewed studies [84, 88]. Daniels et al. [84] utilized Superpower Glass, which was described as a machine-learning-assisted software system that runs on Google Glass and an Android smartphone. The system was designed as a wearable tool for social-affective learning in children with autism for use during social interactions in the child's natural environment. Liu et al. [88] used similar technology called the Brain Power System (BPS), which is also a smart glasses-based augmented reality system. The system utilized customized smart glasses to provide coaching through gamified augmented-reality applications for skills such as emotion recognition, face-directed gaze, eye contact, and behavioral self-regulation.

**Game-based software with AI** Game-based software powered by AI represented another form of intervention employed in the reviewed studies [92]. Sosnowski et al. [92] implemented a video game-based digital therapeutic known as Lookware, which was delivered using a consumer-grade laptop, a low-cost eye tracker, and an Xbox game controller. The game integrated Applied Behavior Analysis (ABA) techniques with Gaze-Contingent Eye Tracking (GCET) within an immersive 3D environment, featuring simulated social interactions with animated car-

**Table 2** Overview of AI tools, outcomes, Generalization/Maintenance, and social validity

| Author(s)/Year | AI Tool/Technology | Outcome | Generalization/Maintenance | Social Validity |
|---|---|---|---|---|
| Ali et al. [82] | NAO humanoid robot/<br>Adaptive multi-robot system, reinforcement learning. | The frequency and duration of eye contact for each participant improved over the experiments. The delay in eye contact with the robot after the stimulus was reduced. | NR | NR |
| Chung [83] | NAO humanoid robot/<br>The robot was structured with a closed-loop autonomous system to provide natural interaction and feedback to children. | The frequency and duration of eye contact were significantly increased from the pre-intervention phase to the mid- and end-of-intervention phases. | The skills learned were maintained three weeks after the intervention ceased. However, the study did not evaluate generalization to other settings or people. | NR |
| Chung [35] | NAO humanoid robot/<br>The robot was structured with a closed-loop autonomous system to provide natural interaction and feedback to children. | Robot-mediated intervention was effective in enhancing both the frequency and duration of eye contact. | Improvements in eye contact were sustained after the robot was withdrawn in the generalization phase. | NR |
| Daniels et al. [84] | A machine-learning-assisted software system runs on wearable Google Glass/<br>Machine-learning-assisted software system, facial expression recognition, audio-visual feedback, hierarchical Bayesian domain adaptation. | Parents reported increased eye contact in their children. Data showed significant changes pre- and post-Glass usage on sub-domain questions, including changes in eye contact. | NR | Families found the system to be engaging, useful, and fun. 13 of 14 families reported an overall increase in quality family time. Most children wanted to use the tool in social settings outside of the home. |
| Fachantidis et al. [85] | A socially assistive robot named Daisy/Pre-programmed or controlled by a human operator, lacking the ability to autonomously adapt to individual children's responses or learning patterns. | There were more instances of eye contact during sessions with the robot than during those with the teacher. Children displayed high levels of eye contact when they interacted with a robot compared to a human. | NR | NR |
| Gkiolnta et al. [86] | A socially assistive robot named Codey Rocky/Programmable robotics using block-based/text-based coding to support social interaction. | The intervention led to an increased frequency of eye contact from 7 to 16 occurrences in a 20-minute session. | NR | NR |
| Holeva et al. [87] | NAO humanoid robot/<br>Machine vision algorithms to recognize actions and gestures and speech recognition algorithms to recognize answers. | Participants in both the robot-assisted group and the control group showed improvement in eye contact. | Due to COVID-related challenges, the limited response of the 3-month follow-up did not allow for exploring the sustainability of the intervention. | Both parents and children in both groups reported high satisfaction rates with the intervention. |
| Liu et al. [88] | Augmented reality smartglasses with games/<br>Emotion recognition and machine learning for adaptive, real social coaching. | Caregivers reported improved eye contact during the intervention. | NR | Caregivers reported the intervention was engaging, enjoyable and fun to use. |

**Table 2** (continued)

| Author(s)/ Year | AI Tool/ Technology | Outcome | Generalization/ Maintenance | Social Validity |
|---|---|---|---|---|
| Mutawa et al. [89] | NAO humanoid robot/ A mobile application to improve the robot's ability (voice recognition, speech synthesis, and picture identification) to recognize a child's profile and provide a personalized learning path. | Participants exhibited a significantly increased frequency of eye contact after the intervention. | NR | NR |
| Scassellati et al. [90] | A socially assistive robot/The robot was designed with adaptive learning to adjust the difficulty of tasks based on the child's performance. | Caregivers reported increased eye contact in children with ASD. | The study demonstrated improvements in eye contact with adults even when the robot was not present during the follow-up. | Caregivers reported that the system has a user-friendly design to implement the therapy at home. |
| So et al. [91] | NAO humanoid robot/ Pre-programmed to speak and produce 14 gestures. | Children in the robot-based intervention group established eye contact with the social robots more often than those in the human-based intervention group. | The positive learning outcomes were maintained for at least two weeks for both groups of children when no training was provided. | NR |
| Sosnowski et al. [92] | An immersive 3D video game/The game had an adaptive learning feature using the eye-tracking data and performance data to adjust the difficulty level of the exercises. | Staff thought that the game was valuable for teaching and/or improving the participants' eye contact (indirectly reported-eye tracker data not reported). | NR | All children reported enjoying the game, with most finding it easy. Nearly all staff said they would recommend it and found it valuable for improving eye contact. |
| Yoshikawa et al. [55] | An android (humanoid) robot called Actroid-F/ It uses mimic human-like interaction, with responses and movements controlled by human operators using the 'Wizard of Oz' technique, rather than by an autonomous AI system. | Individuals with ASD looked more at the area around the eyes of the android than that of the human. The time to look at the eye of the human interlocutor increased with the increasing number of sessions. | NR | NR |
| Yu et al. [61] | A Virtual Reality System of the Hide-and-Seek Game/Deep learning-based computer vision and voice manipulation techniques to enable affordable customization of game characters within VR devices. | Children in the customized avatar group showed increased gaze fixation over the intervention period. | NR | The VR system was engaging for children with ASD. Parental feedback via questionnaires showed significant improvements, indicating the intervention was perceived as beneficial. |

**Table 2** (continued)

| Author(s)/ Year | AI Tool/ Technology | Outcome | Generalization/ Maintenance | Social Validity |
|---|---|---|---|---|
| Yun et al. [93] | A mobile humanoid robot named iRobiQ and a clinical assistive robot named CARO/ Human Perception module for gaze detection, Interaction Manager for adaptive responses, Robot Effector for executing behaviors | The study showed that children's eye contact rates were maintained or even increased over sessions with the robot, with an average eye contact rate of 86.5% using the robotic system compared to 86.8% by manual observation. | NR | NR |
| Yun et al. [94] | A mobile humanoid robot named iRobiQ and a clinical assistive robot named CARO/ Eye Contact Detector, Object Detection and Tracking, and Human Classifier | After treatment, eye contact percentages significantly increased in both the treatment group (robot-assisted) and the control group (human-assisted). The treatment group initially showed higher percentages of eye contact. The frequency of eye contact increased significantly in the eighth sessions in both groups. | The effects on eye contact were not maintained long-term; post-treatment, the eye contact percentage decreased back to levels similar to baseline. | The children showed clear interest and positive responses to the robots, suggesting the intervention was acceptable to participants. |

*ASD: Autism spectrum disorder; NR: Not reported

**Table 3** Effect sizes and significance of eye contact outcomes across studies

| Author(s)/ Year | AI Tool/Technology | Eye Contact Outcome | Statistics/Effect Size | Significance |
|---|---|---|---|---|
| Ali et al. [82] | NAO humanoid robot/multi-robot adaptive system | EC duration increased, EC delay decreased | $F=4.52$, $p=0.0185$/ES:NR | Significant |
| Chung [83] | NAO humanoid robot (closed-loop) | EC frequency & duration increased | $\chi^2$ (3) = 20.143, $p=0.000$/ES: Cohen's d = 0.4 (medium) | Significant |
| Chung [35] | NAO humanoid robot (closed-loop) | EC frequency & duration increased | Tau-$U$ = 0.83–0.89, $p<0.01$/ES: Tau-$U \geq 0.8$ (very large) | Significant |
| Daniels, et al. [84] | Superpower Glass (machine learning) | EC & social acuity increased | $F=33.20$, $p<0.001$/ES:NR | Significant |
| Fachantidis et al. [85] | Robot "Daisy" | EC increased | $t=-10.328$, $p=0.000$/ES:NR | Significant |
| Gkiolnta et al. [86] | Educational robot (Codey Rocky) | EC frequency increased | Descriptive only/NA | Positive trend |
| Holeva et al. [87] | NAO humanoid robot (vision & speech recognition) | EC increased in both groups, no group difference | $F=3.131$, $p=0.056$/ES:NR | Non-significant |
| Liu et al. [88] | Smartglasses (AR, emotion recognition) | Caregiver-reported EC increased | Descriptive only/NA | Positive trend |
| Mutawa et al. [89] | NAO robot + mobile app | EC increased | $Z=-11.966$, $p=0.000$/ES:NR | Significant |
| Scassellati et al. [90] | Socially assistive robot (adaptive learning) | EC & initiation increased | $t=-2.462$, $p=0.032$/ES:NR | Significant |
| So et al. [91] | NAO humanoid robot | EC increased | $t=2.21$, $p<0.04$/ES: $\beta=0.96$ (SE = 0.24) | Significant |
| Sosnowski et al. [92] | Lookware™ digital therapeutic | EC indicators increased | $F=17.48$, $p<0.001$/ES: partial $\eta^2=0.25$ | Significant |
| Yoshikawa et al. [55] | Android robot (Actroid-F) | Looking-eye ratio increased | $F=9.844$, $p<0.05$/ES:NR | Significant |
| Yu et al. [61] | VR (customized avatars) | Gaze fixation increased | $t=6.43$, $p<0.001$/ES:NR | Significant |
| Yun et al. [93] | Robots iRobiQ & CARO | EC declined across sessions | Average EC rate 86.5%/ES:NR | Mixed |
| Yun et al. [94] | Robots iRobiQ & CARO | EC increased in both groups, no group difference | $Z=-0.116$, $p=0.955$/ES:NR | Non-significant |

*EC: Eye Contact; Effect Size: ES; NR: Not reported; NA: Not Applicable

toon characters. The game featured an intelligent adaptive system that personalized the training experience for each child, maintaining them within an optimal challenge zone, which was sufficiently demanding to promote engagement, yet not overwhelming. This adaptive mechanism dynamically adjusted the difficulty level of exercises based on the child's performance; if a child encountered difficulty with a task, the game automatically reduced the level of difficulty to better match their capabilities.

**Study outcomes** The outcome of the interventions was positive for most studies related to eye contact or gaze fixation in children with ASD. Among the 16 studies summarized in Table 3, 13 studies (81.3%) reported some form of positive outcome, trend, or perceived improvement in eye contact or gaze metrics following the intervention [82, 35, 55, 61, 83–92]. These positive findings included statistically significant increases in the frequency and duration of eye contact [35, 82, 83, 89], improved gaze fixation ability [61], and significant improvements in joint attention, which involves visual attention and gaze [90]. Caregiver/parent [84, 90] and staff [84] reports indicated increased eye contact. In addition, studies found significantly more eye contact with a robot compared to a human facilitator/teacher [85, 91], an increased ability to look at the robot's eyes and an increasing tendency to look at human eyes over sessions in the ASD group after robot exposure [55], and an increase in the frequency of eye contact in a 20-minute session [86]. These results indicate that a variety of AI-based intervention strategies were effective at promoting eye contact and improving gaze patterns.

While one study reported mixed results concerning eye contact outcomes [93], two studies reported no statistically significant difference in eye contact improvements between participants receiving the AI-based intervention and those in the control/comparison groups [87, 94]. In the study by Yun et al. [93], although the number of eye-contact attempts detected was maintained or even increased in some sessions, the total eye contact rate tended to decline gradually across sessions. In the study by Yun et al. [94], participants in both the robot-assisted group and the human-only control group showed improvements in eye contact, but the level of change did not differ significantly between the groups post-treatment. Similarly, Holeva et al. [87] reported that participants in both the robot-assisted intervention group and the control group demonstrated improvements in eye contact; however, no statistically significant differences were observed between the groups in clinical outcome indicators, including those related to eye contact.

These findings suggest that while most AI-based interventions demonstrated positive effects on eye contact, the outcomes varied according to the type of technology and level of AI sophistication. Robotic systems, particularly humanoid robots such as NAO, were most frequently studied and showed the most consistent and significant improvements in both the frequency and duration of eye contact. Socially assistive and android robots also produced positive outcomes, though their effects were less consistently significant and often limited by small sample sizes. Wearable technologies showed promise for feasibility and acceptability, but with fewer robust statistical outcomes reported. Game-based and VR systems, while fewer in number, highlighted the potential of adaptive, AI-driven personalization to enhance eye contact and gaze-related skills. Importantly, interventions with higher levels of AI sophistication (e.g., adaptive learning, machine vision, deep learning-driven customization) tended to demonstrate stronger or more sustainable effects compared to pre-programmed or Wizard-of-Oz systems.

### Generalization/maintenance and social validity

Generalization and/or maintenance of treatment effects were reported in six of the 16 reviewed studies (38%). Of these, three studies [35, 90, 91] demonstrated at least partial generalization or transfer of eye contact improvements beyond the immediate training context. For instance, Scassellati et al. [90] reported increased eye contact with adults in follow-up sessions conducted without the robot, and Chung [35] reported sustained eye contact during the generalization phase when the robot was no longer present. However, Chung [83] did not evaluate generalization to other settings or individuals, limiting conclusions about the broader applicability of the intervention outcomes.

The maintenance of treatment effects was assessed in five studies [35, 83, 87, 91, 94]. Of these, four studies [35, 83, 90, 91] reported at least short-term maintenance of gains, ranging from 2 to 3 weeks following the conclusion of the intervention. So et al. [91] reported that children retained improvements in social gaze for at least 2 weeks post-treatment. Conversely, Yun et al. [94] was the only study to report a failure to maintain effects over time, with eye contact levels returning to baseline following the intervention's cessation. Due to logistical challenges related to the COVID-19 pandemic, Holeva et al. [87] were unable to assess maintenance reliably beyond the initial follow-up period. The remaining studies ($n = 10$) did not report any assessment of generalization or maintenance in their reports.

Social validity data were reported in seven of the reviewed studies (44%). Five studies [61, 84, 87, 88, 90] provided evidence that caregivers or parents found the interventions to be appropriate, user-friendly, and beneficial. For instance, Scassellati et al. [90] reported that caregivers viewed the system as user-friendly and practical for home implementation, while Yu et al. [61] noted significant parental satisfaction through questionnaire data, indicating the perceived benefit of the VR-based interventions. Two studies [84, 87] explicitly reported strong positive feedback from both parents and children. In Daniels et al. [84], 13 out of 14 families reported improved family interaction and an interest in using the tool in broader social contexts. Similarly, Holeva et al. [87] documented high satisfaction ratings across both treatment groups.

Three studies [88, 92, 94] reported positive participant engagement and enjoyment. Children in the Sosnowski et al. [92] study found the game enjoyable and easy to use, and nearly all staff expressed that they would recommend it to others due to its educational value. Liu et al. [88] also highlighted child enjoyment and caregiver approval, describing the intervention as fun and engaging. Yun et al. [94] reported that children showed clear interest and positive responses to the robotic system, suggesting

**Table 4** Distribution of quality ratings by study design

| Study Design | High Quality | Moderate Quality | Poor Quality | Total Studies |
|---|---|---|---|---|
| Quasi-Experimental | 3 | 4 | 0 | 7 |
| Randomized Controlled | 3 | 1 | 0 | 4 |
| Single-Case Experimental | 3 | 0 | 0 | 3 |
| Qualitative Research | 0 | 1 | 0 | 1 |
| Case Report | 1 | 0 | 0 | 1 |
| Total | 10 | 6 | 0 | 16 |

strong acceptability of the approach. The remaining studies ($n=9$) did not include social validity data, limiting conclusions about the broader acceptability and feasibility of the interventions in other settings.

### Risk of bias in studies and quality of the evidence

The methodological quality of the included studies was assessed using appropriate Joanna Briggs Institute (JBI) Critical Appraisal Tools and the Single-Case Experimental Design (SCED) Scale. A total of 16 studies were included in the quality assessment, encompassing five distinct study designs. The overall quality ratings ranged from moderate to high across these designs. The distribution of quality ratings by study design for the included studies is presented in Table 4, which provides an overview of each study's assessed quality. For the quasi-experimental studies, the overall quality ranged from moderate to high, with scores varying from 55% to 88%. A consistent strength across all studies was the clear identification of cause and effect and the use of multiple outcome measurements, both pre- and post-intervention. Outcomes were also consistently measured in the same and reliable way across the studies. However, a notable limitation was the absence of a control group in four studies [82–84, 93]. The RCT studies demonstrated an overall quality ranging from moderate to high, with scores ranging from 54% to 100%. All of these studies employed true randomization for participant assignment and ensured that the treatment groups were similar at baseline. Furthermore, outcome assessors were consistently blinded to treatment assignment, and follow-up was complete and well-described across all trials. However, the absence of blinding for participants was a significant and consistent limitation across all studies.

The SCED showed an overall high quality, with scores ranging from 91% to 100%. These studies consistently demonstrated clear clinical history, precise target behaviors, and designs that allowed for the examination of cause and effect. Baselines and sampling behavior during treatment were sufficiently established, and raw data records were available to represent variability. The only minor limitations were that inter-rater reliability was absent in one study [90], and generalization was absent in another [85]. The single qualitative research study [86] received an overall moderate quality rating with a 50% score. While congruity between methodology, research question, data collection, and analysis was evident, several critical aspects were unclear or absent, including the stated philosophical perspective and the researcher's cultural/theoretical location or influence. The single case report [88] showed high overall quality with an 80% score. Congruity across research methodology, objectives, data collection, representation, analysis, and interpretation was strong. The influence of the researcher was addressed, and ethical approval was granted. However, the researcher's cultural or theoretical location was not stated, and participants' voices were not adequately represented.

Overall, while diverse in design and specific methodological strengths and limitations, a significant proportion of the included studies demonstrated high methodological quality, particularly among the RCTs and SCEDs. The detailed scores and ratings for each study are presented in the Supplementary Materials Tables (S1–S5) for comprehensive reference.

## Discussion

The purpose of this study was to systematically review published articles on the AI interventions to improve eye contact in children with ASD. We discuss the main findings in the following section. Additionally, we present recommendations for future research and practice.

### Geographical distribution and feasibility of AI-Based interventions

The geographical distribution of the included studies reflects a global interest in AI-based interventions for children with ASD. However, studies were conducted in developed countries except Pakistan [95]. This suggests that the capacity to conduct AI-based research may be influenced by national resources and technological infrastructure. Accordingly, the level of development of countries appears to be positively correlated with the prevalence of AI-based studies. There was, however, little discussion of implementation feasibility, cost-effectiveness, and scalability, which are critical factors influencing the sustainability of AI-based interventions in a variety of educational and clinical settings [96].

Feasibility, cost, and accessibility varied across the interventions. For example, wearable AI tools such as Superpower Glass were low-cost, portable, and integrated smoothly into family routines, which may make them preferable for parents seeking minimally disruptive support [84]. In contrast, socially assistive robots provided high levels of engagement and novelty value but demanded considerable financial resources, technical expertise, and infrastructure, raising questions about long-term family uptake and equity of access [89, 93]. Multi-robot and hybrid robot–app models reduce therapist burden and enrich training environments. However, their complexity may reduce feasibility and accessibility in less resourced or real-world settings. These findings indicate that, while children may be more motivated by robots, parents and service providers prefer modalities that balance affordability and practicality. Future research should address these practical aspects using implementation science frameworks such as RE-AIM (Reach, Effectiveness, Adoption, Implementation, Maintenance), which provide guidance for evaluating not only efficacy but also for evaluating accessibility, adoption, and long-term integration [97]. This approach will help ensure that AI-based technologies for eye contact are developed and implemented equitably worldwide.

#### Gender representation, sample characteristics, and research design

The studies revealed a significant gender imbalance, with female participants comprising only 14% of the total sample. This predominance of male participants likely reflects both the higher prevalence of ASD diagnoses among males and the potential underdiagnosis of females. Epidemiological evidence indicates that ASD is diagnosed approximately four times more frequently in males than in females [1, 98]. However, research suggests that this disparity may partly stem from diagnostic biases and the subtler social presentation of autism traits in females [99–101]. Therefore, it is difficult to generalize the findings to females with ASD. Future studies should aim for a more balanced sex distribution to better capture gender-related differences in intervention outcomes. Moreover, the overall sample sizes across studies were relatively small, often fewer than 20 participants, and age ranges varied widely from preschoolers to adolescents. This heterogeneity, coupled with limited reporting of ASD subtypes or severity levels, complicates the interpretation of intervention outcomes and the comparison of results across studies.

Regarding research design, most studies adopted quantitative methodologies (14 out of 16), with a predominance of quasi-experimental, single-subject, and repeated-measures designs. Although these research designs allow for evaluation of behavioral change, the minimal use of qualitative or mixed-method designs limits understanding of participants' subjective experiences and contextual influences on intervention effectiveness [102]. Future research should employ larger and more diverse samples, include balanced gender representation, and integrate mixed-method approaches to enhance the validity, generalizability, and social relevance of findings [103, 104].

#### Settings

Only two studies were conducted in multiple settings, such as combinations of school, clinical, and home settings [86, 92]. It is particularly important to implement the intervention in multiple settings to promote the generalization of the outcomes [105, 106] and assess implementation feasibility. Future AI-based interventions should be conducted in multiple settings so that generalization can be enhanced and feasibility can be evaluated.

#### Operational definitions and measurement approaches of eye contact

There was considerable variation in how eye contact was defined and measured across the included studies. Most commonly, eye contact was defined as the frequency and/or duration of eye contact during social interactions with robots, teachers, facilitators, or peers (e.g. [84–86]), while some (e.g. [55, 92]) adopted broader definitions emphasizing gaze directed toward facial regions. This lack of standardization in operational definitions may influence the interpretation and comparability of outcomes among the studies, potentially leading to skewed effects depending on the criteria used.

Similarly, measurement approaches varied widely, ranging from direct observation to advanced technological systems. Some studies (e.g. [83, 89, 91]) relied on direct observation, with researchers manually recording the frequency and duration of eye contact during interaction; other studies supplemented these data with parent-reported measures (e.g. [84, 90]), adding contextual insights into children's behavior. Studies also employed advanced technological systems, including robotic systems with integrated eye trackers and wearable or screen-based eye-tracking devices [82, 87, 90, 93, 94]. In direct observation, participants' behaviors are hand-coded by observers [107]. In this approach, eye contact can be described as looking at the face, looking at the expert, or looking at the researcher (e.g. [108–111]). Because eye movements are very rapid, it is difficult to observe them behaviorally [112]. To overcome these limitations, eye-tracking devices are recommended when measuring eye contact, as they provide precise and objective data [113]. With eye tracking, eye contact can be defined as looking directly into a person's eyes, which provides more explicit evidence of eye contact behavior [4]. This approach can also promote a more objective and standardized definition across studies. A standardized operational definition can facilitate the accurate interpretation and comparison of results among studies, especially in meta-analyses, where heterogeneity in measurement can bias the results.

### Variability in AI modalities and technological sophistication

The included studies employed a range of AI-based tools to improve eye contact in children with ASD, encompassing diverse technological modalities such as robotic, wearable, virtual, and game-based systems. Robotic systems were the most frequently used systems, appearing in 75% of the studies, and included humanoid, socially assistive, and android robots, each designed to support eye contact through tailored, interactive features. Wearable technologies, VR-based interventions, and game-based software incorporating AI were less common. These diverse applications reflect growing interest in leveraging AI interventions to improve eye contact. However, while these studies utilized AI-based tools to improve eye contact in children with ASD, the level of AI sophistication varied considerably.

Some interventions incorporated advanced AI features such as machine learning, adaptive algorithms, emotion recognition, and deep learning-based personalization (e.g., wearable systems with facial expression recognition, augmented reality smart glasses, and adaptive VR environments). These tools allowed for real-time adjustments based on the child's performance or emotional state, offering a more personalized and responsive intervention experience [61, 82, 84, 88, 90, 92]. In contrast, several studies employed pre-programmed or operator-controlled robots with limited or no autonomous AI functionality, such as the Wizard of Oz approach or static gesture-based programming (e.g. [55, 85, 86, 91]). This variability in AI implementation highlights a spectrum of technological complexity within current interventions and suggests that while many tools are considered as AI-based, the degree to which they leverage true AI capabilities remains inconsistent. Future research should clarify and standardize the role of AI in such interventions to better assess their comparative effectiveness.

AI-based interventions for children with ASD have been developed using a wide range of tools, including robots, wearables, VR systems, and game-based platforms. Robotic systems, particularly humanoid robots, demonstrated the most consistent improvements in eye contact, reflecting their capacity to engage children in structured, socially meaningful interactions. In contrast, wearable technologies showed high feasibility and acceptability, but evidence of their effectiveness for improving eye contact remains limited, highlighting the need for more rigorous outcome evaluation. Game-based and VR systems, while representing a smaller subset of interventions, underscore the potential of immersive and adaptive AI to promote engagement and gaze-related learning in naturalistic contexts.

Importantly, the level of AI sophistication appeared to influence outcomes. Interventions that employed adaptive reinforcement learning, computer vision, or deep learning–driven customization tended to show stronger and more sustainable improvements compared to systems that relied on pre-programmed scripts or Wizard-of-Oz methods. This suggests that the personalization and responsiveness afforded by more advanced AI may be a key mechanism of effectiveness [114]. However, due to variability in study design, outcome measures, and sample sizes, these trends remain preliminary. Future research should explicitly test whether greater AI sophistication translates into improved outcomes by directly comparing adaptive versus non-adaptive systems within similar intervention frameworks. Additionally, broader attention is needed to address issues of feasibility, cost-effectiveness, and scalability, since highly sophisticated systems may be more difficult to implement in community or educational settings without appropriate support.

AI modalities also differ in their influence on motivation, attention, and generalization. Socially assistive robots can increase motivation and engagement because of their embodied, predictable interactions. However, their effects on human–human generalization are inconsistent unless caregivers or peers are integrated into sessions [94, 90]. Gaze-contingent games directly shape attention allocation by linking feedback to children's gaze, strengthening attentional flexibility and emotion recognition, though evidence of transfer to everyday interactions is still limited [92]. Wearables such as AI-based glasses embed prompts in naturalistic contexts, which may be less engaging than robots but are more effective in supporting generalization to human-human communication [84]. These findings indicate that robots optimize motivation, gaze-contingent systems enhance attention, and wearables support real-world generalization. Therefore, it is important to align the choice of intervention modality with the specific objectives of the intervention.

### Reported outcomes

The included studies demonstrated variability in the reported outcomes across different AI-based tools. Most studies (81.3%) reported improvement in eye contact following AI-based interventions, though the magnitude and consistency of these effects varied. Robotic systems were the most frequently implemented, and several studies indicated that participants displayed relatively higher frequencies of eye contact with robots compared to human facilitators [85, 91]. A few studies also noted that exposure to robotic systems was followed by gradual increases in eye contact with humans, suggesting potential transfer effects [55].

Duration is a critical parameter for evaluating the effectiveness, replicability, and practical implementation of AI-based interventions, as well as for contextualizing outcome comparisons across diverse study designs.

Reported intervention periods varied substantially, ranging from brief feasibility studies conducted within 1 day [55] or a single session [88] to longitudinal trials extending over 3 to 6 months (e.g. [82, 87]). Short-term interventions, such as those involving 10-minute sessions over 5 days [61] or a limited number of conversational trials within 1 day, demonstrated engagement and usability but provided limited insight into sustained behavioral change. In contrast, longer and more intensive protocols, such as a 1 month home-based program requiring daily 30-minute sessions [90], produced more enduring behavioral improvements, including generalized gains in eye contact beyond the intervention context. Overall, these differences in intervention duration highlight the need for future studies to articulate the rationale behind selected time frames and to examine how duration relates to study design, participant characteristics, and intervention context. Since the optimal length of AI-based interventions is likely influenced by multiple factors such as individual learning needs, support intensity, feasibility, and technological features, clear reporting and justification of these parameters are essential to interpret findings meaningfully and to inform evidence-based practice.

#### Affective and ethical considerations

Consistent with neurodiversity-informed perspectives, emerging evidence indicates that robot-mediated interventions may provide a less socially demanding context for practicing gaze-related behaviors. Given that some individuals with autism experience discomfort, anxiety, or distress during direct eye contact [29, 30], robotic systems may help minimize affective arousal by offering predictable and nonjudgmental social interactions. These conditions could support gradual familiarization with eye contact within a safe and adaptive framework. Therefore, it can be a more acceptable intervention for children with autism. Nevertheless, even when mediated through robots, eye contact interventions must be implemented with caution, as the use of technology alone does not guarantee comfort for every participant. Practitioners and researchers should not reinforce or impose eye contact upon the child if such behavior causes distress. Monitoring affective responses during interventions is also essential to ensure that increases in eye contact are the result of meaningful engagement and not merely compliance. The inclusion of social validity measures is therefore essential when evaluating whether eye contact interventions are both effective and acceptable to participants and their families.

#### Gaps in generalization, maintenance, and social validity

The limited number of studies examining generalization and maintenance (six out of 16) highlights critical gaps in the current literature on AI-based eye contact interventions for children with ASD. While several studies demonstrated short-term maintenance of gains and positive perceptions from participants and caregivers, most were limited to assessing whether improvements are generalized across stimuli, people, or settings. We cannot evaluate the generalization of the outcomes as a result of this gap. Given that eye contact is a foundational social behavior [4, 29, 30] and outcomes are more meaningful when they are generalized beyond the intervention context, it is crucial for future studies to investigate whether improvements in eye contact observed in controlled settings persist across other people and contexts.

Limited social validity assessment (seven out of 16) is also a significant gap. It is not sufficient to state that the intervention is significant and acceptable merely because the studies produced positive experimental outcomes. The acceptability of intervention goals, procedures, and outcomes can be determined through social validity [115]. Eye contact interventions must be critically evaluated, as emphasis on gaze can produce discomfort or sensory overload for some autistic children [29, 30]. In these cases, alternative social attention outcomes such as joint attention or flexible face-directed gaze without enforced fixation may offer more appropriate and ethical indicators of engagement. This makes social validity assessment essential rather than optional, ensuring that intervention goals and procedures are not only effective but also acceptable to children and families. As a result, integrating social validity assessment into future AI-based eye contact interventions must be considered an essential component of the research design. Incorporating social validity assessment into the study framework may facilitate the advancement of ethical, person-centered AI intervention approaches.

#### Methodological quality and strength of evidence

The quality indicator revealed variation across the included studies, which directly affects the strength of the evidence. High-quality studies, such as the randomized trials of Yun et al. [94] and the single-case experiments of Chung [35] and Fachantidis et al. [85], increase confidence by demonstrating methodological rigor. In contrast, several quasi-experimental studies (e.g. [83, 84]) and small pilot trials (e.g. [82, 89]) were more limited, lacking control groups, adequate reporting, or sufficient sample sizes, which constrains causal effects and reduces the stability of their findings. Case reports (e.g. [88]) provided valuable descriptive insights but offered little causal evidence. The predominance of positive results across these lower-quality designs also raises the possibility of publication bias. Overall, while high-quality studies strengthen confidence in the benefits of AI-based interventions, the evidence base remains preliminary and should be interpreted with caution. Future studies should be designed with larger samples, stronger controls, and transparent reporting.

### Limitations of the review and included studies

A key consideration when interpreting the study's findings is recognizing its limitations. Studies published in native languages or in other databases may have been excluded from the review due to specific inclusion criteria. The review findings should therefore be interpreted with caution, since they may not represent the full scope of AI-based interventions to improve eye contact. Although we organized our findings according to the type and sophistication of AI technology, we did not statistically analyze the association between AI advancement and outcomes, as meta-analysis is outside the scope of our analysis. To investigate this relationship, future studies should use meta-analytic methods and clarify whether technological sophistication contributes to effectiveness. Another methodological consideration is that the review protocol was registered retrospectively after the screening stage had begun, which may have reduced strict adherence to the initial protocol and should therefore be acknowledged as a limitation.

In addition to the methodological limitations of the present review itself, it is also necessary to consider the limitations of the included studies, as these factors shape how the current findings can be interpreted. The heterogeneity in operational definitions of eye contact and measurement tools, ranging from parent reports and manual coding to eye-tracking systems, reduces comparability across studies and limits confidence in cross-study trends [84, 90, 92–94]. This definitional heterogeneity limits comparability across studies and underscores the need for a standardized and uniform operationalization of eye contact in future research. In addition, the wide range of intervention durations represents a limitation, as it complicates the interpretation of immediate efficacy and makes it more challenging to assess the long-term potential and real-world applicability of these AI-based tools.

Measurement tools also varied widely, ranging from parent or teacher reports and manual observational coding to advanced robotic sensors and eye-tracking devices [89, 90]. This inconsistency makes it difficult to compare results across studies. Future research should provide clear and consistent definitions and measurement methods. Moreover, small sample sizes further weaken statistical power and increase the likelihood of inflated effect estimates, especially in pilot and feasibility studies [82, 89]. Further, the absence of systematic assessments of cost, feasibility, affective responses, and social validity restricts understanding of whether observed gains would translate into sustained, acceptable, and scalable interventions in everyday contexts. Collectively, these issues suggest that while the evidence base points to promising short-term benefits of AI-based interventions for improving eye contact, the strength and generalizability of these findings remain tentative and should be interpreted with caution.

## Conclusions

This systematic review revealed that AI-based interventions are developing technology for improving eye contact behavior in children with ASD. Overall, preliminary findings suggest that AI technologies, particularly robotic systems, are often associated with increases in the frequency and duration of eye contact in children with ASD. However, the reviewed studies are limited in scale, and the findings should therefore be interpreted cautiously. However, variations in definitions, measurement methods, and technological frameworks were noted across studies. Furthermore, data on generalization and social validity of interventions were limited. The limited number of findings regarding generalization and social validity assessments raises questions about the overall effectiveness and acceptability of interventions. Consequently, future studies should not only focus on more advanced AI systems but also evaluate the acceptability of eye contact interventions from the perspective of key stakeholders and assess their effectiveness across different stimuli, individuals, and settings. It is also difficult to gain a deeper understanding of participant experiences, perceptions of the intervention process, and contextual factors due to the limited use of qualitative data in current research. Therefore, future research should use mixed-method designs to gain a deeper understanding of intervention outcomes and provide insight into the development of more effective interventions.

## Supplementary information

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Supplementary Material 1

### Author contributions

Conceptualization, S.D. and M.B.; methodology, S.D.; software, M.B.; validation, S.D. and M.B.; formal analysis, S.D. and M.B.; investigation, S.D. and M.B.; resources, S.D. and M.B.; data curation, M.B.; writing original draft preparation, S.D. and M.B.; writing review and editing, S.D. and M.B.; visualization, M.B.; project administration, S.D.. All authors have read and agreed to the published version of the manuscript.

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### Data availability

No new data were created or analyzed in this study. Data sharing is not applicable to this article.

## Declarations

### Ethics approval and consent to participate
The study did not involve direct human participants, and therefore, specific declarations regarding human ethics and consent to participate are not applicable.

### Competing interests
The authors declare no competing interests.

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