Психология человека в образовании, 2025, т. 7, № 4
Psychology in Education, 2025, vol. 7, no. 4
www.psychinedu.ru

Клинические, образовательные и социальные аспекты психологии здоровья

УДК 159.99

EDN BJFLBV
https://www.doi.org/10.33910/2686-9527-2025-7-4-492-503

Research article

Integrating artificial intelligence and parent-child interactions in the assessment of autism spectrum disorder risks: A theoretical analysis

M. Sirisety[1], O. El Hamzaoui[2], E. V. Patrakov[✉2], V. I. Borisov[2], T. R. Navasconi Berbert[3], R. S. Datti[1], A. A. Hungaro[3], H. Amílcar Martins[3], O. V. Sokolova[2]

[1] Department of Applied Psychology, School of Humanities and Social Sciences, GITAM (Deemed to be University), Rushikonda, Visakhapatnam 530045, India
[2] Ural Federal University Named After the First President of Russia B. N. Yeltsin, 19 Mira Str., Ekaterinburg 620002, Russia
[3] Integrated University Center, Campo Mourão, 670 Pereira Brothers Ave., Paraná 87301-010, Brazil

For citation: Sirisety, M., El Hamzaoui, O., Patrakov, E. V., Borisov, V. I., Navasconi Berbert, T. R., Datti, R. S., Hungaro, A. A., Amílcar Martins, H., Sokolova, O. V. (2025) Integrating artificial intelligence and parent-child interactions in the assessment of autism spectrum disorder risks: A theoretical analysis. *Psychology in Education*, vol. 7, no. 4, pp. 492–503. https://www.doi.org/10.33910/2686-9527-2025-7-4-492-503 EDN BJFLBV

Received 24 September 2025; reviewed 8 October 2025; accepted 9 October 2025.

Funding: The research was carried out with the financial support of the Russian Science Foundation and the Government of the Sverdlovsk region, project No. 24-28-20414 "Adaptation to professional activity in the digital environment: 'price' and values (based on the material of socionomic professions)".

Abstract
Introduction. Artificial intelligence (AI) is increasingly being integrated into medicine and related fields. Successful applications of AI in the differential diagnosis of autism spectrum disorders (ASD) have been documented. These studies, however, typically utilize large amounts of data, including electroencephalography. The authors explore the theoretical feasibility of using AI to assess ASD risk at an early age using data from only a smartphone video camera and a parental questionnaire.
Materials and Methods. The study is theoretical in nature; therefore, the methodology involves a theoretical analysis and comparison of psychological research with current AI capabilities, alongside consideration of the potential application of the proposed model in India, Brazil, and Russia. Within psychology, an analysis of methods for assessing the most significant risk factors for ASD development was conducted. Within information technology, principles for creating an AI methodology are given.
Results. It is potentially feasible to develop and implement a neural network-based method capable of analysing relatively simple behavioural factors in infants during interactions with a parent. Such a method could be implemented as a smartphone application for parents or as a web-based program. However, analysis indicates that in a cross-cultural context, significant challenges may arise concerning data privacy and the need for extensive, culturally diverse datasets (requiring hundreds of thousands of entries) to train a robust AI model. The authors posit that the simplicity of the proposed application — requiring parents to complete a brief questionnaire several times a month and record a video of their child's emotions or reactions — could facilitate the creation of such a dataset.
Conclusion. Early diagnosis of ASD can significantly improve outcome for children's mental development. Signs of ASD can be detected in children as young as 18 to 24 months.

Keywords: artificial intelligence, autism spectrum disorders, early age, neural networks, risk assessment

Научная статья

Интеграция искусственного интеллекта и взаимодействия родителей и детей в процесс оценки рисков расстройств аутистического спектра: теоретический анализ

М. Сирисети [1], У. Эль Хамзауи [2], Э. В. Патраков[✉2], В. И. Борисов[2], Т. Р. Наваскони Берберт[3], Р. Ш. Датти[1], А. А. Хунгаро[3], Х. Амилкар Мартинс[3], О. В. Соколова[2]

[1] Университет ГИТАМ, 530045, Индия, г. Вишакхапатнам, Рушиконда
[2] Уральский Федеральный Университет имени первого Президента России Б. Н. Ельцина, 620062, Россия, г. Екатеринбург, ул. Мира, д. 19
[3] Интегрированный Университетский центр Кампо Мурао, 87301-010, Бразилия, г. Парана, пр. Братьев Перейра, д. 670

Для цитирования: Сирисети, М., Эль Хамзауи, У., Патраков, Э. В., Борисов, В. И., Наваскони Берберт, Т. Р., Датти, Р. Ш., Хунгаро, А. А., Амилкар Мартинс, Х., Соколова, О. В. (2025) Интеграция искусственного интеллекта и взаимодействия родителей и детей в процесс оценки рисков расстройств аутистического спектра: теоретический анализ. *Психология человека в образовании*, т. 7, № 4, с. 492–503. https://www.doi.org/10.33910/2686-9527-2025-7-4-492-503 EDN BJFLBV

Получена 24 сентября 2025; прошла рецензирование 8 октября 2025; принята 9 октября 2025.

Финансирование: исследование выполнено при финансовой поддержке Российского научного фонда и Правительства Свердловской области, проект № 24-28-20414 «Адаптация к профессиональной деятельности в цифровой среде: «цена» и ценности (на материале социономических профессий)».

Аннотация

Введение. Искусственный интеллект (ИИ) все больше внедряется в медицину и смежные области знаний. ИИ успешно применяется в дифференциальной диагностике нозологических форм расстройств аутистического спектра (РАС). При этом в исследованиях речь идет о применении большого количества данных, в т. ч. данных энцефалографии и т. д. В статье авторы ставят вопрос о теоретической возможности использования ИИ для оценки рисков РАС в раннем возрасте с помощью приложения для смартфона.

Материалы и методы. Исследование носит теоретический характер, поэтому используются теоретический анализ, сравнение психологических исследований и актуальных возможностей ИИ, а также потенциального применения предполагаемой модели в Индии, Бразилии и России. В области психологии проведен анализ методик, которые позволяют оценивать наиболее значимые факторы риска для развития РАС. В области информационных технологий приведены возможные принципы создания нейросетевой методики.

Результаты исследования. Показано, что потенциально возможно создание и применение нейросетевой методики, которая может анализировать достаточно простые факторы в поведении младенцев, а также во взаимодействии матери (родителей) и младенца, с применением краткой видеосъемки реакций младенца на различные стимулы. Такая методика может применяться как приложение для смартфона родителей либо как браузерная программа. При этом показано, что в кросс-культурном контексте могут возникнуть риски использования персональных данных, необходимость сбора достаточно больших баз данных для обучения программы ИИ. Авторы полагают, что простота использования приложения (необходимо несколько раз в месяц ответить на простой опросник и снять видео эмоций или реакций малыша) потенциально могут внести вклад в создание такой методики.

Заключение. Ранняя диагностика расстройств аутистического спектра может значительно улучшить результаты психического развития детей с РАС. Признаки расстройств аутистического спектра могут быть обнаружены у детей в возрасте от 18 месяцев до 2 лет.

Ключевые слова: искусственный интеллект, расстройства аутистического спектра, ранний возраст, нейронные сети, оценка рисков

Introduction

Autism Spectrum Disorder (ASD) is a complex neurodevelopmental condition characterized by persistent challenges in social communication and interaction alongside restricted and repetitive patterns of behavior, interests, or activities. Globally, ASD affects approximately 1 in 100 children, with early diagnosis being critical for effective intervention and improved developmental outcomes. However, traditional diagnostic approaches, which rely heavily on subjective clinical observations and standardized tests, face limitations such as variability in practitioner expertise, time consumption, and accessibility (Chakrabarti 2023). Clinical diagnosis is typically conducted at three years of age or older, which reduces the opportunity to identify risk factors at an earlier stage (Sawicki et al. 2021). Another complicating factor is that parents, particularly mothers, may lack skills in interpreting the child's emotional state and can feel disempowered by factors such as unsupportive family environments (Bhavnani et al. 2022). The diagnostic process is also challenged by the heterogeneous clinical manifestations of ASD in early childhood (Sozonov et al. 2024).

Artificial Intelligence (AI) algorithms have emerged as a promising tool in healthcare, offering opportunities to enhance the speed, accuracy, and accessibility of ASD risk assessment (Wankhede et al. 2024). By leveraging AI's capacity to analyze large datasets and detect patterns imperceptible to the human eye, early diagnosis can be revolutionized (Chaddad et al. 2022). The aim of this article is to explore the theoretical foundations, potential applications, benefits, and challenges of employing AI for early assessment of ASD risk. A similar large-scale study was conducted relatively recently (Joudar et al. 2023). However, this study relied on extensive datasets, such as magnetic resonance imaging (MRI), electroencephalography (EEG), genetic, sociodemographic, and medical data.

This article focuses specifically on the psychological aspects of autism *risk* assessment, rather than diagnosing the disorder itself. The authors posit that this approach will help parents identify potential concerns earlier and mitigate later challenges. The study may also be of interest to psychologists. Numerous studies confirm the effectiveness of early intervention programs designed to address social and communication deficits in children with or at risk of ASD (Alatar et al. 2025; Evangelou et al. 2025). However, the absence of unified algorithms for identifying and alerting parents and specialists about developmental characteristics associated with this diagnosis means most families continue to lack timely, high-quality support.

Emerging technologies like Facial Emotion Recognition (FER) systems offer a promising alternative to traditional diagnostic approaches. By tracking a child's emotional responses and behavioral patterns over time, FER systems trained on large, diverse datasets of facial expressions and behaviors associated with ASD could provide objective, longitudinal data. Such technology could offer valuable feedback on the effectiveness of therapeutic programs, enabling personalized adjustments to better meet a child's needs. For instance, therapists could use FER-based tools to monitor progress during social skills training or behavioral therapy sessions, thereby improving the overall quality of care.

Cross-cultural context: Brazil, India, Russia

Indian context. Research on ASD within the Indian context reveals a scarcity of high-quality, population-based epidemiological studies, complicating efforts to establish accurate prevalence rates (Uke et al. 2024). A parallel lack of translational research underscores the need to evaluate the impact of evidence-based interventions within standard healthcare practices (Patra, Kar 2021). In recent years, however, increasing technological adoption has spurred efforts by healthcare professionals and researchers to develop tools for early ASD screening, usable even by non-specialists. For instance, the user-friendly START application utilizes artificial intelligence to assess autism phenotypic domains — including social, sensory, and motor functions — by analyzing child performance and parent reports (Dubey et al. 2024). Such advancements show the potential of technology to bridge gaps in ASD screening in India.

Brazilian context. Analysis of ASD within Brazil indicates that most epidemiological data derive from administrative databases. The 2022 Demographic Census identified 2.4 million individuals with an autism spectrum disorder diagnosis, corresponding to 1.2% of the population. Prevalence was higher among men (1.5%) than women (0.9%), totaling 1.4 million men and 1.0 million women diagnosed by a health professional. Among age groups, the highest prevalence was observed in children aged 5 to 9 years (2.6%) (IBGE, 2022).

Data from the Outpatient Health Care Procedures Registry identified 23,657 children up to 12 years old whose first care occurred between 2013 and 2019, with diagnoses recorded per ICD-10. The year 2013 accounted for the highest proportion of cases (18.9%,

 https://www.doi.org/10.33910/2686-9527-2025-7-4-492-503

approximately 4,470 children). From 2014 onward, cases increased progressively, peaking between 2017 and 2018 before declining in 2019. Regarding early diagnosis, the proportion increased significantly over this period, from 23.3% in 2013 to 32.8% in 2019 ($p < 0.001$), suggesting gradual improvements in ASD recognition and identification within the Brazilian Unified Health System (Girianelli et al. 2023).

Russian context. In 2024, 76,096 children with ASD and 5,059 adults with ASD were registered in Russia, according to Rosstat data provided by the Russian Ministry of Health (Rosstat 2024). This corresponds to 1 in 391 children diagnosed with ASD, a rate nearly four times lower than global WHO statistics and the prevalence recognized by the Ministry of Health in 2013. It is estimated that parents of more than 200,000 children remain unaware of their child's diagnosis or its causes, thereby unable to use this information for life planning, education, and other trajectories.

Thus, significant challenges in the timely identification and support of individuals with ASD are evident across these diverse national contexts.

Psychological context

With sufficient input data, neural network-based diagnostics hold significant promise. However, researchers note that the boundaries of the concept of 'autism spectrum disorder' are exceptionally broad. This diagnostic group includes early infantile/childhood autism (very close to Childhood Disintegrative Disorder, CDD), atypical autism, classic autism, and Asperger's autism. It also includes individuals with intellectual development disorders, speech impairments, and Rett syndrome (Makarov and Avtenyuk 2018). The ICD-11 focuses on three key diagnostic criteria: impairments in social communication and interaction, alongside a range of inflexible, restricted, and repetitive patterns of behavior and interests. A formal diagnosis of autistic disorder should therefore be made by a qualified psychiatrist. Since this discussion pertains specifically to the analysis of risk, however, a digital screening model may serve as an acceptable tool for supporting parents, psychologists, and care staff.

A study by L. O. Tkacheva and colleagues identified the following observable markers of ASD risk in early childhood (Tkacheva et al. 2023):

1. Decreased social attention, manifesting as poor eye contact, lack of response to directed speech, and reduced engagement in play or social interaction.
2. Lowered orientation toward social stimuli, such as facial stimuli (photographs of familiar people, other children, smileys, emoticons), accompanied by diminished social smiling and positive emotions;
3. Delayed development of speech and gestural communication;
4. Atypical postures and movement patterns, abnormal muscle tone, increased auditory sensitivity, and decreased visual attention.

Furthermore, social and communicative impairments in young children with ASD are observed more frequently than repetitive behaviors. Impaired motor skills and sensory processing are also common in children with general developmental delays, reducing their specificity for an ASD diagnosis in early childhood (Tkacheva et al. 2023).

In an examination of children aged 9 months to 4 years, S. Pereverzeva and colleagues delineated nine clusters of potential ASD symptom markers (Pereverzeva et al. 2015):

1. Disturbances in autonomic-instinctive functions, appearing 1–3 months postnatally and persisting in subsequent years, including sleep disturbances (difficulty falling asleep, frequent awakenings, 'quiet' insomnia), feeding difficulties (weak sucking and other breastfeeding disorders, early weaning), and poor appetite.
2. Persistent gastrointestinal disturbances, such as regurgitation, constipation, appetite disorders, and feeding inversion.
3. Avoidance of eye contact with adults; lack of response to direct verbal address despite reaction to other sounds; active avoidance of or distress during social engagement; lack of distress at parental departure.
4. Indifferent behavior toward caregivers and, by the second year, a lack of interest in other children.
5. General detachment from surroundings; absence of pointing gestures and imitation of facial expressions, sounds, or speech; delayed reciprocal smiling and laughter; an underdeveloped social 'animation complex' ('bright flash of activity', 'infant's smiling response', 'startle complex').
6. Limited emotional expressiveness, weak facial affect, and a pervasive 'serious' expression from infancy.
7. Decreased and stereotyped interest in toys (e.g., lining up, spinning), often replaced by a preoccupation with household objects as something of special value; lack of situational and imitative play with adults.
8. Delayed pre-speech and speech development; poor babbling; absence of syllables or words or their replacement with vocal self-stimulation; a key marker under one year is

lack of response to one's own name (typically present by 6–8 months); by one year, lack of comprehension of spoken language; if speech is present, absence of personal pronouns and failure to use one's own name.
9. Motor delays, including absence of crawling; prevalent muscle hypotonia or dystonia; and frequent toe-walking.

Current methods for ASD diagnosis:
1. Autism Diagnostic Observation Schedule, Second Edition (ADOS-2): a semi-structured, standardized assessment of communication, social interaction, and play, often considered as a 'gold standard' in ASD diagnosis.
2. Autism Diagnostic Interview — Revised (ADI-R): a structured caregiver interview covering full developmental history and behaviors relevant to ASD, commonly used in conjunction with the ADOS-2 for a more comprehensive assessment (Le Couteur et al. 2003).
3. Childhood Autism Rating Scale (CARS): a behavior rating scale that assesses a child's behavior, characteristics, and abilities to determine the severity of autism (Schopler et al. 1980).
4. Social Communication Questionnaire (SCQ): a parent/caregiver-completed screening tool evaluating communication skills and social functioning to identify children needing comprehensive ASD assessment; derived from the ADI-R (Berument et al. 1999).
5. Developmental, Dimensional and Diagnostic Interview (3Di): a computerized parental interview assessing autistic traits and related developmental disorders, providing dimensional profiles of social reciprocity, communication, and repetitive behaviors (Skuse et al. 2004).

The available literature on the prevalence of ASD in Brazil presents significant limitations. Estimates come exclusively from medium- and large-sized urban centers located in two wealthier states, São Paulo and Rio Grande do Sul, and are restricted to the period between 2010 and 2015, which precludes longitudinal analysis. Furthermore, only one study employed a standardized clinical diagnostic instrument like the ADI-R. Other studies, including both phases of the Pelotas cohort, relied on screening instruments or structured interviews administered by lay interviewers, thereby compromising diagnostic accuracy. These methodological challenges, combined with limited access to gold-standard tools like the ADOS and the ADI-R, which require specialized time and expertise, are also observed in other national contexts (Dellazari et al. 2025).

Specific questionnaires for India:
1. Trivandrum Autism Behavior Checklist (TABC): TABC a standard screening tool used by health professionals for early detection of ASD in India. It assesses dimensions such as 'social interaction, communication, behavioral characteristics, and sensory integration' (Nair et al. 2014).
2. Chandigarh Autism Screening Instrument (CASI): a 37-item dichotomous screening instrument used by healthcare professionals to screen the general Hindi-speaking population in India, without sub-dimensions (Arun, Chavan 2018).

In subsequent developmental stages, differences between neurotypical children and those with developmental concerns become more pronounced, allowing for the application of other, more comprehensive diagnostic methods. A high-quality assessment for autism spectrum disorders before the age of one year currently relies on a detailed analysis of the child's developmental history and dynamic behavioral observation. It is crucial for parents to monitor their children's development from an early age and report any observed deviations to specialists.

Thus, nearly all psychological indicators — a child's behavior, emotional reactions, and interactions with adults — can be relatively easily identified visually (via smartphone video) and formulated into questions that parents could answer periodically, for example, once every few weeks. However, this approach requires dynamic analysis of parent-child interactions, both by a neural network and through parental reflection, as identified risks can primarily be mitigated through these very interactions. In our earlier research, we developed a risk assessment model based on parents evaluating the following parameters:
1) the frequency of concerning events (increasing or decreasing),
2) their perceived ability to cope with these problems,
3) the degree of their concern.

Based on the theoretical analysis conducted, we propose a set of questions that could be included in an assessment for the risk of developing autism spectrum disorders in a child during the first year of life:

To the Parent of Caregiver,

Please answer all questions by **circling one number in each of the three columns (Frequency, Anxiety, Overcoming) for every item.** If you have more than one child, please complete a separate form for each child. Your thoughtful responses will contribute to developing supportive resources for parent-child interaction.

No	Situation or a child's behavior	***FREQUENCY*** *How often do you notice this behavior?* *1 = Never* *2 = Sometimes* (a few times a week) *3 = appeared recently* *4 = Frequently* *5 = Constantly* (several times a day)	***ANXIETY*** *How much does this behavior concern you?* *1 = Not at all* *2 = A little* *3 = Moderately* *4 = Quite a bit* *5 = Very much*	***OVERCOMING*** *How well do you manage this behavior?* *1 = Very well* *2 = Well enough* *3 = Moderately well* *4 = Rather poorly* *5 = Cannot cope; need help*
1	Does the child smile in response to a parent's smile?	1 2 3 4 5	1 2 3 4 5	1 2 3 4 5
2	Does the child smile with a wide, open mouth?	1 2 3 4 5	1 2 3 4 5	1 2 3 4 5
3	Does the child make an eye contact with an adult?	1 2 3 4 5	1 2 3 4 5	1 2 3 4 5
4	Does the child become still (freeze/pause) when spoken to?	1 2 3 4 5	1 2 3 4 5	1 2 3 4 5
5	Does the child purse their lips forward when spoken to?	1 2 3 4 5	1 2 3 4 5	1 2 3 4 5
6	Does the child produce cooing sounds (e.g., 'koo', 'ooo', 'agu', 'gee', 'khee', 'aga', 'ga', 'ege', 'aa')?	1 2 3 4 5	1 2 3 4 5	1 2 3 4 5
7	Does the child actively wave arms and/or legs when seeing an adult?	1 2 3 4 5	1 2 3 4 5	1 2 3 4 5
8	Does the child laugh loudly?	1 2 3 4 5	1 2 3 4 5	1 2 3 4 5
9	Does the child attract attention by screaming?	1 2 3 4 5	1 2 3 4 5	1 2 3 4 5
10	Does the child produce sound combinations (e.g., 'ma', 'ba', 'pa', 'da', 'na')?	1 2 3 4 5	1 2 3 4 5	1 2 3 4 5
11	Does the child recognize close relatives (e.g., becomes lively, coos, etc.)?	1 2 3 4 5	1 2 3 4 5	1 2 3 4 5
12	Does the child respond to their own name?	1 2 3 4 5	1 2 3 4 5	1 2 3 4 5
13	Does the child become lively when seeing a rattle?	1 2 3 4 5	1 2 3 4 5	1 2 3 4 5
14	Does the child distinguish between 'familiar' and 'unfamiliar' adults?	1 2 3 4 5	1 2 3 4 5	1 2 3 4 5
15	Does the child display at least three distinct emotions?	1 2 3 4 5	1 2 3 4 5	1 2 3 4 5
16	Does the child reach out arms toward a parent to be picked up?	1 2 3 4 5	1 2 3 4 5	1 2 3 4 5
17	Does the child show excitement upon a parent's return (e.g., smiles, vocalizes, moves arms/legs)?	1 2 3 4 5	1 2 3 4 5	1 2 3 4 5

18. Child's gender: M ☐ F ☐
19. Child's age: ____________ months and __________ days
20. Has your child experienced any of the following? (Check one):
    - ☐ Yes (e.g., brain trauma, central nervous system infection, or congenital condition related to brain pathology)
    - ☐ No
    - ☐ Not sure

Thank you for your participation.

Theoretical framework: AI in healthcare and wellness

AI encompasses a range of technologies, including machine learning (ML), deep learning (DL), computer vision (CV), and natural language processing (NLP), enabling machines to perform tasks traditionally requiring human intelligence. In healthcare and wellness, AI is increasingly applied to disease prediction, medical imaging analysis, and decision support systems. For ASD assessment, AI leverages the following capabilities (Jiao et al. 2020):

Pattern recognition. ML algorithms can detect subtle behavioral and physiological patterns associated with ASD that may be missed during traditional clinical assessments.

Predictive analytics. AI can analyze longitudinal data to identify children at risk of ASD even before observable symptoms emerge (Zhang et al. 2025).

Anomaly detection. Unsupervised learning models can flag atypical behaviors or responses by comparing individual data against large datasets of typical and atypical development (Gao et al. 2023).

AI methods implemented for early ASD diagnosis use distinct or combined techniques to enhance robustness and accuracy (Jeon et al. 2024):

1. FER analyzes video data of children's behavior to identify patterns associated with ASD (Abdullah and Al-Allaf 2021).
2. Speech and voice analysis models process vocal features (e.g., pitch, duration, frequency) to detect atypical speech patterns or delays in language development. Multimodal systems can integrate FER and speech analysis, prioritizing acoustic features alongside facial cues most relevant for ASD prediction. NLP can be used to analyze spoken language or identify delays in speech milestones (Themistocleous et al. 2024).
3. Analysis of genetic and biological markers (e.g., large datasets of genetic information and neuroimaging data) is instrumental in identifying biological patterns and correlations associated with ASD.
4. Deep learning models process neuroimaging data (e.g., MRI, EEG) to identify brain activity and connectivity patterns linked to ASD (Mengi and Malhotra 2022). Graph-based models can also map the interdependencies of behavioral traits to detect complex ASD markers (Subah et al. 2021).

These capabilities make AI particularly suited for addressing the multifaceted nature of ASD diagnosis.

AI applications in early ASD assessment

Behavioral analysis. Behavioral markers, such as reduced eye contact, atypical gestures, and repetitive movements are key indicators of ASD. AI-powered tools can analyze video recordings of children to identify these behaviors with greater precision and consistency than human observations alone (Kojovic et al. 2019). For instance, advanced computer vision algorithms can track gaze patterns, facial expressions, and body movements in real time.

Automated assessment tools. AI platforms can standardize behavioral evaluations, reducing inter-rater variability and improving diagnostic consistency.

Speech and communication pattern analysis

Children with ASD often exhibit delays in speech development, atypical prosody, or other linguistic anomalies. AI-driven NLP tools can (Washington et al. 2023):

1. Analyze audio recordings to detect speech delays or unusual vocal characteristics, such as pitch and rhythm.
2. Evaluate parent-child interactions to measure conversational turn-taking and response times.
3. Process text-based data, such as language transcripts, to identify structural differences in sentence formation and vocabulary usage.

Biometric data and wearable devices

Wearable technologies equipped with AI can continuously monitor physiological signals, providing valuable insights into atypical responses associated with ASD. Examples include (Zhang et al. 2025):

1. Heart rate monitoring to detect elevated heart rates in response to sensory stimuli (Frasch et al. 2021).
2. Electrodermal activity analysis to measure stress levels during social interactions.
3. Sleep pattern analysis to identify sleep disruptions, which are common in children with ASD.

Genetic and neurological data analysis

AI can analyze complex biological data to uncover biomarkers linked to ASD. This includes:

1. Genetic analysis to identify mutations or genetic variants associated with the condition.
2. Neuroimaging analysis of MRI or EEG data to detect structural and functional brain

https://www.doi.org/10.33910/2686-9527-2025-7-4-492-503

abnormalities indicative of ASD (Schielen et al. 2024).

Theoretical benefits of AI in ASD assessment

Improved accuracy. AI algorithms trained on large, diverse datasets can achieve high diagnostic accuracy, minimizing the subjectivity inherent in traditional methods. By identifying subtle patterns, AI tools can detect ASD earlier and more reliably (Washington et al. 2023).

Scalability. AI-driven solutions are highly scalable and can be deployed via mobile applications or cloud-based platforms. This makes early diagnostic tools accessible to underserved populations, including rural and low-income communities (Themistocleous et al. 2024).

Personalization. AI can generate individualized diagnostic profiles by integrating behavioral, linguistic, and physiological data. This tailored approach enhances the understanding of each child's unique developmental trajectory (Ali et al. 2023).

Efficiency. By automating repetitive tasks, AI reduces the time burden on clinicians and allows for continuous monitoring of developmental progress. This efficiency enables quicker intervention planning (Landowska et al. 2022).

An example: Analysis of dominant emotions. A practical application involves the automated analysis of dominant emotions from video data. Four primary emotions — *Happy, Sad, Angry*, and *Neutral* — are typically extracted. Each detected face is assigned a *dominant emotion* with a corresponding confidence score (e.g., Emotion: Happy (95%); Emotion: Neutral (88%)).

These specific emotions were selected as foundational in understanding social interaction and behavior:

1. *Happy*. Indicates positive engagement and contentment.
2. *Sad*. Helps detect distress or negative mood changes.
3. *Angry*. Useful for identifying frustration, aggression, or tension.
4. *Neutral*. Serves as a baseline for periods without strong emotional response.

In the context of analyzing autistic and non-autistic faces, research shows that individuals on the spectrum may exhibit different facial expressions, including more frequent neutral expressions in social settings (Keating and Cook 2020). By focusing on Happy, Sad, Angry, and Neutral, the system could detect patterns such as reduced emotional expressivity or atypical responses to emotional stimuli, which are characteristic of ASD.

Challenges and limitations

Ethical concerns

Data privacy. The collection and storage of sensitive data, including videos and biometric readings, pose significant privacy risks.

Bias in AI models. Datasets used to train AI models may lack diversity, leading to biased outcomes that disadvantage certain demographic groups.

Technological challenges

Data quality. The effectiveness of AI models depends on access to large, high-quality datasets, which can be challenging to obtain in clinical settings.

Over-reliance on AI. Over-dependence on AI tools could lead to reduced emphasis on human clinical expertise, which remains critical for nuanced diagnosis.

Interpretability

AI systems often function as 'black boxes,' making it difficult for clinicians and families to understand how diagnostic decisions are made (Mengi and Malhotra 2022). Explainable AI (XAI) approaches are needed to build trust and ensure accountability.

Future directions and research needs

Interdisciplinary collaborations. Effective implementation of AI in ASD assessment requires partnerships between AI researchers, clinicians, psychologists, and educators. These collaborations can ensure that AI tools align with clinical needs and ethical standards.

Ethical guidelines and regulations. Establishing clear guidelines for data collection, usage, and sharing is essential. Regulatory frameworks must prioritize patient rights and address the unique ethical considerations of using AI in pediatric settings.

Multi-modal AI systems. Future research should focus on developing AI models that integrate multiple data streams (e.g., behavioral, linguistic, and biometric) for a holistic assessment of ASD.

Developmental progress tracking. AI can also be employed to monitor the effectiveness of interventions, providing insights into developmental progress and enabling dynamic adjustments to therapy plans.

Conclusion

The integration of AI into the early assessment of ASD risk has the potential to transform the field, offering unprecedented accuracy, accessibility, and personalization. While significant challenges related to ethics, bias, and interpretability persist, ongoing advancements in AI technology and interdisciplinary research promise to address these concerns. By complementing human expertise, primarily that of parents and caregivers, AI can play a pivotal role in ensuring that children with ASD receive timely and effective support, ultimately improving their quality of life and reducing the long-term societal and economic burden of the condition.

Early diagnosis of ASD can significantly improve developmental outcomes for children. Signs of ASD can often be detected in children between 18 months to 24 months of age, with early indicators commonly including delays in communication and atypical behaviors (Fiza and Shukla 2023).

Research utilizing Facial Emotion Recognition highlights several observable markers relevant to early ASD detection (Keating and Cook 2020):

1. Lack of or atypical eye contact.
2. Limited or absent response to one's own name.
3. Unusual repetitive motor behaviors (e.g., hand flapping, body rocking).
4. Difficulties with social engagement (e.g., avoiding peer play).
5. Reduced or absent use of social communication gestures (e.g., pointing, waving).
6. Preference for routines and resistance to change.

Конфликт интересов

Авторы заявляют об отсутствии потенциального или явного конфликта интересов.

Conflict of Interest

The authors declare that there is no conflict of interest, either existing or potential.

References

Abdullah, N. M., Al-Allaf, A. F. (2021) Facial expression recognition (FER) of autism children using deep neural networks. In: *4th International Iraqi Conference on Engineering Technology and Their Applications (IICETA) 21–22 September 2021*. Najaf: IEEE Publ., pp. 111–116. https://doi.org/10.1109/IICETA51758.2021.9717550 (In English)

Alatar, W., Knott, F., Loucas, T. (2025) The effectiveness of telemedicine in coaching parents of autistic children using naturalistic developmental early interventions: A rapid review. *Review Journal of Autism and Developmental Disorders*, vol. 12, pp. 273–289. https://doi.org/10.1007/s40489-023-00393-3 (In English)

Ali, M. T., Gebreil, A., ElNakieb, Y. et al. (2023) A personalized classification of behavioral severity of autism spectrum disorder using a comprehensive machine learning framework. *Scientific Reports*, vol. 13, article 17048. https://doi.org/10.1038/s41598-023-43478-z (In English)

Arun, P., Chavan, B. S. (2018) Development of a screening instrument for autism spectrum disorder: Chandigarh autism screening instrument. *Indian Journal of Medical Research*, vol. 147, no. 4, pp. 369–375. https://doi.org/10.4103/ijmr.IJMR_1968_16 (In English)

Berument, S. K., Rutter, M., Lord, C. et al. (1999) Autism screening questionnaire: Diagnostic validity. *The British Journal of Psychiatry*, vol. 175, no. 5, pp. 444–451. https://doi.org/10.1192/bjp.175.5.444 (In English)

Bhavnani, S., Lockwood Estrin, G., Arora, R. et al. (2022) "I was confused … and still am" barriers impacting the help-seeking pathway for an autism diagnosis in urban North India: A mixed methods study. *Journal of Autism and Developmental disorders*, vol. 52, pp. 1778–1788. https://doi.org/10.1007/s10803-021-05047-z (In English)

Chaddad, A., Li, J., Lu, Q. et al. (2021) Can autism be diagnosed with artificial intelligence? *A narrative review. Diagnostics*, vol. 11, no. 11, article 2032. https://doi.org/10.3390/diagnostics11112032 (In English)

Chakrabarti, B. (2023) Autism in India: Time for a national programme. *The Indian Journal of Medical Research*, vol. 157, no. 4, pp. 227–229. https://doi.org/10.4103/ijmr.ijmr_506_23 (In English)

Dellazari, L., de Bem, É. B., Falcão, A. B. et al. (2025) Mind the gap: The inconceivable void in the epidemiology of autism spectrum disorders in Brazil. *Brazilian Journal of Psychiatry*, vol. 47, article e20243956. https://doi.org/10.47626/1516-4446-2024-3956 (In English)

Dubey, I., Bishain, R., Dasgupta, J. et al. (2024) Using mobile health technology to assess childhood autism in low-resource community settings in India: An innovation to address the detection gap. *Autism*, vol. 28, no. 3, pp. 755–769. https://doi.org/10.1177/13623613231182801 (In English)

Esterbruk, R. L., Esterbruk, S. A. (2013) Effektivnye metody diagnostiki, obucheniya i psikhoterapii detej s autisticheskimi narusheniyami [Effective methods of diagnosis, education and psychotherapy of children with autistic disorders]. *Razvitie lichnosti — Development of Personality*, no. 3, pp. 152–162. (In Russian)

Evangelou, C., Pappa, A., Gkanis, I. et al. (2025) Towards developing early intervention programmes supporting social skills for autistic children in early childhood: A systematic review. European Journal of Special Needs Education, pp. 1–19. https://doi.org/10.1080/08856257.2025.2491193 (In English)

Fiza, S., MP, S., Shukla, G. (2023) Predictive analytics and AI for early diagnosis and intervention in autism spectrum disorders. In: *2023 IEEE international conference on ICT in business industry & government (ICTBIG) 8–9 December 2023*. Indore: IEEE Publ., pp. 1159–1167. https://doi.org/10.1109/ICTBIG59752.2023.10456267 (In English)

Frasch, M. G., Shen, C., Wu, HT et al. (2021) Can a composite heart rate variability biomarker shed new insights about autism spectrum disorder in school-aged children? *Journal of Autism and Developmental Disorders*, vol. 51, pp. 346–356. https://doi.org/10.1007/s10803-020-04467-7 (In English)

Gao, J., Jiang, X., Yang, Y. et al. (2023). Unsupervised video anomaly detection for stereotypical behaviours in autism. In: *ICASSP 2023–2023 IEEE international conference on acoustics, speech and signal processing (ICASSP) 4–10 June 2023*. Rhodes Island: IEEE, pp. 1–5. https://doi.org/10.1109/ICASSP49357.2023.10094676 (In English)

Girianelli, V. R., Tomazelli, J., Silva, C. M. F. P., Fernandes, C. S. (2023) Diagnóstico precoce do autismo e outros transtornos do desenvolvimento, Brasil, 2013–2019 [Early diagnosis of autism and other developmental disorders, Brazil, 2013–2019]. *Revista de Saúde Pública*, vol. 57, no. 1, article e21. https://doi.org/10.11606/s1518-8787.2023057004710 (In Portuguese)

Siqueira, B. (2022) *Censo Demográfico 2022 identifica 2,4 milhões de pessoas diagnosticadas com Transtorno do Espectro Autista no Brasil* [*2022 Census identifies 2.4 million persons diagnosed with autism spectrum disorder in Brazil*]. [Online]. Available at: https://agenciadenoticias.ibge.gov.br/agencia-noticias/2012-agencia-de-noticias/noticias/43464-censo-2022-identifica-2-4-milhoes-de-pessoas-diagnosticadas-com-autismo-no-brasil (accessed 23.09.2025). (In Portuguese)

Jeon, I., Kim, M., So, D. et al. (2024) Reliable autism spectrum disorder diagnosis for pediatrics using machine learning and explainable AI. *Diagnostics*, vol. 14, no. 22, article 2504. https://doi.org/10.3390/diagnostics14222504 (In English)

Jiao, Z., Li, H., Fan, Y. (2020) Improving diagnosis of autism spectrum disorder and disentangling its heterogeneous functional connectivity patterns using capsule networks. In: *2020 IEEE 17th International Symposium on Biomedical Imaging (ISBI) 3–7 April 2020*. Iowa City: IEEE Publ., pp. 1331–1334. https://doi.org/10.1109/ISBI45749.2020.9098524 (In English)

Joudar, S. S., Albahri, A. S., Hamid, R. A. et al. (2023) Artificial intelligence-based approaches for improving the diagnosis, triage, and prioritization of autism spectrum disorder: a systematic review of current trends and open issues. *Artificial Intelligence Review*, vol. 56, pp. 53–117. https://doi.org/10.1007/s10462-023-10536-x (In English)

Keating, C. T., Cook, J. L. (2020) Facial expression production and recognition in autism spectrum disorders: A shifting landscape. *Child and Adolescent Psychiatric Clinics of North America*, vol. 29, no. 3, pp. 557–571. https://doi.org/10.1016/j.chc.2020.02.006 (In English)

Kojovic, N., Natraj, S., Mohanty, S. P. et al. (2021) Using 2D video-based pose estimation for automated prediction of autism spectrum disorders in young children. *Scientific Reports*, vol. 11, article 15069. https://doi.org/10.1038/s41598-021-94378-z (In English)

Landowska, A., Karpus, A, Zawadzka, T. et al. (2022) Automatic emotion recognition in children with autism: A systematic literature review. *Sensors*, vol. 22, no. 4, article 1649. https://doi.org/10.3390/s22041649 (In English)

Le Couteur, A., Haden, G., Hammal, D., McConachie, H. (2008) Diagnosing autism spectrum disorders in pre-school children using two standardised assessment instruments: the ADI-R and the ADOS. *Journal of autism and developmental disorders*, vol. 38, no. 2, pp. 362–372. https://doi.org/10.1007/s10803-007-0403-3 (In English)

Makarov, I. V., Avtenyuk, A. S. (2018) Diagnostika detskogo autizma: oshibki i trudnosti [Diagnosis of childhood autism: Errors and difficulties]. *Sotsial'naya i Klinicheskaya Psikhiatriya*, vol. 28, no. 3, 74–81. (In Russian)

Mengi, M., Malhotra, D. (2022) A systematic literature review on traditional to artificial intelligence based socio-behavioral disorders diagnosis in India: Challenges and future perspectives. *Applied Soft Computing*, vol. 129, article 109633. https://doi.org/10.1016/j.asoc.2022.109633 (In English)

Nair, M. K. C., Russell, P. S. S., George, B. et al. (2014) CDC Kerala 10: diagnostic accuracy of the severity scores for childhood autism rating scale in India. *The Indian Journal of Pediatrics*, vol. 81, 120–124. https://doi.org/10.1007/s12098-014-1623-0 (In English)

Patra, S., Kar, S. K. (2021) Autism spectrum disorder in India: A scoping review. *International Review of Psychiatry*, vol. 33, no. 1–2, pp. 81–112. https://doi.org/10.1080/09540261.2020.1761136 (In English)

Pereverzeva, D. S., Danilina, K. K., Batysheva, T. T. (2015) Kognitivnye markery rasstrojstv autisticheskogo spektra. Perspektivy rannej diagnostiki [Cognitive markers of autism spectrum disorders. Perspectives of early detection]. *Detskaya i Podrostkovaya Reabilitatsiya — Child and Adolescent Rehabilitation,* vol. 2, no. 25, pp. 43–47. (In Russian)

Rosstat. Federal State Statistics Service (2024) *Khronicheskie neorganicheskie psikhozy, detskie psikhozy i neutochnennye psikhoticheskie rasstrojstva* [*Chronic inorganic psychoses, childhood psychoses, and unspecified psychotic disorders*]. [Online]. Available at: https://rosstat.gov.ru/search?q=Хронические+неорганические+психозы%2C+детские+психозы%2C+неуточненные+психотические+расстройства&smart_search=on&date_from=31.12.2023&sections%5B%5D=204&content=doc&date_to=&search_by=all&sort=relevance (accessed 23.09.2025). (In Russian)

Sawicki, T., Ruszkowska, M., Danielewicz, A. et al. (2021) A review of colorectal cancer in terms of epidemiology, risk factors, development, symptoms and diagnosis. *Cancers*, vol. 13, no. 9, article 2025. https://doi.org/10.3390/cancers13092025 (In English)

Schopler, E., Reichler, R. J., DeVellis, R. F., Daly, K. (1980) Toward objective classification of childhood autism: Childhood autism rating scale (CARS). *Journal of Autism and Developmental Disorders*, vol. 10, pp. 91–103. https://doi.org/10.1007/BF02408436 (In English)

Schielen, S. J. C., Pilmeyer, J., Aldenkamp, A. P., Zinger, S. (2024) The diagnosis of ASD with MRI: A systematic review and meta-analysis. *Translational Psychiatry*, vol. *14*, no. 1, article 318. https://doi.org/10.1038/s41398-024-03024-5 (In English)

Skuse, D., Warrington, R., Bishop, D. et al. 2004) The developmental, dimensional and diagnostic interview (3di): A novel computerized assessment for autism spectrum disorders. *Journal of the American Academy of Child & Adolescent Psychiatry*, vol. 43, no. 5, pp. 548–558. https://doi.org/10.1097/00004583-200405000-00008 (In English)

Sozonov, A. S., Sviderek, E. S., Didenko, A. V., Choinzonova, E. E. (2024) Problemy rannej diagnostiki rasstrojstv autisticheskogo spektra (analiz klinicheskogo sluchaya) [Problems of early diagnosis of autism spectrum disorders (case vignette)]. *Sibirskij vestnik psikhiatrii i narkologii — Siberian Herald of Psychiatry and Addiction Psychiatry*, vol. 1, no. 122, pp. 80–87. https://doi.org/10.26617/1810-3111-2024-1(122)-80-87 (In Russian)

Subah, F. Z., Deb, K., Dhar, P. K., Koshiba, T. (2021) A deep learning approach to predict autism spectrum disorder using multisite resting-state fMRI. *Applied Sciences*, vol. 11, no. 8, article 3636. https://doi.org/10.3390/app11083636 (In English)

Themistocleous, C. K., Andreou, M., Peristeri, E. (2024) Autism detection in children: Integrating machine learning and natural language processing in narrative analysis. *Behavioral Sciences*, vol. 14, no. 6, article 459. https://doi.org/10.3390/bs14060459 (In English)

Tkacheva, L. O., Nasledov, A. D., Miroshnikov, S. A. (2023) Rannie markery autizma u detej v vozraste ot 1-go do 2-kh let [Early markers of autism in children aged 1 to 2 years]. In: *Anan'evskie chteniya — 2023. Chelovek v sovremennom mire: potentsialy i perspektivy psikhologii razvitiya. Sbornik materialov Mezhdunarodnoj nauchno-prakticheskoj konferentsii 18–20 oktyabrya 2023 goda* [*Ananyevsky readings — 2023. Man in the Modern World: Potentials and Prospects of Developmental Psychology. Proceedings of the International Scientific Conference October 18–20, 2023*]. Saint Petersburg: Kirillitsa Publ., p. 232. (In Russian)

Uke, P., Gaikwad, S., Vagha, K., Wandile, S. (2024) Unraveling the spectrum: A comprehensive review of autism spectrum disorder in India. *Cureus*, vol. 16, no. 6, article e62753. https://doi.org/10.7759/cureus.62753 (In English)

Wankhede, N., Kale, M., Shukla, M. et al. (2024) Leveraging AI for the diagnosis and treatment of autism spectrum disorder: Current trends and future prospects. *Asian Journal of Psychiatry*, vol. 101, article 104241. https://doi.org/10.1016/j.ajp.2024.104241 (In English)

Washington, P., Wall, D. P. (2023) A review of and roadmap for data science and machine learning for the neuropsychiatric phenotype of autism. *Annual Review of Biomedical Data Science*, vol. *6*, pp. 211–228. (In English)

Zhang, S. (2025) AI-assisted early screening, diagnosis, and intervention for autism in young children. *Frontiers in Psychiatry*, vol. 16, article 1513809. https://doi.org/10.3389/fpsyt.2025.1513809 (In English)

Authors

Maneela Sirisety, PhD Student, Department of Applied Psychology, School of Humanities and Social Sciences, GITAM (Deemed to be University)

ResearcherID: HHN-3132-2022, Scopus AuthorID: 58302585400, ORCID: 0000-0003-4567-6947, e-mail: maneelasirisety@gmail.com

El Hamzaoui Oussama, PhD Student, Engineering School of Information Technologies, Telecommunications and Control Systems, Ural Federal University named after the first President of Russia B. N. Yeltsin, e-mail: oussama.hmz44@gmail.com

Eduard V. Patrakov, Candidate of Sciences (Pedagogy), Associate Professor, Head of the Educational Laboratory, Ural Federal University named after the first President of Russia B. N. Yeltsin, SPIN: 8596-2861, Scopus AuthorID: 55948530300, ResearcherID: M-9430-2015, ORCID: 0000-0001-7564-9136, e-mail: e.v.patrakov@urfu.ru

Vasilii I. Borisov, Candidate of Sciences (Technical), Associate Professor Engineering School of Information Technologies, Telecommunications and Control Systems, Ural Federal University named after the first President of Russia B. N. Yeltsin, ORCID: 0000-0003-0486-7552, e-mail: v.i.borisov@urfu.ru

Taisa Rocha Navasconi Berbert, Course Coordinator Department of Medicine, School of Medicine, Centro Universitário Integrado, ORCID: 0000-0001-5553-8922, e-mail: cood.medicina@grupointegrado.br

Ravi Shanker Datti, Assistant Professor, Department of Applied Psychology, School of Humanities and Social Sciences, GITAM (Deemed to be University), ResearcherID: KRQ-9214-2024, Scopus AuthorID: 58302640900, ORCID: 0000-0002-8353-3384, e-mail: rdatti@gitam.edu

Anai Adario Hungaro, Professor at the Department of Medicine, School of Medicine, Centro Universitário Integrado, ORCID: 0000-0002-0914-5308, e-mail: anai.hungaro@grupointegrado.br

Heber Amílcar Martins, Director of Medicine Department of Medicine, School of Medicine, Centro Universitário Integrado, ORCID: 0000-0003-1808-8138, e-mail: diretoria.medicina@grupointegrado.br

Olga V. Sokolova, Master student, Institute of Physics and Technology, Ural Federal University named after the first President of Russia B. N. Yeltsin, e-mail: helga444@mai.ru

Сведения об авторах

Манила Сирисети, аспирантка, Кафедра прикладной психологии, Школа гуманитарных и социальных наук, Университет ГИТАМ, ResearcherID: HHN-3132-2022, Scopus AuthorID: 58302585400, ORCID: 0000-0003-4567-6947, e-mail: maneelasirisety@gmail.com

Эль Хамзауи Уссама, аспирант, Институт радиоэлектроники и информационных технологий-РТФ, Уральский федеральный университет имени первого президента России Б. Н. Ельцина, e-mail: oussama.hmz44@gmail.com

Эдуард Викторович Патраков, кандидат педагогических наук, доцент, заведующий учебной лабораторией, Уральский федеральный университет имени первого президента России Б. Н. Ельцина, SPIN-код: 8596-2861, Scopus AuthorID: 55948530300, ResearcherID: M-9430-2015, ORCID: 0000-0001-7564-9136, e-mail: e.v.patrakov@urfu.ru

Василий Ильич Борисов, кандидат технических наук, доцент Учебно-научного центра Искусственный интеллект Института радиоэлектроники и информационных технологий-РТФ, Уральский федеральный университет имени первого президента России Б. Н. Ельцина, ORCID: 0000-0003-0486-7552, e-mail: v.i.borisov@urfu.ru

Таиса Роча Наваскони Берберт, координатор курса кафедры медицины, Медицинская школа, Интегрированный Университетский центр, ORCID: 0000-0001-5553-8922, e-mail: cood.medicina@grupointegrado.br

Рави Шанкер Датти, доцент кафедры прикладной психологии, Школа гуманитарных и социальных наук, Университет ГИТАМ, ResearcherID: KRQ-9214-2024, Scopus AuthorID: 58302640900, ORCID: 0000-0002-8353-3384, e-mail: rdatti@gitam.edu

Анаи Адарио Хунгаро, профессор кафедры медицины, Медицинская школа, Интегрированный Университетский Центр, ORCID: 0000-0002-0914-5308, e-mail: anai.hungaro@grupointegrado.br

Хебер Амилкар Мартинс, директор Департамента медицины, Медицинская школа, Интегрированный Университетский Центр, ORCID: 0000-0003-1808-8138, e-mail: diretoria.medicina@grupointegrado.br

Ольга Викторовна Соколова, магистрант, Физико-технологический институт, Уральский федеральный университет имени первого президента России Б. Н. Ельцина, e-mail: helga444@mai.ru