ISSN 2616-5791 Vol. 7, Issue 2: 1-7, DOI: 10.25236/AJMHS.2026.070201

AI-Driven Early Diagnosis of Autism Spectrum Disorder: Current Status and Future Perspectives

Cong Luo[1,a,*], Yaqi Xu[1,b]

[1]School of Health Science and Engineering, University of Shanghai for Science and Technology, Shanghai, China
[a]1848329044@qq.com, [b]233352577@st.usst.edu.cn
[*]Corresponding author

Abstract: *Autism Spectrum Disorder (ASD) is a complex neurodevelopmental condition characterized by challenges in social communication, restricted interests, and repetitive behaviors. Early diagnosis and intervention are critical for improving long-term outcomes for individuals with ASD. In recent years, artificial intelligence (AI) and machine learning (ML) techniques have emerged as powerful tools for assisting in the early detection and diagnosis of ASD. This review provides a comprehensive analysis of the current state of AI-driven approaches for ASD early diagnosis, examining applications across various data modalities including neuroimaging, eye-tracking, electroencephalography (EEG), clinical questionnaires, and genomic data. We systematically review recent advances in deep learning, traditional machine learning, and multimodal fusion techniques, evaluating their diagnostic performance and clinical applicability. Furthermore, we discuss current challenges including data heterogeneity, model interpretability, algorithmic fairness, and the need for large-scale validation studies. Finally, we outline future research directions and potential pathways for translating AI-based diagnostic tools into clinical practice. Our findings suggest that while significant progress has been made, continued interdisciplinary collaboration between computer scientists, clinicians, and researchers is essential for developing robust, interpretable, and clinically deployable AI systems for the early diagnosis of ASD.*

Keywords: *Autism Spectrum Disorder, Machine Learning, Early Diagnosis, Deep Learning, Neuroimaging, Eye-tracking, EEG, Multimodal Analysis, Artificial Intelligence*

1. Introduction

Autism Spectrum Disorder (ASD) is a neurodevelopmental condition affecting approximately 1-2% of the global population, with prevalence rates continuing to rise[1]. The disorder is characterized by persistent deficits in social communication and interaction, accompanied by restricted, repetitive patterns of behavior, interests, or activities[2]. The heterogeneous nature of ASD, combined with its complex etiology involving genetic, environmental, and epigenetic factors, presents significant challenges for early and accurate diagnosis.

Current diagnostic practices rely primarily on behavioral observations and standardized assessment tools administered by trained clinicians, a process that can be time-consuming, resource-intensive, and subject to diagnostic delays[3]. The average age of ASD diagnosis remains around 4-5 years in many regions, despite the fact that reliable identification is possible as early as 18-24 months[4]. This diagnostic delay represents a critical lost opportunity for early intervention, as research consistently demonstrates that early therapeutic interventions significantly improve developmental outcomes for children with ASD.

The emergence of artificial intelligence (AI) and machine learning (ML) technologies has opened new avenues for addressing these diagnostic challenges. AI-driven approaches offer the potential to identify subtle patterns in diverse data types that may not be apparent to human observers, enabling earlier and more objective detection of ASD-related characteristics[5]. These computational methods can process and integrate information from multiple sources, including neuroimaging data, eye-tracking recordings, electrophysiological signals, behavioral assessments, and genetic information, providing a comprehensive framework for ASD characterization.

This review aims to provide a comprehensive examination of the current landscape of AI-driven

ISSN 2616-5791 Vol. 7, Issue 2: 1-7, DOI: 10.25236/AJMHS.2026.070201

approaches for ASD early diagnosis. We systematically analyze recent advances across different data modalities, evaluate the performance and limitations of existing methods, discuss critical challenges facing the field, and outline promising directions for future research and clinical translation.

2. AI Applications in ASD Early Diagnosis

2.1. Neuroimaging-Based Approaches

Neuroimaging techniques, particularly structural and functional magnetic resonance imaging (MRI/fMRI), have been extensively employed in ASD research to identify brain-based biomarkers. Machine learning analysis of neuroimaging data has shown considerable promise for distinguishing individuals with ASD from typically developing controls.

Several studies have demonstrated the utility of supervised machine learning for diagnostic classification using large-scale neuroimaging datasets. Lanka et al.[6] addressed concerns about generalizability in neuroimaging-based classification, developing robust approaches that maintain performance across different imaging protocols and sites. Their work highlighted the importance of accounting for confounding variables such as head motion and scanner differences when building predictive models.

Deep learning techniques have emerged as particularly powerful tools for neuroimaging analysis. Qiang et al.[7] proposed a deep learning method for ASD identification based on the interactions of hierarchical brain networks derived from functional MRI data. Their approach leveraged the complex network structure of brain connectivity patterns, achieving improved classification accuracy compared to traditional feature-based methods. Similarly, Yang et al.[8] developed a graph attention network framework that explicitly models spatial-constrained sparse functional brain networks, demonstrating the value of incorporating neuroanatomical constraints into deep learning architectures.

Reproducibility remains a critical concern in neuroimaging-based ASD classification. Mellema et al.[9] focused on identifying reproducible neuroimaging features for ASD diagnosis, emphasizing the need for biomarkers that maintain stability across different datasets and imaging protocols. Their work underscored the importance of rigorous validation procedures to ensure that identified features reflect genuine ASD-related brain differences rather than dataset-specific artifacts.

Cross-site generalization represents another significant challenge. Bhaumik et al.[10] investigated domain-adaptive approaches for cross-site evaluation, demonstrating that models trained on data from one imaging center often experience performance degradation when applied to data from different sites. Their findings highlighted the need for domain adaptation techniques and harmonization methods to improve model generalizability.

2.2. Eye-Tracking and Computer Vision Approaches

Atypical visual attention patterns represent one of the most consistently reported characteristics in ASD, making eye-tracking a valuable tool for diagnostic assessment. Machine learning analysis of eye-tracking data has shown considerable promise for identifying ASD-related attention patterns.

Wei et al.[11] developed a machine learning framework for early ASD identification using eye-tracking data, demonstrating that computational analysis of gaze patterns can effectively distinguish children with ASD from typically developing peers. Their approach integrated multiple gaze features, including fixation duration, saccade characteristics, and attention allocation patterns, achieving high classification accuracy.

The detection of eye contact represents a particularly important application. Chong et al.[12] showed that deep neural networks can detect eye contact with accuracy comparable to human experts, opening possibilities for automated assessment of this critical social behavior. Their work demonstrated the potential for AI systems to augment clinical assessments by providing objective, quantifiable measures of social attention.

Beyond traditional eye-tracking, computer vision approaches analyzing facial images and videos have shown promise. Atlam et al.[13] developed explainable deep learning models for automated ASD identification from facial images, incorporating attention mechanisms to highlight facial regions contributing to classification decisions. This work addressed the important issue of model interpretability, which is crucial for clinical acceptance of AI-based diagnostic tools.

ISSN 2616-5791 Vol. 7, Issue 2: 1-7, DOI: 10.25236/AJMHS.2026.070201

Home video analysis represents an emerging approach with significant potential for increasing diagnostic accessibility. Tariq et al.[14] demonstrated that machine learning analysis of short home videos can accurately classify ASD, enabling remote screening in underserved areas. Their mobile detection system showed promising results in prospective validation studies, suggesting potential for scalable deployment.

2.3. Electroencephalography (EEG) Based Approaches

EEG offers a non-invasive, cost-effective method for assessing brain function with high temporal resolution. Machine learning analysis of EEG signals has been extensively explored for ASD detection, with several studies reporting high classification accuracies.

Alotaibi and Maharatna[15] developed classification approaches based on EEG functional brain connectivity analysis, demonstrating that patterns of connectivity between brain regions can effectively distinguish individuals with ASD. Their work highlighted the utility of graph-theoretic measures for characterizing atypical brain network organization in ASD.

Feature extraction plays a critical role in EEG-based classification. Djemal et al.[16] proposed a computer-aided diagnosis system combining wavelet analysis, entropy measures, and artificial neural networks, achieving robust classification performance. The integration of multiple signal processing techniques allowed for comprehensive characterization of EEG characteristics associated with ASD.

Deep learning approaches have also been applied to EEG data. Baygin et al.[17] developed lightweight hybrid deep features for automated ASD detection, combining convolutional neural networks with traditional signal processing methods. Their approach demonstrated the potential for end-to-end learning from raw EEG signals while maintaining computational efficiency suitable for clinical deployment.

Barik et al.[18] explored fusion-based machine learning approaches using magnetoencephalography (MEG) signals, demonstrating that combining features from multiple frequency bands and brain regions can improve classification accuracy. Their work highlighted the value of multimodal signal fusion within the electrophysiological domain.

2.4. Clinical Questionnaire and Electronic Health Record Approaches

Clinical questionnaires and electronic health records (EHRs) represent rich sources of information for ASD prediction. Machine learning analysis of these structured and unstructured data types has shown considerable promise for risk stratification and early identification.

Rajagopalan et al.[3] developed a machine learning model for predicting ASD using a minimal set of medical screening and background history items available before 24 months of age. Their approach demonstrated that accurate prediction is possible using readily available clinical information, potentially enabling earlier identification than traditional diagnostic pathways.

Screening tool optimization represents another important application. Achenie et al.[19] developed machine learning strategies for autism screening in toddlers using the Modified Checklist for Autism in Toddlers, Revised (M-CHAT-R), demonstrating that computational approaches can improve screening efficiency while maintaining accuracy. Their work addressed practical challenges in pediatric screening, including time constraints and training requirements.

EHR-based prediction models have shown potential for population-level screening. Dick et al.[20] developed a transformer-based deep learning ensemble framework using health administrative and birth registry data, demonstrating the feasibility of identifying children at increased likelihood of developing ASD using routinely collected healthcare data. This approach could enable proactive outreach and early intervention for high-risk children.

Algorithmic fairness represents a critical consideration in clinical prediction models. Angell et al.[21] examined fairness in machine learning prediction of autism using EHR data, highlighting the importance of ensuring that AI systems perform equitably across different demographic groups. Their findings underscored the need for careful evaluation of model performance across subpopulations to prevent disparities in diagnostic access.

ISSN 2616-5791 Vol. 7, Issue 2: 1-7, DOI: 10.25236/AJMHS.2026.070201

2.5. Genomic and Biomarker Approaches

Advances in genomic technologies have enabled the identification of molecular signatures associated with ASD. Machine learning analysis of genetic, transcriptomic, and proteomic data has shown promise for developing biomarker-based diagnostic approaches.

Voinsky et al.[22] developed a machine learning-based blood RNA signature for ASD diagnosis, identifying a panel of differentially expressed genes that could distinguish individuals with ASD from controls. Their work demonstrated the potential for blood-based molecular biomarkers to complement behavioral assessments in the diagnostic process.

Proteomic approaches have also shown promise. Tang et al.[23] investigated plasma proteomics combined with machine learning methods for screening ASD biomarkers, identifying protein panels with diagnostic potential. The integration of proteomic data with clinical information may enhance diagnostic accuracy and provide insights into underlying biological mechanisms.

Ismail et al.[24] proposed a hybrid stacking ensemble model with Synthetic Minority Oversampling Technique (SMOTE) for predicting autistic genes, addressing the challenge of class imbalance in gene expression datasets. Their approach demonstrated improved prediction of disease-causing genes, potentially contributing to better understanding of ASD pathophysiology.

2.6. Multimodal Fusion Approaches

Given the heterogeneous nature of ASD, multimodal approaches that integrate information from multiple data sources have gained increasing attention. These methods leverage the complementary information provided by different assessment modalities to improve diagnostic accuracy and robustness.

Several studies have demonstrated the value of combining neuroimaging with clinical data. Dekhil et al.[25] developed personalized ASD diagnosis systems integrating resting-state fMRI with clinical information, showing that multimodal fusion can achieve higher accuracy than single-modality approaches. Their work highlighted the importance of individualized models that account for inter-subject variability.

Abbas et al.[26] developed machine learning approaches combining questionnaire and home video screening, demonstrating that the integration of parent-reported information with behavioral observations can enhance early detection. Their findings suggested that multimodal screening approaches may be particularly valuable for increasing diagnostic accessibility in underserved communities.

Deep learning architectures have been increasingly applied to multimodal ASD classification. Aarthi and Kannimuthu[27] proposed hybrid deep learning models that integrate multiple data types, achieving state-of-the-art performance on benchmark datasets. The ability of deep networks to learn hierarchical representations from diverse inputs makes them well-suited for multimodal fusion tasks.

3. Current Challenges

3.1. Data Heterogeneity and Generalizability

One of the most significant challenges facing AI-driven ASD diagnosis is the heterogeneity of available datasets. Variations in data collection protocols, participant demographics, and diagnostic criteria across studies can substantially impact model performance when the models are applied to new populations[28]. The development of harmonization techniques and domain adaptation methods remains an active area of research.

3.2. Model Interpretability and Explainability

The "black box" nature of many machine learning models, particularly deep learning approaches, presents challenges for clinical acceptance. Clinicians and patients require understandable explanations for diagnostic decisions[29]. The development of interpretable AI methods that provide transparent, clinically meaningful explanations represents a critical research priority.

ISSN 2616-5791 Vol. 7, Issue 2: 1-7, DOI: 10.25236/AJMHS.2026.070201

3.3. Sample Size and Data Quality

Many studies in this field are limited by relatively small sample sizes, which can lead to overfitting and poor generalization. The collection of large, well-characterized datasets with comprehensive phenotypic information remains essential for advancing the field[29].

3.4. Clinical Translation and Deployment

The translation of research findings into clinically deployable tools faces numerous practical challenges, including regulatory approval, integration with existing clinical workflows, and demonstration of cost-effectiveness[30]. Close collaboration between researchers, clinicians, and healthcare administrators is necessary to facilitate successful clinical implementation.

4. Future Perspectives

4.1. Large-Scale Collaborative Studies

Future progress in AI-driven ASD diagnosis will require large-scale collaborative efforts that aggregate data from multiple sites and populations. Initiatives such as the Autism Brain Imaging Data Exchange (ABIDE) have demonstrated the value of data sharing, and expanded efforts along these lines will be essential for developing robust, generalizable models[31].

4.2. Integration with Digital Health Technologies

The proliferation of digital health technologies, including wearable sensors and mobile applications, offers new opportunities for continuous, unobtrusive monitoring of behaviors relevant to ASD. Integration of these data streams with AI-based analysis could enable more comprehensive phenotyping and earlier detection[32].

4.3. Personalized Medicine Approaches

Moving beyond binary classification toward personalized characterization of individual strengths and challenges represents an important future direction. AI systems that can predict treatment response and guide personalized intervention planning could significantly enhance clinical utility[33].

4.4. Ethical and Regulatory Frameworks

The development of appropriate ethical and regulatory frameworks for AI-based diagnostic tools is essential. Issues including data privacy, informed consent, algorithmic fairness, and clinical liability must be carefully addressed to ensure responsible deployment of these technologies[34].

5. Conclusion

AI-driven approaches for ASD early diagnosis have made significant progress in recent years, with machine learning models demonstrating promising performance across diverse data modalities. Neuroimaging-based methods have identified reproducible brain-based biomarkers, eye-tracking and computer vision approaches have enabled objective assessment of atypical attention patterns, EEG-based methods have provided cost-effective screening tools, and multimodal fusion approaches have shown the potential for enhanced diagnostic accuracy.

However, several challenges remain to be addressed before these technologies can be widely deployed in clinical practice. Issues of generalizability, interpretability, and clinical integration require continued attention. Future research should focus on large-scale validation studies, development of interpretable models, and close collaboration with clinical stakeholders to ensure that AI tools meet real-world healthcare needs.

The integration of AI technologies into ASD diagnostic pathways holds significant promise for reducing diagnostic delays, increasing access to assessment services, and ultimately improving outcomes for individuals with ASD and their families. Continued interdisciplinary collaboration

ISSN 2616-5791 Vol. 7, Issue 2: 1-7, DOI: 10.25236/AJMHS.2026.070201

between computer scientists, clinicians, neuroscientists, and ethicists will be essential for realizing this potential and ensuring that AI-driven diagnostic tools are developed and deployed in a responsible, equitable manner.

References

[1] Lord C, Elsabbagh M, Baird G, Veenstra-Vanderweele J. Autism spectrum disorder. The Lancet. 2018;392(10146):508-520.

[2] American Psychiatric Association. Diagnostic and Statistical Manual of Mental Disorders. 5th ed. Arlington, VA: American Psychiatric Publishing; 2013.

[3] Rajagopalan SS, Zhang Y, Yahia A, Tammimies K. Machine Learning Prediction of Autism Spectrum Disorder From a Minimal Set of Medical and Background Information. JAMA Netw Open. 2024 Aug 1;7(8):e2429229.

[4] Zwaigenbaum L, Bauman ML, Stone WL, Yirmiya N, Estes A, Hansen RL, McPartland JC, Natowicz MR, Choueiri R, Fein D, Kasari C, Pierce K, Buie T, Carter A, Davis PA, Granpeesheh D, Mailloux Z, Newschaffer C, Robins D, Roley SS, Wagner S, Wetherby A. Early Identification of Autism Spectrum Disorder: Recommendations for Practice and Research. Pediatrics. 2015 Oct;136 Suppl 1(Suppl 1):S10-40.

[5] Thabtah F, Kamalov F, Rajab K. A new computational intelligence approach to detect autistic features for autism screening. Int J Med Inform. 2018 Sep;117:112-124.

[6] Lanka P, Rangaprakash D, Dretsch MN, Katz JS, Denney TS Jr, Deshpande G. Supervised machine learning for diagnostic classification from large-scale neuroimaging datasets. Brain Imaging Behav. 2020 Dec;14(6):2378-2416.

[7] Qiang N, Gao J, Dong Q, Li J, Zhang S, Liang H, Sun Y, Ge B, Liu Z, Wu Z, Liu T, Yue H, Zhao S. A deep learning method for autism spectrum disorder identification based on interactions of hierarchical brain networks. Behav Brain Res. 2023 Aug 24;452:114603.

[8] Yang C, Wang P, Tan J, Liu Q, Li X.Autism spectrum disorder diagnosis using graph attention network based on spatial-constrained sparse functional brain networks. Comput Biol Med. 2021 Dec;139:104963.

[9] Mellema CJ, Nguyen KP, Treacher A, Montillo A. Reproducible neuroimaging features for diagnosis of autism spectrum disorder with machine learning. Sci Rep. 2022 Feb 23;12(1):3057.

[10] Bhaumik R, Pradhan A, Das S, Bhaumik DK. Predicting Autism Spectrum Disorder Using Domain-Adaptive Cross-Site Evaluation. Neuroinformatics. 2018 Apr;16(2):197-205.

[11] Wei Q, Dong W, Yu D, Wang K, Yang T, Xiao Y, Long D, Xiong H, Chen J, Xu X, Li T. Early identification of autism spectrum disorder based on machine learning with eye-tracking data. J Affect Disord. 2024 Aug 1;358:326-334.

[12] Chong E, Clark-Whitney E, Southerland A, Stubbs E, Miller C, Ajodan EL, Silverman MR, Lord C, Rozga A, Jones RM, Rehg JM. Detection of eye contact with deep neural networks is as accurate as human experts. Nat Commun. 2020 Dec 14;11(1):6386.

[13] Atlam ES, Aljuhani KO, Gad I, Abdelrahim EM, Atwa AEM, Ahmed A. Automated identification of autism spectrum disorder from facial images using explainable deep learning models. Sci Rep. 2025 Jul 22;15(1):26682.

[14] Tariq Q, Daniels J, Schwartz JN, Washington P, Kalantarian H, Wall DP. Mobile detection of autism through machine learning on home video: A development and prospective validation study. PLoS Med. 2018 Nov 27;15(11):e1002705.

[15] Alotaibi N, Maharatna K. Classification of Autism Spectrum Disorder From EEG-Based Functional Brain Connectivity Analysis. Neural Comput. 2021 Jun 11;33(7):1914-1941.

[16] Djemal R, AlSharabi K, Ibrahim S, Alsuwailem A. EEG-Based Computer Aided Diagnosis of Autism Spectrum Disorder Using Wavelet, Entropy, and ANN. Biomed Res Int. 2017;2017:9816591.

[17] Baygin M, Dogan S, Tuncer T, Datta Barua P, Faust O, Arunkumar N, Abdulhay EW, Emma Palmer E, Rajendra Acharya U. Automated ASD detection using hybrid deep lightweight features extracted from EEG signals. Comput Biol Med. 2021 Jul;134:104548.

[18] Barik K, Watanabe K, Bhattacharya J, Saha G. A Fusion-Based Machine Learning Approach for Autism Detection in Young Children Using Magnetoencephalography Signals. J Autism Dev Disord. 2023 Dec;53(12):4830-4848.

[19] Achenie LEK, Scarpa A, Factor RS, Wang T, Robins DL, McCrickard DS. A Machine Learning Strategy for Autism Screening in Toddlers. J Dev Behav Pediatr. 2019 Jun;40(5):369-376.

[20] Dick K, Kaczmarek E, Ducharme R, Bowie AC, Dingwall-Harvey ALJ, Howley H, Hawken S, Walker MC, Armour CM. Transformer-based deep learning ensemble framework predicts autism spectrum disorder using health administrative and birth registry data. Sci Rep. 2025 Apr

ISSN 2616-5791 Vol. 7, Issue 2: 1-7, DOI: 10.25236/AJMHS.2026.070201

7;15(1):11816.

[21] Angell AM, Li Y, Bian J, Parchment C, Yin L, Chamala S, Hakimjavadi H, Thompson L, Guo Y. Algorithmic Fairness in Machine Learning Prediction of Autism Using Electronic Health Records. Stud Health Technol Inform. 2025 Aug 7;329:1180-1184.

[22] Voinsky I, Fridland OY, Aran A, Frye RE, Gurwitz D. Machine Learning-Based Blood RNA Signature for Diagnosis of Autism Spectrum Disorder. Int J Mol Sci. 2023 Jan 20;24(3):2082.

[23] Tang X, Ran X, Liang Z, Zhuang H, Yan X, Feng C, Qureshi A, Gao Y, Shen L. Screening biomarkers for autism spectrum disorder using plasma proteomics combined with machine learning methods. Clin Chim Acta. 2025 Jan 15;565:120018.

[24] Ismail E, Gad W, Hashem M. A hybrid Stacking-SMOTE model for optimizing the prediction of autistic genes. BMC Bioinformatics. 2023 Oct 6;24(1):379.

[25] Dekhil O, Hajjdiab H, Shalaby A, et al. Using resting state functional MRI to build a personalized autism diagnosis system. Frontiers in Neuroscience. 2022;16:892857.

[26] Abbas H, Garberson F, Glover E, Wall DP. Machine learning approach for early detection of autism by combining questionnaire and home video screening. Journal of the American Medical Informatics Association. 2020;27(6):900-907.

[27] Aarthi D, Kannimuthu S. Hybrid deep learning model for autism spectrum disorder diagnosis. Sci Rep. 2025 Dec 29;15(1):44707.

[28] Ferrari E, Bosco P, Calderoni S, Oliva P, Palumbo L, Spera G, Fantacci ME, Retico A. Dealing with confounders and outliers in classification medical studies: The Autism Spectrum Disorders case study. Artif Intell Med. 2020 Aug;108:101926.

[29] Leroy G, Bisht P, Kandula SM, Maltman N, Rice S. Deep learning for autism detection using clinical notes: A comparison of transfer learning for a transparent and black-box approach. Artificial Intelligence in Medicine. 2023;138:102508.

[30] Pan N, Chen L, Wu B, Chen F, Chen J, Huang S, Guo C, Wu J, Wang Y, Chen X, Yang S, Jing J, Weng X, Lin L, Liang J, Wang X. Developing a simplified measure to predict the risk of autism spectrum disorders: Abbreviating the M-CHAT-R using a machine learning approach in China. Psychiatry Res. 2025 Feb;344:116353.

[31] Curtin P, Neufeld J, Curtin A, Arora M, Bölte S. Altered Periodic Dynamics in the Default Mode Network in Autism and Attention-Deficit/Hyperactivity Disorder. Biol Psychiatry. 2022 Jun 1;91(11):956-966.

[32] Perochon S, Di Martino JM, Carpenter KLH, Compton S, Davis N, Eichner B, Espinosa S, Franz L, Krishnappa Babu PR, Sapiro G, Dawson G. Early detection of autism using digital behavioral phenotyping. Nat Med. 2023 Oct;29(10):2489-2497.

[33] Ali MT, Gebreil A, ElNakieb Y, et al. Ali MT, Gebreil A, ElNakieb Y, Elnakib A, Shalaby A, Mahmoud A, Sleman A, Giridharan GA, Barnes G, Elbaz AS. A personalized classification of behavioral severity of autism spectrum disorder using a comprehensive machine learning framework. Sci Rep. 2023 Oct 9;13(1):17048.

[34] Ben-Sasson A, Yom-Tov E. Online Concerns of Parents Suspecting Autism Spectrum Disorder in Their Child: Content Analysis of Signs and Automated Prediction of Risk. J Med Internet Res. 2016 Nov 22;18(11):e300.