



Machine Learning-Based Prognostic Modeling for Autism Spectrum Disorder: A Comprehensive Review

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Abstract

Autism Spectrum Disorder (ASD) is a heterogeneous neurodevelopmental condition characterised by persistent differences in social communication and interaction, together with restricted or repetitive patterns of behaviour. The considerable variation in symptom presentation, developmental progression and response to intervention makes prognosis particularly challenging. Machine learning (ML) has emerged as a promising computational approach for identifying complex patterns within behavioural, clinical, neuroimaging, physiological and other high-dimensional datasets. This review examines the application of ML-based prognostic modelling in ASD, focusing on early prediction, symptom-severity estimation, developmental trajectory modelling and prediction of intervention outcomes. The review synthesises evidence on conventional ML techniques, including logistic regression, decision trees, random forests and support vector machines, alongside artificial neural networks and deep-learning approaches. Existing studies demonstrate that ML can generate useful predictions from relatively small sets of clinical and developmental variables, while more complex approaches can exploit neuroimaging, EEG, video and multimodal information. However, the evidence base remains constrained by small samples, heterogeneous datasets, class imbalance, overfitting, limited external validation and inadequate representation of diverse populations. Deep-learning studies have reported high diagnostic performance, but substantial heterogeneity across studies limits direct translation into clinical practice (Ding et al., 2024). Evidence specifically addressing prognosis is more limited, although early studies indicate potential for predicting treatment response and developmental outcomes (Thabtah et al., 2022). The review concludes that the future of ML in ASD prognosis depends on longitudinal datasets, independent validation, interpretable models, clinically meaningful outcomes and representative populations. ML should ultimately complement, rather than replace, clinical judgement in individualised ASD assessment and intervention planning.

Keywords: Autism spectrum disorder; Machine learning; Prognostic modelling; Deep learning; Predictive analytics; Developmental trajectories; Treatment response.

I. Introduction

Autism Spectrum Disorder (ASD) is a neurodevelopmental condition characterised by persistent differences in social communication and social interaction, alongside restricted, repetitive patterns of behaviour, interests or activities. The presentation of ASD varies considerably between individuals, with differences in language, cognition, adaptive functioning, behavioural characteristics and social development. This heterogeneity presents significant challenges for clinicians seeking to determine not

only whether an individual meets diagnostic criteria but also how the individual's developmental profile may evolve over time (Lord et al., 2020; Washington & Wall, 2023).

The importance of prognosis in ASD arises from the fact that diagnosis represents only one stage in an individual's developmental pathway. Families and clinicians are often interested in whether symptoms will change, how communication and adaptive skills may develop, and whether an individual is likely to respond to a particular intervention. Longitudinal research has demonstrated that autism-related symptoms do not follow a single developmental pattern. For example, Gotham et al. (2012) identified different trajectories of autism severity across childhood, demonstrating that some individuals experienced relatively stable symptom profiles while others showed changes in severity over time. These findings indicate that prognostic assessment needs to accommodate substantial individual variation.

Early intervention further increases the importance of reliable prognostic modelling. Evidence reviewed by Pires et al. (2024) indicates that early intervention can influence developmental outcomes, although access, timing, intervention characteristics and individual response remain important challenges. Consequently, a method capable of identifying children who may follow different developmental or treatment-response trajectories could contribute to more personalised intervention planning.

Traditional statistical approaches have contributed substantially to understanding ASD prognosis. However, conventional models may be limited when datasets contain numerous interacting, nonlinear or highly correlated predictors. Machine learning (ML) offers an alternative framework because algorithms can identify patterns within complex datasets without requiring all relationships to be specified in advance. The application of ML to autism has expanded from diagnostic classification to behavioural monitoring, digital phenotyping and potentially prognostic modelling (Washington & Wall, 2023).

Recent studies illustrate the rapid development of this field. Rajagopalan et al. (2024), for example, developed an ML model using 28 relatively basic medical and background variables available before 24 months of age. Their model, subsequently validated on independent datasets, demonstrated that useful prediction could be achieved without requiring expensive neuroimaging or genomic information. Such findings suggest that ML-based prediction may eventually be incorporated into routine developmental assessment if adequate external validation and clinical evaluation are achieved.

Nevertheless, it is important to distinguish diagnostic prediction from prognostic prediction. Diagnostic prediction concerns the probability that an individual currently has ASD, whereas prognostic modelling concerns future outcomes following a defined baseline point. Prognostic outcomes may include future symptom severity, developmental trajectory, adaptive functioning or response to intervention. A model that accurately distinguishes autistic from non-autistic individuals does not automatically constitute a prognostic model.

This review therefore examines the development and application of ML-based prognostic modelling in ASD. It focuses on the principal data sources, algorithms and prognostic applications while considering methodological limitations, ethical issues and future research directions.

2. Conceptualising Machine Learning-Based Prognostic Modelling

2.1 Prognostic Modelling in Autism Spectrum Disorder

Prognostic modelling refers to the use of baseline characteristics to estimate the probability of future outcomes. Within ASD research, these outcomes may include changes in core symptoms, language development, cognitive functioning, adaptive behaviour, social functioning and response to intervention.

The need for prognostic modelling is closely connected with ASD heterogeneity. Individuals who meet the same diagnostic criteria may have substantially different developmental outcomes. Lord et al. (2020) emphasised the heterogeneity of autism at clinical, behavioural and biological levels, reinforcing the need for approaches capable of recognising individual variation.

Longitudinal studies provide evidence that autism-related symptoms can follow different trajectories. Gotham et al. (2012), for example, identified multiple developmental trajectories using repeated Autism Diagnostic Observation Schedule assessments. Such findings establish an empirical basis for attempting to predict developmental patterns using computational methods.

Machine learning can extend this approach by combining multiple predictors simultaneously. Rather than examining one variable at a time, ML algorithms can identify combinations of developmental, behavioural, clinical and biological characteristics associated with particular outcomes. Washington and Wall (2023) argued that the heterogeneity and complexity of autism-related behaviours create opportunities for data-science approaches capable of supporting longitudinal monitoring and personalised assessment.

2.2 Machine Learning and Predictive Analytics

Machine learning encompasses computational techniques through which algorithms learn relationships between input variables and outcomes from data. Supervised ML is particularly relevant to prognostic modelling because the algorithm is trained using known predictors and outcomes and subsequently applied to previously unseen observations.

The general prognostic process can be represented as:

Baseline data → Feature extraction/selection → Model training → Validation → Future outcome prediction

The input data can include demographic characteristics, developmental assessments, behavioural observations, clinical records, neuroimaging, EEG, genetic information and digital behavioural measures. The outcome can be binary, categorical, continuous or longitudinal.

An important advantage of ML is its capacity to model complex relationships. However, predictive performance does not necessarily establish causality. A variable may improve prediction without being a causal determinant of the outcome. Consequently, prognostic ML should be interpreted primarily as a predictive tool rather than as a substitute for causal research.

3. Review Method

This article adopts a comprehensive narrative review approach. Relevant peer-reviewed studies were identified from biomedical and multidisciplinary literature using combinations of the terms *autism spectrum disorder*, *autism*, *machine learning*, *deep learning*, *prognostic modelling*, *prediction*, *developmental trajectory*, *symptom severity*, *treatment response*, *neuroimaging* and *artificial intelligence*. Recent systematic reviews, meta-analyses and empirical studies were prioritised, while earlier influential publications were retained where they provided important conceptual or methodological foundations. The review concentrated on studies involving prediction of ASD-related outcomes and studies that demonstrate techniques potentially applicable to prognosis. Diagnostic ML research was included where it provided methodological evidence relevant to the development of prognostic systems, but diagnostic classification was distinguished from true prognostic modelling.

The literature was synthesised under five major themes: (1) early prediction and risk stratification; (2) symptom-severity prediction; (3) developmental trajectory modelling; (4) prediction of intervention outcomes; and (5) methodological developments involving multimodal and deep-learning approaches.

4. Machine Learning Algorithms Used in ASD Research

4.1 Logistic Regression

Logistic regression remains an important benchmark for binary prediction because of its simplicity and interpretability. It estimates the probability of an outcome based on a set of predictor variables. In ASD research, logistic regression can be applied to clinical, demographic and developmental information.

Its principal limitation is that simple logistic regression assumes a particular functional relationship between predictors and the log odds of the outcome. ASD prognosis can involve nonlinear interactions and complex dependencies that may not be adequately represented through conventional linear specifications. Nevertheless, logistic regression remains valuable as a benchmark against which more complex algorithms can be evaluated.

Rajagopalan et al. (2024), for example, compared logistic regression with decision tree, random forest and XGBoost models when developing an ML system for ASD prediction from a minimal set of background and medical variables. This comparison illustrates the continuing importance of conventional statistical models even within ML-oriented research.

4.2 Decision Trees and Random Forests

Decision trees classify observations through sequential decision rules. Their relative interpretability makes them attractive for clinical research. However, individual decision trees can be unstable and susceptible to overfitting.

Random forests address some of these limitations by combining multiple decision trees. They can accommodate nonlinear relationships and interactions and provide measures of feature importance. These characteristics make random forests potentially useful for ASD prediction where developmental and clinical predictors interact.

Rajagopalan et al. (2024) included both decision trees and random forests in their comparison of algorithms. Their findings showed that the XGBoost approach performed better than the other tested algorithms, illustrating how ensemble-based methods can provide strong predictive performance in ASD-related data.

4.3 Support Vector Machines

Support Vector Machines (SVMs) are supervised learning algorithms that identify a boundary separating observations belonging to different classes. Through kernel functions, SVMs can model nonlinear relationships.

SVMs have been particularly common in ASD neuroimaging research because they can handle high-dimensional feature spaces. Santana et al. (2022), in a systematic review and meta-analysis of resting-state functional MRI and ML for ASD diagnosis, found SVM among the commonly applied algorithms. Their findings demonstrated considerable potential for neuroimaging-based ML but also substantial heterogeneity among studies.

Although such work primarily concerns diagnosis, the methodological implications extend to prognosis. Neuroimaging features that distinguish individuals according to symptom severity or developmental outcomes may eventually contribute to prognostic models.

4.4 Artificial Neural Networks and Deep Learning

Artificial neural networks are computational models inspired by interconnected neural structures. Deep learning extends these approaches through multiple computational layers capable of learning increasingly complex representations from data.

Deep learning has become particularly relevant where the data are high-dimensional, such as neuroimaging, video and physiological signals. Ding et al. (2024) conducted a systematic review and meta-analysis of deep-learning approaches for ASD prediction involving 11 studies and 9,495 ASD participants. The pooled sensitivity, specificity and area under the curve were 0.95, 0.93 and 0.98, respectively. However, the authors noted substantial heterogeneity and cautioned that further research is required to establish clinical applicability.

Huda et al. (2024) similarly identified substantial growth in the use of deep learning and resting-state functional MRI for automated ASD assessment. These findings suggest that deep learning has considerable potential, although diagnostic performance should not be equated with prognostic validity.

5. Data Sources for ASD Prognostic Modelling

5.1 Behavioural and Developmental Data

Behavioural and developmental information represents one of the most clinically accessible sources for prognostic modelling. Variables may include language development, cognitive ability, social responsiveness, adaptive behaviour, motor development and autism symptom measures.

The longitudinal nature of these variables makes them particularly suitable for prognosis. Gotham et al. (2012) demonstrated that repeated symptom measurements can reveal different developmental trajectories. ML can potentially extend this work by combining multiple developmental indicators to estimate the probability of an individual's future trajectory.

Washington and Wall (2023) highlighted the growing importance of digital behavioural measurement in autism research, particularly through technologies capable of quantifying behaviours repeatedly and objectively.

5.2 Clinical and Demographic Information

Clinical and demographic information can include age, sex, family history, developmental history, previous assessments and healthcare records. One advantage of these data is their potential accessibility within routine healthcare settings.

Rajagopalan et al. (2024) demonstrated the feasibility of developing an ML model using a relatively small set of medical and background variables available before 24 months of age. Their XGBoost-based model achieved an AUROC of 0.895 in the development sample and 0.790 when validated on an independent cohort. Importantly, the study illustrates the distinction between model development and generalisability: performance decreased when the model was applied to an independent dataset.

Electronic health records and population-level medical databases represent another important data source. Rajagopalan et al. (2024) and related work demonstrate how routinely collected information can potentially support earlier identification of developmental risk without requiring specialised testing.

5.3 Neuroimaging Data

Neuroimaging represents one of the most intensively investigated sources of ML features in autism research. Functional MRI can provide information about patterns of brain connectivity, while structural imaging can capture anatomical characteristics.

Santana et al. (2022) reviewed resting-state functional MRI studies using ML for ASD classification and found substantial research activity involving connectivity-based features. Huda et al. (2024) similarly reported increasing use of deep learning with resting-state functional MRI.

Although most neuroimaging research remains diagnostic, the same techniques have potential prognostic applications. If neural connectivity patterns are associated with symptom severity, cognitive functioning or treatment response, ML could potentially use such features to estimate future outcomes.

The major limitation is that neuroimaging datasets are often expensive, heterogeneous and relatively small. Consequently, the number of potential features can greatly exceed the number of participants, increasing the risk of overfitting.

5.4 EEG and Physiological Data

Electroencephalography (EEG) provides temporally detailed information about electrical brain activity. ML can be applied to EEG features such as frequency characteristics, connectivity and signal complexity. Recent reviews indicate increasing interest in combining EEG and ML for ASD-related prediction and biomarker identification. However, differences in recording protocols, preprocessing methods, sample characteristics and outcome definitions make comparisons between studies difficult.

Other physiological measures are also being investigated. The broader trend is towards identifying objective digital or biological indicators that can supplement behavioural assessment. Mehmetbeyoglu et al. (2023) highlighted the growing role of ML in identifying potential prognostic biomarkers, although much of this literature remains exploratory.

5.5 Video and Digital Behavioural Data

Video-based analysis offers the possibility of quantifying social behaviours, facial expressions, gaze and joint attention. Deep-learning algorithms can automatically extract features that would otherwise require extensive manual coding.

Ko et al. (2023), for example, developed a deep-learning system for quantifying joint attention and investigated its capacity to support ASD detection and symptom-severity assessment. Such systems illustrate how ML can transform observable behaviours into quantitative features.

Washington and Wall (2023) noted that digital behavioural measurement may contribute to scalable assessment and longitudinal monitoring. Nevertheless, privacy, consent, data quality and generalisability remain important concerns when video-based systems are applied to children.

6. Applications of Machine Learning-Based Prognostic Modelling

6.1 Early Prediction and Risk Stratification

Early prediction is one of the most prominent applications of ML in ASD research. Earlier identification of developmental risk can facilitate closer monitoring and potentially earlier intervention.

ML can integrate several developmental indicators simultaneously. Rajagopalan et al. (2024) showed that developmental milestones and eating behaviour were among the most influential predictors in their model

based on information available before 24 months. However, prediction at very young ages remains challenging because developmental behaviours change rapidly during infancy. A model that performs well at one age may not necessarily perform equally well at another. Furthermore, models developed in high-risk populations may not generalise to the general population.

Consequently, early prediction should be viewed as a probability-based risk assessment rather than a definitive diagnosis or prognosis.

6.2 Symptom-Severity Prediction

A particularly important direction is predicting variation in symptom severity among individuals already identified as autistic. Such modelling is potentially more relevant to personalised care than simple ASD-versus-non-ASD classification.

ML can combine behavioural and biological features to estimate symptom scores. Deep-learning systems based on video-derived social behaviours have demonstrated the feasibility of estimating symptom-related measures (Ko et al., 2023).

Similarly, neuroimaging-based ML may provide information about symptom variation. Santana et al. (2022) demonstrated the extensive use of connectivity features in ASD ML research, suggesting opportunities for extending neuroimaging models from diagnostic classification towards within-ASD prognostic prediction.

6.3 Developmental Trajectory Prediction

Developmental trajectory prediction represents one of the clearest forms of prognosis. Rather than predicting a current diagnostic category, the objective is to estimate how symptoms or functioning may change over time.

Gotham et al. (2012) demonstrated that autism symptom severity can follow different trajectories. Such findings suggest that individuals should not necessarily be expected to follow a uniform developmental pathway.

ML may support trajectory prediction by integrating baseline cognitive, behavioural, demographic and clinical characteristics. However, longitudinal ML studies require repeated observations and carefully defined outcomes. Cross-sectional datasets cannot adequately capture developmental change.

The development of such models could be particularly valuable for adaptive functioning, communication and independent living because these outcomes may be more directly relevant to everyday quality of life than diagnostic classification alone.

6.4 Prediction of Treatment and Intervention Response

Predicting intervention response is one of the most promising and challenging applications of prognostic ML. Children with ASD may respond differently to the same intervention, making individualised prediction potentially valuable.

Thabtah et al. (2022) examined five ML algorithms for estimating prognosis among children with autism receiving early behavioural intervention. The models were used to predict adaptive functioning and autistic symptoms and performed better than random sampling. The authors nevertheless emphasised that comparisons with predictions made by qualified practitioners remain necessary.

This finding is significant because it demonstrates that ML can potentially contribute to treatment prognosis rather than merely diagnosis. Nevertheless, a predictive model should not be interpreted as demonstrating that a specific treatment will cause a particular outcome. Prediction and causal inference remain conceptually distinct.

ML has also been applied to predicting outcomes associated with exercise interventions. Sun et al. (2023) demonstrated the potential of supervised ML to predict outcomes following exercise intervention among children with ASD, further expanding the scope of computational prognosis.

7. Comparative Assessment of Major ML Approaches

ML approach	Common ASD data	Potential prognostic application	Major advantage	Main limitation
Logistic regression	Clinical and demographic data	Risk prediction	Highly interpretable	Limited nonlinear modelling
Decision tree	Clinical and behavioural data	Risk classification	Easy to interpret	Vulnerable to overfitting
Random forest	Clinical, behavioural and multimodal data	Severity and outcome prediction	Captures nonlinear relationships	Less interpretable
Support Vector Machine	Neuroimaging, EEG and behavioural data	Classification and severity prediction	Effective in high-dimensional data	Sensitive to feature selection
Artificial neural network	Clinical and physiological data	Outcome prediction	Learns complex relationships	Requires adequate training data
Deep learning	Imaging, video and time-series data	Behaviour and symptom prediction	Handles complex representations	Computationally demanding
Ensemble models	Multimodal data	Risk and prognosis prediction	Combines multiple learners	Increased model complexity

The choice of algorithm should be determined by the research question, data characteristics, sample size and intended application rather than by predictive performance alone. For clinical applications, interpretability, calibration and external validity are particularly important.

8. Methodological Challenges

8.1 Small Sample Sizes

Small sample sizes remain a major limitation in ASD ML research. High-dimensional datasets such as neuroimaging can contain thousands of potential features while including relatively few participants. This creates a high risk that the algorithm will learn sample-specific noise.

Washington and Wall (2023) identified dataset size, behavioural complexity and translational challenges as important issues in autism data science. These problems are particularly relevant to prognostic models because future outcomes may contain additional sources of variability.

8.2 Overfitting

Overfitting occurs when a model learns patterns specific to the training sample rather than generalisable relationships. It is particularly problematic when researchers test many predictors on relatively small datasets.

Appropriate cross-validation, feature selection, regularisation and independent test datasets are therefore essential. The difference between the development and external-validation performance reported by Rajagopalan et al. (2024) illustrates why independent validation is important.

8.3 Class Imbalance

ASD datasets may contain unequal numbers of autistic and non-autistic participants. An algorithm can therefore achieve apparently high accuracy by favouring the majority class.

Researchers should consequently consider sensitivity, specificity, precision, recall, F1 score, AUROC and calibration rather than relying solely on accuracy. The importance of evaluating several metrics is evident in the approach used by Rajagopalan et al. (2024), who reported multiple performance measures across development and validation datasets.

8.4 Limited External Validation

A major weakness of the current literature is the limited number of studies demonstrating generalisability across independent populations. Ding et al. (2024) reported high pooled deep-learning performance but

also noted substantial heterogeneity among studies, limiting the conclusions that can be drawn regarding clinical implementation.

External validation should therefore become a standard requirement. Models should ideally be tested in different healthcare systems, geographical regions, demographic groups and clinical settings.

8.5 Interpretability

Deep-learning systems can be difficult to interpret. This creates challenges in clinical contexts where healthcare professionals may need to understand why a particular prediction was generated.

Explainable AI methods can provide information about feature contributions. Rajagopalan et al. (2024), for example, incorporated explainable AI to investigate the influence of individual features in their ASD prediction model. Such approaches can improve transparency but should not be regarded as substitutes for rigorous validation.

8.6 Data Heterogeneity

ASD datasets differ substantially in terms of age, sex, symptom presentation, diagnostic procedures, geographic setting and data-collection methods. Combining datasets can therefore introduce substantial heterogeneity.

Santana et al. (2022) identified methodological heterogeneity across neuroimaging studies, while Ding et al. (2024) similarly reported substantial heterogeneity among deep-learning studies. Standardised protocols and carefully designed multicentre studies are consequently necessary.

9. Ethical and Clinical Considerations

The use of ML in ASD raises important ethical questions because the data involved can be highly sensitive. Clinical records, behavioural assessments, genetic information, brain images and videos of children all require appropriate privacy and security protections.

Another concern is representativeness. If training datasets disproportionately contain participants from particular demographic or geographic groups, model performance may differ across populations. Washington and Wall (2023) emphasised the need for careful consideration of translation, privacy and real-world implementation in autism data science.

Algorithmic predictions should also avoid reinforcing deficit-oriented assumptions about autistic people. Prognostic modelling should focus on clinically meaningful and person-centred outcomes such as communication, adaptive functioning, participation and quality of life.

Furthermore, ML predictions should complement clinical judgement. A model estimates probability based on patterns found in its training data; it does not determine an individual's future. Thabtah et al. (2022) accordingly recommended further comparison between ML-generated prognosis and predictions made by qualified practitioners.

10. Future Directions

Future research should prioritise longitudinal datasets. Prognosis inherently concerns future outcomes, and repeated measurements provide substantially more information about developmental change than isolated cross-sectional observations.

Second, multimodal modelling deserves further investigation. Combining behavioural, clinical, neuroimaging and physiological information may improve predictive capacity. However, additional variables should only be incorporated when they provide demonstrable incremental predictive value.

Third, independent external validation should become a standard requirement. Models should be tested across multiple institutions and populations before claims about clinical utility are made.

Fourth, research should focus increasingly on clinically meaningful outcomes. Prediction of adaptive functioning, language development, educational participation, treatment response and quality of life may be more valuable for clinical decision-making than prediction of diagnostic status alone.

Fifth, explainable ML should receive greater attention. Clinicians need to understand not only what a model predicts but also which features contribute to its prediction and how confident the system is.

Sixth, future studies should address population diversity and algorithmic fairness. Greater representation of females, adults, underrepresented ethnic groups and populations from low- and middle-income countries is required to establish whether models generalise across different contexts.

Finally, prospective clinical studies are needed to determine whether ML-assisted prognosis actually improves clinical decision-making. High statistical accuracy alone does not demonstrate clinical effectiveness.

11. Discussion

The literature demonstrates that ML has progressed from relatively simple ASD classification towards increasingly sophisticated forms of prediction. Early research largely concentrated on distinguishing autistic from non-autistic individuals, whereas more recent research has begun to investigate symptom severity, developmental trajectories and intervention response (Washington & Wall, 2023).

The expansion of available data has been central to this development. Behavioural assessments provide clinically meaningful information, while neuroimaging and physiological measures provide potentially complementary biological information. Digital technologies additionally make it possible to capture behaviour repeatedly and objectively (Washington & Wall, 2023).

Deep learning is particularly promising for complex data. Ding et al. (2024) found high pooled sensitivity, specificity and AUC across deep-learning studies. However, the substantial heterogeneity identified in the meta-analysis demonstrates that high pooled performance should not be interpreted as evidence that a single model is ready for routine clinical use.

The distinction between diagnosis and prognosis is especially important. Much of the current ML literature is still diagnostic. For example, Rajagopalan et al. (2024) developed a model to predict ASD using minimal medical and background information. Although this represents an important advance in early prediction, it does not by itself establish an individual's future developmental or treatment trajectory.

The smaller body of research directly examining prognosis is nevertheless encouraging. Thabtah et al. (2022) demonstrated the feasibility of predicting outcomes among children receiving early behavioural intervention, while Sun et al. (2023) showed that supervised ML could be applied to predicting outcomes following exercise intervention. These studies indicate that ML may eventually contribute to personalised intervention planning.

However, prognosis is inherently more complex than classification because future outcomes are influenced by developmental processes, interventions and environmental factors. Consequently, prognostic models require longitudinal evidence, carefully defined outcomes and rigorous external validation.

The future value of ML-based ASD prognosis should therefore not be judged solely by whether an algorithm produces a high accuracy or AUC. A clinically useful model should demonstrate predictive accuracy, calibration, generalisability, interpretability, fairness and clinical utility. These requirements reinforce the need for collaboration between data scientists, clinicians, developmental researchers, autistic people and families.

12. Conclusion

Machine learning-based prognostic modelling represents an important emerging direction in ASD research. ML provides opportunities to integrate behavioural, clinical, neuroimaging, physiological and digital data to estimate future developmental outcomes and intervention responses. Existing research demonstrates promising applications in early prediction, symptom-severity estimation, developmental trajectory modelling and treatment prognosis (Thabtah et al., 2022; Washington & Wall, 2023).

Nevertheless, the evidence base remains constrained by small samples, data heterogeneity, overfitting, class imbalance, limited external validation and inadequate representation of diverse populations. Deep-learning studies, in particular, have demonstrated impressive predictive performance, but substantial methodological heterogeneity limits direct translation into clinical practice (Ding et al., 2024).

Future research should therefore emphasise longitudinal datasets, independent validation, clinically meaningful outcomes, transparent algorithms and representative populations. Rather than replacing clinical assessment, ML should function as a decision-support mechanism that complements professional judgement. With rigorous validation and appropriate ethical safeguards, prognostic ML could contribute to more individualised monitoring, intervention planning and support for people with ASD.

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