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Review

OUTCOMES IN MACHINE LEARNING MODELS FOR CHILD PSYCHIATRY: A SYSTEMATIC REVIEW OF THE LITERATURE

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SUMMARY

Machine learning (ML) offers powerful tools to address the complexity and data richness of mental health research. By detecting subtle patterns, integrating diverse datasets, and supporting precise decision-making, ML holds promise for enhancing diagnosis, prognosis, and personalized treatment. In child and adolescent psychiatry - characterized by marked clinical heterogeneity and developmental variability - ML may help disentangle complexity and guide clinical care. This systematic review examined studies applying ML to psychiatric disorders in individuals aged 0–18 years. Of 65 identified studies, 33 met inclusion criteria. Most focused on attention-deficit/hyperactivity disorder (ADHD) and autism spectrum disorder (ASD), with others addressing schizophrenia, bipolar disorder, eating disorders, suicidal behaviors, and depression. Overall, the emphasis was on diagnostic applications. Findings were heterogeneous due to variability in algorithms, datasets, and outcome measures, with performance ranging from modest to high. However, small sample sizes, lack of external validation, and overfitting remain major barriers. ML in child and adolescent psychiatry is at an early stage but shows considerable promise, requiring standardized methods, interpretability, and ethical safeguards for clinical translation.

Key words: *machine learning - child psychiatry - data science - personalised medicine - computational psychiatry*

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INTRODUCTION

Mental illness remains one of the leading causes of disability worldwide, as reported by the World Health Organization (WHO) (Murray & Lopez 2002). A substantial body of prospective and retrospective research indicates that the majority of psychiatric disorders have their onset during childhood or adolescence (Merikangas et al. 2009). In recent years, epidemiological data have underscored the urgent need to improve diagnostic methods in child and adolescent psychiatry (Merikangas et al. 2009).

Approximately 15% of children and adolescents are diagnosed with conditions such as autism spectrum disorder (ASD), attention-deficit/hyperactivity disorder (ADHD), anxiety disorders, depression, or schizophrenia (Dalsgaard et al. 2020). These diagnoses are often preceded by untreated developmental disturbances associated with poorer long-term outcomes (Dwyer & Koutsouleris 2022; McGorry & Mei 2018). In some cases, subthreshold or prodromal symptoms emerge, impairing daily functioning and increasing the risk of transition to full-blown disorders in early adulthood (Dwyer & Koutsouleris 2022; Fusar-Poli et al. 2013). Such vulnerabilities may disrupt critical neurodevelopmental windows (Dwyer & Koutsouleris 2022), and negatively influence academic, social, and psychological trajectories, thereby increasing the likelihood of chronic impairment (Dwyer & Koutsouleris 2022).

The clinical presentation of psychiatric disorders in youth is often complex and heterogeneous. Traditional categorical approaches - focused on discrete diagnostic entities - frequently fail to capture the dynamic and evolving nature of symptoms during development. In children and adolescents, psychiatric symptoms are shaped by neurodevelopmental maturation as well as by the influence of family, educational, and social environments. Given these contextual factors and the rapid developmental changes occurring throughout youth, it is misleading to view symptoms as stable or isolated at any single point in time (Borsboom, 2017).

Given the high demand for mental health services in child and adolescent psychiatry, early identification and intervention are essential to reduce the impact of comorbidities and improve life outcome (Belfer, 2008; Kieling et al. 2011).

In this new era of industrial and digital transformation, artificial intelligence (AI) is reshaping the landscape of medical research and practice. Despite ongoing debates regarding its clinical utility, researchers have been actively exploring how AI - and more specifically, machine learning (ML), a subfield of AI - can support early detection, precise diagnosis, outcome prediction, and personalized treatment planning in psychiatry (Borsboom 2017; Géron 2022).

Machine learning (ML) has emerged as a powerful computational approach for addressing complex and data-rich problems in mental health research. Particularly well-suited to situations requiring the detection of subtle patterns, fine-tuned decision-making, or the integration of large and heterogeneous datasets, ML methods offer the potential to improve diagnostic accuracy, prognosis, and personalized treatment strategies (Dwyer & Koutsouleris 2022). In child and adolescent psychiatry - where clinical heterogeneity and developmental variability are the norms - ML provides new avenues to disentangle complexity and enhance clinical decision-making.

There are two main paradigms in machine learning: supervised learning, in which the algorithm is trained on labeled data (i.e., the outcome is known), and unsupervised learning, which involves discovering patterns in data without predefined labels (Dwyer & Koutsouleris 2022; Géron 2022). Supervised learning is commonly used to build predictive models that can estimate future outcomes based on input variables, while unsupervised learning is typically used to detect hidden structures or clusters within the data (Dwyer & Koutsouleris 2022; Murphy 2012).

Among supervised techniques, linear regression and logistic regression are foundational models used to predict continuous and categorical outcomes, respectively. More advanced models include support vector machines (SVMs), which construct an optimal hyperplane in a high-dimensional space to separate data points belonging to different classes (Hastie et al. 2001). Decision trees represent another approach, splitting the data into branches based on decision rules to produce interpretable classification or regression outputs. Random forests, an ensemble method, build multiple decision trees and combine their predictions - typically using a bagging strategy - to improve accuracy and reduce overfitting (Archer & Kimes 2008; Boulesteix et al. 2012).

In addition, deep learning, a subfield of machine learning, has garnered increasing attention for its ability to model high-dimensional, unstructured data such as neuroimaging, speech, or raw behavioral signals. Deep learning models - particularly artificial neural networks (ANNs) - are composed of multiple interconnected layers that progressively extract more abstract representations of the input data (Shrestha & Mahmood, 2019). These architectures have demonstrated success in capturing intricate patterns that may be imperceptible to traditional statistical methods.

Overall, machine learning techniques enable researchers to analyze large, complex datasets in child psychiatry, identify key predictive variables, and ultimately develop models that support earlier and more precise clinical interventions.

In this article, we first describe the methodology used to conduct this literature review. We then present a selection of key studies identified in the field, highlighting the use of machine learning techniques in child and adolescent psychiatry. Finally, we conclude by discussing the main findings, their clinical implications, and the limitations of the current literature.

METHOD

This literature search was conducted using the PubMed database. The following keywords were used: “child psychiatry” AND “machine learning”, as well as “machine learning” AND “psychiatry” AND “child” AND “applications”.

This systematic review focuses on studies involving minors aged 0 to 18 years, targeting the use of machine learning (ML) in the field of child and adolescent psychiatry. Inclusion criteria were defined as follows: studies had to involve human participants under the age of 18, address psychiatric conditions in this population, and describe concrete clinical applications of ML related to psychiatric assessment, diagnosis, or intervention. Studies focusing exclusively on adult populations (participants over 18 years old) or lacking full-text access were excluded. Both prospective and retrospective studies were considered, regardless of study duration or follow-up period, and inclusion was not limited to studies with a specific comparator; both controlled and uncontrolled designs were eligible. Studies conducted in any setting - clinical, academic, or research - were included, provided they met the core eligibility criteria.

The selection process consisted of an initial screening based on titles and abstracts to identify potentially relevant studies. This was followed by a full-text review applying the inclusion and exclusion criteria. Finally, selected studies were categorized according to the primary psychiatric diagnosis addressed (e.g., ADHD, autism spectrum disorder), the type of screening or assessment method used, and the specific machine learning techniques applied. The primary outcomes of interest included the clinical applicability and impact of ML in improving diagnostic precision, supporting clinical decision-making, or enhancing psychiatric evaluation in children and adolescents.

RESULTS

The initial PubMed search yielded 65 articles. After screening titles and abstracts, 36 articles were selected for full-text review. Upon closer examination, 3 articles were excluded due to failure to meet inclusion criteria - most notably, the absence of clinical applications of machine learning. As a result, a total of 33 articles were included in the final analysis (Figure 1).

Of these 33 studies, 12 focused on attention-deficit/hyperactivity disorder (ADHD), 6 on autism spectrum disorder (ASD), and 2 addressed both ADHD and ASD. Additionally, 2 studies investigated schizophrenia, 1 focused on bipolar disorder, 1 on eating disorders, 2 on suicidal behaviors, and 3 on depression. The remaining 7 articles explored various topics including perinatal responses (e.g., Still-Face paradigm), psychotherapy experiences, irritability, and Tourette syndrome. A comprehensive table summarizing the analysis of all included articles is provided in the appendix.

The majority of studies aimed to develop or evaluate diagnostic tools using machine learning techniques. A wide range of data modalities was employed: eye-tracking data were used in 5 studies, neuroimaging (e.g., MRI, fMRI) in 8, and electroencephalography (EEG) in 2.

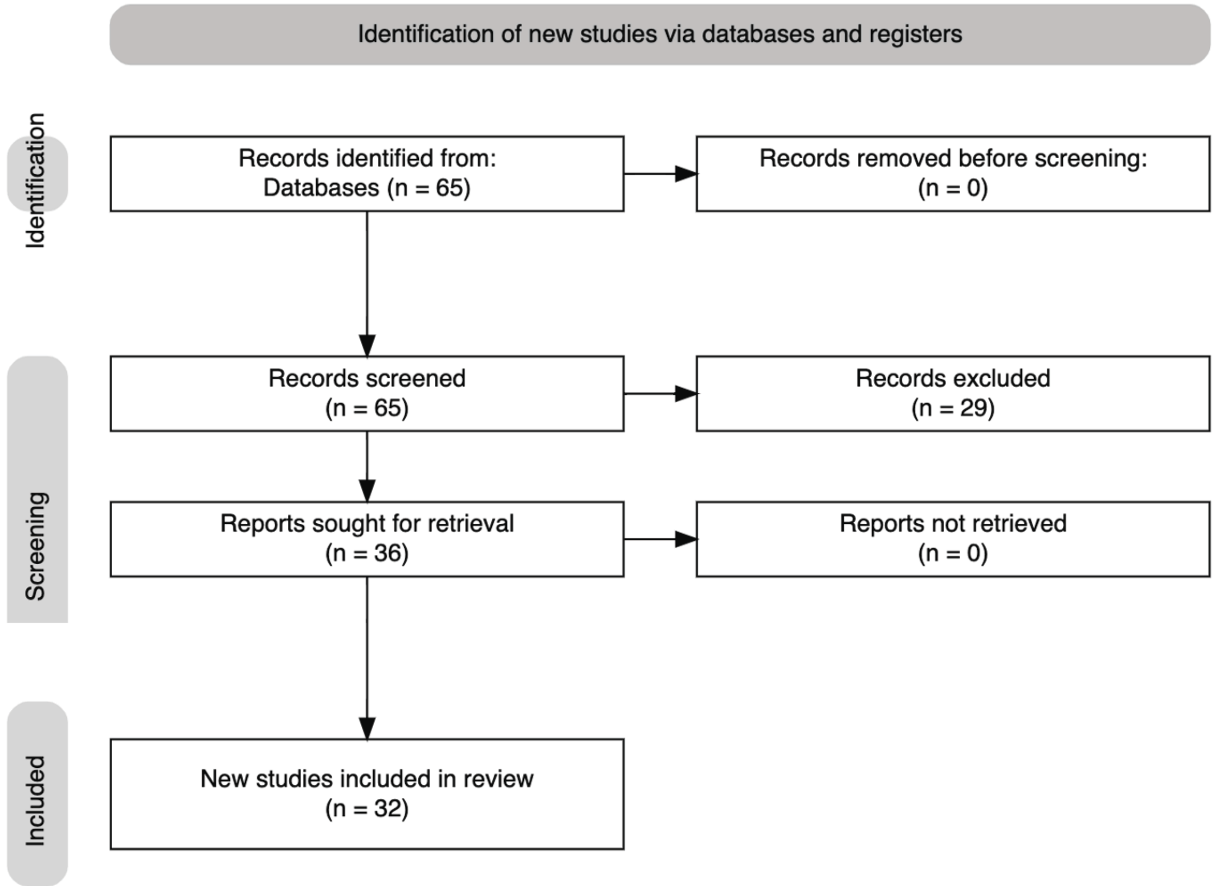

Figure 1. PRISMA Flow Diagram for Article Selection (Haddaway et al. 2022)

Seven studies relied on psychometric scales or symptom-based assessments to detect risk factors or improve early detection. These approaches highlight the growing interest in leveraging multimodal data to support clinical decision-making in child and adolescent psychiatry.

ADHD

Several studies explored the detection of ADHD using a variety of modalities, including electroencephalography (EEG), neuropsychological testing, and brain imaging techniques. In addition, one study focused on identifying early-life risk factors for ADHD among adult populations previously diagnosed with the disorder.

For example, the study conducted by Chu et al. evaluated the diagnostic performance of the Test of Variables of Attention (TOVA), a neuropsychological assessment, in a sample of 95 children aged 6 to 12 years. Among the participants, 74 were in the ADHD group and 21 served as controls. Three machine learning models were compared: logistic regression, classification and regression trees (CART), and artificial neural networks. The area under the ROC curve (AUC) reached 0.848, indicating a good overall predictive performance (Chu et al. 2023).

ASD

Several studies have explored the use of eye-tracking techniques to aid in the detection of autism spectrum disorder in young children. These studies typically involve recording eye movements during exposure to stimuli either through computer screens equipped with cameras or via mobile applications designed for this purpose. Eye movement patterns are analyzed to identify potential biomarkers associated with ASD.

Another approach involves the use of the Modified Checklist for Autism in Toddlers (M-CHAT) (Pan et al. 2025). For instance, Nig Pan et al. conducted a study involving 6,049 toddlers, of whom 71 were diagnosed with ASD and 5,978 were not. They identified 20 relevant M-CHAT items for ASD detection and applied six different machine learning algorithms. Among these, a Bagging-Support Vector Machine (Bagging-SVM) model trained on a specific subset of features (subset 2) demonstrated the best raw performance metrics. However, statistical comparisons using DeLong's test indicated no significant superiority of this model over the other tested algorithms (Pan et al. 2025).

Depression

Symptom rating scales were frequently utilized in the studies addressing depression. For example, Xu et al. highlighted the utility of the Center for Epidemiologic Studies Depression Scale (CES-D) in a large sample of 179,000 young individuals. Their study proposed an efficient and reliable approach that optimizes assessment burden while maintaining strong psychometric properties. The stratified design of this tool makes it suitable for large-scale mental health screening programs, enabling effective risk stratification and targeted follow-up assessments (Xu et al. 2025).

The resulting stratified screening system consists of an initial rapid screening phase using four items encompassing emotional, cognitive, and interpersonal dimensions to detect probable depression, with an area under the curve (AUC) of 0.982, sensitivity of 0.945, and specificity of 0.926. This is followed by an enhanced assessment phase adding five more items. Together, these nine items accurately predict the total CES-D-20 score ($R^2 = 0.957$). The stratified approach demonstrated robust generalizability across different age groups ($R^2 > 0.94$, accuracy > 0.91) and time points. Calibration analyses and decision curve analyses confirmed optimal clinical utility, especially within critical risk thresholds(Xu et al. 2025).

Suicide Prevention in Adolescents

In the study by Raymond Su et al. predictive factors for self-harm and suicide attempts among adolescents were identified (Su et al. 2023). The study included 2,809 adolescents, of whom 296 (10.54%) reported at least one act of self-harm and 145 (5.16%) reported attempting suicide within the past 12 months. Random forest classification models were employed, selecting features such as depressive symptoms, scores from the Strengths and Difficulties Questionnaire, self-perception measures, and school- and parent-related factors as important predictors (Su et al. 2023).

Schizophrenia

Regarding schizophrenia, one study by Gyllenberg was noted but excluded from the final selection because it did not involve a sample of minors (Gyllenberg et al. 2020).

A study by Greenstein et al. utilized 74 anatomical brain MRI subregions along with Random Forest (RF), a machine learning method, to classify 98 patients with childhood-onset schizophrenia (COS) and 99 healthy controls matched by age, sex, and ethnicity (Greenstein et al. 2012). The analysis revealed that a higher brain-based probability of illness was significantly associated with worse functional outcomes (p=0.0004) and fewer developmental delays (p=0.02). Additionally, the presence of copy number variants (CNVs) was linked to a lower probability of being classified as having schizophrenia (p=0.001). The brain regions most influential in group classification included the left temporal lobes, bilateral dorsolateral prefrontal cortex, and left medial parietal lobes (Greenstein et al. 2012).

DISCUSSION

Artificial intelligence (AI), particularly machine learning (ML), represents a transformative force in modern medicine, poised to significantly reshape tradetional clinical approaches. Its potential lies in its ability to analyze large-scale datasets and model highly complex, multidimensional phenomena - capabilities that could substantially enhance diagnostic accuracy, risk prediction, and treatment planning in psychiatry. As data-driven medicine continues to evolve, AI may become a powerful ally for clinicians and researchers alike.

However, current applications of machine learning in child and adolescent psychiatry face several critical limitations that must be addressed before these tools can be integrated into clinical workflows.

One of the most prevalent methodological issues in the reviewed literature is the small sample size. Several studies included fewer than 100 participants, which undermines statistical power and model generalizability (Varoquaux 2018). In response, some researchers have expanded their training datasets artificially; more concerning, however, is the augmentation of test sets, which introduces bias and overestimates model performance.

Machine learning is particularly suited to complex, high-dimensional datasets where traditional statistical methods are insufficient. However, its use in low-complexity scenarios - where simpler methods might suffice - may be unnecessary or even misleading. The improper selection of machine learning techniques can result in spurious conclusions and hinder the interpretability and replicability of findings.

Overfitting is another recurrent problem (Cawley & Talbot, n.d.). Many models are trained and tested on the same or closely related datasets, inflating accuracy metrics while failing to demonstrate robustness on new data. True generalizability requires external validation with independent samples - a standard that many studies fail to meet (Cawley & Talbot, n.d.).

Moreover, several studies used unclear or inappropriate data-handling procedures. For example, repeated random splits with undersampling (e.g., 500 iterations) are often employed to mitigate the effects of random noise (Scheinost et al. 2019). While this can reduce variance, it also leads to the exclusion of substantial portions of the data, potentially reducing the ecological validity of the results. Additionally, such methods do not ensure equal representation across training and testing subsets, unlike exhaustive cross-validation strategies.

Despite promising findings, the translation of ML-based tools into clinical practice remains limited. For instance, eye-tracking technology, proposed as a diagnostic aid for autism spectrum disorder (ASD), is not routinely used in clinical settings such as Belgium, where diagnosis continues to rely heavily on behavioral assessments and structured clinical interviews. Similarly, neuroimaging and neuropsychological tests proposed for attention-deficit/hyperactivity disorder (ADHD) detection are not part of standard diagnostic protocols, which still rely primarily on DSM-based criteria and clinical judgment.

The use of sophisticated technologies - such as gaze-tracking devices or neuroimaging tools - raises additional concerns. These systems require not only regulatory approval (e.g., by the FDA or the European AI Act) but also significant financial investment, technical infrastructure, and personnel training. Without these, implementation in real-world clinical settings remains impractical (Proposal for a Regulation Laying down Harmonised Rules on Artificial Intelligence | Shaping Europe's Digital Future, n.d.).

Furthermore, many ML models maintain a categorical framework, aligning with traditional psychiatric diagnoses. Yet, emerging perspectives in psychiatry advocate for dimensional and developmental models that better capture the evolving nature of mental health symptoms. Future algorithms should aim to reflect the fluidity of psychiatric presentations, especially in children and adolescents.

Another critical limitation is the lack of cross-cultural validation. Most models are trained and tested within single geographic or cultural contexts. A model developed using data from a Chinese cohort, for example, may not generalize to European populations unless rigorously adapted and validated using new, local datasets. This issue raises significant concerns about equity, inclusiveness, and the safe deployment of ML tools across diverse settings (Vokinger et al. 2021).

Despite these limitations, certain applications appear particularly promising. Tools designed to predict suicide risk in adolescents could be highly valuable in emergency departments, offering support to pediatricians, emergency physicians, and child psychiatrists. Their relative ease of use and rapid output make them practical candidates for near-term clinical integration, provided they undergo appropriate validation and regulatory approval.

CONCLUSION

Machine learning has the potential to profoundly impact the future of child and adolescent psychiatry. However, methodological rigor, transparency, regulatory oversight, and clinical feasibility must be addressed before these tools can be responsibly and effectively deployed in real-world settings.

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