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Machine learning from data to diagnosis: A comprehensive review of AI applications in mental health assessment

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ABSTRACT

This systematic review examines machine learning and artificial intelligence applications in mental health disorder diagnosis, prediction, and management to identify current trends, knowledge gaps, and future research directions. We conducted comprehensive database searches across PubMed, IEEE Xplore, Scopus, and ScienceDirect from 2013-2024, following PRISMA guidelines for systematic review methodology. After screening 1,156 records, 46 peer-reviewed studies met inclusion criteria for analysis. Studies employed supervised learning methods, deep learning architectures, and natural language processing techniques across depression, anxiety, schizophrenia, bipolar disorder, autism spectrum disorder, ADHD, and OCD. Data sources included neuroimaging, wearable sensors, social media content, electronic health records, and multimodal data integration approaches. Depression and schizophrenia dominated research focus due to public health impact, with publication frequency increasing significantly after 2017. Most studies reported performance using accuracy, sensitivity, specificity, and F1-scores, though validation protocols varied considerably across investigations. Machine learning models demonstrated promising diagnostic accuracy and early detection capabilities across multiple mental health conditions. However, significant challenges persist including limited model generalizability, inconsistent external validation, data quality heterogeneity, algorithmic bias concerns, and clinical implementation barriers. Future research should prioritize developing explainable AI models, establishing standardized evaluation frameworks, implementing robust ethical guidelines, and fostering interdisciplinary collaboration between technology developers and healthcare providers to translate AI innovations into clinical practice for improved early detection, personalized treatment approaches, and enhanced diagnostic accuracy in mental healthcare.

Contribution/Originality: This study contributes to the existing literature by systematically synthesizing ML applications across multiple mental health conditions using data from 2013 to 2024. It documents temporal trends in AI adoption, variations in performance metrics, and implementation barriers. The primary contribution of the paper is identifying gaps in the standardized evaluation framework within current psychiatric AI research.

1. INTRODUCTION

Mental health disorders represent a significant global health challenge, affecting millions of people and placing a substantial burden on healthcare systems [1, 2]. The World Health Organization reported a steep increase in mental disorders during the COVID-19 pandemic, underscoring the urgency of developing effective strategies for early diagnosis and intervention [2]. Traditional diagnostic methods, often relying on subjective assessments and clinical interviews, can be time-consuming, costly, and prone to variability [1]. In this context, the application of machine learning (ML) and artificial intelligence (AI) has emerged as a promising avenue for enhancing the accuracy, efficiency, and accessibility of mental health care [3, 4]. This article extends our earlier work [5] which provided a broad review of AI-based tools in mental health. In contrast to that narrative overview, the present study applies a systematic PRISMA framework to analyze and synthesize evidence from 46 empirical studies published between 2013 and 2024.

This review paper will delve into the current state of research on the application of machine learning and artificial intelligence for diagnosing and predicting mental health disorders. We will examine a wide range of studies published between 2013 and 2024, focusing on the diverse data sources and machine learning algorithms that have been explored [1, 2, 6, 7]. The primary goal of this review is to provide a comprehensive overview of the field, highlighting key findings, methodological considerations, challenges, and future directions.

The paper includes: Methods in Section II; Literature review in Section III covering data sources, machine learning techniques, psychological applications, clinical implementations, challenges, and future directions; Results and Discussion in Section IV; and Conclusions in Section V. This comprehensive structure provides a foundation for advancing AI in mental healthcare research.

This review distinguishes itself from previous publications by focusing specifically on multimodal data integration challenges and providing a temporal analysis of research evolution from 2013-2024. Unlike existing reviews that examine individual techniques or single conditions, our study comprehensively evaluates ML applications across multiple psychiatric disorders while emphasizing clinical implementation barriers and standardization needs.

2. MATERIALS AND METHODS

2.1. Search and Selection Process

We systematically searched PubMed, IEEE Xplore, Scopus, and ScienceDirect (2013–2024) using mental health and machine learning terms. Reference lists were manually screened. Studies were included if peer-reviewed, in English, ML-focused, and empirical; excluded if conceptual-only, non-ML, pre-2013, non-English, or non-peer-reviewed. Title/abstract screening and full-text review were done by two reviewers, with a third resolving disputes.

2.2. Data Extraction and Analysis

Extracted data included study details, conditions, ML methods, data types, sample information, performance metrics, and limitations. Quality was assessed based on design, sample size, ML rigor, validation, reporting, and bias. We used both quantitative and qualitative synthesis to evaluate ML effectiveness, clinical relevance, and challenges.

This review synthesized data from published studies rather than utilizing primary datasets. We employed a narrative synthesis approach combined with tabular data extraction to aggregate findings across heterogeneous studies. Data extraction focused on standardized elements including study characteristics (author, year, sample size), mental health conditions examined, machine learning methodologies employed, data modalities utilized, performance metrics reported, and identified limitations.

For quantitative synthesis, we categorized studies by mental health condition and ML technique type, creating summary tables to facilitate cross-study comparisons. Given the heterogeneity in study designs, outcome measures, and ML approaches across the included literature, meta-analysis was not feasible. Instead, we employed thematic analysis to identify recurring patterns, challenges, and future directions across the reviewed studies. This approach allowed us to synthesize both quantitative performance metrics and qualitative insights regarding implementation challenges and clinical applicability.

2.3. Review Process and Selection Criteria

Our systematic review followed a structured PRISMA approach [8] as illustrated in Figure 1. Initial database searches across PubMed, IEEE Xplore, Scopus, and ScienceDirect yielded 1,247 articles, with an additional 98 records identified through reference screening. After duplicate removal, 1,156 records underwent title and abstract screening, resulting in 189 articles for full-text assessment. Following rigorous evaluation against inclusion criteria, 46 studies were included in the final qualitative synthesis. The quality assessment evaluated study design rigor, sample size adequacy, machine learning methodology soundness, validation approaches, and potential bias sources, using established criteria for systematic reviews of machine learning applications in healthcare.

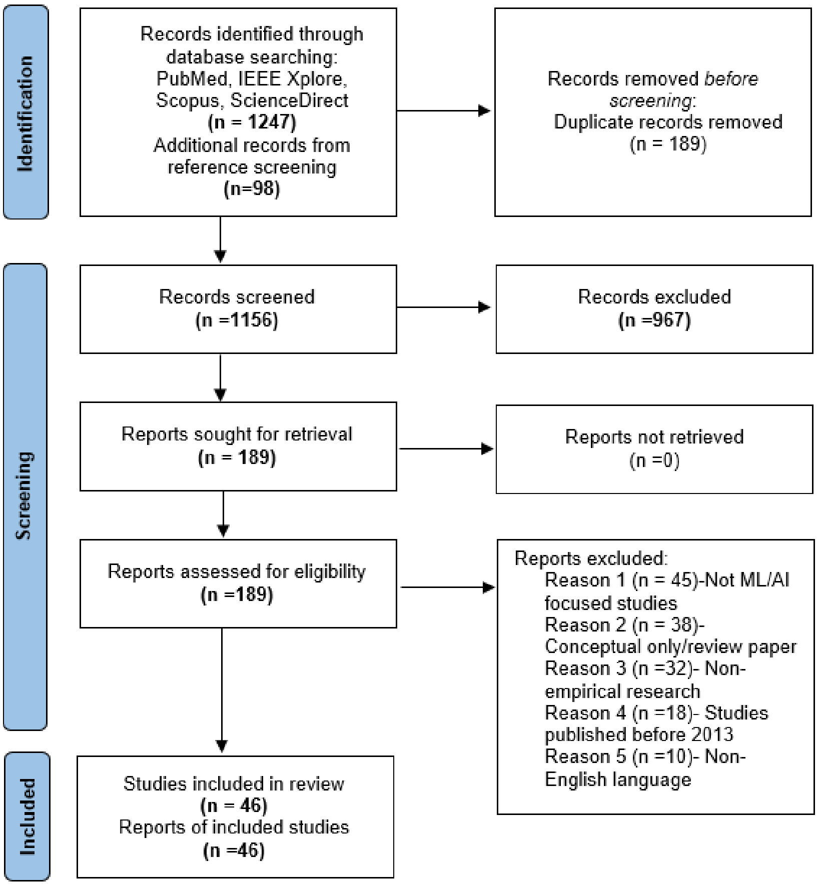

Figure 1. PRISMA flowchart for machine learning in mental health research.

3. LITERATURE REVIEW

3.1. Data Sources for AI in Mental Health Research

- Neuroimaging Data: MRI scans capture structural brain changes associated with mental disorders [9] while functional MRI (fMRI) measures neural activity patterns. EEG recordings identify specific biomarkers for conditions like depression [10, 11], providing objective physiological measurements.
- Wearable Sensor Data: Continuous physiological monitoring (heart rate, skin conductance) enables real-time stress detection [12] while passive behavioral sensing captures daily activity patterns revealing mental state changes [7].
- Social Media Data: Natural language processing analyzes social media content to identify linguistic patterns associated with mental health conditions [1, 13], creating opportunities for early intervention.
- Electronic Health Records: Clinical data mining uncovers risk factors and predicts treatment outcomes [3, 14], leveraging existing healthcare documentation for improved decision-making.

- Multimodal Data: Combined voice/speech analysis with smartphone sensor data creates comprehensive assessment tools [7, 15] capturing both verbal and behavioral indicators simultaneously.

Table 1 summarizes the primary data types utilized in contemporary mental health research, detailing their descriptions, analytical techniques, and associated research contributions.

Table 1. Data types and their applications in mental health research.

Data type	Description	Techniques/Methods	Authors
Neuroimaging	Brain structure/activity (MRI, fMRI, EEG)	Convolutional autoencoders, deep neural networks	Abd Rahman, et al. [1]; Pigoni, et al. [3]; Alam, et al. [16]; Sharma and Chariar [2]; Seal, et al. [10]; Rasheed, et al. [11] and Huang, et al. [17]
Wearable Sensor	Physiological data (heart rate, skin conductance, temperature)	Pattern recognition, passive sensing	Gedam and Paul [12] and Khoo et al. [6]
Social Media	Text and multimedia content	NLP (Tokenization, stemming), SVM, deep learning	Kim, et al. [13] and Abd Rahman, et al. [1]
Electronic Health Records (EHR)	Clinical data (Diagnoses, medications, lab results)	Risk prediction, mortality modeling	Zafar, et al. [18]; Tsang, et al. [19]; Banerjee, et al. [14]; Pigoni, et al. [3] and Tapia-Galisteo, et al. [20]
Voice/Speech Analysis	Vocal patterns and linguistic features	Speech feature analysis	Barua, et al. [15] and Khoo, et al. [7]
Multimodal Data	Combined data sources	Integrated analysis, passive sensing	Khoo, et al. [7]

3.2. Machine Learning Techniques in Mental Health Research

Supervised methods such as Random Forests identify key diagnostic features [19, 21], Logistic Regression quantifies risk factors [14], Naive Bayes classifies text indicators [1], and K-Nearest Neighbors detect EEG patterns in depression [17]. Unsupervised learning, including clustering, uncovers hidden subtypes [22], while dimensionality reduction improves model focus. Deep learning techniques such as CNNs analyze neuroimaging data [2, 10], RNNs handle time-series signals [2], and DNNs extract patterns from unstructured social media inputs [13, 23, 24]. Table 2 provides a comprehensive overview of machine learning techniques employed in mental health research, categorized by learning type with specific applications and supporting literature.

Table 2. Machine learning techniques in mental health.

Machine learning technique	Type	Description	Key applications	Authors
Support vector machines (SVM)	Supervised	Finds an optimal hyperplane to separate classes; used for classification and regression.	Suicide prediction, treatment success modeling	Sharma and Chariar [2]; Abd Rahman, et al. [1]; Mirbabaie, et al. [6]; Pigoni, et al. [3] and Tapia-Galisteo, et al. [20]
Decision trees	Supervised	Creates a hierarchical structure to classify data based on decisions.	Feature identification	Sharma and Chariar [2]; Abd Rahman, et al. [1]; Mirbabaie, et al. [6]
Random forests	Supervised	An ensemble of decision trees that reduces overfitting and improves accuracy.	Feature identification, suicide/treatment prediction	Sharma and Chariar [2]; Abd Rahman, et al. [1]; Mirbabaie, et al. [6]; Tapia-Galisteo, et al. [20] and Pigoni, et al. [3]

Machine learning technique	Type	Description	Key applications	Authors
Logistic regression	Supervised	Models the probability of a binary outcome.	Risk prediction, mortality assessment	Abd Rahman, et al. [1]; Mirbabaie, et al. [6]
Naive bayes	Supervised	A probabilistic classifier based on Bayes' theorem assumes independence between features.	Text classification, social media analysis	Abd Rahman, et al. [1] and Mirbabaie, et al. [6]
K-nearest neighbors (KNN)	Supervised	Classifies data based on the majority class among its k-nearest neighbors.	EEG-based depression classification	Mirbabaie, et al. [6] and Madububambachu, et al. [25]
Clustering algorithms	Unsupervised	Groups of similar individuals based on patterns in data, for example, K-means and hierarchical clustering.	Disorder subtype identification	Vaishnavi, et al. [26]
Dimensionality Reduction	Unsupervised	Reduces the number of features in a dataset while preserving important information, for example, Principal Component Analysis (PCA).	Model optimization	Mirbabaie, et al. [6]
Convolutional neural networks (CNN)	Deep learning	Uses multiple layers to learn complex patterns in data, especially image analysis.	Neuroimaging analysis, EEG processing	Sharma and Chariar [2]; Seal, et al. [10]; Abd Rahman, et al. [1]; Pigoni, et al. [3] and Alam, et al. [16]
Recurrent neural networks (RNN)	Deep learning	Designed to handle sequential data.	Time-series analysis	Sharma and Chariar [2]
Deep neural networks (DNN)	Deep learning	Feedforward neural networks with multiple layers.	Social media content analysis	Vaishnavi, et al. [26]; Kim, et al. [22] and Baek and Chung [21]

3.3. Applications of ML/AI to Specific Mental Health Conditions

- Depressive Disorders: AI systems analyze social media text for depression indicators [13], identify EEG biomarkers [10], and use wearable sensor data to recognize depression patterns [27], enabling earlier intervention.
- Anxiety Disorders: ML models detect anxiety-related patterns in social media usage and physiological measurements [2, 28], providing continuous monitoring between clinical visits.
- Schizophrenia: Advanced algorithms analyze neuroimaging data to identify markers of schizophrenia [26], assess medication effectiveness through EHR analysis, and predict mortality risk [14, 29].
- Bipolar Disorder: ML techniques identify biomarkers through neuroimaging and genetic data [20, 30] and monitor mood fluctuations through behavioral patterns, improving episode prediction.
- Autism Spectrum Disorder: AI systems analyze behavioral video recordings [15] and classify MRI scans [9, 31] to support earlier diagnosis and intervention planning.
- ADHD & OCD: ML analyzes neuroimaging and behavioral data to guide targeted interventions [2, 32, 33], personalizing treatment approaches.

Table 3 illustrates specific applications of ML/AI technologies across various mental health conditions, highlighting data sources and corresponding research contributions.

Table 3. Applications of ML/AI to specific mental health conditions.

Mental health condition	Data sources	ML/AI applications	Authors
Depressive disorders	Social media, EEG, wearables	Prediction, biomarker identification	Kim, et al. [13]; Abd Rahman, et al. [1]; Seal, et al. [10] and Vaishnavi, et al. [26]
Anxiety disorders	Social media, wearables	Detection, management	Sharma and Chariar [2]
Schizophrenia	Neuroimaging, EHR	Diagnosis, medication effectiveness, mortality	Tsang, et al. [19]; Sharma and Chariar [2] and Banerjee, et al. [14]
Bipolar/Autism/ADHD	Neuroimaging, genetics, behavioral data	Biomarkers, diagnosis, intervention assessment	Huang, et al. [17]; Sharma and Chariar [2]; Barua, et al. [15]; Martinez-Murcia, et al. [9] and Pigoni, et al. [3]
OCD	Brain activity data	Disorder understanding, intervention	Sharma and Chariar [2]

3.4. Clinical Implementations

Prediction Systems identify depression risk factors [34], detect mental illness in social media [35], monitor stress [12], and assess students' mental health risks [36] while personalized interventions deliver customized psychological treatments [37] and assistive tools for neurodevelopmental disorders [15, 38]. Treatment monitoring uses EEG to detect early psychosis [39], improve classification accuracy [40], and identify response biomarkers [41]. Digital Solutions include AI chatbots, IoT systems for remote monitoring [42], and applications extending treatment access [43]. Table 4 presents some of the applications of AI in Mental Health.

Table 4. Applications of AI in mental health.

Application	Description	Authors
Prediction and detection	Risk identification, condition onset detection	Baek and Chung [21]; Abd Rahman, et al. [1]; Kim, et al. [13]; Gedam and Paul [12]; Parekh, et al. [23] and Martinez-Murcia, et al. [9]
Personalized interventions	Tailored treatment approaches	Mukhiya, et al. [30] and Barua, et al. [15]
Assistive technologies	Cognitive/Developmental support tools	Barua, et al. [15] and Jacob, et al. [31]
Treatment and monitoring	Progress tracking, biomarker detection	Barua, et al. [15]; Chen, et al. [32]; Ahmedt-Aristizabal, et al. [33]; He, et al. [34] and Akella, et al. [35]
Treatment and diagnosis	Chatbots, IoT systems, psychotherapy apps	D'Alfonso [36]; D'alfonso, et al. [37]; Dosovitsky, et al. [38]; Al Nahian, et al. [39] and Tekin [40]
Predictive applications	Student mental health, eating disorders, workload	Zhai, et al. [24]; Ralph-Nearman, et al. [27]; Zhang, et al. [28] and Prendinger, et al. [29]
Evaluation of apps	Mental health app utility assessment	Oyebode, et al. [41]

3.5. Challenges and Future Directions

Current Limitations include inconsistent data quality [7, 44], limited validation studies [3, 45], "black box" interpretability issues [14, 46], potential algorithmic bias [45, 47], privacy concerns, clinical translation barriers [3, 48], and causation establishment difficulties.

Future Improvements require standardized data protocols [7, 26], rigorous external validation [3], explainable AI models [14, 49], bias mitigation strategies [50, 51], robust ethical frameworks [46] and collaborative clinical implementation.

4. RESULTS AND DISCUSSION

4.1. Quantitative Results

Machine learning applications in mental health have grown exponentially in the last decade, as evidenced by the increased number of publications [3]. Table 5 summarizes AI research timelines and key approaches for major mental disorder categories (2017-2024). Most publications emerged after 2017, reflecting rapid ML advances and recognition of its potential for global mental health challenges. This surge indicates a shift toward data-driven approaches. Figure 2 illustrates the distribution of research papers across various mental health disorders from 2017-2024, demonstrating that depression and miscellaneous mental disorders constitute the largest proportion of AI/ML research publications in the field.

Table 5. Mental disorders and years of publication.

Disorder category	Year(s) of publication	Key areas of work
Mood and anxiety disorders (depression, bipolar disorder, anxiety)	2019–2024	Detection, prediction, social media & speech analysis, neuroimaging, multimodal data, AI applications
Neurodevelopmental disorders (ASD, ADHD)	2022, 2024	Diagnosis, feature fusion, EEG analysis, AI in education, neuroimaging
Psychotic disorders (Schizophrenia)	2019, 2021, 2022, 2024	Neuroimaging, AI-based monitoring and prediction
Obsessive/Compulsive & Trauma (OCD, PTSD)	2020, 2024	Social media analysis, application of ML
Cognitive Disorders (Dementia/Alzheimer's, Cognitive Impairment)	2020, 2021	Neuroimaging, machine learning for diagnosis, speech and cognition assessment, treatment outcomes
Eating & personality disorders	2021, 2024	Behaviour detection via sensors, AI for diagnosis, expert systems
Suicidal ideation/Attempts	2019, 2020	Social media and text analysis
General mental health/Stress	2017, 2019–2021	Detection via social media, wearables, ML
Miscellaneous mental illness/Disorder	2017, 2020–2024	Edge AI, general ML use, social media, data-driven approaches

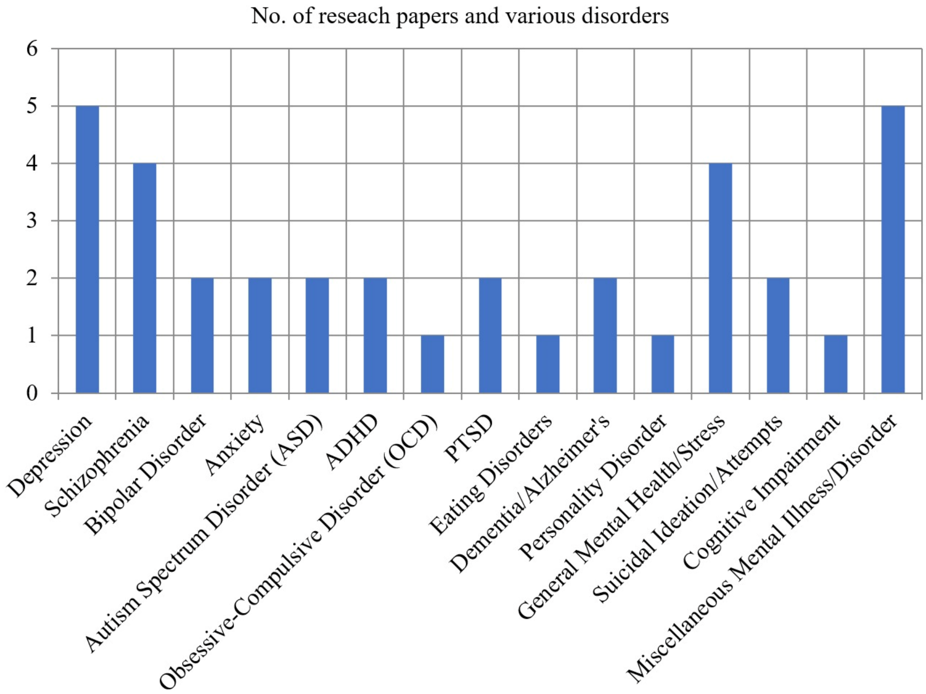

Figure 2. No. of research papers and various disorders observed.

- Key Observations - Mental health research shows significant AI integration since 2020, peaking in 2024. Depression and schizophrenia dominate due to their public health impact, with many studies addressing multiple disorders simultaneously. Recent research increasingly utilizes social media, wearable sensors, and advanced machine learning techniques.

4.2. Thematic Insights

- Specific Applications - Depression research employs regression for risk prediction [21], CNNs for EEG analysis [10], and speech pattern assessment [48]. Anxiety studies use ML to identify anxiety in cancer patients and predict treatments [41]. Stress applications leverage wearables for real-time monitoring and intervention [12]. Suicide prevention utilizes algorithms to identify risk factors from patient data [3]. Additional applications include dementia detection [19], eating disorder identification [7], and addiction management [20].
- Performance Metrics - The performance of machine learning models for mental health is evaluated using various performance metrics [7].
- Accuracy: The ratio of correct predictions to total predictions. It is used to evaluate the overall performance of the models.
- Sensitivity: The proportion of actual positives that are correctly identified. It measures the ability of the model to identify true cases of mental health conditions [7].
- Specificity: The proportion of actual negatives that are correctly identified. It measures the ability of the model to correctly identify those without the condition [7].
- F1-score: The harmonic mean of precision and recall. It is used when there is a class imbalance [7].
- MCC (Matthews correlation coefficient): A correlation coefficient between the observed and predicted classifications. It is used to measure the performance of a model, especially when dealing with imbalanced datasets [44].
- Data handling - Data preprocessing is a crucial step in machine learning and is done to improve the quality and suitability of data for training the models [1, 41].
- Data Imbalance: Oversampling techniques such as Borderline-SMOTE (Synthetic Minority Oversampling Technique) are used to address data imbalance in training sets. Data imbalance occurs when the number of samples for each class is not equal [44].
- Feature extraction: Feature extraction methods are used to identify relevant features from the raw data, which depends on the modality of the data [1, 10, 41, 48]. Spectral analysis is often used to identify relevant features in EEG signals [10]. NLP techniques are used for analyzing and extracting features from textual data [1, 41].
- Data Augmentation: Data augmentation techniques are applied when there is a limited number of samples to train the model [44]. Data augmentation involves creating new synthetic data points to improve the training of the model [44].
- Natural language processing: Techniques like lemmatization, tokenization, stemming, and removal of stop words are used when working with text-based data [41].
- Adaptive Interventions -Machine learning enhances internet-delivered psychological treatments (IDPT) [30] via rule-based, feedback-loop, goal-driven, and ML-based adaptations to personalize therapy.
- Privacy-Preserving Machine Learning - Techniques such as Federated Learning, Differential Privacy, and Secure Multi-Party Computation address data privacy in decentralized mental health applications [44].

5. CONCLUSIONS

This review paper has explored the application of machine learning and artificial intelligence in the diagnosis and prediction of mental health disorders [2, 3]. The increasing prevalence of mental health issues has made the development of innovative techniques for early detection and intervention a public health priority [1]. This review has synthesized information from numerous studies, revealing the potential of AI to improve the accuracy, efficiency, and accessibility of mental healthcare [3, 4].

We have demonstrated that the application of machine learning and artificial intelligence in mental health relies on various data sources, such as neuroimaging, wearable sensors, social media, and electronic health records [12, 13, 17]. We discussed that these data sources can be analyzed using various techniques such as supervised and unsupervised machine learning, deep learning models, and feature selection methods [2, 6]. The applications of these techniques to conditions including depression, anxiety, schizophrenia, bipolar disorder, autism, ADHD, and OCD are also discussed [2, 9, 10, 14, 26].

For clinicians, we recommend gradual integration of AI tools with robust validation in clinical settings before widespread adoption. Researchers should prioritize developing explainable AI models and establishing standardized evaluation protocols across institutions. Policymakers must create regulatory frameworks addressing data privacy, algorithmic transparency, and clinical validation requirements while supporting interdisciplinary collaboration between technology developers and healthcare providers.

However, there are still some major limitations in the current landscape of AI application in mental health, such as data quality and heterogeneity, the need for external validation, the lack of explainable AI, and addressing issues of bias [6]. These challenges highlight that future research must focus on improving data collection and management, prioritizing external validation, developing explainable AI models, addressing algorithmic bias, ensuring ethical and privacy compliance, and prioritizing the clinical translation of these techniques [3, 7, 14].

Further, the field of ML and AI in mental health is rapidly evolving and holds significant promise for transforming mental healthcare. By addressing the existing limitations and focusing on future directions, researchers, clinicians, and policymakers can leverage the power of AI to achieve better outcomes for people with mental health disorders. This will lead to improvements in early detection, individualized interventions, and a more efficient use of healthcare resources.

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REFERENCES

[1] R. Abd Rahman, K. Omar, S. A. M. Noah, M. S. N. M. Danuri, and M. A. Al-Garadi, "Application of machine learning methods in mental health detection: A systematic review," *IEEE Access*, vol. 8, pp. 183952-183964, 2020. https://doi.org/10.1109/ACCESS.2020.3029154

[2] C. M. Sharma and V. M. Chariar, "Diagnosis of mental disorders using machine learning: Literature review and bibliometric mapping from 2012 to 2023," *Heliyon*, vol. 10, no. 12, p. e32548, 2024. https://doi.org/10.1016/j.heliyon.2024.e32548

[3] A. Pigoni *et al.*, "Machine learning and the prediction of suicide in psychiatric populations: A systematic review," *Translational Psychiatry*, vol. 14, no. 1, p. 140, 2024. https://doi.org/10.1038/s41398-024-02852-9

[4] S. Graham *et al.*, "Artificial intelligence for mental health and mental illnesses: An overview," *Current Psychiatry Reports*, vol. 21, no. 11, p. 116, 2019. https://doi.org/10.1007/s11920-019-1094-0

[5] R. Kumari and H. Marwaha, "A comprehensive review on AI-based tools for mental health disorders," *IITM Journal of Information Technology*, vol. 11, pp. 15–20, 2025.

[6] M. Mirbabaie, S. Stieglitz, and N. R. J. Frick, "Artificial intelligence in disease diagnostics: A critical review and classification on the current state of research guiding future direction," *Health and Technology*, vol. 11, no. 4, pp. 693-731, 2021. https://doi.org/10.1007/s12553-021-00555-5

[7] L. S. Khoo, M. K. Lim, C. Y. Chong, and R. McNaney, "Machine learning for multimodal mental health detection: A systematic review of passive sensing approaches," *Sensors*, vol. 24, no. 2, p. 348, 2024. https://doi.org/10.3390/s24020348

[8] PRISMA 2020 Flow Diagram — PRISMA Statement, "PRISMA 2020 flow diagram," Retrieved: https://www.prisma-statement.org/prisma-2020-flow-diagram. [Accessed August 4, 2025], 2020. [Online]. Available: https://www.prisma-statement.org/prisma-2020-flow-diagram

[9] F. J. Martinez-Murcia, A. Ortiz, J.-M. Gorriz, J. Ramirez, and D. Castillo-Barnes, "Studying the manifold structure of Alzheimer's disease: A deep learning approach using convolutional autoencoders," *IEEE Journal of Biomedical and Health Informatics*, vol. 24, no. 1, pp. 17-26, 2020. https://doi.org/10.1109/JBHI.2019.2914970

[10] A. Seal, R. Bajpai, J. Agnihotri, A. Yazidi, E. Herrera-Viedma, and O. Krejcar, "DeprNet: A deep convolution neural network framework for detecting depression using EEG," *IEEE Transactions on Instrumentation and Measurement*, vol. 70, pp. 1-13, 2021. https://doi.org/10.1109/TIM.2021.3053999

[11] K. Rasheed *et al.*, "Machine learning for predicting epileptic seizures using EEG signals: A review," *IEEE Reviews in Biomedical Engineering*, vol. 14, pp. 139-155, 2021. https://doi.org/10.1109/RBME.2020.3008792

[12] S. Gedam and S. Paul, "A review on mental stress detection using wearable sensors and machine learning techniques," *IEEE Access*, vol. 9, pp. 84045-84066, 2021. https://doi.org/10.1109/ACCESS.2021.3085502

[13] J. Kim, J. Lee, E. Park, and J. Han, "A deep learning model for detecting mental illness from user content on social media," *Scientific Reports*, vol. 10, no. 1, p. 11846, 2020. https://doi.org/10.1038/s41598-020-68764-y

[14] S. Banerjee, P. Lio, P. B. Jones, and R. N. Cardinal, "A class-contrastive human-interpretable machine learning approach to predict mortality in severe mental illness," *npj Schizophrenia*, vol. 7, no. 1, p. 60, 2021. https://doi.org/10.1038/s41537-021-00191-y

[15] P. D. Barua *et al.*, "Artificial intelligence enabled personalised assistive tools to enhance education of children with neurodevelopmental disorders—a review," *International Journal of Environmental Research and Public Health*, vol. 19, no. 3, p. 1192, 2022. https://doi.org/10.3390/ijerph19031192

[16] M. G. R. Alam, R. Haw, S. S. Kim, M. A. K. Azad, S. F. Abedin, and C. S. Hong, "EM-psychiatry: An ambient intelligent system for psychiatric emergency," *IEEE Transactions on Industrial Informatics*, vol. 12, no. 6, pp. 2321-2330, 2016. https://doi.org/10.1109/TII.2016.2610191

[17] Y. Huang *et al.*, "Innovative neuroimaging biomarker distinction of major depressive disorder and bipolar disorder through structural connectome analysis and machine learning models," *Diagnostics*, vol. 14, no. 4, p. 389, 2024. https://doi.org/10.3390/diagnostics14040389

[18] S. Zafar, A. P. Dekker, G.-A. S. Sidhu, A. T. Stammer, and N. Ashwood, "Assessing patient understanding and satisfaction in orthopedic trauma and elective surgery admissions," *Cureus*, vol. 16, no. 8, p. e66924, 2024. https://doi.org/10.7759/cureus.66924

[19] G. Tsang, X. Xie, and S.-M. Zhou, "Harnessing the power of machine learning in dementia informatics research: Issues, opportunities, and challenges," *IEEE Reviews in Biomedical Engineering*, vol. 13, pp. 113-129, 2020. https://doi.org/10.1109/RBME.2019.2904488

[20] J. Tapia-Galisteo *et al.*, "Prediction of cocaine inpatient treatment success using machine learning on high-dimensional heterogeneous data," *IEEE Access*, vol. 8, pp. 218936-218953, 2020. https://doi.org/10.1109/ACCESS.2020.3041895

[21] J.-W. Baek and K. Chung, "Context deep neural network model for predicting depression risk using multiple regression," *IEEE Access*, vol. 8, pp. 18171-18181, 2020. https://doi.org/10.1109/ACCESS.2020.2968393

[22] L. Kim, M. Han, and R. Guo, "Machine learning in the analysis of mental disease," in *Proceedings of the 2020 ACM Southeast Conference*, 2020, pp. 316-317.

[23] V. Parekh, D. Shah, and M. Shah, "Fatigue detection using artificial intelligence framework," *Augmented Human Research*, vol. 5, no. 1, p. 5, 2020. https://doi.org/10.1007/s41133-019-0023-4

[24] Y. Zhai *et al.*, "Machine learning predictive models to guide prevention and intervention allocation for anxiety and depressive disorders among college students," *Journal of Counseling & Development*, vol. 103, no. 1, pp. 110-125, 2025. https://doi.org/10.1002/jcad.12543

[25] U. Madububambachu, A. Ukpebor, and U. Ihezue, "Machine learning techniques to predict mental health diagnoses: A systematic literature review," *Clinical Practice & Epidemiology in Mental Health*, vol. 20, no. 1, pp. 1-16, 2024. https://doi.org/10.2174/0117450179315688240607052117

[26] K. Vaishnavi, U. N. Kamath, B. A. Rao, and N. V. S. Reddy, "Predicting mental health illness using machine learning algorithms," *Journal of Physics: Conference Series*, vol. 2161, no. 1, p. 012021, 2022. https://doi.org/10.1088/1742-6596/2161/1/012021

[27] C. Ralph-Nearman *et al.*, "Using machine learning with passive wearable sensors to pilot the detection of eating disorder behaviors in everyday life," *Psychological Medicine*, vol. 54, no. 6, pp. 1084-1090, 2024. https://doi.org/10.1017/S003329172300288X

[28] P. Zhang, X. Wang, J. Chen, W. You, and W. Zhang, "Spectral and temporal feature learning with two-stream neural networks for mental workload assessment," *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 27, no. 6, pp. 1149-1159, 2019. https://doi.org/10.1109/TNSRE.2019.2913400

[29] H. Prendinger, K. Puntumapon, and M. Madruga, "Extending real-time challenge balancing to multiplayer games: A study on eco-driving," *IEEE Transactions on Computational Intelligence and AI in Games*, vol. 8, no. 1, pp. 27-32, 2016. https://doi.org/10.1109/TCIAIG.2014.2364258

[30] S. K. Mukhiya, J. D. Wake, Y. Inal, and Y. Lamo, "Adaptive systems for internet-delivered psychological treatments," *IEEE Access*, vol. 8, pp. 112220-112236, 2020. https://doi.org/10.1109/ACCESS.2020.3002793

[31] S. Jacob, V. G. Menon, F. Al-Turjman, P. G. Vinoj, and L. Mostarda, "Artificial muscle intelligence system with deep learning for post-stroke assistance and rehabilitation," *IEEE Access*, vol. 7, pp. 133463-133473, 2019. https://doi.org/10.1109/ACCESS.2019.2941491

[32] H. Chen, Y. Lin, Y. Li, W. Wang, P. Wang, and Y. Lei, "Hybrid feature embedded sparse stacked autoencoder and manifold dimensionality reduction ensemble for mental health speech recognition," *IEEE Access*, vol. 9, pp. 28729-28741, 2021. https://doi.org/10.1109/ACCESS.2021.3057382

[33] D. Ahmedt-Aristizabal *et al.*, "Identification of children at risk of schizophrenia via deep learning and EEG responses," *IEEE Journal of Biomedical and Health Informatics*, vol. 25, no. 1, pp. 69-76, 2021. https://doi.org/10.1109/JBHI.2020.2984238

[34] Y. He *et al.*, "External validation of a machine learning model for schizophrenia classification," *Journal of Clinical Medicine*, vol. 13, no. 10, p. 2970, 2024. https://doi.org/10.3390/jcm13102970

[35] A. Akella *et al.*, "Classifying multi-level stress responses from brain cortical EEG in nurses and non-health professionals using machine learning auto encoder," *IEEE Journal of Translational Engineering in Health and Medicine*, vol. 9, pp. 1-9, 2021. https://doi.org/10.1109/JTEHM.2021.3077760

[36] S. D'Alfonso, "AI in mental health," *Current Opinion in Psychology*, vol. 36, pp. 112-117, 2020. https://doi.org/10.1016/j.copsyc.2020.04.005

[37] S. D'alfonso *et al.*, "Artificial intelligence-assisted online social therapy for youth mental health," *Frontiers in Psychology*, vol. 8, p. 796, 2017. https://doi.org/10.3389/fpsyg.2017.00796

[38] G. Dosovitsky, B. S. Pineda, N. C. Jacobson, C. Chang, and E. L. Bunge, "Artificial intelligence chatbot for depression: Descriptive study of usage," *JMIR Formative Research*, vol. 4, no. 11, p. e17065, 2020. https://doi.org/10.2196/17065

[39] M. J. Al Nahian, T. Ghosh, M. N. Uddin, M. M. Islam, M. Mahmud, and M. S. Kaiser, "Towards artificial intelligence driven emotion aware fall monitoring framework suitable for elderly people with neurological disorder," presented at the International Conference on Brain Informatics Cham: Springer International Publishing., 2020, 275-286.

[40] Ş. Tekin, "Is big data the new stethoscope? Perils of digital phenotyping to address mental illness," *Philosophy & Technology*, vol. 34, no. 3, pp. 447-461, 2021. https://doi.org/10.1007/s13347-020-00395-7

[41] O. Oyebode, F. Alqahtani, and R. Orji, "Using machine learning and thematic analysis methods to evaluate mental health apps based on user reviews," *IEEE Access*, vol. 8, pp. 111141-111158, 2020. https://doi.org/10.1109/ACCESS.2020.3002176

[42] R. Subbaiah and O. Pineno, "Artificial intelligence: The future of mental health treatment," *Neurology - Research & Surgery*, vol. 3, no. 1, pp. 1–2, 2020.

[43] G. Acampora, D. J. Cook, P. Rashidi, and A. V. Vasilakos, "A survey on ambient intelligence in healthcare," *Proceedings of the IEEE*, vol. 101, no. 12, pp. 2470-2494, 2013. https://doi.org/10.1109/JPROC.2013.2262913

[44] A. Aminifar, M. Shokri, F. Rabbi, V. K. I. Pun, and Y. Lamo, "Extremely randomized trees with privacy preservation for distributed structured health data," *IEEE Access*, vol. 10, pp. 6010-6027, 2022. https://doi.org/10.1109/ACCESS.2022.3141709

[45] C. Burr, J. Morley, M. Taddeo, and L. Floridi, "Digital psychiatry: Risks and opportunities for public health and wellbeing," *IEEE Transactions on Technology and Society*, vol. 1, no. 1, pp. 21-33, 2020. https://doi.org/10.1109/TTS.2020.2977059

[46] S. Li, J. Shi, C. Shao, K. K. Sznajder, H. Wu, and X. Yang, "Predicting depression, anxiety, and their comorbidity among patients with breast cancer in China using machine learning: A multisite cross-sectional study," *Depression and Anxiety*, vol. 2024, no. 1, p. 3923160, 2024. https://doi.org/10.1155/2024/3923160

[47] M. Awais *et al.*, "LSTM-based emotion detection using physiological signals: IoT framework for healthcare and distance learning in COVID-19," *IEEE Internet of Things Journal*, vol. 8, no. 23, pp. 16863-16871, 2021. https://doi.org/10.1109/JIOT.2020.3044031

[48] Z. Zhao *et al.*, "Automatic assessment of depression from speech via a hierarchical attention transfer network and attention autoencoders," *IEEE Journal of Selected Topics in Signal Processing*, vol. 14, no. 2, pp. 423-434, 2020. https://doi.org/10.1109/JSTSP.2019.2955012

[49] N. Prentzas, A. Kakas, and C. S. Pattichis, "Explainable AI applications in the medical domain: A systematic review," arXiv:2308.05411, 2023. https://arxiv.org/abs/2308.05411

[50] F. Hasanzadeh, C. B. Josephson, G. Waters, D. Adedinsewo, Z. Azizi, and J. A. White, "Bias recognition and mitigation strategies in artificial intelligence healthcare applications," *npj Digital Medicine*, vol. 8, no. 1, p. 154, 2025. https://doi.org/10.1038/s41746-025-01503-7

[51] S. V. Chinta *et al.*, "AI-driven healthcare: A survey on ensuring fairness and mitigating bias," *PLOS Digital Health*, vol. 4, no. 5, e0000864, 2025. https://doi.org/10.1371/journal.pdig.0000864