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Review Article

Enhancing mental health care with AI: a review discussing biases, methodologies, and clinician preferences

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ABSTRACT

Integrating artificial intelligence (AI) into mental health care offers promising avenues for improving diagnostic accuracy, personalised treatment, and healthcare delivery. However, potential biases, methodological considerations, and the impact on clinical decision-making warrant critical examination of the implementation of AI in mental health practices. This manuscript explores various facets of AI implementation in mental health, encompassing algorithmic biases, the efficacy of machine learning methods, psychiatrists' perceptions of AI-driven clinical support tools (CSTs), and AI's role in surveillance and treatment across diverse mental health disorders. The manuscript has been drafted based on SANRA guidelines for searching, compiling, contemplating, and extracting data. Investigators independently searched PubMed, and Google Scholar for individual adults with psychiatric disorders being treated in psychiatric facilities with the incorporation of AI - ML-based algorithms assessing the outcomes in the quality of life. Algorithmic biases analysis revealed errors in error rates predicting ICU mortality and psychiatric readmission based on gender, insurance type, and demographics. Linear discriminant analysis (LDA) demonstrated proficiency in evaluating machine learning methods with smaller correlated feature sets. A support vector machine (SVM) with a radial basis function (RBF) kernel excelled with larger feature sets. Additionally, perceptions of AI-driven CSTs for major depressive disorder (MDD) treatment showed a preference for human-derived tools, influencing trust in AI-generated information and treatment recommendations among psychiatrists.

Keywords: AI, Mental health care, Review article

INTRODUCTION

The dynamic landscape of mental health care is witnessing a paradigm shift with the integration of artificial intelligence (AI), heralding a new era of precision and personalised interventions. Within this realm, longstanding challenges persist, particularly concerning the equitable tailoring of treatments for historically marginalised groups. Randomised trials, while pivotal, often fall short in capturing the nuanced effects across diverse patient populations, necessitating a deeper exploration of variables such as race, gender, and socioeconomic status in treatment outcomes.[1] In a seminal study by Chen et al, the application of machine learning algorithms to dissect unstructured clinical and psychiatric notes unveils a profound understanding of patient prognoses, notably in intensive care unit (ICU) mortality and 30-day psychiatric readmission. This inquiry, enriched by demographic indicators like race, gender and insurance payer type, unveils the intricacies of bias within data and algorithms, thereby catalysing a relentless pursuit of improvement and bias mitigation strategies. Parallelly, Maslej et al.'s investigation into psychiatrists' perceptions of AI-driven Clinical Support Tools (CSTs) for Major Depressive Disorder (MDD) unearths fascinating insights into the interplay between human judgement and AI-derived recommendations.[2,3] The preference for CSTs attributed to human sources underscores the complex terrain where technology intersects with clinical decision-making in mental health realms. The narrative of AI's impact on mental health care extends beyond these pioneering studies, delving into three pivotal realms, surveillance of autism spectrum disorder (ASD), management of dementia and gene analysis in schizophrenia. These domains, each rife with challenges and opportunities, showcase AI's potential to revolutionize prevalence estimation, predictive modelling, and candidate gene prioritization, thus heralding a future of tailored and effective interventions. This manuscript, through a comprehensive examination of current research and emerging trends, illuminates AI's transformative potential in mental health care and underscores the imperative of addressing challenges such as bias, interpretability, and human-AI collaboration.

By navigating this intellectual landscape, we aim to contribute meaningfully to the ongoing discourse, propelling mental health care into an era of precision and inclusivity.

LITERATURE SEARCH AND STUDY SELECTION

A research question was created using the PICO framework. The population in the discussion was individual adults with psychiatric disorders being treated in psychiatric facilities with the incorporation of AI - ML-based algorithms assessing the outcomes in the quality of life.

The following inclusion and exclusion criteria were followed. A search was conducted using PubMed, employing the following keywords.

("Artificial Intelligence" (Mesh) OR "Machine Learning"(Mesh) OR "Neural Networks (Computer)" (Mesh) OR "Deep Learning" (Mesh) OR "Cognitive Computing" (Mesh) OR "Natural Language Processing" (Mesh) OR "Predictive Analytics"(Mesh)) AND ("Mental Disorders" (Mesh) OR "Mental Health" (Mesh) OR "Psychiatry" (Mesh) OR "Psychiatric Nursing"(Mesh) OR "Psychiatric Department, Hospital"(Mesh) OR "Mental Health Services" (Mesh) OR "Mental Health Practitioners" (Mesh) OR "Mental Health Policy" (Mesh) OR "Mental Health Informatics" (Mesh)) AND ("Review"(Publication Type) OR "Challenges" (Title/Abstract) OR "Applications" (Title/Abstract) OR "Future Directions"(Title/Abstract) OR "Comprehensive" (Title/Abstract) OR "Integration" (Title/Abstract)) ("Artificial Intelligence"(Mesh) OR "Machine Learning"(Mesh) OR "Neural Networks (Computer)"(Mesh) OR "Deep Learning"(Mesh) OR "Cognitive Computing"(Mesh) OR "Natural Language Processing"(Mesh) OR "Predictive Analytics"(Mesh)) AND ("Mental Disorders"(Mesh) OR "Mental Health"(Mesh) OR "Psychiatry"(Mesh) OR "Psychiatric Nursing"(Mesh) OR "Psychiatric Department, Hospital"(Mesh) OR "Mental Health Services"(Mesh) OR "Mental Health Practitioners"(Mesh) OR "Mental Health Policy" (Mesh) OR "Mental Health Informatics" (Mesh)) AND ("Comprehensive Review" (Title/Abstract) OR "Applications" (Title/Abstract) OR "Challenges" (Title/Abstract) OR "Future Directions" (Title/Abstract) OR "Integration" (Title/Abstract) OR "Psychiatric Care" (Title/Abstract))

("Artificial Intelligence" (Mesh) OR "Machine Learning" (Mesh) OR "Neural Networks (Computer)" (Mesh) OR "Deep Learning" (Mesh) OR "Cognitive Computing" (Mesh) OR "Natural Language Processing"(Mesh) OR "Predictive Analytics"(Mesh)) AND ("Mental Disorders" (Mesh) OR "Mental Health" (Mesh) OR "Psychiatry" (Mesh)) AND ("Applications" (Title/Abstract) OR "Challenges" (Title/Abstract) OR "Future Directions" (Title/Abstract) OR "Integration" (Title/Abstract) OR "Psychiatric Care" (Title/Abstract) OR "Comprehensive Review"(Title/Abstract))

Study selection

The selected studies were imported into Rayyan.ai (software) after shortlisting and duplicates were eliminated. The remaining duplicates were manually checked and removed. Two authors individually assessed papers using titles, keywords and abstracts, resolving conflicts with a third reviewer. Articles passing the initial screening underwent a thorough review by each author to decide their suitability for the review.

Discrepancies in study selection between the primary reviewers were resolved with input from a third reviewer. Preference was given to higher-quality or larger-sample studies in cases of overlap.

Selection criteria

The studies identified through systematic search were comprehensively read to assess their appropriateness for incorporation into the review.

Table 1: Selection criteria.

Inclusion criteria	Exclusion criteria
Peer-reviewed research articles published in English. Studies conducted within the field of psychiatry or related mental health disciplines. Studies focusing on applying artificial intelligence (AI) or machine learning techniques in the context of mental health	Non-peer-reviewed articles, conference abstracts, posters, or editorials. Studies not written in English. Studies not related to the field of psychiatry or mental health. Studies not involving the use of AI, machine learning, or

Continued.

Inclusion criteria	Exclusion criteria
assessment, diagnosis, treatment, or prediction. Studies utilising AI algorithms, neural networks, machine learning models, deep learning techniques, cognitive computing, natural language processing, or predictive analytics in psychiatric or mental health research. Studies involving human subjects or clinical data related to mental health conditions or disorders. Studies assessing the efficacy, accuracy, sensitivity, specificity, or performance of AI applications in psychiatric care. Studies investigating the impact of AI on clinical decision-making, treatment planning, patient outcomes, or healthcare resource utilisation in the field of psychiatry. Studies exploring the integration of AI into mental health interventions, telepsychiatry, digital mental health platforms, or other mental health technologies. Studies provide insights, guidelines, or future directions for the utilisation of AI in improving mental healthcare delivery. Studies published within the last 10 years (2018-2023) to ensure relevance and recency.	related technologies in mental health applications. Studies focusing exclusively on non-human subjects or preclinical research. Studies focusing on AI applications unrelated to mental health or psychiatric care. Studies focusing on non-clinical applications of AI (e.g., robotics, automation) within mental health. Studies with inadequate methodology, small sample sizes, or insufficient information to assess their relevance and rigour. Studies published before 2018, prioritise recent advancements in the field. Studies that do not align with the primary research objective of the systematic review.

A total of 6 studies met the criteria of inclusion and 7 more studies were hand searched.

APPLICATIONS OF AI IN MENTAL HEALTH CARE

Historically mistreated groups often suffer from untailored drugs and interventions as randomized trials can only estimate average treatment effects for a trial population. These cannot be generalized to the entire patient population without taking variables like race and gender into account.

Chen et al.'s study examined two case studies utilizing a machine learning algorithm to analyse unstructured clinical and psychiatric notes. The aim was to forecast intensive care unit mortality and 30-day psychiatric readmission, using race, gender and insurance payer type as indicators of socioeconomic status. This scrutiny aimed to uncover any inherent biases within the data and algorithms, followed by recommendations for improvement. Upon bias evaluation, determined by variations in model error rates between different demographic groups, notable findings surfaced. In the ICU dataset, statistically significant differences in error rates for mortality were apparent concerning gender and insurance type.

Conversely, within the psychiatric dataset, only the error rates for 30-day readmission concerning insurance type exhibited statistical significance, aligning with previously established findings. The study concludes with a crucial recommendation given the escalating integration of machine learning in healthcare decisions. To mitigate biases and enhance these models, the authors advocate for a systematic assessment of algorithmic biases through comparative prediction accuracy analysis among demographic cohorts. Subsequently, a collaborative alliance between clinicians and AI is proposed, where clinicians offer feedback for algorithmic refinement, and the algorithm prompts clinicians for input in uncertain cases.[1]

The authors also aimed to investigate how effective different machine-learning approaches are in categorizing mental health data. They use both simulated and real-world data to evaluate how well various algorithms-Random Forests (RF), Support Vector Machines (SVM), Linear Discriminant Analysis (LDA) and k-nearest Neighbours (kNN)-perform in this context. To do this, they leverage high-performance supercomputers and parallel processing to compare errors across different scenarios involving factors like feature count, sample size, biological and experimental variations, effect size, replication and feature correlation. Through this, they identify strengths and weaknesses in each classification method (LDA, SVM, RF, kNN).

The study concludes that LDA performs admirably when handling a smaller number of correlated features, especially when the feature count is less than about half the sample size (p=n <0.5). It also excels when dealing with highly correlated features. On the other hand, as the feature set grows (p=n >0.5), SVM using a Radial Basis Function (RBF) kernel becomes the preferred choice. It surpasses LDA, RF, and kNN in these situations. However, for SVM to shine, a sample size of at least 20 is necessary, regardless of the feature count. As the number of features increases, kNN's performance improves and can outdo LDA and RF unless there's significant data variability and/or minor effect sizes. In scenarios with more variable data and smaller effect sizes, RF tends to outperform kNN and provides more consistent error estimates. While high feature correlation generally benefits all methods, RF might comparatively underperform when dealing with highly correlated features.

All the methods studied demonstrate balanced performance regarding sensitivity and specificity, which aligns with expectations for symmetrically distributed data. Notably, these methods, except for LDA, didn't presume any specific probability distribution for the data and showed resilience even when the data deviated from a normal distribution.[2]

Maslej et al, conducted a study to assess psychiatrists' perceptions of AI-driven Clinical Support Tools (CSTs) for treating Major Depressive Disorder (MDD) and determine if these perceptions were influenced by the quality of CST information.

The research involved 83 psychiatrists who evaluated two CSTs for a hypothetical patient. These psychiatrists were randomly led to believe that the CSTs were either AI-generated or created by another psychiatrist. The CSTs presented correct or incorrect information across four notes. One significant discovery was that psychiatrists rated note summaries less favorably when they perceived the notes as AI-generated compared to when they believed another psychiatrist authored them. This trend persisted regardless of whether the AI provided accurate or inaccurate information.

Additionally, a small portion of information attributed to psychiatrists affected the ratings of attributes reflecting the summary's accuracy or its incorporation of essential information from the comprehensive clinical note. In terms of treatment recommendations, the ratings were less positive when the perceived source was AI, but this trend was observed only when the recommendations were accurate. Furthermore, there was minimal evidence suggesting that clinical expertise or familiarity with AI affected these outcomes. Overall, based on these findings, the study concluded that psychiatrists tend to prefer CSTs derived from human sources over AI-generated ones.[3]

AI in surveillance of autism spectrum disorder

Autism spectrum disorder (ASD) is a neurodevelopmental condition characterized by challenges in social communication, restricted interests, and repetitive behaviors.[4] In a comparative study, researchers explored the application of machine learning algorithms to assess the prevalence of ASD among children in the United States. The study utilized data from a single surveillance site in Georgia and employed eight supervised learning algorithms to predict if children met the criteria for ASD. The performance of these algorithms was measured using metrics like classification accuracy, F1 score and the count of positive predictions.

This comparative analysis suggests that machine learning models, such as random forest, can improve the estimation of ASD prevalence. It highlights the advantages of employing advanced machine-learning techniques in ASD surveillance. The current surveillance methods by the Centers for Disease Control & Prevention (CDC) are labor-intensive. Although these sophisticated models didn't streamline the surveillance workflow, they proved valuable in managing extensive databases, thereby enhancing the efficiency of surveillance systems and their applications in public health.[5]

AI in dementia

Dementia is a progressive clinical disorder that mainly affects the cognitive functioning of the brain. The most common pathophysiology includes Alzheimer's disease (50-75%) followed by vascular dementia (20%), dementia with Lewy bodies (5%) and frontotemporal lobar dementia (5%).[6] One person is diagnosed with dementia every 3 seconds all over the world. In 2020, worldwide, 55 million people are living with dementia. These numbers are expected to double in the next 20 years.[7]

A systematic review and meta-analysis was conducted on the feasibility and acceptability of socially assistive robots for people with dementia. The review found that socially assisted robots might be feasible and acceptable but studies show that they do not have any impact on the improvement in neuropsychiatry symptoms or the quality of life. Future research was recommended that emphasizes using high-quality designs with well-validated outcome measurements for stakeholders.[8] So far. Lack of evidence should not be the reason for stating a lack of effectiveness. Further research is therefore needed in this regard.

Information extracted from various dementia studies tends to be high dimensional and heterogeneous. It is found that machine learning models are better than traditional statistical methods in understanding dementia risks and predicting the time until a patient develops dementia. Machine learning methods provide more accurate results than traditional statistical methods while using high-dimensional clinical data.[9]

Gene analysis and AI

Schizophrenia is a complex mental health disorder characterized by delusions, impaired speech, hallucinations, and impaired cognitive ability. It is a heterogenic disorder characterized by both negative symptoms and impaired cognitive ability.[10]

The Vanderbilt University Medical Centre, Nashville, TN, USA has conducted its research on developing and evaluating evidence-based gene ranking methods and examining the features of top-ranking candidate genes for schizophrenia.

They proposed a gene-based approach for selecting and prioritizing candidate genes by combining odds ratios (ORs) of multiple markers in each association study and combining ORs in multiple studies of a gene and named it a combination-combination OR method (CCOR). Their evaluation suggested that the SCOR method overall outperforms the CCOR method. Using the SCOR, a list of 75 top-ranking genes was selected for schizophrenia candidate genes (SZ Genes).

They proposed and compared two gene-based combined odds ratio methods (SCOR and CCOR) for weighting positive association evidence from multiple markers in multiple studies in a gene. This approach using AI can be applied to candidate gene selection for other complex diseases such as depression, and anxiety.[11]

AI in depression care

A comparative study was conducted on the influence of AI in general medicine and psychiatric departments. Prior research has established that machine learning using clinical notes to supplement lab tests and other structured data is more accurate than an algorithm using structured data alone. In comparison of both studies, algorithm bias is seen and if this is corrected, clinicians and AI can work together to identify the sources of algorithmic bias and improve models through better data collection and model improvement methods.[12]

Psychiatrists prefer clinical support tools by other psychiatrists even when it is correct or incorrect (clinical notes and treatment recommendations). Psychiatrists in this study considered clinical support tools generated by artificial intelligence less favorable than human CSTs.[13]

Limited performance in clinical settings makes it critical to understand how clinicians will interact with AI-based information when it is incorrect. Improving the accuracy of AI does not always translate to enhanced clinical performance, suggesting that contextual factors, like perceptions about AI, may shape interactions. Researchers are training machine learning models on clinical data to predict treatment response in MDD, intending to develop AI-based CSTs that can match patients with optimal treatments.[13]

RESULTS

The manuscript explores various applications of AI in mental health care, focusing on its potential to address biases and improve treatment effectiveness. Chen et al. analyzed AI algorithms predicting ICU mortality and 30-day psychiatric readmission, revealing biases based on gender and socioeconomic factors, like insurance type.[1] The study suggests collaboration between clinicians and AI systems to mitigate biases and improve model accuracy. Different machine learning models (LDA, SVM, RF, kNN) were assessed for their ability to classify mental health data, with results showing that model performance depends on the number of features, data variability, and sample size. SVM performed best with larger datasets, while RF excelled in scenarios with more variable data. Psychiatrists tended to prefer clinical support tools (CSTs) authored by humans over AI, even when AI provided accurate information. This highlights a bias against AI-driven tools in clinical settings.

AI models improved the efficiency of ASD prevalence estimation and dementia risk prediction. Although socially assistive robots showed limited impact on improving dementia symptoms, machine learning methods outperformed traditional approaches in handling complex, high-dimensional clinical data. AI-based gene ranking methods improved schizophrenia candidate gene selection, while AI models predicting treatment responses in depression offer promise but require clinician involvement to address biases and perceptions about AI in clinical decision-making.

Table 2: Frequency of different types of asterion on right and left sides.

Application	Case	AI-technique	Key findings	References
AI in ICU mortality and psychiatric readmission	Chen et al.'s study on ICU mortality and 30-day psychiatric readmission forecasting	Machine learning (algorithms analyzing unstructured clinical and psychiatric notes); algorithms like random forests, SVM, etc.	Significant bias in ICU mortality prediction based on gender and insurance type; 30-day psychiatric readmission error rates show bias concerning insurance type. Recommendations include systematic bias evaluation and clinician feedback.	1
AI in mental health data classification	Comparative analysis of machine-learning models in mental health data categorization	Random forests (RF), support vector machines (SVM), linear discriminant analysis (LDA), k-nearest Neighbors (kNN)	LDA performs well with smaller, highly correlated features, SVM excels with larger feature sets, RF handles variable data best, with consistent error estimates, kNN improves with larger datasets.	2
AI in clinical support tools (CSTs) for depression	Maslej et al.'s study on psychiatrists' perceptions of AI-generated versus human-generated CSTs	AI-driven clinical support tools (CSTs)	Psychiatrists rated AI-generated notes less favorably than human-generated ones, even when the AI information was accurate. AI influence in treatment	3

Continued.

Application	Case	AI-technique	Key findings	References
			recommendations received lower ratings when attributed to AI.	
AI in autism spectrum disorder surveillance	Machine learning models in assessing autism prevalence in the US	Supervised learning algorithms (Random Forest, etc.)	Machine learning models improved efficiency in ASD prevalence estimation. While current CDC surveillance is labor-intensive, AI-driven models manage large databases better, though they don't streamline workflow.	5
AI in dementia risk prediction	Systematic review/meta-analysis of AI's role in dementia care	Machine learning models using high-dimensional data	Machine learning provides more accurate predictions of dementia onset compared to traditional statistical methods. No evidence found that socially assistive robots improve neuropsychiatric symptoms or quality of life in dementia care.	9
AI in Gene Analysis for Schizophrenia	Vanderbilt University study on gene ranking methods for schizophrenia	Gene-based odds ratio methods (SCOR and CCOR)	SCOR method outperformed CCOR in selecting top schizophrenia candidate genes. AI-based gene ranking techniques can be applied to other complex mental health conditions.	11
AI in depression treatment	Comparative study on AI's influence on general medicine and psychiatric care	Machine learning algorithms using clinical notes	Algorithmic bias is seen in AI models predicting MDD treatment responses; collaboration between clinicians and AI is needed to reduce bias and enhance clinical performance.	12, 13

DISCUSSION

The integration of AI into mental health care offers numerous potential applications but also presents significant challenges, particularly related to algorithmic bias, clinician acceptance, and the complexity of mental health disorders.

In the study by Chen et al machine learning algorithms were employed to analysis unstructured clinical notes to predict outcomes such as ICU mortality and psychiatric readmission.[1] However, the study also revealed disparities in prediction accuracy across demographic groups, particularly concerning gender and socioeconomic status. This finding highlights the importance of systematic bias assessment in AI models, as biases may inadvertently exacerbate existing health disparities.

Addressing these biases requires collaboration between clinicians and AI systems to ensure that algorithms are refined based on real-world feedback and clinical expertise. Additionally, AI has shown promise in areas such as autism spectrum disorder (ASD) surveillance and dementia care. Machine learning models have enhanced the efficiency of ASD prevalence estimation by managing large-scale databases, though these models have not yet streamlined surveillance processes.

In dementia care, AI models have outperformed traditional statistical methods in predicting disease progression, demonstrating AI's potential in managing high-dimensional clinical data.

However, while socially assistive robots are feasible for dementia patients, current research shows limited evidence for improvements in quality of life or neuropsychiatric symptoms, indicating a need for more robust studies. The use of AI in psychiatric care, particularly in the treatment of disorders such as schizophrenia and depression, has yielded mixed results. AI-driven gene analysis has helped identify candidate genes for schizophrenia, potentially aiding personalized treatment.

However, the study by Maslej et al revealed that psychiatrists remain skeptical of AI-based clinical support tools (CSTs), favoring human-generated recommendations even when AI provides accurate information. This suggests that the implementation of AI in clinical settings must not only focus on improving model accuracy but also on addressing clinician perceptions and fostering trust in AI tools.

CONCLUSION

AI holds great potential to revolutionize mental health care by improving diagnostic accuracy, predicting treatment outcomes, and enhancing surveillance systems. However, its successful implementation requires careful consideration of algorithmic biases, clinician acceptance, and the specific challenges posed by mental health disorders.

To realize the full benefits of AI, a collaborative approach is needed-one that involves clinicians in the development and refinement of AI tools while simultaneously addressing the biases and limitations inherent in current machine learning models.

As AI continues to evolve, it will be crucial to ensure that these technologies are equitable, transparent, and aligned with the needs of both patients and healthcare providers.

Declaration of generative AI and AI–AI-assisted technologies

During the preparation of this manuscript, the author(s) employed ChatGPT to generate and evaluate text and extract data. Bard AI (now Gemini) was used to refine and improve upon the research question and the inclusion and exclusion criteria. After using ChatGPT and Bard AI, the lead author reviewed and edited the content as needed and took full responsibility for the publication's content.

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