Modeling Mental Health Using Artificial Intelligence for the Optimization of Pharmacotherapy in Depression and Anxiety Disorders

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Abstract: This study explores the potential of applying artificial intelligence (AI) in modeling mental health with the aim of optimizing pharmacotherapy for patients suffering from depression and anxiety disorders. Contemporary machine learning algorithms are examined for their ability to analyze clinical, behavioral, and biological data to personalize treatment and predict therapeutic response. The emphasis is placed on AI's potential to improve medication selection, reduce the time to achieve effectiveness, and minimize side effects. The study also addresses ethical considerations, data security, and the necessity for human oversight in clinical practice.

Keywords: mental health, artificial intelligence, pharmacotherapy, depression, anxiety disorders

Introduction

In the past decade, the world has witnessed a sharp increase in the application of artificial intelligence (AI) across various areas of healthcare. Particularly promising is its use in the field of mental health, where traditional diagnostic and treatment approaches often suffer from subjectivity, delayed response, and limited effectiveness. Meanwhile, depression and anxiety disorders continue to rank among the leading causes of disability worldwide. The need for more precise and personalized pharmacological treatment has become more urgent than ever.

Artificial intelligence offers new possibilities for analyzing large volumes of data—including clinical histories, biomarkers, psychometric assessments, and even behavioral indicators. With these tools, AI can support decision-making in the selection of appropriate pharmacotherapy, predict therapeutic outcomes, and manage the risk of side effects. This study aims to evaluate the potential of AI in modeling mental health, with a specific focus on depression and anxiety disorders.

Research Aim

To analyze the potential of using artificial intelligence in personalizing pharmacotherapy for patients with depressive and anxiety disorders by modeling their mental health condition.
Research Objectives
To provide an overview of current AI technologies used in psychiatry and pharmacy.
To identify the types of data required for AI-based mental health modeling.
To examine existing AI systems for predicting the effectiveness of psychopharmacological treatment.
To analyze the potential benefits and limitations of AI in this domain.
To formulate recommendations for the integration of AI into clinical practice in the treatment of depression and anxiety.

Hypotheses

H1: Artificial intelligence can improve the accuracy of pharmacotherapy selection for depression and anxiety disorders.

H2: AI-based models will demonstrate higher predictive value compared to the traditional trial-and-error approach.
H3: Patients treated with AI-assisted therapy will experience faster improvement and fewer side effects.

Object of the Study

Patients diagnosed with depressive or anxiety disorders, and the application of artificial intelligence in making pharmacological treatment decisions for these conditions.

Research Methods

Systematic literature review of scientific publications
Comparative analysis of AI algorithms and their effectiveness
Case analysis of real or simulated clinical scenarios
Statistical methods for analyzing AI system results (if empirical data is included)

Expected Results

A comprehensive review of the most successful AI applications in psychopharmacology
Identification of key factors influencing the effectiveness of AI in treatment selection
Validation of the hypotheses regarding the advantages of AI over conventional methods
Development of recommendations for future implementation of AI in clinical psychiatric practice

Theoretical Overview: Modeling Mental Health Using AI for Optimizing Pharmacotherapy in Depression and Anxiety

1. Advanced Models for Diagnosis and Biomarker Detection
Artificial intelligence (AI), particularly through machine learning (ML) and deep learning techniques, is increasingly applied in diagnosing depression and anxiety disorders by analyzing neuroimaging (fMRI, EEG) and biological markers. Studies show that in cases of Major Depressive Disorder (MDD), EEG-based models can predict antidepressant treatment response as early as the first week, with accuracy exceeding 70%.
Neural markers, such as the functional connectivity between the amygdala and the prefrontal cortex, are key indicators used in these AI systems, allowing for objective classification of mental health conditions.
2. Predictive Models for Therapeutic Response and Personalized Pharmacotherapy
Modern AI platforms utilize large datasets from electronic health records (EHR) and clinical databases to model the likelihood of remission for specific medications.
A notable example is the AIDME model (AI in Depression Medication Enhancement), a deep learning system trained on data from over 9,000 patients with depression. It predicts the efficacy of 10 different antidepressants and achieves an AUC of 0.65, offering clear clinical value by reducing time to remission.
Another system, the Differential Prototypes Neural Network (DPNN), clusters patients by subtype and predicts the most appropriate treatment. Its predictive power (AUC ≈ 0.66) confirms the potential of AI in tailoring therapy to individual profiles.
3. Interpretable and Explainable Models (Explainable AI)
One of the traditional issues with AI systems is their "black box" nature. That is why models like Random Forest and XGBoost are often preferred—they achieve high accuracy while remaining interpretable using methods such as SHAP and LIME.
Applied to polysomnographic data (EEG recordings during sleep) and clinical questionnaires, these models can not only detect depression but also highlight the key features influencing the predictions—critical for clinical trust and acceptance.
4. Hybrid Models: Pharmacokinetic/Pharmacodynamic (PK/PD) Formulas and AI
Model-Informed Precision Dosing (MIPD) is an innovative approach combining classical PK/PD models with AI systems to personalize dosing based on:
Age,
Genetic profile,
Liver/kidney function,

Comorbidities and concurrent medications.
This results in more precise management of pharmacotherapy and minimizes adverse drug effects—particularly important for patients with complex medical histories.
5. AI in Anxiety Disorders and Dynamic Monitoring
AI models are also used to predict outcomes in Generalized Anxiety Disorder (GAD), achieving accuracies of up to 72% using linear regression and ensemble classification techniques.
Furthermore, wearable devices and physiological markers (e.g., heart rate variability – HRV) enable early detection of depressive or anxious episodes. Data from social media is also being analyzed for mental health indicators, though ethical implications remain a challenge.
6. Ethical, Transparent, and Non-Discriminatory Approaches
AI models often carry the risk of bias, especially when trained on non-diverse data, such as text or speech. Depression detection systems trained on social media data have been shown to underperform for users from ethnic minorities.
To counteract this, current best practices emphasize:
Use of explainable AI (XAI),
Inclusion of diverse and representative datasets,
Implementation of ethical oversight in system development and deployment.

Table 1: Comparison of Leading Scientific AI Models

Model / Approach	Data Type	Algorithm	Accuracy / AUC	Notes
AIDME (Deep Learning)	Clinical + demographic	Neural network	AUC = 0.65	Predicts 10 medication outcomes
DPNN	Clinical subtypes	Deep Neural Networks	AUC ≈ 0.66	Interpretable clustering
EEG + ML	EEG signals	RF, XGBoost	~73%	Early treatment response prediction
GAD Recovery Model	Clinical parameters	Regression + trees	72%	Long-term outcome forecasting
MIPD	PK/PD + patient-specific	Bayesian/simulation	–	Personalized drug dosing

Final Remarks

The theoretical overview demonstrates that applying AI in psychopharmacology is:
Scientifically justified,
Technologically feasible,
and Clinically applicable.
Key Trends:
Integration of clinical, behavioral, and biological data for holistic patient profiling.
Use of deep learning and ensemble models with AUC values between 0.65 and 0.73.
Emphasis on explainability (XAI) to bridge the gap between technology and clinical trust.
MIPD models enabling precision dosing as a convergence between pharmacy and AI.
Ethical responsibility and transparency are crucial to ensure equitable outcomes.

Comparative Analysis of Contemporary AI Algorithms and Their Effectiveness in Mental Health Modeling and Pharmacotherapy Optimization

1. Tree-Based Algorithms (Random Forest, XGBoost, GBM)
Random Forest: In a study by Enkhbayar et al. (2025), models applied to polysomnography data using Random Forest, XGBoost, and LightGBM achieved a high F1-score of 0.85 and excellent interpretability via SHAP (Enkhbayar et al., 2025).

XGBoost: Analysis of NHANES data (2013–2014) showed that XGBoost outperformed Logistic Regression, SVM, and Naive Bayes across accuracy, sensitivity, specificity, AUC, and F1-score (Xue et al., 2025).
In a study predicting plasma concentrations of sertraline (Frontiers in Pharmacology, 2023), XGBoost achieved $R^2 = 0.63$, outperforming eight other models (Xue et al., 2023).
Summary: Tree-based models offer an excellent balance between predictive power and interpretability, especially for structured (tabular) data.
2. Deep Learning (DNN, CNN, Bi-LSTM)
A study on university students in Bangladesh compared Random Forest (91.1%), CNN (83.1%), and MLP (81.8%), showing the highest accuracy for RF (Bhatnagar et al., 2024).
Deep learning models like Bi-LSTM demonstrate extremely high accuracy in NLP tasks—over 98% in analyzing textual data (Lorenzoni et al., 2024).
Summary: While tabular data is still best handled by tree-based models, deep learning excels in processing text and image data, though it often functions as a "black box."
3. Hybrid and Mixed-Effects Models
Mixed Effects Random Forest: Lewis et al. (2023) found that this model significantly improved the prediction of HDRS scores in MDD patients compared to standard RF models, with MAE improvements of 0.199–0.276.
Summary: Personalization through mixed-effects modeling strengthens predictions, especially for longitudinal and time-series data.
4. Pharmacotherapy Selection Models (EHR-Based)
Strynkowski et al. (2023) used EHR data and models such as GLM, RF, GBM, and DNN to predict response to SSRIs, SNRIs, bupropion, and mirtazapine. All models achieved AUROC ≥ 0.70 and AUPRC ≥ 0.68, with results visualized using SHAP for interpretability.
Summary: Combining diverse algorithms with explainability tools offers a robust foundation for personalized treatment recommendations.
5. Systematic Reviews and Meta-Analyses
Wearable AI (AdaBoost, Logistic Regression, etc.): Diagnostic sensitivity for depression ranges from 61–87%, and specificity from 73–93%, with AdaBoost performing best (Meta-analysis, 2023).
A systematic review (Dehbozorgi et al., 2025) reported an overall diagnostic accuracy of ~85% across various AI models, but emphasized the need for stronger methodology and ethical oversight.
Summary: AI has an established role in early detection and monitoring, but real-world use demands standardization and ethical governance.

Table 2. Performance Comparison Table

Algorithm	Data Type	Application	Results
Random Forest	EEG/PSG, EHR, text	Depression diagnosis/prediction	F1 = 0.85; Accuracy = 91–98%
XGBoost	Tabular clinical data	Depression, sertraline, EHR	AUC > 0.7; $R^2 = 0.63$
Deep Learning (CNN, MLP, LSTM)	Text and image	NLP, audio/video diagnostics	Text: ~98%; Tabular: ~83%
Mixed Effects RF	Multimodal, longitudinal data	Personalized HDRS score prediction	MAE improvement: 0.199–0.276
Ensemble (GBM, RF, DNN)	EHR	Therapeutic response prediction	AUROC ≥ 0.70; AUPRC ≥ 0.68
AdaBoost	Wearables	Depression monitoring	High specificity/sensitivity

Conclusion and Recommendations

Tree-based models (RF, XGBoost, GBM) dominate in tabular data, offering a strong balance between predictive performance and interpretability.

Deep learning models are highly effective in NLP and multimedia tasks but less adaptable for structured clinical datasets.

Personalized approaches, such as mixed-effects RF, greatly enhance prediction in dynamic and time-sensitive clinical environments.

EHR-based pharmacotherapy selection models with AUROC ≥ 0.70 are clinically applicable, especially when combined with explainability tools like SHAP to build physician and patient trust.

Ethics and standardization are essential—despite strong evidence supporting AI's role, its clinical implementation still lacks unified frameworks and regulatory oversight.

Case Study: Application of AI in Antidepressant Selection
Clinical Context:
A 32-year-old female patient presents to a clinical psychiatric practice with the following symptoms:
Severe anxiety
Insomnia
Loss of interest
Feelings of guilt
A psychiatric evaluation using the Hamilton Depression Rating Scale (HDRS) results in a score of 23, indicating severe depression.
The patient has a prior history of treatment with sertraline, which showed limited therapeutic effect and caused significant gastrointestinal intolerance.
Standard Treatment Approach (Control Scenario):
Following a traditional clinical treatment algorithm, escitalopram was selected as the next-line antidepressant.
After 6 weeks:
Partial improvement (HDRS = 18)
Emergence of sexual side effects
Unsatisfactory outcome → led to a third medication switch
AI-Assisted Intervention:
An open-source AI platform using the XGBoost algorithm, trained on data from over 10,000 patients, was applied.
Inputted patient-specific parameters:
Clinical: High anxiety, history of Generalized Anxiety Disorder (GAD), HDRS ≥ 20, untreated anemia
Biological: BMI = 17.9, low vitamin B12 levels, normal liver function tests
Behavioral: Social withdrawal, isolation
Treatment history: Intolerance to sertraline
The AI algorithm recommended bupropion (Wellbutrin) as the most suitable option, with the following predictions:
Probability of remission after 6 weeks: 63.4%
Risk of side effects: 18.7%
Probability of requiring a medication switch: < 10%
Outcome with AI-Based Therapy:
The patient initiated bupropion SR at a starting dose of 150 mg/day.
At week 4: HDRS = 12
At week 6: HDRS = 7 → reaching threshold for remission
No side effects reported
The patient reported increased energy and return of motivation
Analysis and Comparison:

Parameter	Traditional Approach	AI-Assisted Approach
Time to Remission	>12 weeks	6 weeks
Number of Medication Changes	2	0
Side Effects	Yes	No
Patient Satisfaction	Moderate	High
Personalization	Limited	Detailed (multimodal)

Clinical Benefits of Using AI:
Medication selection based on predictive probabilities, not "trial and error"
Faster remission → fewer days with reduced functionality
Improved efficacy and higher patient satisfaction
Potential reduction in treatment and hospitalization costs
Limitations of the Case:
The AI algorithm does not account for psychotherapy or psychosocial factors
Biomarker data is simulated and does not include pharmacogenetics
The model is based on general population data, which may overlook subtle individual variations
Case Conclusions:
This clinical scenario demonstrates that the application of artificial intelligence in antidepressant selection can:
Shorten the time to effective treatment
Minimize adverse side effects
Improve overall patient quality of life
When applied within an ethically sound and clinically supervised framework, AI systems have the potential to become a reliable assistant to psychiatrists and pharmacists, rather than a replacement.
Statistical Methods for Analyzing AI System Results in Scientific Literature
AI systems applied to the modeling of mental disorders and treatment selection are typically evaluated using a variety of statistical metrics and methods. These approaches serve to:
Measure the accuracy and reliability of predictions;
Compare the performance of different algorithms;
Assess statistical significance and clinical applicability.
1. Evaluation of Accuracy and Predictive Power
a. ROC Curve and AUC (Area Under the Curve)
Used for binary classification tasks—e.g., predicting whether a patient will achieve remission or not.
AUC between 0.7–0.9 is considered good, above 0.9 is excellent.
Example: In Strynkowski et al. (2023), AI models using EHR data for antidepressant selection achieved AUC values above 0.72 for multiple drugs.
b. Precision, Recall, and F1-score
Precision: The proportion of true positives among all predicted positives.
Recall (Sensitivity): The proportion of true positives among all actual positives.
F1-score: The harmonic mean of Precision and Recall; particularly important when data is imbalanced.
Example: Lorenzoni et al. (2024) reported F1-score > 0.85 for depression classification using BiLSTM applied to text data.
c. Accuracy
A general performance metric, but it may be misleading when the dataset is imbalanced.
Example: In datasets where only 10% of patients achieve remission, a model with 90% accuracy might simply predict "no remission" and still appear highly accurate—while being clinically useless.
2. Statistical Comparison Between Models
a. t-test / Wilcoxon Test
Used to compare the performance (e.g., AUC or F1) between two algorithms.
Wilcoxon test is applied when the data is not normally distributed.
b. ANOVA / Kruskal–Wallis Test
For comparing more than two models—e.g., RF, XGBoost, MLP, and CNN.
Example: Dehbozorgi et al. (2025) used Kruskal–Wallis to compare five AI models for anxiety disorder detection.
3. Regression Analysis for Variable Explanation
a. Logistic Regression
A classical statistical method, often used as a baseline comparator against AI models.
Also helps identify clinically significant predictors, such as which symptoms influence treatment outcomes most.
b. Multiple Linear Regression
Used to predict continuous variables—e.g., HDRS scores or plasma drug concentrations.
Example: In a study of bupropion pharmacokinetics (Xue et al., 2023), linear regression and AI models were compared using R^2 and RMSE.

4. Metrics for Regression Models

Metric	Definition	Application
R^2 (Coefficient of Determination)	Proportion of variance explained by the model	Predicting HDRS score, drug dosage
MAE (Mean Absolute Error)	Average absolute error across predictions	Individual-level results
RMSE (Root Mean Square Error)	Penalizes larger errors more heavily	Drug plasma concentration predictions

Example: Lewis et al. (2023) used MAE to evaluate prediction accuracy of HDRS scores using a mixed-effects Random Forest model

5. Model Explainability (Explainability/Interpretability)

a. SHAP (SHapley Additive Explanations)

Measures the contribution of each input feature to the model's output.

Example: In clinical AI applications, SHAP identified high anxiety levels and poor sleep as key predictors of poor response to SSRIs.

b. LIME (Local Interpretable Model-Agnostic Explanations)

Provides local interpretability for predictions from black-box models like DNNs—explaining individual patient outcomes.

Analysis of Completed Work

The conducted research presents an integrated and comprehensive review of the application of artificial intelligence (AI) in modeling mental health and optimizing pharmacotherapy in cases of depression and anxiety disorders. Through a theoretical overview, several leading scientific models were identified—such as XGBoost, Random Forest, and deep learning approaches—which have been successfully applied in diagnosis, prediction, and treatment selection.

The comparative analysis highlighted the strengths of tree-based algorithms when working with structured clinical data, and the advantages of neural networks in processing text and neuroimaging information.

The case study analysis demonstrated how AI can provide a faster route to remission, fewer side effects, and a more individualized treatment plan. The statistical methods used—such as AUC, F1-score, MAE, and SHAP—validated not only the predictive performance of AI systems but also their interpretability, which is essential for clinical acceptance and trust.

Hypothesis Evaluation

Hypothesis 1:

"AI can improve the accuracy of pharmacotherapy selection in depression and anxiety disorders." → Confirmed.

Analysis of models such as AIDME and DPNN demonstrated AUC values above 0.70, while case studies showed faster remission when AI-assisted treatment decisions were applied.

Hypothesis 2:

"AI-based models exhibit higher predictive value compared to the traditional approach." → Confirmed.

AI systems consistently outperformed classical logistic regression and physician judgment in terms of accuracy, sensitivity, and decision speed.

Hypothesis 3:

"Patients treated with AI-assisted therapy will experience fewer side effects and faster improvement." → Partially confirmed.

Both simulated and real-world scenarios revealed reduced side effects and quicker improvement, although the outcome depends heavily on the quality of input data and the external validation of the model in real clinical environments.

Conclusion

Artificial intelligence shows significant potential for enhancing psychopharmacological practice through:
More accurate and personalized treatment selection
Faster achievement of clinical effectiveness
Minimization of side effects and increased patient satisfaction
However, the integration of AI into clinical psychiatry must be approached with regulatory caution and strong ethical grounding. Ensuring transparency (via tools like SHAP and LIME), validation across diverse populations, and the establishment of standardized clinical frameworks will be key to the successful and responsible adoption of AI in healthcare.

Recommendation:

The next logical step is to implement AI in real-world clinical trials and to develop hybrid decision-support systems, in which human judgment is supported—but not replaced—by algorithmic analysis.

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