An Analysis of the Application of Artificial Intelligence Technology in the Clinical Management of Depression

Ran Li[1], Jianchuan Chi[2]

[1] *School of Marxism, Qilu University of Technology, Ji'nan 250353, China*
[2] *School of History and Culture, Shandong Normal University, Ji'nan 250358, China*

ABSTRACT

As one of the psychiatric disorders with the heaviest disease burden globally, the clinical management of depression faces the "three lows" dilemma: low detection rate, low treatment rate, and high relapse rate. The development of Artificial Intelligence (AI) technology offers a new paradigm to address this predicament. This paper systematically analyzes the current application status and technical pathways of AI across the entire "screening-diagnosis-treatment-management" process of depression: In the early identification and screening stage, AI integrates scale data, physiological indicators, digital footprints, and multimodal information, significantly enhancing early warning capabilities. In the diagnosis and differential diagnosis stage, AI assists structured interviews and quantitative assessments, combined with neuroimaging and peripheral biomarkers to achieve precise differentiation. In the treatment domain, AI promotes individualized medication decisions, digital psychotherapy, and parameter optimization for physical treatments. In the prognosis management and relapse prevention stage, through remote monitoring, dynamic relapse risk prediction, and self-management support systems, AI facilitates a shift from intermittent follow-up to continuous monitoring. The role of AI should be positioned as "augmented intelligence." The future integrated model of "human-AI collaboration" is expected to drive mental health services towards a more predictive, preventive, personalized, and participatory direction, ultimately serving patient well-being and dignity.

Keywords: *Artificial intelligence, Depression, Clinical management.*

1. INTRODUCTION

Depression is a major mental disorder characterized by persistent low mood, loss of interest, and cognitive dysfunction.[1] According to World Health Organization statistics, approximately 280 million people worldwide are affected by it, and the disease burden it causes ranks among the highest globally. However, the clinical management of depression has long faced the dilemma of "two lows and one high": low detection rate, low treatment rate, and high relapse rate. Traditional management models heavily rely on patients' subjective reports and doctors' clinical experience, leading to significant efficiency bottlenecks in all aspects from early screening to long-term follow-up.

The leapfrog development of Artificial Intelligence (AI) technology, particularly breakthroughs in machine learning, deep learning, and large language models, provides a completely new technical paradigm to overcome the above predicament. AI can efficiently process massive, high-dimensional, unstructured medical data, uncovering subtle patterns imperceptible to the human eye – from spectral features of speech and subtle changes in facial micro-expressions, to behavioral trajectories on social media, and abnormal functional connectivity in neuroimaging.[2] This shift from macroscopic symptoms to microscopic digital phenotyping is reshaping the clinical management logic for depression. By systematically analyzing the application status, technical core, and clinical value of AI across the entire "screening – diagnosis –

treatment - management" chain of depression, this paper aims to provide a clear roadmap for subsequent research and clinical translation.

2. APPLICATION OF AI IN EARLY IDENTIFICATION AND SCREENING OF DEPRESSION

Early identification is the "golden window" for depression management. However, in primary care and community settings, a large number of patients are missed due to atypical symptoms or being masked by somatic symptoms. AI technology is breaking through this bottleneck by expanding the dimensions and precision of screening.

2.1 Intelligent Screening Based on Scales and Questionnaires

Traditional self-report scales, such as the Patient Health Questionnaire (PHQ-9), although widely used, are susceptible to recall bias and social desirability. The intervention of AI is not merely digitalization but enables "dynamic" and "adaptive" screening. Computerized Adaptive Testing (CAT) based on Item Response Theory (IRT) can adjust subsequent questions in real-time based on the patient's answers to previous items, reducing assessment time by over 50% while maintaining reliability and validity. More cutting-edge is the use of Natural Language Processing (NLP) to analyze responses to open-ended questions. For example, through semantic embedding analysis, AI can capture implicit feelings of hopelessness or anhedonia in patients' wording, which are often masked in structured scales. Furthermore, by combining unstructured text from clinical Electronic Medical Records (EMR), AI models using Named Entity Recognition (NER) can automatically extract depression-related keywords and emotional tendencies, enabling large-scale, unobtrusive initial screening of asymptomatic populations, with sensitivity reaching above 0.85.

2.2 Identification Based on Physiological Indicators

AI makes physiological signals an objective "window" into emotional state. At the neurophysiological level, electroencephalography (EEG) is highly regarded for its high temporal resolution and portability. Deep learning models can extract specific frequency bands and nonlinear features from resting-state EEG to differentiate depressed patients from healthy controls, achieving accuracy rates of 80%-90%. At the peripheral physiological level, heart rate variability (HRV), electrodermal activity (EDA), and body surface temperature continuously monitored by wearable devices, after modeling using Random Forest or Support Vector Machines (SVM), can reflect autonomic nervous system dysfunction, a core pathophysiological change in depression. Studies have confirmed that AI models based on disrupted circadian HRV rhythms can predict the risk of a depressive episode on average four weeks before clinical diagnosis.

2.3 Screening Based on Digital Footprints and Behavioral Data

In the digital age, human behavior leaves behind "breadcrumbs," which AI uses as projections of mental state. Passive metadata from smartphones contains clues of social withdrawal and psychomotor retardation. For example, reduced location entropy (fixed range of activity) and a sharp decrease in social app usage time have been shown to be significantly correlated with depression severity (PHQ-9 score). Furthermore, subtle features of voice and facial expressions are also crucial. AI models can analyze speech features while reading a text and facial Action Units (AU) during semi-structured interviews, such as drooping mouth corners and reduced orbicularis oculi activity. This screening model based on behavioral digital phenotyping has shown high convergent validity with clinical diagnosis.

2.4 Early Warning Based on Multimodal Fusion

Single-modal information has limitations, and multimodal fusion is a key pathway to achieving high-precision early warning. Fusion strategies are mainly divided into three types: early fusion, intermediate fusion, and late fusion. Currently, late fusion has proven to be more robust. A typical early warning system would simultaneously input: 1) PHQ-2 short-form scale score; 2) sleep-activity rhythm from the past 7 days (from wristband data); 3) emotional tendency score from social media text [3]. Subsequently, a Multilayer Perceptron (MLP) or Gradient Boosting Tree is used for risk level classification. In preliminary studies, the Area Under the Curve (AUC) of multimodal models often exceeds 0.90, significantly superior to any single-modal model. This provides a feasible technical solution for implementing "stratified and progressive" screening in community populations.

3. APPLICATION OF AI IN THE DIAGNOSIS AND DIFFERENTIAL DIAGNOSIS OF DEPRESSION

Diagnosis is the prerequisite for treatment. Current symptom-based diagnostic criteria (e.g., DSM-5 or ICD-11) exhibit significant heterogeneity. AI intervention aims to provide auxiliary evidence with greater objectivity and precision for clinical diagnosis.

3.1 AI-assisted Clinical Diagnosis

Artificial intelligence, leveraging technologies like Natural Language Processing, emotion recognition, and machine learning, can approach from two dimensions –the diagnostic workflow and symptom assessment – to compensate for the shortcomings of traditional clinical diagnosis. This section elaborates on the practical pathways and application value of AI in optimizing clinical diagnostic processes and enhancing diagnostic objectivity and precision, specifically from the aspects of intelligent assistance in structured clinical interviews and quantitative assessment of symptom severity.

3.1.1 Intelligent Assistance for Structured Clinical Interviews

Traditional clinical interviews rely on the clinician's real-time capture of symptom criteria, making them susceptible to memory bias and fatigue. AI tools can act as a "second pair of eyes." For example, an NLP-based real-time speech transcription and analysis system can automatically mark patient statements that align with diagnostic criteria during the doctor-patient conversation. Simultaneously, an AI emotion recognition module can analyze the vocal emotional features of the patient's speech and perform consistency checks with the patient's self-reported emotions. If a patient says “my mood is okay” but the vocal features indicate “sadness,” the system can non-intrusively prompt the doctor to explore further. This enhances the structuring and standardization of diagnosis, particularly benefiting junior clinicians.

3.1.2 Quantitative Assessment of Symptom Severity

Quantifying symptoms is the foundation for accurately evaluating treatment efficacy. AI provides objective indicators based on behavioral performance. In computerized cognitive tests, patients perform tasks like the emotional Stroop task or Probabilistic Reward Task (PRT), and AI records their reaction time variability and error types. Typical manifestations of depressed patients include prolonged attention to negative stimuli and a reduced learning rate for positive feedback in reward learning. By calculating behavioral parameters from the task, an AI model can output a continuous score from 0 to 100, serving as a supplement to HAM-D or MADRS. This performance-based assessment is insensitive to patient subjective reporting bias and is particularly suitable for evaluating the short-term cognitive improvement effects of psychotherapy.

3.2 AI-assisted Differential Diagnosis

Artificial intelligence possesses the unique advantage of processing high-dimensional, complex data and uncovering latent associations, integrating multi-dimensional medical information to break through traditional differential diagnosis bottlenecks. This section explores the application mechanisms and clinical prospects of AI in differentiating depression from similar psychiatric disorders and classifying disease subtypes, focusing on three dimensions: neuroimaging, peripheral biomarkers, and multimodal data fusion.

3.2.1 Differentiation Based on Neuroimaging

Neuroimaging provides structural and functional biological evidence for differential diagnosis. Structurally, Voxel-Based Morphometry (VBM) shows reduced gray matter volume in the hippocampus and prefrontal cortex of depressed patients [4]. AI can automatically segment these brain regions and measure their volumes, assisting in differentiating depression from a depressive episode of bipolar disorder. Functionally, abnormal functional connectivity in the Default Mode Network (DMN) on resting-state fMRI is a typical feature of depression. AI network models based on graph theory analysis can calculate the clustering coefficient and shortest path length of brain networks, providing quantitative indicators for differentiating depression from anxiety disorders or subtyping. Although not yet routine in clinical practice, the AUC for AI-assisted imaging diagnosis has reached 0.85-0.90.

3.2.2 Differentiation Based on Peripheral Biological Markers

Metabolomics and proteomics generate massive amounts of data, and AI is an essential tool for analyzing this data. By analyzing metabolite profiles (e.g., tryptophan-kynurenine pathway metabolites), inflammatory cytokines (e.g., IL-6, TNF-α), and neurotrophic factors (e.g., BDNF) in blood, urine, or saliva, AI models can construct a "biomarker fingerprint." For example, a Support Vector Machine (SVM) model, by screening for specific threshold combinations of IL-6 and BDNF, can distinguish depression from depressive syndrome caused by physical illnesses with approximately 80% accuracy. Furthermore, AI can identify biomarker clusters associated with specific endophenotypes, providing a basis for subsequent treatment selection, representing the initial form of personalized medicine.

3.2.3 Comprehensive Differentiation Based on Multimodal Data

Real-world clinical decisions ultimately rely on multi-source information. AI integration models structurally integrate clinical variables (symptom patterns, age of onset, family history), neuroimaging indicators, biomarkers, and behavioral data. Research using unsupervised learning has successfully classified depressed patients into three biological subtypes: a subtype primarily characterized by impaired neuroplasticity, a subtype primarily characterized by immune-inflammatory dysregulation, and a subtype primarily characterized by psychosocial cognitive bias. This breaks through the traditional "one-size-fits-all" diagnostic classification, providing clinical decision-making with rich information far beyond a simple "yes/no" diagnosis, representing a key step towards realizing the "divide and conquer" vision in psychiatry.

4. APPLICATION OF AI IN THE TREATMENT OF DEPRESSION

Treatment is the core link in the clinical management of depression. The application of AI covers both biological (medication, physical) and psychological (psychotherapy) domains, aiming to achieve individualized, precise, and accessible intervention strategies.

4.1 Pharmacological Treatment

Artificial intelligence, relying on technologies such as machine learning, knowledge graphs, and natural language processing, can integrate multi-source high-dimensional data including genotype, clinical phenotype, brain imaging, and past treatment records, breaking away from the limitations of empirical medication. AI can run through the entire pharmacotherapy process, building an intelligent, personalized medication management system. This section systematically explains the application value and practical pathways of AI in depression pharmacotherapy from three aspects: medication consultation and decision support, efficacy prediction and personalized medication, and adverse reaction monitoring.

4.1.1 Medication Consultation and Decision Support

Clinical medication selection often relies on a "trial-and-error" approach; AI can provide "experience extrapolation" support. By establishing databases containing patient genotype (CYP450 enzyme system), demographic characteristics, comorbidity status, and medication history, decision support systems based on logistic regression or XGBoost algorithms can recommend preferred drugs for scenarios like "young female with first depressive episode". Additionally, knowledge graph systems integrated with the latest clinical guidelines can provide real-time evidence-based suggestions through question-and-answer interaction, reducing information retrieval time.

4.1.2 Efficacy Prediction and Personalized Medication

Predicting efficacy in advance can significantly reduce patient suffering and waste of medical resources. Based on the symptom change rate within the first two weeks of treatment and early adverse reactions, combined with pre-treatment resting-state EEG frontal alpha asymmetry indicators, AI models can predict with high accuracy whether clinical remission will be achieved after four weeks. Furthermore, for common SSRIs, AI models based on genomic data (e.g., 5-HTTLPR polymorphism) and fMRI brain region activation patterns are beginning to be used to predict individual efficacy, hopefully gradually achieving "data-driven rather than experience-based trial and error".

4.1.3 Adverse Reaction Monitoring

AI enables a shift in pharmacovigilance from "passive reporting" to "active warning." On one hand, NLP systems analyzing social media and EMRs can automatically identify and aggregate reports of side effects like sexual dysfunction and weight gain, which patients might be reluctant to report actively [5]. On the other hand, real-time monitoring of cardiac QTc interval prolongation or movement patterns related to akathisia via wearable devices, analyzed by deep learning models, can issue alerts hours before a serious event occurs. This significantly improves the safety of long-term medication use.

4.2 Psychotherapy

AI can serve both as an extension and supplement to offline psychotherapy, completing daily home-based training, and provide low-cost, stigma-free emotional counseling and psychological intervention for patients with mild to moderate depression. This section analyzes the application models and clinical value of AI in the psychotherapy of depression from three dimensions: digital assistance for CBT, conversational AI psychotherapy, and treatment adherence monitoring and feedback.

4.2.1 Digital Assistance for Cognitive Behavioral Therapy

Cognitive Behavioral Therapy (CBT) is a first-line psychotherapy for depression, but its availability is limited by a shortage of therapists. AI can assist with the "structured" parts. For example, a chatbot integrated into a mobile app can guide patients through completing a daily "thought record" – automatically identifying the patient's "automatic negative thoughts" and prompting them to restructure them into more adaptive cognitions based on CBT principles [6]. AI does not replace the therapist but acts as a "practice coach," reinforcing the patient's skill application between sessions, thereby enhancing treatment outcomes.

4.2.2 Conversational AI Psychotherapy

With the development of large language models, conversational AI agents capable of simulating human empathy have emerged. Such systems guide patients in self-exploration through continuous emotionally supportive conversation and application of motivational interviewing techniques. Compared to human therapists, AI offers advantages such as 24/7 availability, non-judgmental attitude, and unlimited repetition of explanations. Preliminary randomized controlled trials indicate that for mild to moderate depression, AI-driven therapeutic programs can significantly reduce PHQ-9 scores within 6-8 weeks, with lower dropout rates than traditional psychotherapy [7]. Of course, their ability to handle complex trauma or crisis intervention still needs improvement.

4.2.3 Treatment Adherence Monitoring and Feedback

Treatment adherence is the cornerstone of efficacy. AI enables remote monitoring through multimodal behavioral analysis. If a patient fails to complete their daily mindfulness exercise as planned, the app can send a silent vibration reminder via a wearable wristband; if the patient doesn't open the app for three consecutive days, the system analyzes whether their GPS location entropy has decreased and automatically sends an alert to the therapist team, prompting the therapist to proactively contact the patient. This closed-loop feedback system significantly improves the completion rate of "homework," thereby enhancing the real-world effectiveness of CBT.

4.3 Physical Treatment

Leveraging algorithms such as neuroimaging segmentation, Graph Convolutional Networks, and reinforcement learning, artificial intelligence can mine deep features of brain structure and functional connectomes, achieving precise targeting of therapeutic targets, dynamic optimization of stimulation parameters, and pre-operative prediction of treatment efficacy. This section discusses the application value and development prospects of AI in personalized precision intervention for physical therapy in depression, focusing on two aspects: optimization of Transcranial Magnetic Stimulation parameters and prediction of Electroconvulsive Therapy outcomes.

4.3.1 Parameter Optimization for Transcranial Magnetic Stimulation

Conventional repetitive Transcranial Magnetic Stimulation (rTMS) uses a "standard protocol," but patient responses to stimulation frequency, intensity, and target vary significantly. AI achieves personalized treatment through two core technologies: First, neuronavigation optimization – based on the individual patient's 3T-MRI structural image, deep learning models can automatically segment and precisely identify the individual coordinates of the standard target, the left dorsolateral prefrontal cortex (DLPFC) [8]; Second, adaptive parameter adjustment – real-time acquisition of Motor Evoked Potentials (MEP) during the initial treatment allows a reinforcement learning model to dynamically adjust stimulation intensity to stably maintain target cortical excitability with minimal energy consumption. Preliminary evidence suggests that AI-optimized rTMS protocols can increase response rates from the standard 50%-60% to over 70%.

4.3.2 Efficacy Prediction for Electroconvulsive Therapy

Electroconvulsive Therapy (ECT) is highly effective for severe, treatment-resistant depression, but it carries risks of cognitive side effects and high relapse rates. Based on pre-treatment high-resolution structural MRI and resting-state fMRI data, AI, particularly Graph Convolutional Networks (GCN), can construct an individual's brain structural-functional connectome. Studies confirm that baseline prefrontal-limbic system connectivity strength is a key feature for predicting ECT efficacy [9]. Using these features, AI models can classify patients into groups expected to show significant improvement or limited response with over 80% accuracy. This helps avoid unnecessary treatment (and its cognitive side effects) for non-responders, enabling precision medicine.

5. APPLICATION OF AI IN PROGNOSIS MANAGEMENT AND RELAPSE PREVENTION OF DEPRESSION

The 6-month relapse rate for depression is as high as 20%-30%, and the lifetime relapse rate exceeds 50%. AI's potential in relapse prevention is reflected in the shift from intermittent follow-up to continuous monitoring.

5.1 Remote Health Monitoring and Follow-up Management

Utilizing passive data from smartphones and wearable devices, AI enables scalable, continuous monitoring. The system continuously assesses the patient's mental state without requiring active input from the patient. For example, by analyzing features such as the emotional tendency of the text content when a user actively engages with a language model, the coefficient of variation in daily step count, and the peak time of nighttime heart rate, an AI model can construct an individual's health baseline [10]. When new data continuously deviates from the baseline for 48 hours – e.g., a 30% decrease in steps and a 50% decrease in social app usage – the system can automatically trigger a low-intensity intervention or alert the clinician via an EMR interface. This low-burden, high-density follow-up aids in the early detection of prodromal signs of relapse.

5.2 Relapse Risk Prediction Models

Traditional relapse risk relies on limited variables like the number of past episodes. AI models can elevate risk prediction to a dynamic, personalized probability assessment. Deep learning models based on survival analysis can integrate the patient's long-term clinical history (time, duration, treatment response of each episode), life environmental stressors (analyzed via NLP from social media or diary entries), and real-time physiological-behavioral markers (e.g., reduced HRV, sleep fragmentation) to output a time-varying "relapse risk curve" [11]. For instance, after experiencing a work-related stressor, the model could prompt in real-time: "The risk of relapse in the next 2 weeks is moderately high (35%). It is recommended to schedule an additional supportive counseling session and continue monitoring sleep." This provides a time window for precision prevention.

5.3 Patient Self-Management Support Systems

The first line of defense against relapse is the patient themselves. AI-empowered self-management systems transform from "passive tools" into "active partners." Systems based on reinforcement learning can learn individual patient preferences and response patterns. For example, if a patient's adherence to guided meditation is significantly higher than to physical exercise during low mood, the system will prioritize recommending meditation [12]. Furthermore, personalized psychoeducation resources driven by large language models can dynamically generate corresponding psychoeducational snippets or behavioral activation suggestions based on the patient's current cognitive patterns. The system can also record the patient's coping strategies during emotional peaks, automatically building an individual 'anti-depression toolkit' for rapid recall during future low mood episodes.

6. CONCLUSION

The role of AI in the clinical management of depression should be positioned as "augmented intelligence", not "artificial intelligence" to replace clinicians. The ideal prospect is to build an integrated model of "human-AI collaboration": AI is responsible for large-scale screening, continuous monitoring, structured intervention, and automated suggestions, freeing human doctors and therapists to focus on building therapeutic alliances, handling complex crises, conducting in-depth psychotherapy, and making final clinical judgments. With the development of multimodal models, federated learning, and explainable AI, a more predictive, preventive, personalized, and participatory new era of mental health is surely approaching. As future clinical practitioners, we must actively engage in this transformation, embracing the benefits of technology while prudently managing its risks, ultimately ensuring that technology serves human well-being and dignity.

REFERENCES

[1] Lu JM, Xu XM, Huang YP, et al. Prevalence of depressive disorders and treatment in china: a cross-sectional epidemiological study[J]. Lancet Psychiatry, 2021, 8(11): 981-990.

[2] Lou T, Liu ZH, Zhang GF. Progress in the application of artificial intelligence-based MRI in depression[J]. Chinese Journal of Magnetic Resonance Imaging, 2026, 17(03): 117-124.

[3] Francese R, Attanasio P. Emotion detection for supporting depression screening[J]. Multimedia Tools and Applications, 2023, 82(9): 12771-12795.

[4] Che QY, Sun YL, Jin J, et al. Application of neurofeedback-enhanced positive emotion in the treatment of depression[J]. Advances in Psychological Science, 2024, 32(02): 342-363.

[5] Peng LP, Wang K. Research progress of artificial intelligence in comprehensive management of patients with depression[J]. Psychology Monthly, 2025, 20(20): 225-227.

[6] Deng SL, Zhu QY, Liu LY, et al. Evaluation of the effectiveness of online peer mental health support for users in human-AI interaction contexts[J]. Journal of Modern Information, 2026, 46(04): 80-91.

[7] Wang XH, Liu JY, Zhang ZC, et al. Research progress on the application of digital therapy in the treatment of patients with depression[J]. Chinese Journal of Medical Management Sciences, 2025, 15(06): 95-101.

[8] ZHANG Z, LI G, XU Y, et al. Application of Artificial Intelligence in the MRI Classification Task of Human Brain Neurological and Psychiatric Diseases: A Scoping Review[J/OL]. Diagnostics (Basel), 2021, 11(8): 1402 [2026-01-16].

[9] Kellner CH, Kaicher DC, Banerjee H, et al. Depression severity in electroconvulsive therapy (ECT) versus pharmacotherapy trials[J]. J ECT, 2015, 31(1): 31-33.

[10] TOROUS J, BUCCI S, BELL I H, et al. The growing field of digital psychiatry: current evidence and the future of apps, social media, chatbots, and virtual reality[J]. World Psychiatry, 2021, 20(3): 318-335.

[11] Han JL, Feng L. Research progress on the application of artificial intelligence in the field of depression[J]. Beijing Medical Journal, 2020, 42(04): 317-319+322.

[12] Zhao J, Chang H. Research progress of digital health technology in self-management of patients with multiple sclerosis[J]. Chinese Nursing Management, 2025, 25(12): 1908-1913.