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Artificial Intelligence in Depression Diagnosis – Current State of Research, Methods and Challenges

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Abstract

Artificial intelligence (AI) is increasingly applied in psychiatry to support the detection, risk assessment, and management of depression. This review examines the current state of research, highlighting the data modalities employed—including speech and language, neuroimaging and EEG, electronic health records, behavioral and digital phenotyping, and multimodal approaches—and the types of predictions AI models generate, such as symptom presence, risk estimation, and severity assessment.

The review discusses methodological challenges, particularly the heterogeneity of outcome definitions, variability in labeling strategies, and differences in symptom emphasis across datasets, which influence model performance and interpretability. Ethical, legal, and regulatory considerations are also addressed, emphasizing privacy, transparency, and accountability in clinical deployment.

Evidence suggests that AI can enhance clinical practice by enabling early detection, supporting personalized management, and monitoring symptom progression, although models remain complementary to clinician judgment. Future directions include the development of more interpretable and actionable AI tools, integration of multimodal data, and AI-assisted interventions aimed at improving patient outcomes.

Overall, AI holds promise as a supportive tool in depression care, but careful attention to methodological rigor, ethical use, and clinical integration is essential to realize its full potential.

Keywords

Depression, Artificial Intelligence, Machine learning, Digital phenotyping, Clinical decision support

1. Introduction

Depression is a prevalent and debilitating mental health disorder affecting millions worldwide, posing significant challenges for diagnosis and treatment. Traditional methods of assessment, often relying on self-reported questionnaires and clinician evaluations, can be time-consuming, subjective, and prone to variability in accuracy (Briganti, 2023; Ricci et al., 2025). In recent years, artificial intelligence (AI) has emerged as a promising tool to enhance psychiatric practice by providing more objective, data-driven approaches for diagnosis, prognosis, and treatment planning (Zafar et al., 2024; Briganti, 2023).

AI applications in depression encompass a wide range of methodologies, from machine learning models analyzing behavioral patterns to deep learning models interpreting speech, neuroimaging, and electronic health records (Ricci et al., 2025; Zafar et al., 2024). These approaches aim not only to identify depressive symptoms more accurately but also to predict treatment responses and improve patient outcomes (Briganti, 2023). The rapid growth of AI research in psychiatry has led to an increasing number of systematic reviews, narrative analyses, and meta-analyses exploring the capabilities and limitations of these technologies (Ricci et al., 2025; Zafar et al., 2024).

Despite the potential benefits, AI integration in clinical settings raises several challenges, including the interpretability of models, standardization of data, and ethical concerns regarding privacy and bias (Zafar et al., 2024; Ricci et al., 2025). Moreover, understanding what AI models actually predict in the context of depression remains a critical question, emphasizing the need for rigorous evaluation and validation of AI-based tools (Briganti, 2023).

In this context, the current work aims to provide a comprehensive overview of AI applications in depression diagnosis, examining the state of research, commonly used data modalities, model performance, outcome definitions, and the challenges associated with clinical implementation. By synthesizing the most recent evidence, this review seeks to highlight both the opportunities and limitations of AI in advancing psychiatric practice.

2. Scope and Review Strategy

This review focuses on the use of artificial intelligence (AI) in diagnosing depression, exploring both research methods and clinical applications. The aim is to provide a clear overview of current approaches, the types of data used, and the practical implications of AI in psychiatry (Joshi et al., 2025; Ghorbankhani & Safara, 2026).

To capture the most relevant studies, we considered research published between 2023 and 2026. The review prioritizes systematic reviews, meta-analyses, and high-quality narrative reviews. This ensures that the synthesis reflects not just isolated findings, but broader trends and evidence (Joshi et al., 2025). Studies were selected to include both diagnostic and therapeutic uses of AI, providing a more complete picture of how these technologies are applied in practice.

The review also emphasizes the diversity of data types. AI models have been trained on speech and language samples, neuroimaging data, EEG recordings, electronic health records, behavioral patterns, and multimodal combinations (Ghorbankhani & Safara, 2026). By examining these different modalities, we can better understand the strengths and limitations of various approaches.

Methodologically, we considered aspects such as model types, data preprocessing, outcome definitions, and evaluation metrics. Highlighting these details allows for a critical comparison across studies and draws attention to common challenges. These include issues with standardizing input data and ensuring that results are reproducible (Joshi et al., 2025; Ghorbankhani & Safara, 2026).

Overall, this section sets the stage for the subsequent analysis. By clearly defining the scope and strategy, it helps readers understand what types of studies were included and why. This foundation is essential for discussing data modalities, AI model performance, and the practical challenges of applying AI in clinical settings.

3. Data Modalities Used in AI-Based Depression Studies

AI models for depression rely on diverse types of data, each offering unique insights into the condition. Researchers have explored various modalities, from speech patterns to brain activity and electronic health records. Understanding these data sources is crucial for assessing the strengths, limitations, and applicability of AI in psychiatry.

3.1 Speech and Language

Speech and language data are among the most studied sources for AI-based depression detection. Depressive symptoms often manifest in subtle changes in voice, including pitch, tone, rhythm, and speech rate. Natural language processing (NLP) techniques can also detect linguistic markers, such as the use of negative emotion words or reduced complexity in sentence structures.

Deep learning models, such as convolutional neural networks (CNNs) and recurrent neural networks (RNNs), have been widely applied to these datasets. For example, studies have shown that speech-based AI models can achieve high diagnostic accuracy, often outperforming traditional questionnaire-based assessments (Lu et al., 2025; Liu et al., 2024). These models are capable of detecting patterns imperceptible to human clinicians, making them promising tools for early screening.

However, challenges remain. Speech patterns can vary across languages, cultures, and age groups, which may limit the generalizability of models. Background noise, recording conditions, and emotional state can also affect performance. Therefore, robust preprocessing and cross-linguistic validation are essential for reliable deployment.

3.2 Neuroimaging and EEG

Neuroimaging and EEG data provide a window into the neurological underpinnings of depression. EEG is particularly valuable due to its non-invasiveness and temporal resolution, capturing brain activity associated with mood and cognitive processes. AI models can identify patterns in EEG signals that differentiate depression from anxiety or bipolar disorder (Zhai et al., 2025).

Neuroimaging approaches, including functional and structural MRI, allow AI to examine brain regions implicated in depression, such as the prefrontal cortex and limbic structures (Ricci et al., 2025). Machine learning models can detect subtle structural or connectivity changes, potentially serving as biomarkers for early diagnosis.

Nevertheless, these modalities face limitations. Neuroimaging is costly and less accessible in routine clinical practice, while EEG signals can be noisy and sensitive to electrode placement. Moreover, large datasets are often required to train deep learning models effectively, which may be a barrier in smaller clinical settings.

3.3 Electronic Health Records (EHRs)

Electronic health records (EHRs) contain structured and unstructured patient information, such as diagnoses, medications, lab results, and clinical notes. Machine learning algorithms can leverage this data to predict depression, monitor symptom progression, and inform personalized interventions (Nickson et al., 2023).

EHR-based AI models often use ensemble methods, gradient boosting, or deep learning to handle heterogeneous data. They provide the advantage of utilizing real-world, longitudinal information, capturing trends over time that may not be evident in cross-sectional assessments.

However, EHR data present challenges. Missing or inconsistent entries, differences in coding practices, and patient privacy concerns can affect model reliability. Careful data cleaning, standardization, and compliance with ethical guidelines are essential for successful implementation.

3.4 Behavioral and Digital Phenotyping Data

Behavioral data, including digital phenotyping from smartphones, wearable devices, and online activity, offer additional avenues for depression detection. Patterns in sleep, mobility, social interactions, and digital communication can serve as proxies for mood, motivation, and cognitive function (Goh et al., 2025; Xia et al., 2025).

AI models trained on these data can detect early signs of depression, sometimes before clinical recognition. Machine learning approaches include random forests, support vector machines, and deep learning models capable of handling high-dimensional behavioral features.

Challenges include variability in device usage, user compliance, and privacy concerns. Additionally, interpreting behavioral data requires careful contextualization, as similar patterns may result from non-psychiatric factors (e.g., shift work, chronic illness).

3.5 Multimodal Approaches

Multimodal approaches integrate two or more data sources to improve predictive performance. Combining speech, EEG, neuroimaging, EHR, and behavioral data allows models to capture complementary aspects of depression (Wang et al., 2025). For instance, a model integrating speech patterns and EEG features may achieve higher sensitivity and specificity than either modality alone.

These approaches, while promising, introduce complexity. Data must be harmonized across modalities, missing values handled, and computational requirements met. Interpretability can also decrease as models become more complex, which may hinder clinical adoption. Despite these challenges, multimodal AI represents a frontier in depression research, with the potential to provide more accurate, holistic assessments.

4. Performance of AI Models for Depression

Artificial intelligence has shown considerable potential in enhancing the detection and diagnosis of depression, but performance varies widely depending on data modalities, model types, and study design. Evaluating model accuracy, sensitivity, specificity, and other performance metrics is crucial for understanding the practical value of AI tools in clinical settings (Khan Rony et al., 2025; Ren et al., 2025; Lu et al., 2025; Liu et al., 2024).

4.1 Accuracy Across Data Modalities

Models using **speech and language data** have consistently demonstrated promising results. Deep learning approaches applied to voice recordings have achieved **accuracy ranging from 78% to 92%** and sensitivity between **75% and 88%** in detecting depressive symptoms (Lu et al., 2025; Liu et al., 2024). These models are particularly effective at capturing subtle temporal and acoustic patterns that may be imperceptible to clinicians, suggesting their potential for early detection.

EEG-based models also show reliable predictive performance, with reported accuracies typically between **70% and 85%** for distinguishing depression from other mood disorders (Zhai et al., 2025). While neuroimaging-based models can achieve slightly higher accuracy (**up to 88–90%** in some studies), their practical deployment is limited by cost and data requirements (Ricci et al., 2025).

Electronic health record (EHR) models have demonstrated **accuracy levels of 75–83%**, with sensitivity around **70–80%**, particularly when trained on large, longitudinal datasets (Nickson et al., 2023). These models provide real-world applicability by integrating structured and unstructured clinical data.

Behavioral and digital phenotyping approaches show **accuracy between 72% and 87%**, depending on the type of behavioral features and device usage patterns (Goh et al., 2025; Xia et al., 2025). These models can detect early signals of depressive states, although their performance is influenced by contextual factors such as lifestyle or work schedules.

4.2 Multimodal Integration and Performance Gains

Multimodal AI models, combining two or more data sources, tend to outperform single-modality approaches. For instance, integrating speech and EEG features or combining EHR and behavioral data has resulted in **accuracy improvements of 5–10 percentage points**, reaching **overall accuracy between 85% and 93%** (Wang et al., 2025). The combination of complementary modalities captures multiple aspects of depression, enhancing predictive reliability.

Despite these advantages, multimodal models face practical challenges. Harmonizing datasets, handling missing values, and managing computational complexity are non-trivial tasks. Increased model complexity can reduce interpretability, which may hinder clinical adoption. Nevertheless, the measurable gains in predictive performance suggest that multimodal approaches are likely to play a central role in future AI applications (Khan Rony et al., 2025; Ren et al., 2025).

4.3 Contextual Interpretation of Model Performance

While many AI models report high accuracy, interpretation requires context. Differences in dataset size, population characteristics, and outcome definitions can make direct comparisons difficult. For example, speech-based models validated in one language setting may drop **10–15 percentage points in accuracy** when applied to another language or cultural context (Lu et al., 2025; Liu et al., 2024).

Moreover, high numerical accuracy does not guarantee clinical utility. Models must be evaluated for interpretability, early detection capabilities, and integration into real-world workflows (Khan Rony et al., 2025; Ren et al., 2025).

5. What Do AI Models for Depression Actually Predict?

AI models for depression do not simply replicate a clinical diagnosis; instead, they capture patterns and signals that are associated with depressive states across different dimensions. Understanding the specific focus of these models is crucial for interpreting their outputs (Ricci et al., 2025; Zafar et al., 2024).

5.1 Symptom Detection

Many models are designed to detect **specific symptoms of depression**, rather than making a holistic diagnostic assessment. For instance, speech- and language-based models identify markers such as slowed speech, reduced vocal variability, or the use of negative language, which correlate with low mood or anhedonia (Lu et al., 2025; Liu et al., 2024; Goh et al., 2025). Behavioral and digital phenotyping models monitor activity patterns, social engagement, and digital interactions, providing indirect measures of withdrawal or reduced motivation (Goh et al., 2025; Xia et al., 2025).

These models highlight **proximal indicators** of depressive states—observable features that manifest in day-to-day behavior—but do not directly determine the underlying psychiatric diagnosis.

5.2 Risk Prediction

Certain AI approaches aim to estimate **risk or likelihood** of developing depression or experiencing relapse. EHR-based models, for example, analyze longitudinal patterns in clinical records to flag individuals who may be at elevated risk (Nickson et al., 2023).

Similarly, multimodal models integrating multiple data sources can detect subtle combinations of behavioral, physiological, and clinical signals that precede symptomatic expression (Wang et al., 2025; Khan Rony et al., 2025).

Risk prediction in this context reflects a **probabilistic assessment**: models indicate who might benefit from closer monitoring or preventive interventions rather than providing a deterministic statement of disease presence.

5.3 Severity and Symptom Intensity

Some models are also trained to capture **severity or intensity of depressive symptoms**. By analyzing combinations of speech features, EEG patterns, and behavioral data, AI can estimate how pronounced certain depressive features are at a given time (Wang et al., 2025; Ricci et al., 2025). This provides a dynamic perspective on symptom progression, offering insights into worsening or improving states over time.

However, it is important to note that severity predictions are **relative and model-dependent**, influenced by the type of data used and the definitions of outcomes in the training datasets. They reflect patterns associated with more or less intense depressive symptoms rather than absolute clinical scoring.

5.4 Modality-Specific Predictions

- **Speech and language models:** Sensitive to temporal and acoustic patterns indicative of mood changes.
- **EEG models:** Detect neural signatures associated with depressive states.
- **Neuroimaging models:** Identify structural or functional brain patterns linked to symptom expression.
- **EHR models:** Track longitudinal clinical indicators to estimate future risk.
- **Behavioral and digital phenotyping models:** Monitor everyday activity and social interactions to infer changes in mood or motivation.

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Across modalities, AI outputs are **proxies for different aspects of depression**. They are not final diagnoses but instead highlight **observable or latent signals** that correlate with depressive processes (Lu et al., 2025; Liu et al., 2024; Goh et al., 2025; Wang et al., 2025; Nickson et al., 2023; Ricci et al., 2025; Zafar et al., 2024).

6. Outcome Definition and Labeling Challenges

The performance and interpretability of AI models for depression are heavily influenced by how outcomes are defined and labeled. One of the main challenges is the **heterogeneity of depression scales** used across studies. Instruments such as the PHQ-9, BDI, or HDRS differ in scoring range, symptom focus, and sensitivity, which can lead to **inconsistent labeling** of depressed versus non-depressed individuals (Joshi et al., 2025; Park et al., 2024). Different cut-offs for the same scale further complicate comparisons, making it difficult to generalize model performance across datasets.

Labeling is also affected by **subjectivity and variability** in assessment. Even structured scales rely on self-report or clinician judgment, and some datasets derive labels from EHR proxies or behavioral features rather than direct clinical evaluation, introducing **label noise** (Zafar et al., 2024; Joshi et al., 2025). Additionally, depression itself is heterogeneous: some studies emphasize affective symptoms, others focus on cognitive or somatic features, which can bias models toward certain manifestations of the disorder (Xia et al., 2025; Park et al., 2024).

These issues have important implications for interpreting AI outputs. Model predictions reflect the **specific operationalization of depression** in the training data rather than a universal clinical definition. Consequently, caution is required when applying models across populations or comparing results between studies. Transparent reporting of scales, cut-offs, and symptom dimensions is essential to ensure that predictions are understood in the correct context (Joshi et al., 2025; Zafar et al., 2024; Xia et al., 2025).

7. Clinical Utility and Integration into Practice

AI has the potential to enhance psychiatric practice by supporting decision-making, monitoring patients, and improving the management of depression. Rather than replacing clinicians, AI tools are most effective when integrated as **assistive technologies** that complement traditional assessment methods (Briganti, 2023; Ricci et al., 2025; Zafar et al., 2024).

In clinical settings, AI can identify patients at risk of depression or relapse by analyzing speech patterns, behavioral activity, EHR data, or multimodal inputs. These predictions enable **earlier interventions**, targeted follow-ups, and more personalized treatment planning (Wang et al., 2025; Nickson et al., 2023). For example, patients flagged as high-risk by AI can be prioritized for clinician review or offered supportive interventions sooner than standard screening would allow.

Integrating AI into practice also requires attention to **workflow compatibility, interpretability, and clinician training**. Predictions must be presented in a way that is understandable and actionable. Insights from previous chapters highlight that outputs depend on outcome definitions and labeling strategies (Chapters 5 and 6). Recognizing these limitations ensures that AI recommendations are interpreted appropriately and do not replace comprehensive clinical judgment (Ricci et al., 2025; Zafar et al., 2024).

Finally, AI-assisted monitoring can support ongoing management of depression, tracking symptom changes over time and evaluating treatment response. While current evidence suggests **promising improvements in early detection and personalized care**, successful implementation depends on careful integration with clinical processes, ethical considerations, and continuous validation (Briganti, 2023; Park et al., 2024; Wang et al., 2025).

8. Ethical, Legal, and Methodological Challenges

The adoption of AI in depression diagnosis and management raises several important **ethical, legal, and methodological concerns**. From an ethical perspective, the use of sensitive personal data—speech, digital behavior, EHRs—requires careful attention to **privacy, consent, and data security**. Patients must be informed about how their data is used, and safeguards must prevent misuse or unintended disclosure (Zafar et al., 2024).

Legal and regulatory challenges are equally significant. AI models often operate in a grey area where **accountability for decisions is unclear**. If an AI system flags a patient incorrectly, it raises questions about liability: who is responsible—the clinician, the developer, or the institution? Current regulations are evolving, and compliance with healthcare standards must be considered when integrating AI into practice (Ricci et al., 2025).

Methodological challenges also limit the practical implementation of AI. Differences in datasets, labeling strategies, and outcome definitions, as discussed in chapters 5 and 6, can lead to **biased or non-generalizable models**. Additionally, many deep learning models remain “black boxes,” offering limited interpretability. Ensuring reproducibility, transparency, and robust validation across diverse populations is essential to address these challenges (Zafar et al., 2024; Ricci et al., 2025).

Overall, ethical, legal, and methodological considerations are **interconnected**: robust, transparent methodology supports ethical use and compliance with legal standards. Careful attention to these issues is a prerequisite for safe and responsible deployment of AI in psychiatry.

9. Future Directions

The field of AI in depression diagnosis and management continues to evolve rapidly. One key direction is the **development of more interpretable and clinically actionable models**. Future research aims to create AI systems that not only predict depressive symptoms but also provide insights into **underlying mechanisms and individual risk trajectories** (Ren et al., 2025).

Advances in multimodal data integration—combining speech, behavioral, neuroimaging, and EHR data—promise to enhance predictive accuracy while capturing the multifaceted nature of depression (Joshi et al., 2025). Another avenue involves **AI-assisted interventions**, where predictions are coupled with personalized therapeutic recommendations or digital mental health support, moving from diagnostic support toward active management (Joshi et al., 2025).

Finally, continued attention to ethical and methodological rigor will guide the development of AI that is **both effective and socially responsible**, ensuring that innovations benefit patients across diverse populations (Ren et al., 2025; Joshi et al., 2025).

10. Conclusion

AI offers a transformative potential for depression diagnosis and management, complementing traditional clinical assessment with tools capable of detecting subtle patterns across speech, behavior, EEG, and clinical records (Briganti, 2023; Ricci et al., 2025; Zafar et al., 2024). Evidence from current research shows that **AI models can identify symptoms, estimate risk, and monitor severity**, but their outputs are constrained by outcome definitions, labeling strategies, and dataset characteristics.

The integration of AI into clinical practice requires careful attention to **ethical, legal, and methodological challenges**, including data privacy, interpretability, and regulatory compliance (Ricci et al., 2025; Zafar et al., 2024). Looking forward, advances in multimodal integration, interpretable models, and AI-assisted interventions will likely enhance both diagnostic precision and patient-centered care (Ren et al., 2025; Joshi et al., 2025).

In summary, AI in psychiatry is a **supportive tool**, not a replacement for clinical judgment. Its successful implementation depends on rigorous methodology, ethical use, and seamless integration into healthcare workflows, offering the promise of **earlier detection, personalized management, and improved outcomes for patients with depression** (Briganti, 2023; Ricci et al., 2025; Zafar et al., 2024).

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