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The Role of AI in Mental Health: A Survey of Deep Learning Techniques for Depression Detection and Intervention

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Abstract

Depression presents unique patterns at different life stages, shaped by developmental, societal, and biological influences, requiring tailored artificial intelligence (AI) strategies. This review explores deep learning (DL) methods for identifying and treating depression, categorized by age: adolescents (10–20 years), young adults (21–35 years), middle-aged individuals (36–50 years), and older adults (51–70 years). Synthesizing recent studies from 2023 to 2025, we evaluate data sources including social media, wearable devices, brain imaging, and chat-based AI, as well as architectures such as transformers, long short-term memory networks (LSTMs), and graph neural networks (GNNs). Among adolescents, DL enables passive monitoring through smartphone data; young adults benefit from AI-based therapeutic chatbots. In middle age, models assist in understanding menopause-linked mental health risks, while older adults use AI systems to identify and address loneliness. Key obstacles involve limited data from non-Western populations and algorithmic biases. This age-focused analysis underscores DL's capacity to customize care, easing the worldwide impact of depression through precision psychiatry. Future efforts should prioritize federated learning and diverse, cross-cultural datasets to ensure fairness.

Keywords

Artificial Intelligence (AI); Deep Learning (DL); Depression Detection; Mental Health; Adolescents; Young Adults; Middle Age; Older Adults; Neural Networks; Machine Learning (ML); Federated Learning; Cognitive Behavioral Therapy (CBT); Emotion Recognition; Social Media Analysis; Wearable Devices; Explainable AI; Ethical AI; Multimodal Data; Digital Therapeutics; Age-Wise Analysis.

Introduction

Depression, as a multifaceted condition, exhibits significant variation across age groups, with prevalence reaching 18.6% in individuals aged 18–25 and increasing again in later adulthood due to persistent stressors. Conventional diagnostic methods often fail to account for these age-related differences, resulting in misdiagnosis rates ranging from 30% to 50% across populations. Deep learning (DL), leveraging its strength in multimodal data integration, enables personalized, age-specific approaches—from virtual reality (VR)- based assessments for adolescents to predictive analytics for older adults.

This review, based on research from 2023 to 2025, employs a survey-driven, age-stratified methodology, dividing analysis into four cohorts: adolescents (10–20 years), young adults (21–35 years), middle-aged adults (36–50 years), and older adults (51–70 years)—to clarify DL's contributions to both detection (identifying depressive symptoms) and intervention (customizing therapeutic strategies).

Problem Definition and Research Gap

Despite rapid advances in deep learning for mental health analytics, existing studies often suffer from three critical limitations: (i) lack of age-specific stratification, leading to generalized models that fail to capture developmental and psychosocial differences; (ii) inconsistent reporting of methodological rigor, dataset bias, and validation strategies; and (iii) limited discussion on real-world clinical deployment and ethical compliance. This survey addresses these gaps by systematically analyzing deep learning–based depression detection and intervention techniques through an age-wise analytical lens, emphasizing methodological transparency, performance variability, and clinical applicability.

Methods and Materials

Data Collection and Search Strategy

A systematic literature review was conducted using databases including PubMed, IEEE Xplore, SpringerLink, and Nature Scientific Reports. Search terms included: "Deep Learning for Depression," "AI Mental Health Detection," "Emotion Recognition + Age Group," "CBT Chatbot AI," "Federated Learning Mental Health," and "EEG Depression Classification."

A total of 212 studies published between January 2023 and September 2025 were initially identified. After applying inclusion and exclusion criteria, 62 studies were selected for final analysis.

Inclusion Criteria

Peer-reviewed studies focusing on AI or DL-based depression detection or intervention.
Research involving specific age group segmentation (adolescents, young adults, middle-aged, older adults).
Studies validated with standardized mental health instruments such as PHQ-9, HAM-D, or BDI-II.
Models reporting measurable outcomes such as accuracy, F1-score, or AUC.

Exclusion Criteria

Non-peer-reviewed conference abstracts or blogs.
Studies focusing solely on traditional ML without DL integration.
Research unrelated to age-specific analysis.

Analytical Framework

Each study was analyzed along three key dimensions:

Data Source (social media, wearable, EEG, EHR, or multimodal).
Model Architecture (CNN, LSTM, Transformer, BERT, GNN, etc.).
Outcome Measure (detection accuracy, F1-score, AUC, or intervention success rate).

Tools and Datasets
Prominent datasets utilized included:

DAIC-WOZ (Depression and Anxiety Interview Corpus – multimodal video/audio dataset).
Korean Longitudinal Study of Aging (KLoSA) – for older adult prediction studies.
Reddit Mental Health Corpus – for adolescent and young adult text analysis.
PhysioNet Sleep-EEG Dataset – for physiological pattern identification.
Analyses incorporated Python-based frameworks such as TensorFlow and PyTorch. Statistical reliability was ensured via cross-validation and ROC curve evaluation.

Study Selection and Quality Appraisal
To improve methodological transparency, a structured screening protocol inspired by PRISMA guidelines was followed. After initial retrieval of 212 studies, duplicates were removed and titles and abstracts were screened for relevance. Full-text evaluation was conducted on 94 studies, of which 62 met the inclusion criteria.
Each selected study was further assessed using the following quality indicators:
Dataset size and demographic diversity
Validation strategy (cross-validation, external validation)
Performance metrics reported (accuracy, F1-score, AUC)
Ethical approval or anonymization statements
Studies lacking clear validation protocols or ethical disclosures were retained only for contextual comparison and not emphasized in performance synthesis.

Adolescents (10–20 Years): DL for Early Detection and Intervention

The teenage years represent a pivotal period for the emergence of depression, where 15.4% of American youth faced major depressive episodes in 2024, frequently tied to the influences of social platforms and school-related stress. Deep learning (DL) stands out in this context by utilizing unobtrusive data streams, facilitating seamless and non-invasive assessments.

Detection Techniques

DL frameworks tailored for spotting depression in teens prioritize the integration of multiple data types to identify faint indicators, delivering F1-scores as high as 0.88.
Mobile and Wearable Data: Metrics gathered passively from smartphones—such as location tracking via GPS and patterns in app interactions—forecast depressive states with 85% precision through long short-term memory (LSTM) networks. Research spanning 2022–2025 involving 189 teenagers showcased recurrent neural networks (RNNs) in projecting symptoms based on behavioral routines, surpassing conventional machine learning techniques by 15%. By incorporating early-life and prenatal elements with random

forest algorithms, predictions of depression emergence between ages 12 and 18 achieve an area under the curve (AUC) of 0.82, underscoring the role of environmental signals.

Social Media and Text: Transformers built on BERT examine content from platforms like Reddit and TikTok to uncover language-based signs, attaining 99% accuracy in recognizing emotions. A 2025 machine learning review utilizing real-world data (RWD) factored in social determinants of health (SDoH), pinpointing co-occurring anxiety and depression in 1,200 teens with 78% exactness.

Multimodal Innovations: Virtual reality (VR) systems that blend electroencephalography (EEG), heart rate variability (HRV), and gaze monitoring deliver 92% accuracy in initial screenings, as seen in a 2025 investigation of 150 adolescents, effectively countering limitations of self-assessments. Combined convolutional neural network-LSTM (CNN-LSTM) approaches applied to the DAIC-WOZ audiovisual dataset identify symptoms in educational environments with an F1-score of 0.77.

Challenges: Protecting the privacy of underage users and accounting for cultural differences hinder broader applicability; studies indicate a 20% dip in effectiveness among rural or less urbanized groups.

Intervention Techniques

Therapeutic strategies in this age group emphasize scalable online tools, where DL customizes cognitive behavioral therapy (CBT) through mobile applications.Predictive Apps: Indicators from smartphones anticipate responses to treatments among 300 teens, employing CNNs to analyze vocal tones and sleep patterns for 87% accuracy in projecting remission.

Chatbots and VR: Self-guided CBT bots, such as XiaoE, have led to a 40% drop in symptoms during experimental phases; DL adaptations through fine-tuning on Conversational exchanges boost user involvement. Meta-learning methods foresee mental health results, customizing therapies with 85% reliability.

School-Based Models: AI-enhanced digital counseling identifies concerns among 500 pupils, weaving in natural language processing (NLP) for swift prioritization and support.

Outcomes: Reviews from 2025 report a 30% reduction in symptoms compared to non-intervention groups, although extended randomized controlled trials (RCTs) remain limited.

Young Adults (21–35 Years): DL for High-Risk Urban Cohorts

Young adulthood experiences the highest rates of depression, with a prevalence of 18.6%, largely fueled by shifts in professional life and excessive exposure to digital environments. In this demographic, deep learning (DL) strategies for intervention emphasize dialogue-based AI to promote widespread reach and ease of use.

Detection Techniques

Detection models in this group draw on extended real-world data (RWD) tracking, attaining 89% accuracy in clinical diagnosis.

EEG and Physiological: EEG captured via portable wireless headsets, combined with machine learning (ML), identifies depression among 200 young adults using convolutional neural networks (CNNs), with an F1-score of 0.85. Extended ML analyses of survey responses forecast the development of symptoms with an area under the curve (AUC) of 82%.

Social and Conversational: The X-A-BiLSTM model scrutinizes discussions on virtual forums to spot patterns of repetitive negative thinking, achieving 90% precision. Surveys on user perceptions indicate that 70% express confidence in AI systems for timely notifications of potential issues.

Multimodal: Frameworks integrating BERT with SHAP methods combine textual and auditory inputs, improving transparency and reaching 95% accuracy.

Gaps: Datasets often reflect urban-centric perspectives, leading to skewed results; 2025 evaluations advocate for incorporating varied social determinants of health (SDoH) to broaden applicability.

Intervention Techniques

Cognitive behavioral therapy (CBT) enhanced by ChatGPT configurations results in a 51% decrease in symptoms, according to meta-analyses involving 1,000 participants.

Conversational Agents: AI-driven conversational assistants (CAs), such as Tess, show variable effectiveness tied to user participation levels, achieving a 31% reduction in anxiety.

Prognostic Tools: Comprehensive DL assessments anticipate therapeutic results, delivering 87% accuracy in projections for internet-based CBT (iCBT).

Ethics: Guidance from 2025 highlights the importance of protections akin to those for adolescents, ensuring safety measures for this transitional age group.

Middle-Aged Adults (36–50 Years): DL for Stress and Transition Risks

Depression in midlife impacts 12–15% of individuals, intensified by hormonal shifts during perimenopause and professional stagnation. Deep learning (DL) applications in this phase center on forecasting risks through electronic health records (EHRs) to enable proactive management.

Detection Techniques

Predictive algorithms, including random forests and XGBoost, deliver area under the curve (AUC) values of 0.85–0.90 within European study populations.

Clinical Predictors: Machine learning (ML) augmented by SHAP techniques clarifies influences such as sleep disturbances among 5,000 midlife adults, attaining 88% accuracy.

Menopause-Specific: Tailored DL algorithms for women in perimenopause process symptom profiles, achieving an F1-score of 0.82.

Cancer Contexts: Transparent models designed for patients with cancer anticipate depressive episodes with 85% sensitivity.

Surveys emphasize a 25% rate of overlooked cases stemming from societal stigma.

Intervention Techniques

DL platforms generate 5-year risk estimates, informing medication strategies with 80% accuracy in predicting remission.
Hybrid Models: Combinations of regression and DL pinpoint key contributors, customizing cognitive behavioral therapy (CBT) to foster 75% user retention.

Limited randomized controlled trials (RCTs) exist; 2025 recommendations advocate for embedding these tools in occupational settings.

Older Adults (51–70 Years): DL for Chronic and Loneliness-Driven Depression

Depression prevalence in this age group rises to 7–10%, largely due to coexisting health conditions and social isolation. Deep learning (DL) places a strong emphasis on forecasting psychological resilience to support preventive care and sustained well-being.

Detection Techniques

XGBoost models applied to Korean longitudinal panels achieve 92% accuracy in predicting the onset of depression.
Longitudinal Surveys: Machine learning (ML) analyses of aging cohort studies forecast late-life depression with an area under the curve (AUC) of 0.87.

AI and Robotics: Deep learning models embedded in companion robots, optimized using the Nelder-Mead algorithm, detect depressive states with 97% accuracy.
Cognitive Impairment: Specialized models for older adults with cognitive decline demonstrate 88% sensitivity in identifying depression.
Gaps: Surveys highlight barriers related to technological literacy and recommend the adoption of voice-activated interfaces to improve accessibility.

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Intervention Techniques

AI-driven companion systems reduce loneliness by 35%, while big data analytics enhance emotional and cognitive resilience.
Digital Programs: Layperson-supported cognitive behavioral therapy (CBT) delivered via apps shows a 40% uptake rate in clinical trials.
Predictive Modeling: DL algorithms project two-year depression risk, enabling personalized antidepressant regimens with improved therapeutic alignment.

Cross-Age Synthesis and Challenges

Age Group	Key Modality	Top Model	Avg. Accuracy	Primary Gap
10–20	Mobile/VR	LSTM/CNN	85–92%	Privacy
21–35	Text/EEG	BERT	89–95%	Bias
36–50	HER/SHAP	XGBoost	82–88%	Stigma
51–70	Surveys/Robotics	DL Regression	87–97%	Literacy

DL model performance drops 10–15% when applied across different age groups due to inherent data heterogeneity and developmental differences. Recent surveys strongly advocate for transfer learning techniques to enhance generalizability and maintain accuracy across life stages.

Clinical Translation and Deployment Challenges

While deep learning models demonstrate high performance in controlled research environments, their clinical deployment presents substantial challenges. Data drift, variability in clinical documentation, and differences in healthcare infrastructure significantly affect model generalizability. Furthermore, integration with existing electronic health record (EHR) systems requires interoperability, clinician trust, and regulatory approval.
Human-in-the-loop systems, where AI assists rather than replaces clinicians, have shown higher acceptance and safety. The deployment of AI-driven mental health tools must also consider explainability, especially in high-stakes decisions such as suicide risk assessment. Recent guidelines emphasize that AI systems should support clinical judgment rather than function as autonomous diagnostic tools.

Ethical Considerations

Biases tailored to specific age groups intensify inequities: models for adolescents frequently neglect neurodiversity, while those for older adults often fail to account for multiple coexisting conditions. Federated learning that complies with GDPR and SHAP-based explainability are essential for transparency and privacy. Guidelines issued in 2025 require the use of diverse, representative training datasets to reduce bias and ensure fairness

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across age cohorts.

Ethical Considerations and Compliance

Ethical compliance remains a critical concern in AI-based mental health research. Many datasets rely on sensitive personal data, including behavioral patterns, speech, and emotional expression. This review highlights that a significant proportion of studies lack explicit ethical approval statements or informed consent documentation.

To mitigate these concerns, federated learning, anonymization techniques, and explainable AI (XAI) frameworks are increasingly recommended. Compliance with international regulations such as GDPR and emerging AI governance policies is essential, particularly when deploying systems for vulnerable populations such as adolescents and older adults.

Future Directions

Age-stratified randomized controlled trials (RCTs), seamless integration with wearable technologies, and globally representative datasets have the potential to reduce diagnostic delays by 50% by 2030. Hybrid AI-human systems designed for transitional life stages—such as ages 20–21 and 50–51—show particular promise in delivering adaptive, personalized mental health support.

Ethical Statement

This study is a review article and does not involve new experiments on human or animal subjects. All data analyzed were obtained from previously published studies, which reported compliance with ethical standards and informed consent where applicable.

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