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The intersection of artificial intelligence and assistive technologies in the diagnosis and intervention of mental health conditions

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Abstract
Mental health disorders are becoming a major global health concern and pose a significant burden on global healthcare systems. Nearly one billion people suffer from mental disorders, accounting for 13% of the global disease burden and $1 trillion in annual productivity loss. Depression is the leading cause of disability and suicide is the second leading cause of death among young individuals. Economic uncertainty, social isolation, climate change, shifting societal norms, political conflict, and increasing violence are key factors contributing to the high prevalence of mental health issues. In the future, increasing poverty and inequality are likely to worsen this trend, resulting in a greater incidence and burden of mental illness. Therefore, timely diagnosis and intervention are a high priority. Traditional diagnostic and intervention methods, such as self-report questionnaires, clinical interviews, psychotherapy, medication, electroconvulsive therapy, and occupational therapy, have drawbacks including subjectivity, time commitment, and the potential for prolonged treatment. Due to these limitations, advanced approaches are needed to improve diagnostic accuracy and precision and to develop more effective interventions. This review aims to explore and evaluate the applications of Artificial Intelligence in the diagnosis and treatment of mental health conditions. This study provides a thorough analysis of various artificial intelligence-driven techniques and their advancements in the diagnosis of mental health conditions. Artificial intelligence has the potential to greatly improve the accuracy and effectiveness of mental health conditions. Moreover, this work consolidates the research gaps in current techniques and provides research hypotheses on how to overcome the gaps using a proposed 3-tier solution.

Keywords Artificial intelligence · Mental health · Diagnostics · Intervention

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1 Introduction

Today mental health issues pose a significant risk to the well-being of millions worldwide, emerging as a major societal concern. Despite its pervasive impact, mental illness remains a silent epidemic, with many individuals suffering from conditions such as bipolar disorder, depression, and anxiety disorders. A survey conducted in metropolitan areas underscores the importance of this issue, revealing that persistent underdiagnosis of mental health problems leads to approximately half of all serious depression cases being undetected (Faisal-Cury et al. 2022). The World Economic Forum projects that the global cost of mental illness will soar to $6 trillion by 2030, surpassing the combined costs of diabetes, cancer, and respiratory diseases. Figure 1 illustrates the projected costs of mental health conditions in comparison to other health conditions (diabetes, cancer, respiratory illnesses, and cardiovascular disease) by 2030 (Bloom et al. 2012). Conventional diagnostic methods often rely on subjective evaluations, self-reported symptoms, and clinical observations and are prone to inaccuracies (Rose and Devine 2014). A key limitation of these conventional approaches is the variability in clinician assessments. The same symptoms may be interpreted differently by different clinicians, leading to a potential misdiagnosis.

The reliance on patient self-awareness and self-reported symptoms poses a limitation, particularly in conditions where individuals may lack insight into their mental state (e.g., due to anosognosia). Although clinicians use structured assessments to counterbalance this, incomplete or distorted self-reporting can still reduce diagnostic clarity, especially in early evaluations (McIntosh et al. 2021). Moreover, the effectiveness of self-report questionnaires depends on the patients' ability to accurately describe their mental state, which can be influenced by factors such as current mood and memory recall (Hanlon 2010). These limitations hinder prompt and accurate diagnosis, placing an additional burden on patients and the healthcare system. Misdiagnosis or delayed diagnosis can result in inappropriate or delayed treatment, exacerbating the patient's condition and increasing the overall healthcare costs. Thus, there is a pressing need for more objective, reliable, and consistent diagnostic tools for mental healthcare. Artificial intelligence (AI) is emerging as a transformative tool for mental health, offering novel ways to address the limitations of traditional diagnostic methods (Sun et al. 2023). AI employs advanced algorithms to analyze large amounts of data, thereby enabling accurate, unbiased, and consistent assessments of mental health disorders (Javaid et al. 2022). Unlike traditional methods, which primarily rely on subjective clinical

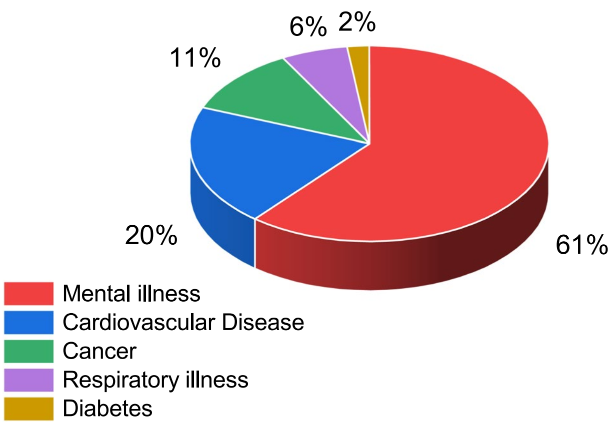


Fig. 1 Projected expenditures of mental health disorders compared to other health conditions (Bloom et al. 2012)

judgments and self-reported symptoms, AI systems can integrate diverse data sources, including genetic data, brain imaging, electronic health records (EHRs), and psychological data from digital devices, to identify patterns and indicators associated with mental health disorders. This multidimensional approach enhances the diagnostic accuracy (Russ et al. 2019; Rivera et al. 2022). This review primarily addresses common psychiatric disorders, including depression, generalized anxiety disorder, bipolar disorder, and schizophrenia, for which AI-based detection and intervention tools have shown considerable promise. Machine learning (ML) provides models for early detection and intervention of mental health disorders. ML can identify patterns and generate precise predictions by using training algorithms on large datasets. ML techniques have facilitated the development of robust algorithms that can handle extensive data and learn from multiple variables (Taye 2023). Deep learning (DL) algorithms applied to EEG signal data have shown improvements in predicting the onset of mental health disorders (Rivera et al. 2022), although EEG data alone may not provide a complete solution for the diagnosis of mental health conditions (Su et al. 2020). DL has emerged as a powerful tool for analyzing complex and unstructured data including text, images, and EEG signals (Javaid et al. 2022). DL architectures, such as long short-term memory networks (LSTMs), recurrent neural networks (RNNs), and convolutional neural networks (CNNs) are used to automatically extract intricate patterns and features from raw data. In mental health research, DL algorithms can identify behavioral signals and subtle biomarkers that may indicate various mental health disorders (Russ et al. 2019). AI-based solutions can also facilitate continuous patient monitoring and provide real-time insights and personalized care recommendations, which are particularly valuable for managing chronic mental health conditions (Basu and Nath 2024). Computer vision and DL algorithms can analyze facial expressions and emotions to detect subtle changes that may suggest underlying conditions such as BD or anxiety. AI can leverage CNNs and DL techniques on brain imaging data to pinpoint structural and functional abnormalities and identify biomarkers associated with mental illnesses. Natural language processing (NLP) algorithms can analyze text data from various sources, including social media posts, therapy session transcripts, and patient records, to identify linguistic markers indicative of mental health disorders (Calvo et al. 2017). Wearable AI technology can collect and analyze physiological data, such as heart rate, sleep patterns, and activity levels, enabling early intervention and continuous monitoring of conditions such as depression and anxiety (Pan et al. 2020; Sameh et al. 2024). Explainable AI (XAI) has several crucial applications in mental health research. It enhances diagnostic transparency by providing detailed explanations of AI-generated diagnoses and fostering trust among healthcare professionals. Recent studies have emphasized that XAI is essential for increasing the clinical adoption of AI by making decisions more interpretable and actionable (Rosenbacke 2024; London 2019). It also facilitates the identification and mitigation of biases in algorithms, ensuring equitable treatment by promoting transparency in AI decision making. Assistive robotics holds significant potential in mental healthcare by offering unique support to individuals with mental health disorders. These robots can provide companionship and social interaction, alleviating symptoms such as loneliness and isolation, which are frequently comorbid with conditions such as anxiety and depression (Rabbitt et al. 2015; Ali et al. 2019) and can assist individuals with cognitive impairments by aiding with daily tasks such as medication reminders. Equipped with sensors and AI algorithms, supportive robots can monitor behavioral and mood changes, detect early signs of mental health crises, and enable timely interventions (Rathnayaka et al. 2022).

Mirror therapy is exploring new applications in mental health, when combined with AI. By adapting visual feedback, AI enhances mirror therapy for psychological conditions such as eating disorders and body dysmorphic disorders. This can help patients address and improve their body image by creating visual representations that offer positive reinforcement. The integration of AI with mirror therapy enables flexible and real-time interventions, improves both mental and physical health, and makes it a more effective and personalized tool (Washington et al. 2020). The convergence of AI with augmented reality (AR), virtual reality (VR), and mixed reality (MR) technologies has great potential to enhance mental health treatment by creating dynamic environments for training, support, and therapy (Stone 2020). These approaches are particularly valuable for treating anxiety disorders through exposure therapy, allowing patients to confront their fears in safe and controlled settings using personalized scenarios. AR, VR, and MR technologies can also assist individuals with autism or social anxiety by providing realistic social situations that boost confidence in social interactions (Karami et al. 2021). They can enhance cognitive-behavioral therapy by developing interactive simulations to help patients modify their maladaptive thought patterns. These immersive technologies have empowered mental health professionals to improve their diagnostic and therapeutic skills. AI has been employed to improve the diagnosis of mental health conditions in several ways and has the potential to overcome the limitations of traditional diagnostic methods, which often rely on subjective assessments, self-reported symptoms, and clinical observations. AI addresses these challenges by leveraging its ability to analyze massive datasets, identify complex patterns, and generate unbiased, data-driven assessments. AI algorithms can process data from various sources including clinical records, EHRs, social media data, sensor data, and other nonclinical sources (Amirahmadi et al. 2023; Rehman et al. 2021). Despite the immense potential of AI in diagnosing mental health disorders, several gaps persist in the literature. Many studies have been limited by their small sample sizes and short-term assessments, hindering the robustness and generalizability of their findings. Most research has focused on single data modalities, neglecting the integration of multimodal data sources such as combining text, speech, facial expressions, and physiological data, which is crucial for capturing the full complexity of mental health disorders. There is also a need for research on the privacy and ethical implications of AI in mental health. Further research is required to develop transparent AI models that safeguard patient privacy and address potential biases in the algorithms and data. Moreover, the lack of standardized protocols in the literature has slowed the adoption and scalability of AI solutions in the healthcare sector. All abbreviations are defined at first use and consolidated in Table 1.

2 Research methodology

The review study protocol is described in the following five subsections.

2.1 Scope of the review

This review aims to explore and evaluate the applications of AI and assistive technologies in the diagnosis and treatment of mental health conditions. It provides a comprehensive overview of prior research and findings, summarizing the current state of AI research in

Table 1 Abbreviations table

Abbreviation	Definition
AI	Artificial intelligence
ML	Machine Learning
DL	Deep Learning
NLP	Natural Language Processing
EHR	Electronic Health Record
EEG	Electroencephalogram
ECG	Electrocardiogram
BCI	Brain–Computer Interface
VR	Virtual Reality
AR	Augmented Reality
MR	Mixed Reality
XAI	Explainable Artificial Intelligence
PRISMA	Preferred Reporting Items for Systematic Reviews and Meta-Analyses
ROC	Receiver Operating Characteristic
AUC	Area Under the Curve
AUROC	Area Under the Receiver Operating Characteristic
SVM	Support Vector Machine
KNN	*k*-Nearest Neighbors
RF	Random Forest
CNN	Convolutional Neural Network
RNN	Recurrent Neural Network
LSTM	Long Short-Term Memory (network)
ASD	Autism Spectrum Disorder
MDD	Major Depressive Disorder
PTSD	Post-Traumatic Stress Disorder
OCD	Obsessive–Compulsive Disorder
DBS	Deep Brain Stimulation

Table 2 Research questions addressed in this review

Sn.	Research question
1	How can artificial intelligence improve the accuracy of mental health diagnoses compared with traditional methods?
2	What are the key applications of machine and deep learning in the detection of mental health disorders?
3	What are the research gaps in current AI-driven approaches to the diagnosis of mental health conditions and interventions?
4	How can emerging technologies, such as wearable devices, virtual reality, and assistive robotics contribute to mental health interventions?

diagnosing and treating mental-health conditions. This review addresses the need for AI-driven approaches to improve diagnosis and intervention efficacy. Table 2 lists the research questions addressed in this study.

2.2 Search strategy

To ensure transparency and reproducibility in identifying the literature, we systematically searched five major academic databases: SCOPUS, Web of Science, Google Scholar, PubMed, and APA PsycInfo. The search was conducted for articles published between 2011 and 2025 using a combination of Boolean operators and keyword-based search strings relevant to AI, digital therapeutics, and mental health. Table 3 summarizes the search strings used for each database. The inclusion of PubMed and PsycInfo ensured the representation of clinically relevant and psychology-focused literature. Figure 2 shows the distribution of included articles by publisher. The results highlight the interdisciplinary nature of AI and mental health research, with contributions spanning computer science, healthcare, and psychology domains. Additional methods, such as citation chaining (forward and backward) and expert consultation, were employed to identify missed but relevant studies. Figure 3 shows the PRISMA flow diagram used to guide the inclusion process of this review.

2.3 Inclusion and exclusion criteria

We established clear criteria for selecting relevant studies to minimize bias. We included only peer-reviewed articles that focused on the diagnosis of mental health conditions and interventions based on machine and deep learning approaches. Articles inaccessible or irrelevant to the topic were excluded. Table 4 lists the inclusion and exclusion criteria used for study selection. Some articles could not be retrieved owing to paywall restrictions or broken DOI links. The study selection procedure is described in the PRISMA flow diagram (Fig. 3. While PRISMA is conventionally applied to systematic reviews, we used a simplified version to visually represent the screening and selection process of our narrative review.). We conducted a comprehensive literature search across multiple databases to minimize publication bias. Google Scholar was used for broad discovery; SCOPUS and Web of Science ensured the inclusion of high-impact, peer-reviewed studies. Duplicates were automatically detected using Zotero and were manually removed. To ensure the methodological rigor of the included studies, we performed a formal quality appraisal as part of the selection

Table 3 Search queries used for literature extraction from various databases

Database	Search query
Web of Science	TS=(“artificial intelligence”) AND TS=(“depression” OR “anxiety”) AND TS=(“digital therapeutics” OR “intervention” AND “detection”) AND PY=(2011–2025)
Scopus	TITLE-ABS-KEY ((“artificial intelligence”) AND (“depression” OR “anxiety”) AND (“digital therapeutics” OR “intervention” AND “diagnosis” OR “mental health support”)) AND (PUBYEAR >2010 AND PUBYEAR < 2025) AND (LIMIT-TO (DOCTYPE, “ar”) OR LIMIT-TO (DOCTYPE, “re”))
Google Scholar	(intitle:“artificial intelligence”) AND (“digital therapeutics” OR “AI-assisted therapy”) AND (“depression” OR “anxiety”) AND after:2010 before:2025
PubMed	(“artificial intelligence”[Title/Abstract] OR “deep learning”[Title/Abstract]) AND (“depression”[Title/Abstract] OR “anxiety”[Title/Abstract]) AND (“digital therapeutics”[Title/Abstract] OR “diagnosis”[Title/Abstract]) AND (“2011/01/01”[Date - Publication] : “2025/12/31”[Date - Publication])
PsycInfo (EBSCOhost)	(TI “artificial intelligence” OR TI “machine learning” OR TI “deep learning”) AND (TI “depression” OR TI “anxiety”) AND (TX “intervention” OR TX “diagnosis” OR TX “digital therapeutics”)

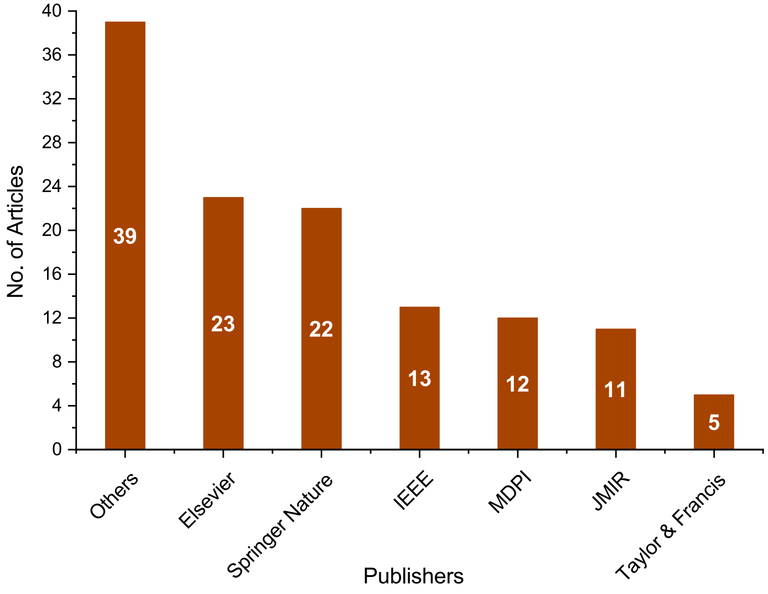


Fig. 2 Literature distribution by publisher

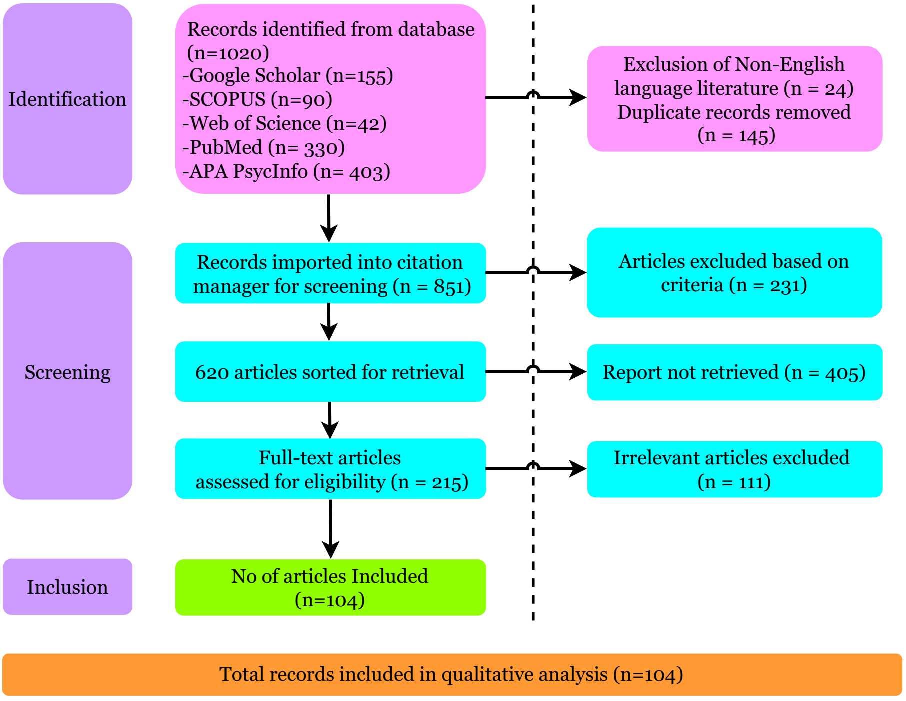


Fig. 3 PRISMA flow chart

Table 4 Inclusion and exclusion criteria for AI in mental health study selection

Inclusion criteria	Exclusion criteria
Peer-reviewed journal articles published between 2011 and 2024	Non-peer-reviewed sources (e.g., blogs, editorials, and preprints without peer review)
Studies that explicitly focus on the diagnosis of mental health conditions or interventions utilizing AI-driven approaches (e.g., ML, DL, NLP, wearable sensors, and digital therapeutics)	Studies not addressing mental health directly (e.g., general healthcare or neurology-focused AI studies without psychiatric relevance)
Articles employing empirical, experimental, or review-based methodologies relevant to AI in mental health	Duplicate publications or inaccessible full-text
Papers written in English and accessible in full-text format	Articles focused solely on theoretical AI without application to mental health contexts

process. For quantitative and mixed-methods studies, we used the Joanna Briggs Institute's (JBI) Critical Appraisal Checklist (Joanna Briggs Institute (JBI) 2024), focusing on study design appropriateness, sample representativeness, statistical validity, and outcome measurement clarity. Only studies that met the minimum quality threshold and demonstrated sufficient methodological transparency and relevance were included in the final narrative synthesis. This dual-tool appraisal approach helped enhance the reliability of the review outcomes.

Critical appraisal and influence on inclusion. Two authors independently appraised each full text using the JBI checklist corresponding to the closest study design (Diagnostic Test Accuracy for model development/evaluation and screening studies; Randomized Controlled Trials for intervention trials; Cohort or Analytical Cross-sectional for observational designs). Non-empirical items (e.g., reviews, scoping/bibliometric articles, commentaries/perspectives, book chapters, theses) and retracted papers were excluded at appraisal. Disagreements were resolved by consensus. Study-level appraisal judgments informed inclusion as follows: (i) empirical studies meeting minimum standards for sampling/measurement validity and analysis were included; (ii) studies with important shortcomings (e.g., unclear sampling, missing validation) were included with caveats and were downgraded in the narrative synthesis; and (iii) studies with critical flaws were excluded. Item-level JBI ratings for all included studies are provided in Supplementary Table 10. No included studies required Critical Appraisal Skills Programme (CASP) because none were qualitative or mixed-methods.

2.4 Content analysis and reporting

The included studies were analyzed and synthesized using a narrative synthesis approach. The MAXQDA software was used for qualitative analysis. The results were categorized as diagnostic and therapeutic interventions to address research gaps. Across included studies, the most frequent methodological concerns were small samples, limited external validation, and incomplete handling of confounders; nevertheless, most met core criteria for outcome validity and appropriate analyses.

2.5 Bibliographic analysis

The trends of the publications were examined to summarize and analyze the characteristics of the included studies. Most of the studies were published after 2018, with major contributions from Europe and North America. This corpus includes various methodological approaches and comprises both original research publications and systematic reviews. Figure 4 illustrates the distribution of included literature by publication year, spanning from 2011 to 2025.

This study follows a structured methodology, as shown in Fig. 5. It begins with an analysis of the contributions of AI to mental health diagnostics with an emphasis on recent advancements in identifying and evaluating psychological conditions. The discourse then proceeds to discuss the role of AI in mental health treatments, specifically, its applications in therapeutic contexts and personalized patient care. It then goes to emerging trends and shows innovative technologies that are on the verge of revolutionizing mental healthcare. This is followed by a critical review of the potential benefits and limitations of these technological advancements. This paper outlines some areas of future research. Finally, the conclusion brings together key findings and implications for the future of AI in mental health.

3 AI role in diagnosis of mental health conditions

AI is advancing the field of mental health diagnostics by utilizing advanced techniques to improve the precision and efficacy of the diagnosis of various diseases. AI approaches, such as ML and DL algorithms, have shown significant potential for diagnosing mental health conditions. In this section, we discuss several mental health diseases and the AI techniques used for their diagnoses (Lee et al. 2021; Javaid et al. 2022).

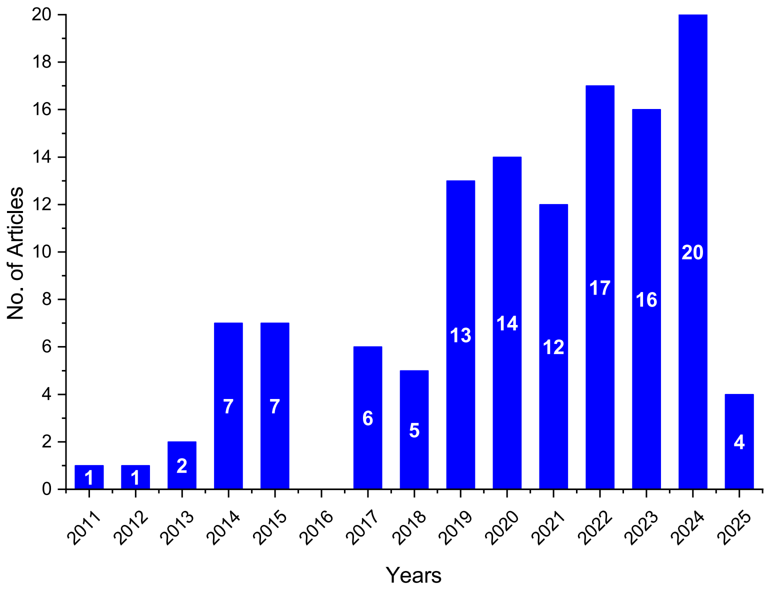
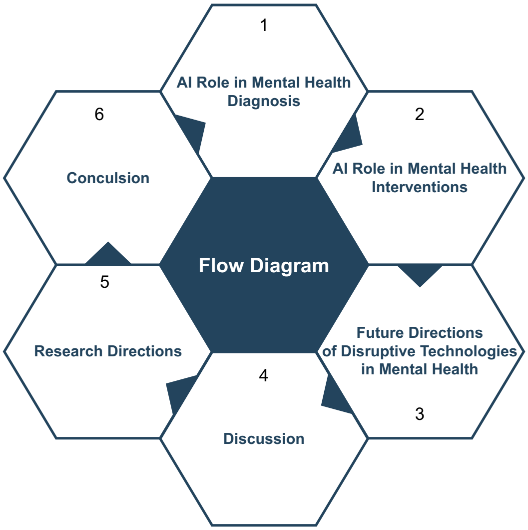


Fig. 4 Literature distribution by year

Fig. 5 Paper flow diagram



3.1 Approaches for emotions classification

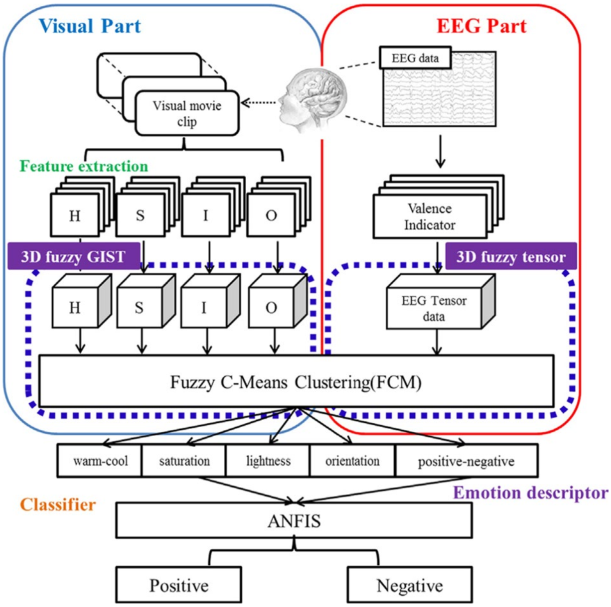
While emotion recognition systems provide a valuable affective context, they do not equate to a psychiatric diagnosis. These technologies are intended to support emotional-state detection, which may contribute to broader diagnostic assessments (Rivera et al. 2022). Lee et al. (2014) proposed an emotion recognition system utilizing EEG signals and facial expressions. In this study, two 3D fuzzy feature extraction methods, 3D Fuzzy GIST, were used to extract low-level visual features, such as color and orientation, and a 3D Fuzzy Tensor was used to extract semantic brain features from EEG signals. Moreover, this study presents an Adaptive Neuro-Fuzzy Inference System to classify two emotional states (positive and negative valence).

Figure 6 shows their emotion recognition system. Wang et al. (2014) developed a system for emotional state classification based on EEG data by the comparison of three different types of features,power spectrum, wavelet and nonlinear dynamical analysis. Researchers introduced the Linear Dynamic System (LDS) method to reduce noise, which helped improve emotion classification accuracy. Siddiqi et al. (2015) developed a facial emotion recognition (FER) system using an active contour model. To reduce the distance between faces and optimize the distance between the context and the face. The researchers used the *Bhattacharyya* and *Chan–Vese* energy functions. The FER using active contour-based face detection is shown in Fig. 7.

To analyze occluded facial regions and address potential biases, Li et al. (2013) proposed a CNN model with the attentional focus function of an attentional Convolutional Neural Network (ACNN). Their approach first combines various representations of facial regions of interest (ROIs) and then employs a gate unit to determine an adaptive weight based on the importance of each area. Figure 8 shows face recognition using the Kinect.

Jung et al. (2015) proposed a FER system employing two CNN models with distinct characteristics. This approach involves two primary stages: extracting presence features from images, and extracting temporal geometry features from facial landmark points. To

Fig. 6 The framework for emotion recognition system while watching a movie clip (Lee et al. 2014)



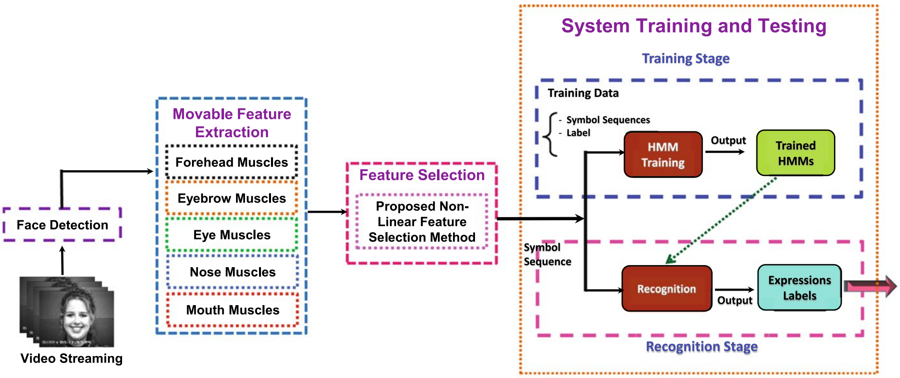


Fig. 7 Architectural diagram for the facial expression recognition (FER) system (Siddiqi et al. 2015)

improve the FER efficiency, these models were integrated using a novel approach. The proposed deep network architecture for facial landmark detection is shown in Fig. 9.

Zheng and Lu (2015) proposed a deep neural networks (DNNs) approach for emotion recognition. Among several models, including SVM, LR, and KNN, the DBN model achieved the highest accuracy of 86.08%, thereby highlighting its superior feature extraction capabilities. Figure 10 shows the emotional brain computer interface cycle. Table 5 presents an overview of the ML and DL techniques used for emotion classification.

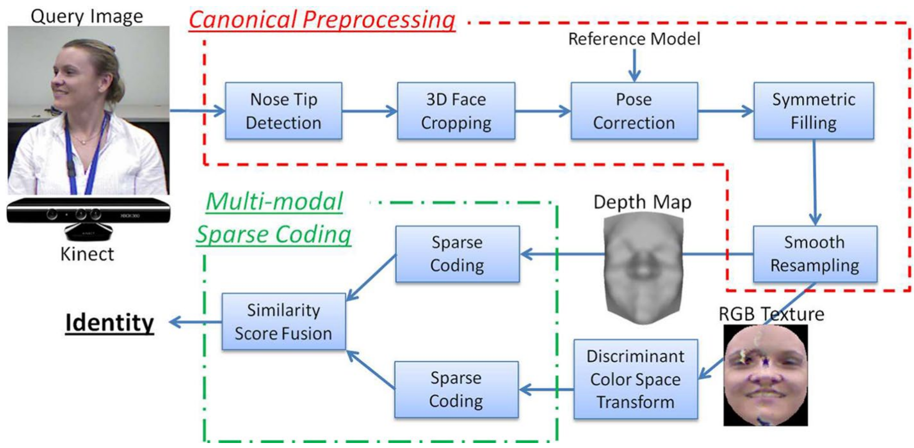


Fig. 8 Using kinect for face recognition under varying poses and expressions (Li et al. 2013)

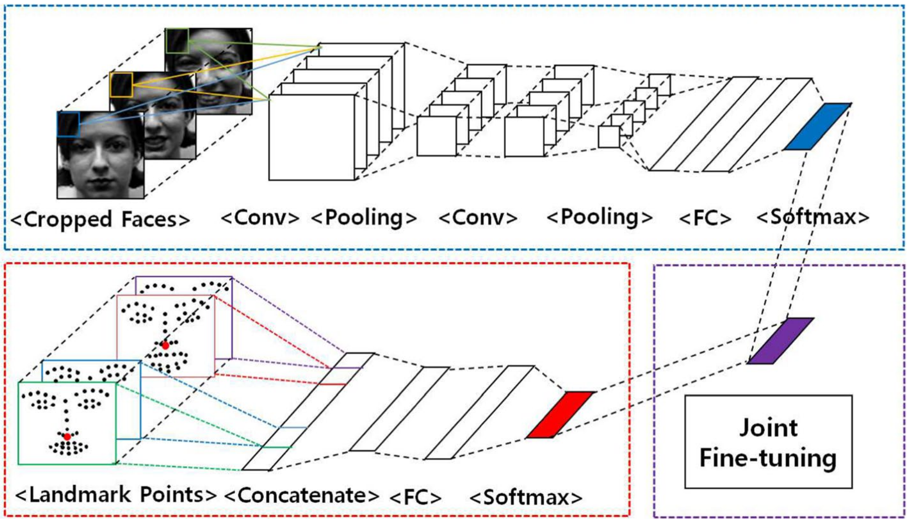


Fig. 9 Joint fine-tuning in deep neural networks (DNN) for facial expression recognition (Jung et al. 2015)

3.2 AI approaches for depression detection

Depression diagnosis has undergone significant advancements through various novel approaches including textual data analysis, voice analysis, and the use of EEG signals. Sharma et al. (2018) proposed a computer-aided depression diagnosis system utilizing a newly designed bandwidth duration localized (BDL) three-channel orthogonal wavelet filter bank (TCOWFB). This method yielded noteworthy results, demonstrating the potential of three-channel filter banks for improving the signal analysis resolution. Shin et al. (2021) explored voice analysis as a biomarker for major and minor depressive disorders, given their

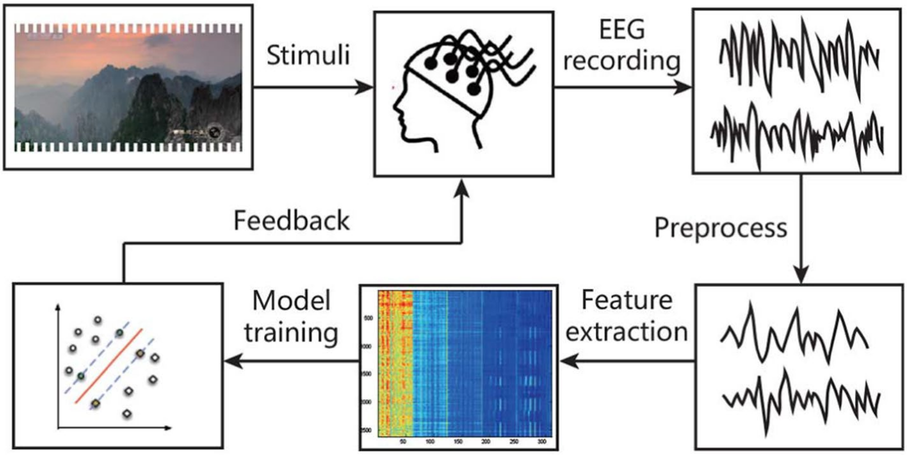


Fig. 10 Emotions based brain–computer interface cycle (Zheng and Lu 2015)

Table 5 Overview of emotion classification techniques and their performance

Sn.	References	Method/techniques	Accuracy	Key points
1	Lee et al. (2014)	3D Fuzzy GIST, 3D Fuzzy Tensor, ICA, STFT, ANFIS	NA	Utilizes visual and EEG features from movie clips; integrates fuzzy clustering and ANFIS for emotion recognition
2	Wang et al. (2014)	Power Spectrum, Wavelet, Nonlinear Dynamical Analysis, LDS, Manifold Learning, LDA	91.77%	Compares EEG feature types and smoothing methods; achieves high accuracy with LDA and effective emotion tracking
3	Siddiqi et al. (2015)	Active Contour Model, Chan–Vese Energy, Bhattacharyya Distance, Wavelet Decomposition, Optical Flow, SWLDA, HMM	99.33% (Yale B), 99.50% (FEI)	Emphasizes robust face detection and feature extraction; achieves high accuracy across multiple datasets
4	Li et al. (2013)	Facial Symmetry, Sparse Approximation, Discriminant Color Space, Kinect 3D Sensor	96.7% (RGB-D), 88.7% (noisy depth)	Demonstrates effective use of low-resolution 3D sensors for face recognition; handles varied poses and conditions
5	Jung et al. (2015)	DTAN (Temporal Appearance Features), DTGN (Temporal Geometric Features), Integration Method	NA	Integrates appearance and geometric features; outperforms weighted summation and feature concatenation
6	Zheng and Lu (2015)	Deep Neural Networks, SVM, LR, KNN	86.08% (DBN)	DBN achieves highest accuracy; excels in feature extraction

significant global social and health impacts. This study highlights the utility of vocal characteristics in accurately and sensitively identifying depression severity (Spinrad et al. 2024).

To enhance feature extraction from EEG signals for depression classification, Liu et al. (2014) introduced a method based on differential evaluation crossover mutation. This approach demonstrated superior accuracy in differentiating moderate depression from normal participants using a kernel neural network for classification, underscoring the effectiveness of differential evolution in feature optimization. Mantri et al. (2015) proposed a depression diagnosis system based on EEG signals, employing Fast Fourier Transform (FFT) and an SVM algorithm. This study demonstrated the efficacy of FFT in converting EEG signals into the frequency domain and how its combination with an Artificial Neural Network (ANN) can lead to improved classification (Akmal et al. 2022; Anik et al. 2024). For depression detection using textual data, Amanat et al. (2022) presented a DL model utilizing LSTM and an RNN, achieving an impressive accuracy rate of 99%. Through extensive preprocessing and feature extraction, this strategy outperformed traditional approaches, demonstrating the potential of advanced neural network techniques for early depression identification. Figure 11 outlines the fundamental process for detecting depressive text in tweets by applying pre-processing and feature engineering steps to the data.

To identify depressive disorder symptoms from text data, Uddin et al. (2022) introduced a novel approach using an LSTM-based RNN. This method offers robust and accurate detection of depression, providing a promising tool for real-time mental health care. A visual search model proposed by Li et al. (2017) to investigate mental retardation in depression found that depressed individuals had longer scan path lengths and durations, indicating greater difficulty and lower effectiveness in processing emotional faces.

Table 6 outlines the different approaches for identifying depression categories, with a special focus on the techniques, accuracy, and key characteristics.

3.3 AI in detection of bipolar and unipolar disorders

Jadhav et al. (2019) proposed an approach to detect BD using a ML technique Decision Tree Classifier (DTS) based on the Mood Disorder Questionnaire (MDQ). The classifier was trained using data collected from various regions, and it successfully identified important factors contributing to BD. The MDQ approach shows promise for early diagnosis and can be used in clinical and educational settings. BD is often misdiagnosed as a major depressive disorder (MDD). Tomasik et al. (2021) addressed this major problem of misdi-

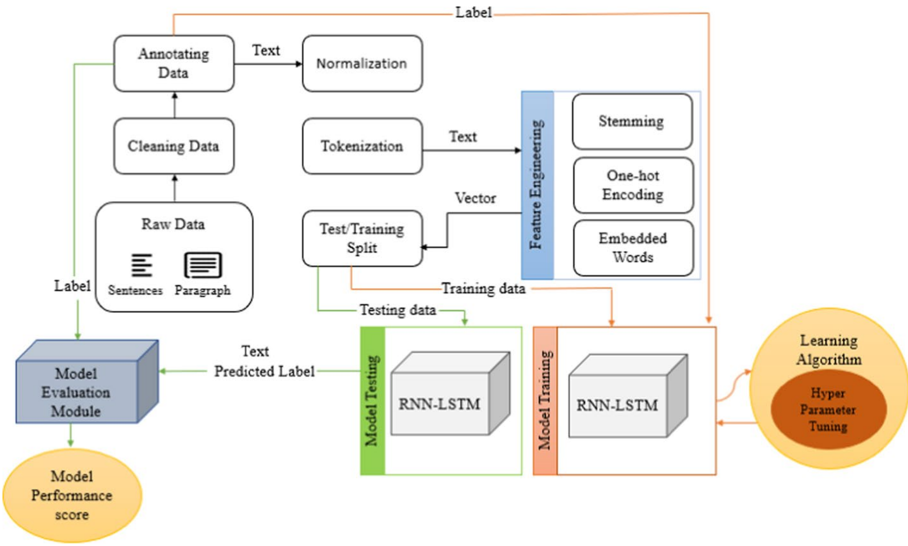


Fig. 11 Depressive tweet classification using preprocessing and feature engineering (Amanat et al. 2022)

Table 6 Summary of techniques and performance in identifying depression categories

References	Method/tech.	Identified depression categories	Accuracy (%)	Key points
Sharma et al. (2018)	Three-channel orthogonal wavelet filter bank	Dominance, Valence, Arousal	78.06 and 58.90	Enhancing signal resolution with three-channel filter banks
Shin et al. (2021)	Voice analysis	Major, Minor, Not Depressed	65.9 AUC	Vocal features can differentiate between major, minor, and non-depressed individuals
Liu et al. (2014)	Differential evaluation cross-over mutation	Mild Depression, Normal	NA	Optimized features from EEG signals, effective in distinguishing mild depression
Mantri et al. (2015)	Fast Fourier Transform and SVM	Normal, Depressed	84	Highlighting the alpha band's role in distinguishing depression
Amanat et al. (2022)	LSTM and RNN for textual data	NA	99	Extensive data preprocessing and feature extraction led to superior performance over traditional methods (Naive Bayes, SVM, CNN)
Uddin et al. (2022)	LSTM-based RNN for textual data	NA	98–99	Used one-hot encoded features representing depressive symptoms, outperformed traditional word frequency based methods
Li et al. (2017)	Visual search model	Happy, Sad, Neutral	NA	Depressed patients show longer scanpath durations and lengths, indicating lower efficiency in processing emotional faces

agnosis of mood disorders. Their study aimed to develop a diagnostic algorithm to increase the accuracy of BD diagnosis by using blood biomarker data and an online questionnaire. Their model successfully distinguished between bipolar illness and MDD with a mean test AUROC of 0.92 using extreme gradient boosting and nested cross-validation. The effectiveness of Early Detect (ED), a combined screening application for BD, was investigated by Yang Liu et al. (2021) and compared to MDQ. The ED application outperformed MDQ in terms of sensitivity and specificity, achieving an accuracy of 80.6 Mumtaz and Qayyum (2019) developed an EEG-based DL framework for diagnosing unipolar depression. The framework employs one-dimensional convolutional neural networks (1DCNNs) coupled with LSTM. This framework presents an affordable and non-invasive alternative to traditional diagnostic techniques. The architecture of the proposed model is illustrated in Fig. 12 through a block diagram.

3.4 Mental stress detection

In this context, stress detection refers to physiological signal-based assessments of stress indicators, not formal psychiatric diagnoses. These methods support early intervention rather than diagnostic classification. Stress detection research has utilized various approaches and strategies to accurately determine stress levels using physiological signals and ML algorithms. Ahuja and Banga (2019) investigated college students' stress levels before exams and during internet use. They employed SVM, Naïve Bayes, Random Forest, and Linear Regression for data analysis, with SVM achieving the highest accuracy of 85.71%. Li and Liu (2020) applied DNN, including a Multilayer Perceptron (MLP) and 1D-CNN, to classify stress and emotions from physiological data collected via wrist and chest worn sen-

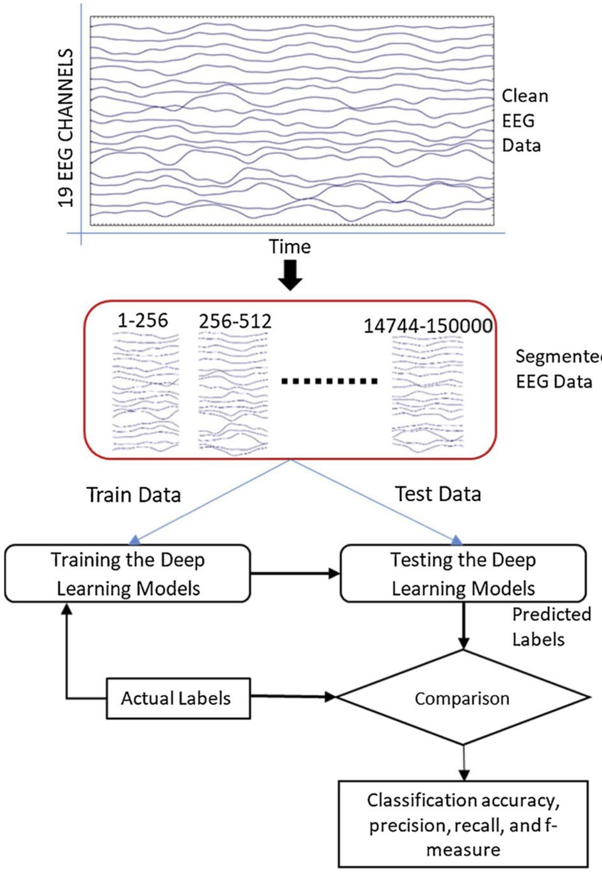


Fig. 12 Architecture of a machine learning model for automated depression diagnosis (Mumtaz and Qayyum 2019)

sors. Their technique exhibited exceptional performance, reaching an accuracy as high as 99.80%. Xiao et al. (2018) proposed that SVM and PCA classifiers, utilizing brain signals, can effectively detect mental stress.

In recent years, the use of ECG data for mental stress detection has gained significant attention. Bin Heyat et al. (2022) developed an automatic mental stress detection system using ECG signals captured by a smart T-shirt. To classify stress levels, they applied different ML classifiers, including DT, Naive Bayes, Random Forest, and Logistic Regression. The DTS outperformed the others, achieving an accuracy of 93.30% with intra-subject classification and 94.10% with inter-subject classification. Figure 13 illustrates the workflow of the research, including ECG signal recording, feature extraction, and classification using DT, NB, RF, and LR classifiers.

To perform individualized stress analysis, Garg et al. (2021) used wearable patches to monitor the ECG data. Different approaches for detecting stress levels, ranging from conventional classifiers like Naive Bayes and SVM to more advanced algorithms such as DNN and PCA-based SVM, are shown in Table 7.

Kim et al. (2020) developed a DL model to assess users' mental states based on their Reddit posts, targeting mental disorders like depression, anxiety disorder, BD, borderline personality disorder, schizophrenia, and autism. The model demonstrated a strong perfor-

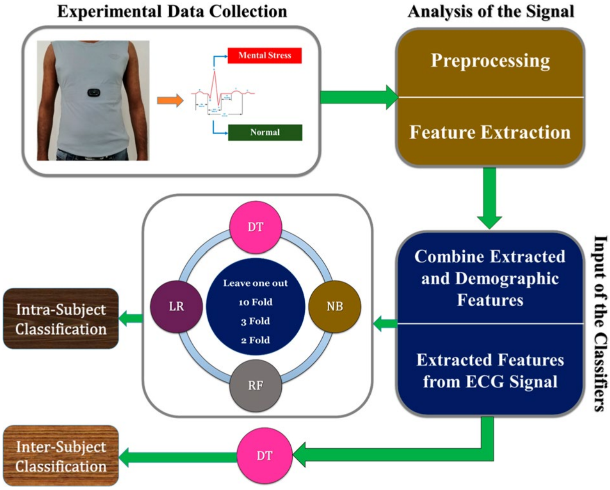


Fig. 13 Automatic mental stress detection system using an ECG signals (Bin Heyat et al. 2022)

Table 7 Summary of methods and techniques used for stress detection and their performance

Sn.	References	Method/tech.	Stress levels detected	Accuracy	Key points
1	Ahuja and Banga (2019)	Linear Regression, Naïve Bayes, Random Forest, SVM	Stress levels before exams, during internet use	85.71%	Analyzed stress in students; recommended Perceived Stress Scale (PSS) for early detection
2	Li and Liu (2020)	1D-CNN, MLP	Stressed vs. non-stressed, baseline, stressed, amused	1D-CNN: 99.80%, MLP: 99.65%	Used deep neural networks for high accuracy in stress and emotion classification
3	Xiao et al. (2018)	PSD-based Feature Extraction, PCA for Dimension Reduction, SVM Classifier	Mental fatigue in assembly operators	95%	Highlights significant variation in individual performances
4	Bin Heyat et al. (2022)	Machine Learning Classifiers (DT, NB, RF, LR)	Mental stress in researchers (after 12 h of continuous work)	DT Classifier: 93.30% (intra-subject), 94.10% (inter-subject)	Highlights the DT classifier's superior performance and potential for big data applications
5	Garg et al. (2021)	Naive Bayes, Decision Tree	Low, medium, high stress levels	Naive Bayes: 100% (high stress), J48: 98%	Focused on personalized stress analysis using ECG monitoring via wearable patches

mance in identifying these conditions from textual content, offering a potential supplementary tool for mental health monitoring among social media users. Recent advancements in neuroimaging and DL have significantly enhanced diagnostic approaches for major psychiatric disorders, such as depression, anxiety, and bipolar disorder. Li et al. (2022) developed a neuroimaging-aided diagnostic system using novel DL networks with attentional mechanisms. Applied to a large dataset of brain structural images, this system outperforms traditional methods in classifying major mental disorders such as MDD, BD, Schizophrenia, and

Obsessive-Compulsive Disorder (OCD). Its design, which incorporates voxel-level features and attention mechanisms, offers a closed-loop diagnostic tool that adapts and improves based on clinical feedback. Djemal et al. (2017) proposed a computer-aided diagnosis system for autism spectrum disorder (ASD) using EEG signals, combining discrete wavelet transform (DWT), Shannon entropy, and an artificial neural network (ANN). EEG signals were decomposed into subbands using DWT, and entropy-based features were extracted to train the ANN. The optimized system with overlapping segments achieved a classification accuracy of 99.7% using real EEG data from King Abdulaziz Hospital. Shafiei et al. (2020) proposed a system to diagnose the mental health status of patients with cancer using a deep neural network that combines CNN and LSTM techniques. This system monitored three mental health metrics (anxiety, mental well-being, and hope) using questionnaires (HPOE, STAI, and WEMWBS), achieving classification accuracies of 93.81%, 94.76%, and 95.00%, respectively.

4 AI role in mental health interventions

AI transforms mental healthcare through personalized data-driven approaches that improve the treatment accuracy (Shah 2022). Key examples of current approaches include personalized treatment plans adapted in real time to patient needs, AI-enhanced medication management, and efficient early detection systems evaluating risk factors, such as suicidal thoughts or self-harm. Developments such as virtual reality exposure therapy (VRET) and brain–computer interfaces (BCIs) offer comprehensive and dynamic treatment options, while digital therapeutics, such as AI-driven chatbots and virtual therapists, offer scalable support. Additionally, breakthrough technologies such as gamification and social robotics provide engaging approaches to enhance treatment outcomes (Sun et al. 2023).

4.1 Personalized treatment

AI technology enables the creation of personalized treatment plans by tailoring interventions to each patient's unique needs, representing a significant advancement in mental healthcare. This approach uses AI to integrate and analyze comprehensive patient data including genetic information, demographics, medical history, symptoms, and behaviors (Johnson et al. 2021). By harnessing this wealth of information, AI facilitates the development of highly personalized therapy plans and effective medication strategies.

4.1.1 Customized therapy plans

Advanced AI algorithms can analyze each patient's unique set of symptoms, demographics, medical records, and even genetic information to develop highly personalized therapy plans. These tailored recommendations may include the most suitable therapies, such as dialectical behavioral therapy (DBT), cognitive behavioral therapy (CBT), or mindfulness-based techniques, depending on the individual's condition. Based on a patient's psychological profile and progress, AI can suggest specific exercise regimens (Stein and Nyer 2023). Figure 14 illustrates the four core modules of DBT. AI-driven therapy plans provide a dynamic approach that adapts to a patient's journey. These plans continuously improve recommenda-

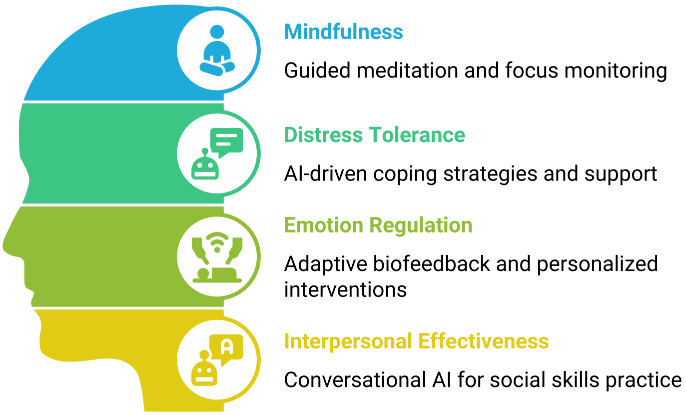


Fig. 14 The core components of Dialectical Behavior Therapy (DBT) (Linehan and Wilks 2015)

tions based on real-time data such as progress metrics and patient feedback. These systems can also help therapists identify minor patterns in symptoms or signs of behavior, which allows for earlier treatment and more tailored therapy sessions.

4.1.2 Medication management

AI systems can help optimize medication selection and dosage by examining the patient's medical history and past treatment responses (Alowais et al. 2023). These algorithms are particularly valuable for challenging mental disorders that require specific pharmaceutical therapies, because they can predict which drugs are likely to be beneficial while minimizing unwanted side effects. AI-driven medication management (Rammal et al. 2024) combines data from multiple sources, enhancing treatment accuracy and leading to improved patient outcomes and adherence to suggested regimens. Figure 15 shows a comprehensive approach that integrates a variety of electronic tools and procedures to expedite medicine delivery and reduce medication errors.

4.2 Early intervention and crisis prevention

AI technologies play a crucial role in enhancing early intervention and crisis prevention, which are two essential components of mental healthcare. By examining a wide range of data sources, including social networking activity, online behavior, patterns of speech, and facial expressions, AI can recognize early warning indicators of suicidal ideation (Dhelim et al. 2023) and self-harm.

4.2.1 Suicide risk assessment

To identify early signs of suicidal ideation (Fonseka et al. 2019), AI models can examine a variety of data sources, such as social media activity, Internet behavior, patterns of speech, and facial expressions. These algorithms can identify high-risk individuals who might otherwise go unnoticed by detecting behavioral changes, emotional shifts, and subtle linguistic

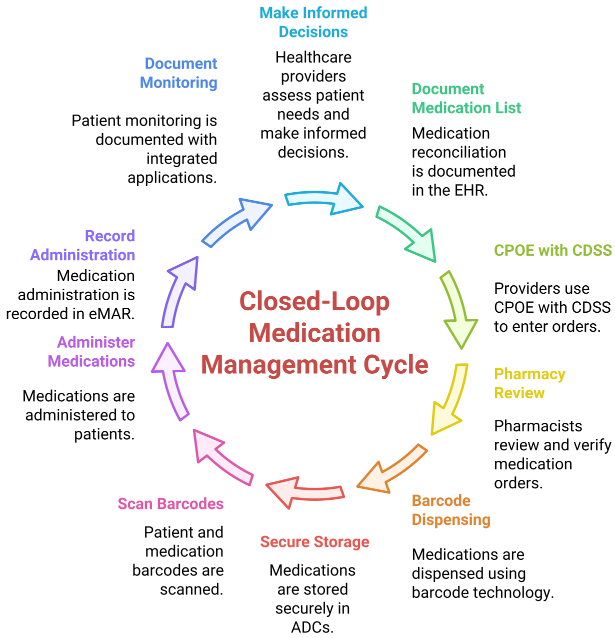


Fig. 15 Closed-loop pharmaceutical administration system for improved effectiveness and safety for patients (Shermock et al. 2023)

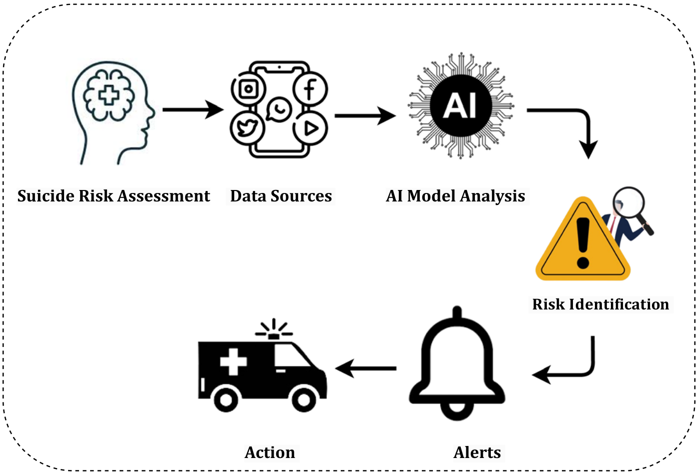


Fig. 16 AI-driven suicide risk assessment

warning signs. AI systems can alert emergency response teams or mental health specialists in real-time, facilitating rapid assistance and outreach. Figure 16 illustrates a system that utilizes AI to analyze data from multiple sources to detect individuals at risk of suicide.

4.2.2 Self-harm detection

AI algorithms are becoming increasingly effective in spotting signs of self-harm by analyzing texts, photos, or videos posted on social networking sites or in private conversations (Ambareen and Meenakshi Sundaram 2023). These models often detect distressing content beyond what human moderation might be able to, such as specific words, keywords, or visual cues, linked to self-harming activities. Upon detection, these systems can automatically notify the emergency response teams or mental health professionals (Kouroubali et al. 2022).

4.3 Digital therapeutics

Digital therapeutics represents a revolutionary development in mental health care by utilizing technology to deliver creative and approachable treatment options. The integration of AI-powered chatbots and virtual therapy systems has shown effectiveness in delivering scalable, accessible, and personalized support. Several digital therapeutic platforms validated in clinical studies have demonstrated promising results in reducing the symptoms of anxiety and depressive disorders (Löchner et al. 2025; Kolenik and Gams 2021).

4.3.1 AI-powered chatbots and virtual therapists

AI-powered chatbots and virtual therapists provide users with personalized guidance, coping methods, and CBT-based therapeutic exercises, in addition to on-demand mental health assistance (Khawaja and Bélisle-Pipon 2023). Through the use of NLP, these chatbots can hold meaningful conversations with users and offer users real-time support for managing symptoms of stress, anxiety, and depressive disorders. Additionally, these online therapists can operate as a link between in-person therapy sessions, providing ongoing supervision and support, while enabling clients to take control of their mental health (Rohrer et al. 2025). Clinical trials of the Woebot chatbot have reported a reduction in depression symptoms with a large effect size (Karkosz et al. 2024). Public-facing AI mental health tools such as Woebot and Wysa have demonstrated high user engagement and accessibility, especially among younger and tech-savvy populations. Woebot has been evaluated in randomized controlled trials for depressive disorder symptoms, whereas platforms such as Wysa have been studied for user engagement and self-reported outcome improvements. However, challenges related to sustained use, cultural adaptability, and trust in automated responses remain the key factors affecting acceptance. Studies have reported mixed results regarding long-term effectiveness, underlining the need for robust clinical evaluation frameworks. Additionally, AI applications have shown promise in the field of mental health nursing by supporting early detection, improving treatment adherence, enabling remote monitoring, and assisting clinical decision making, thus broadening the scope of AI-assisted mental healthcare beyond diagnosis alone (Nashwan et al. 2023; kolenik et al. 2022).

4.3.2 Virtual reality exposure therapy (VRET)

VRET uses safe, controlled virtual environments that gradually introduce patients to things, events, or situations that cause their greatest anxiety. This allows patients to manage their anxiety in a manner that is both safe and monitored. Through the use of realistic environments, such as speaking in front of others traveling or events associated with PTSD, VRET enables therapists to tailor exposure levels and situations based on the patient's development. Furthermore, VRET is a dynamic and interactive therapeutic option that can be employed, in addition to conventional therapies, to increase the overall efficacy of exposure-based interventions (Albakri et al. 2022). Figure 17 shows the process involved in designing and developing a VRET system. In VRET systems, AI models personalize exposure levels by analyzing user responses in real-time (Karthikeyan 2024).

4.4 Brain–computer interfaces

By establishing connections between the brain and external technologies, BCIs have opened new doors for the treatment of mental health problems (Gao et al. 2024; Khorev et al. 2024). These developments have provided novel approaches for mood regulation and mental health management, including deep brain stimulation and neurofeedback.

4.4.1 Neurofeedback for mood regulation

Using BCI technology, neurofeedback tracks brain activity in real-time and provides visual information to help people adjust their brainwaves (Mahmood et al. 2024; Samal and Hashmi 2024). People can enhance their ability to regulate their emotions and better handle stress, anxiety, and depression disorders by learning key brain patterns linked to emotional stability and relaxation. With its customized and collaborative approach to the long-term management of mood and cognitive balance, neurofeedback has been utilized extensively in addition to conventional therapy (Schönenberg et al. 2017). The architecture of the system is shown in Fig. 18 where an individual uses an EEG cap to watch an animated story that is developed in real-time on a monitor as an element of a neurofeedback system that regulates mood.

4.4.2 Deep brain stimulation (DBS)

By delivering electrical impulses to particular brain regions involved in mood and behavioral regulation, AI-guided DBS offers a highly customized approach in situations of serious

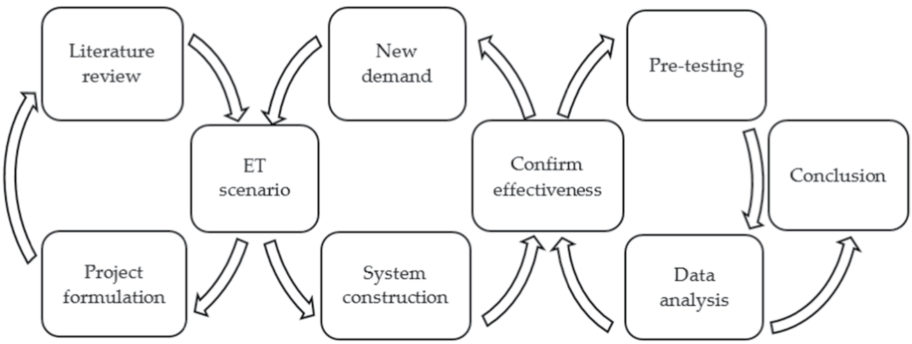


Fig. 17 Process for developing a virtual reality exposure therapy system (Trappey et al. 2020)

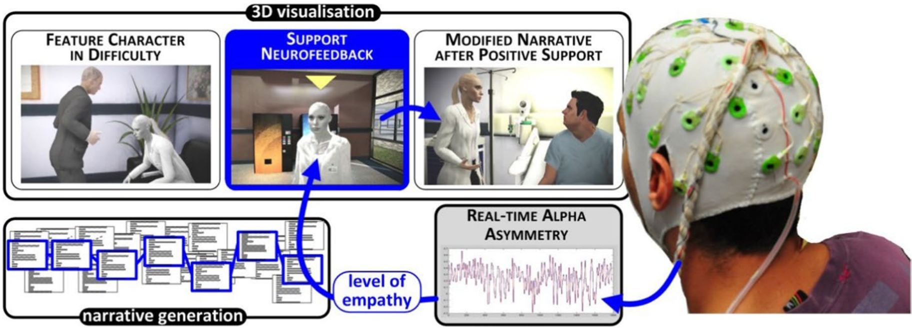
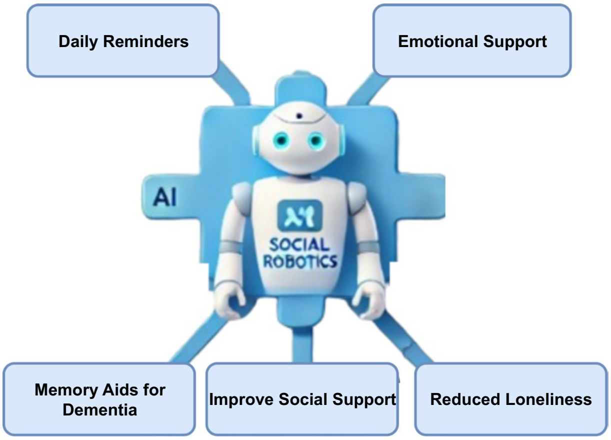


Fig. 18 System architecture of the neurofeedback for mood regulation (Cavazza et al. 2014)

Fig. 19 AI powered social robotics to enhance quality of life



treatment-resistant depression or OCD (Johnson et al. 2024). AI algorithms assist in adjusting stimulation parameters to maximize therapeutic benefits and minimize negative effects by examining the patient data and brain patterns.

4.5 Other emerging interventions

These two innovative methods of social robots and gamification offer unique ways of improving therapy and support.

4.5.1 Social robotics

AI-driven assistant robots have been developed to provide people with disorders such as autism, dementia (Huq et al. 2024), or anxiety about social situations with daily reminders, emotional support, and useful social interactions. These robots can improve communication and social skills among individuals with autism, and serve as memory aids for those with dementia. Social robots can also improve general mental health and quality of life by lowering feelings of loneliness and serving as reliable companions (Chen et al. 2020). Figure 19 illustrating AI-driven social robotics assisting individuals with mental issues.

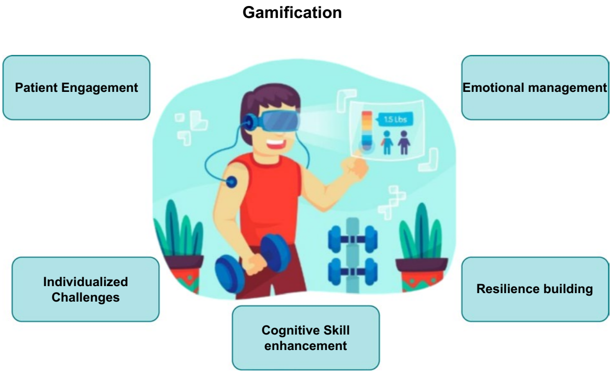


Fig. 20 Gamification in therapy for emotional and cognitive enhancement

Table 8 AI approaches in mental health interventions

Category	Approach	Description
Personalized treatment	Customized therapy plans, medication management	Uses AI to tailor therapies like CBT and DBT based on individual patient data for optimized mental health outcomes. AI also analyzes patient history to optimize drug selection and dosing, improving treatment adherence and outcomes
Early intervention	Suicide risk assessment, self-harm detection	AI models detect early signs of suicidal ideation from data sources like social media and speech patterns. AI algorithms identify signs of self-harm in text and images, providing timely alerts for intervention
Digital therapeutics	AI-powered chatbots and therapists, virtual reality exposure therapy	Offers on-demand mental health support using NLP, providing CBT-based exercises and personalized guidance. VRET uses controlled virtual environments to help patients confront anxieties safely and effectively
Brain–computer interfaces	Neurofeedback for Mood Regulation, Deep Brain Stimulation	Provides real-time feedback to patients to help them regulate brainwaves linked to emotional stability. AI-guided DBS adjusts the brain stimulation to treat severe, treatment-resistant conditions like depression
Emerging technologies	Social Robotics, Gamification	AI-driven robots assist in social and emotional interactions, improving quality of life for individuals with autism or dementia. Gamification incorporates game elements into therapy to enhance engagement and motivation, particularly for resistant patients

4.5.2 Gamification

Gamification integrates enjoyment and competitive elements into therapeutic activities through AI-powered games, which encourage patients to actively engage in medical treatment. AI-powered games can be developed through individualized challenges and benefits to boost emotional management, resilience building, and cognitive skill enhancement. Specifically, for children and those who are resistant to conventional approaches, these gamified experiences make therapy exciting and less terrifying, by adapting to the user's skills and offering immediate feedback (Al-Rayes et al. 2022; Arshad et al. 2024). Figure 20 represents the assistance of Gamification in AI-powered therapeutic activities.

Table 8 presents an overview of the various AI-driven approaches for mental health interventions.

To synthesize the findings across diverse methodologies, we developed a comparative summary table of AI approaches (Supplementary Table 11). This table outlines the clinical utility, implementation requirements, and evidence quality associated with diagnostic and therapeutic applications, offering readers a navigational tool to contextualize the wide range of reviewed technologies. It underscores where the evidence is most robust (e.g. chatbot RCTs, neuroimaging cohorts) and where research remains nascent.

5 Future directions of disruptive technologies in mental health

Future developments in disruptive technologies, such as wearable technology, XAI, assistive robotics, immersive realities (AR, VR, MR), and gene editing, will revolutionize the field of mental health in diagnostics and interventions.

While some of these technologies, such as Neuralink and CRISPR, remain in the early exploratory stages, we have also integrated examples of currently deployed AI-driven tools, such as Woebot, Wysa, and Mindstrong, which are actively used in digital mental health platforms. These real-world applications illustrate how AI already supports patient engagement, continuous monitoring, and early intervention (Prochaska et al. 2021; Wolgast et al. 2025).

5.1 Wearable technologies and AI

Potential future models for the diagnosis of mental health conditions and interventions have been presented in recent developments in wearable technology and AI. Cochrane and Schiphorst (2015) emphasize the need for enhanced design and integration while highlighting the promise of m-Health technology to improve therapist-client interactions for mental health treatment. In their review of wearable and mobile technologies, Bardram and Matic (2020) and Lin et al. (2022) emphasized the importance of verifying clinical measurements and managing data heterogeneity to enhance continuous mental healthcare models. The Carewear project was presented by Debard et al. (2020) and integrated physiological data and self-reports to enhance stress detection and intervention. Long et al. (2022) highlight the use of wearable technology in real-time mental health prediction and recommend for improved data integration and advanced algorithms. The potential benefit of using wearables for high-frequency cognition and mood testing was demonstrated by Cormack et al. (2019) whereas Mélodie Vidal et al. proposed wearable eye tracking as a novel method for mental health monitoring that requires complex algorithms. A recent systematic review demonstrated that AI-powered wearable technologies can reliably detect symptoms of anxiety and depression disorders through the continuous monitoring of multimodal physiological data, supporting their growing role in clinical mental health settings (AlSamhori et al. 2024; Kolenik and Gams 2021). These studies highlight how wearable technology can revolutionize mental health care, while highlighting persistent problems and suggesting directions for further investigation.

5.2 Explainable artificial intelligence

Explainable AI refers to algorithms designed to provide transparent and interpretable outputs, in contrast to black-box models whose internal decision-making processes are opaque. Tools, such as SHAP and LIME, enable stakeholders to understand how input features influence predictions and foster trust in clinical settings. Byeon (2023) demonstrate how XAI could address gaps in mental health services, such as stigma and restricted resources, by using algorithms like SHAP and LIME. A web-based XAI screening tool for Prolonged Grief Disorder (PGD), was developed by She et al. (2022) By using a Random Forest model, their developed model obtained an AUC of 0.772. Using wearable sensors, Moser et al. (2024) presented a unique XAI method for stress prediction. This novel approach not only helps patients and healthcare professionals understand AI choices but also has the potential to be extended to other mental states. For the diagnosis and intervention of schizophrenia disease, Shivaprasad et al. (2024) addressed the use of XAI approaches. A maximum classification accuracy of 86% was achieved in this study, which highlighted significant variables, such as age, sex, and triradius existence. Using tabular medical data, Tang et al. (2024) examined how well the XAI predicts suicide risk. They achieved over 97% accuracy, F1 score, and AUC with their Random Forest model using SHAP for feature importance ranking and integrating ML approaches with data augmentation.

5.3 Assistive robotics

Recent developments in assistive robotics have presented potential methods for improving the diagnosis and treatment of mental-health conditions (Rabbitt et al. 2015). By creating OMMDB, a multimodal dataset that improves the capacity of social robots to recognize deep breathing phases using a convolutional long short-term memory neural network, Matheus et al. (2023) made significant progress in incorporating social robots into anxiety therapies. Expanding upon the application of social robots in mental health, Chen et al. (2018) conducted systematic research to evaluate the effects of these devices on depression in elderly people. Through the application of rigorous evaluation methodologies and data analysis from nine electronic databases, this study determined that social robots have varying degrees of effectiveness in limiting depressive symptoms. Similarly, Dino et al. (2019) evaluated the possibilities of Socially Assistive Robotics (SAR) by creating Ryan, a chatbot intended to provide elderly people with Internet-based CBT. Robots have the potential to improve therapeutic effectiveness and accessibility because they assist in social skills practices and offer constant feedback. The incorporation of social robots into cognitive and behavioral therapy for social anxiety disorders was proposed by Rasouli et al. (2022), who explored the effectiveness of social robots in enhancing PTSD diagnosis and treatment by providing practical and interesting interactions that could improve ongoing symptom monitoring and early identification by encouraging trauma survivors to better control their symptoms.

5.4 Immersive technologies

The immersive technologies offered to address different psychological difficulties are transforming mental-health treatments. While VR provides virtual environments, AR enriches real-world experiences by superimposing digital content, whereas MR seamlessly blends virtual and physical aspects. The revolutionary potential of these technologies in mental healthcare has been demonstrated in a recent study (Stone 2020). Acar et al. (2014) used VRET to treat phobias and obsessions, and they used EEG signals to track anxiety disorder symptoms. When comparing AR and VR for the treatment of claustrophobia, Yeh et al. (2018) concluded that both modes were helpful. However, owing to cost and resource constraints, AR may be more useful for implementation. Syahputra et al. (2018) highlighted how AR may boost therapeutic accuracy and participation in social narrative therapies in children with ASD. A MR system for stroke therapy in the upper limbs was evaluated by Di Loreto et al. (2011) and found that although it has the ability to engage patients, further improvements are required. Mahalil et al. (2014) demonstrated that realistic and immersive surroundings offered by VR-based stress therapy outperformed conventional methods. To customize exposure therapy, Arquissandás et al. (2019) combined AR with physiological monitoring and showed a notable improvement in treatment results.

5.5 Gene editing

Gene-editing technologies, particularly CRISPR-Cas9, are being investigated for their potential to improve the diagnosis and treatment strategies for mental health disorders. These tools enable the precise targeting of genetic and epigenetic elements, which may contribute to more personalized and biologically informed interventions in the future. Tozzo et al. (2020) suggest that gene editing, including CRISPR-Cas9, could become relevant in addressing conditions such as Alzheimer's disease, especially when integrating gender-specific considerations into research design. In a study by Singh et al. (2023), CRISPR-based genome editing was explored for its role in modulating corticosteroid-induced neuropsychiatric disorders (NPDs), such as depression and psychosis. While the potential to target disorder-specific genes is promising, the authors stress the need for future models to improve CRISPR accuracy, delivery systems, and safety mechanisms. Day (2019) reviewed how CRISPR may aid in understanding neural functions and support the development of therapeutic strategies for brain-related genetic conditions. However, they emphasized the early stage nature of these tools and the importance of refining delivery methods in the central nervous system to achieve meaningful clinical outcomes. Finally, Gutiérrez-Rodríguez et al. (2023) cautioned that the complex polygenic nature of psychiatric disorders, along with technical challenges such as mosaicism and off-target effects, must be addressed before widespread application. Ethical concerns, particularly those surrounding germline editing, remain a key consideration for responsible clinical integration.

5.6 Neuralink

Neurostimulation techniques, including emerging work by initiatives such as Neuralink, are being explored for their potential in addressing mental health disorders, such as anxiety and depression (Contreras et al. 2023). While some early stage prototypes show promise in biomarker detection and brain activity monitoring (Deng et al. 2020), these technologies remain largely experimental. The current clinical utility of BCIs is limited, and ethical, technical, and safety concerns must be carefully addressed. Ongoing advancements in neurotechnology and AI-guided neural signal analysis may eventually contribute to more personalized interventions; however, substantial interdisciplinary validation is still required before widespread clinical deployment (Ienca and Andorno 2017). Table 9 provides an overview of AI techniques used in mental health interventions. Each technique is detailed with its specific application and impact on improving mental health treatment.

6 Discussion

Although there has been much advancement and potential in the field of ML and DL for diagnosing and intervening in mental health conditions, there are still several challenges to overcome. The review studies show how various ML and DL approaches, such as SVM, KNN, and LSTM networks, function well in identifying mental health problems from a variety of data sources, such as speech patterns, social media activity, EHRs, textual data, and EEG signals. However, the literature also highlights the complexity and variety of mental health conditions, and calls for more advanced and flexible treatment methods (Lu et al. 2025). The increasing effectiveness of XAI in improving the transparency and reliability of diagnostic models is one of the most important topics of review. As diagnosing mental health disorders involves interpreting complex patterns in data, the clinical adoption of the model depends on the model's explanation of decisions. Furthermore, the use of NLP to analyze social media interactions and therapy session transcripts has the potential to iden-

Table 9 Summary of disruptive technologies for diagnosing and treating mental health conditions

Technology	Approach	Description
Wearable Technologies	m-Health Technology, Eye Tracking, High-Frequency Cognition Testing	Mobile health applications use AI to provide personalized mental health support and real-time monitoring based on user data. Eye-tracking technology monitors eye movements and detects issues like cognitive decline and stress. AI also performs high-frequency cognitive assessments via wearables to detect subtle changes in mental health
Explainable AI	SHAP and LIME, Random Forest Model for PGD, Stress Prediction with XAI	SHAP and LIME explain AI decision-making to validate mental health predictions. Random Forest algorithms predict Prolonged Grief Disorder (PGD) with high accuracy. Explainable AI models also predict stress levels using wearable sensors, providing transparency and improving mental health management
Assistive Robotics	Social Robots for Anxiety and PTSD, Socially Assistive Robotics	Social robots provide therapeutic interventions for anxiety and PTSD, engaging patients and improving outcomes. Socially assistive robots and chatbots deliver CBT to elderly individuals, improving accessibility to care
Immersive Technologies	VR Exposure Therapy, AR for Claustrophobia, MR for Stroke Therapy	VR environments enable exposure therapy for phobias and anxiety, often coupled with EEG monitoring. AR creates virtual experiences to treat claustrophobia, while MR systems assist stroke rehabilitation by integrating interactive therapy
Gene Editing	CRISPR-Cas9, Gene Editing for Psychiatric Diseases	CRISPR-Cas9 modifies genes linked to Alzheimer's and other neuropsychiatric disorders. Gene editing enhances understanding and treatment of psychiatric diseases, advancing both genetic research and clinical applications
Neurotechnology	Neurostimulation Devices, Continuous Monitoring	Neurostimulation modulates brain activity to treat mental health conditions like depression. Continuous monitoring technologies provide personalized, evidence-based interventions while tracking patient progress in real-time

tify early indicators of mental distress and provide proactive mental healthcare (Calvo et al. 2017).

The emphasis in the literature on AI-assisted therapy highlights the potential for customized treatments that can be adjusted to meet the needs of specific patients. Real-time adaptive algorithms and gamification are two strategies that show great promise in encouraging patients to follow their treatment plans.

Despite their computational advantages, AI systems cannot replicate the emotional intelligence, intuition, or empathic engagement of trained mental health professionals. Standardized assessments conducted by clinicians often involve interpreting subtle behavioral cues, nonverbal expressions, and therapeutic relationships, all of which are difficult to quantify or automate. This highlights the importance of viewing AI tools as augmentative and not substitutive, and ensuring that they are integrated under human oversight.

6.1 Barriers to real-world implementation

While AI-driven technologies hold immense promise for transforming mental healthcare, several real-world implementation challenges remain. One major hurdle is the lack of clinical validation for many AI models. Most published studies rely on retrospective datasets or laboratory-controlled environments, which limits the generalizability of the results to real-world clinical settings. Another key challenge is the resistance of healthcare providers to AI adoption. Clinicians may be hesitant to rely on algorithmic decision-making, especially when systems operate as opaque “black boxes.” This skepticism is compounded by the absence of formal training in interpreting AI outputs, which leads to uncertainty and lack of trust. Furthermore, infrastructure limitations such as outdated IT systems, lack of interoperability with electronic health records (EHRs), and insufficient funding create barriers to integrating AI tools into routine psychiatric workflows. Regulatory uncertainty contributes to this challenge. With a few AI-based mental health tools having undergone full FDA or CE certification, questions remain regarding liability, model updates, and long-term oversight. Without clear guidelines, healthcare institutions are reluctant to operationalize these tools on a scale. Bridging these gaps will require pilot studies in clinical settings, stronger regulatory frameworks, and collaboration between AI developers, psychiatrists, and implementation scientists to build trust and validate their effectiveness (Price and Cohen 2019).

Further frontline perspectives on workflow fit, clinical utility, and integration steps from practicing mental health clinicians are summarized in Supplementary Note 8.

6.2 Ethical and legal challenges

The deployment of AI in mental health has introduced several ethical and legal concerns that must be proactively addressed to ensure equitable, responsible, and transparent patient care. Data privacy and protection are of paramount importance. Mental health data are especially sensitive, and ensuring compliance with legal standards, such as the Health Insurance Portability and Accountability Act (HIPAA) in the US and the General Data Protection Regulation (GDPR) in the EU, is critical to avoid legal issues. AI models must be designed to avoid unauthorized access, breaches, or misuse of personal health information (Raji et al. 2020). Bias in algorithms presents another serious concern. AI systems trained on non-diverse datasets may produce skewed outputs that disproportionately misclassify or disadvantage certain demographic groups (e.g., based on race, gender, and socioeconomic status). Without mechanisms to detect and mitigate bias, these models may worsen health disparities. Explainability is also essential in this context. Many mental health AI systems use deep learning models that are inherently difficult to interpret and explain due to their complexity. The lack of transparency in decision making ("black-box" models) can erode patient and clinician trust. Incorporating XAI techniques, such as SHAP or LIME, can provide interpretable insights that improve accountability. Beyond these concerns, ethical governance must include regulatory clarity, public accountability, and equitable access. The absence of international standards for AI in mental health complicates oversight, particularly in cross-border platforms. There is also a risk of overreliance on unregulated AI tools in low-resource settings, potentially replacing human judgment rather than supporting it. Governance frameworks should promote human-in-the-loop mechanisms, enable third-party ethical audits, and mandate impact assessments to prevent harm before deployment. Stakeholder engagement, including that of patients, clinicians, ethicists, and AI developers, is critical for defining acceptable use. Additionally, transparent documentation of model development, performance, and revision histories (model cards and datasheets) can promote accountability and reproducibility (Mittelstadt 2019; Raji et al. 2020; London 2019). Finally, the field must prioritize ethics-by-design, embedding values such as fairness, dignity, and autonomy into the architecture of AI systems rather than treating ethics as an afterthought.

6.3 Research gaps

Despite this progress, there are still some gaps in current research. **Limited Diversity of Datasets**A lot of research uses small, uniform datasets, which restricts the model's generalizability. Therefore, diverse datasets that more accurately reflect the global population are required. **Insufficient Multimodal Integration** Individual modalities, such as speech analysis, textual data, and EEG, have been researched, but there is a lack of research that successfully combines these disparate types of data to provide more comprehensive models. **Emphasis on Binary Classification** The literature mainly focuses on binary classification, such as depression vs non-depression. Research on multiclass classification and capacity to distinguish between different mental health problems is lacking. **Focus on Accuracy** Although accuracy is an important statistic, it is frequently neglected to consider other factors such as model interpretability, explainability, and clinical application. Developing models that healthcare professionals can understand and trust should be the primary aim of this study. **Real-Time Monitoring and Application** The lack of real-time responsiveness in many current models makes them difficult to use in situations that call for constant supervision and immediate action. This limitation restricts their capacity to respond quickly to changing circumstances and take appropriate action, both of which are essential for achieving exceptional results. **Data privacy and ethical considerations** This research does not go far enough to address the ethical implications of AI in mental health, including concerns about data privacy and the possibility of bias, urging a more comprehensive examination of their consequences for patient autonomy, privacy, and equal care delivery.

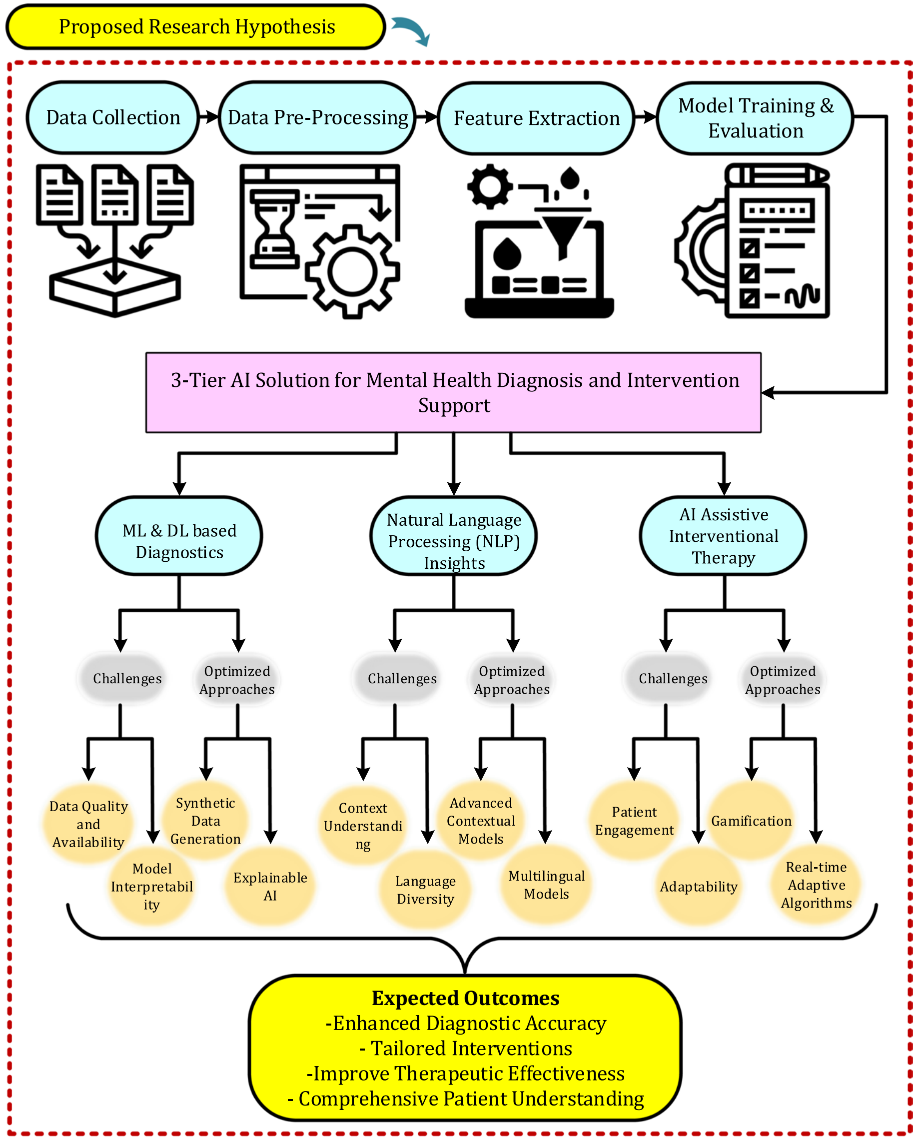


Fig. 21 Proposed research hypothesis for diagnosis of mental health conditions and intervention

7 Research directions

The aforementioned research gaps present opportunities for future investigations to address these limitations by using innovative solutions. In light of these gaps, we proposed a solution and formulated a directional research hypothesis for diagnosing and intervening in mental health conditions. by using a hybrid approach. Figure 21 represents our proposed research hypothesis for improving diagnosis of mental health conditions and interventions using a 3-tier approach that makes use of different AI techniques. The first step is the collection of various forms of data from the patient, including behavioral patterns, brain signals, and other relevant data. The aim of this study was to record a patient's mental state, taking into account both psychological and physiological aspects. These data can be collected from different sources, including wearable technology, clouds, and smartphone applications. After the collection of data, the next step is the preprocessing of data, ensuring that the data are cleaned and in the right format for suitable processing and analysis. Data preprocessing may include steps such as removing noise from EEG signals, managing missing data, scaling to increase dataset size and variety, and normalizing the data. Following pre-processing, the next step is the extraction of features from the data that are essential for diagnosing mental health problems. To extract these features, relevant data elements that offer significant insights into a patient's mental state must be selected. The features extracted from the data can be used to train AI models. Subsequently, we evaluated these models to ensure that they can accurately diagnose or predict mental health issues. Model performance can be assessed using evaluation measures such as the F1 score, accuracy, precision, and recall. Several validation strategies can be used to assess the feasibility and clinical utility of the proposed 3-Tier AI solution. Pilot studies in clinical settings can be used to evaluate real-world performance including diagnostic accuracy, user experience, and therapeutic impact.

Additionally, simulation environments and retrospective datasets could serve as testing grounds to refine model logic and predictability before deployment. Usability testing involving clinicians and patients would further help in assessing the interface design, trust in recommendations, and workflow integration. These multi-pronged validation efforts can help translate conceptual models into implementable and scalable solutions within mental health care systems.

7.1 Enhanced ML and DL techniques

To enhance the model interpretability and diagnostic accuracy, we suggest using XAI along with the development of synthetic data. Our goal was to increase the clinical acceptability and reliability of AI-based diagnostic tools by expanding the diversity and representativeness of the datasets and promoting transparency in model decisions.

7.2 Advanced NLP for interventions

Our approach involves developing multilingual contextual models to enable more accurate analysis of social media interactions and transcripts from therapy sessions. This will make it feasible to recognize tiny signs of emotions and patterns that may contribute to the improvement or decline in mental health, allowing for prompt interventions.

7.3 AI assistive therapy

Our recommendation is to enhance patient engagement and provide more individualized care by integrating gamification and real-time adaptive algorithms into AI-assisted therapy. These algorithms can enhance long-term mental healthcare and boost therapeutic outcomes by continuously adjusting patient responses.

7.4 Outcome analysis

We evaluate the impact of the AI model in two primary areas, focusing on its implications for real-world mental healthcare. This analysis examined the efficacy and diagnostic accuracy of personalized treatment interventions. The AI model significantly enhances the identification and diagnosis of mental health issues by integrating three distinct approaches: ML and DL, NLP, and AI-assisted therapy. It also enables the discovery of hidden patterns and early detection of mental health concerns. Furthermore, this approach facilitates the development of treatment plans tailored to each patient's unique needs. This involves providing real-time emotional support and continuously adapting the treatment plans based on patient feedback.

8 Conclusion

This review highlights the potential of AI in transforming mental health diagnoses and interventions and addresses the limitations of conventional methods. By exploring ML, DL, NLP, and XAI, we demonstrated that AI-driven solutions offer a viable path for more precise, timely, and personalized mental healthcare. AI enhances mental health outcomes by improving diagnostic accuracy and enabling novel and personalized therapeutic approaches. However, several challenges remain in fully harnessing AI's potential of AI for mental health. This review identifies significant research gaps, including the need for more representative and diverse datasets, improved multimodal integration, and development of algorithms beyond binary classification. Moreover, the importance of real-time applications, model interpretability, and ethical considerations such as bias and data privacy cannot be overstated. To address these challenges, we propose a 3-Tier Solution that utilizes DL, AI-assisted therapy, and NLP for mental health diagnoses and interventions. This novel approach aims to improve diagnostic tools, ensure clinical applicability, and promote more effective treatment. Future research must focus on creating transparent XAI models that can be seamlessly and ethically integrated into mental healthcare systems. By doing so, we can move closer to the future, in which AI is widely used to address the global mental health crisis and ultimately improve the lives of millions worldwide.

While AI-driven technologies present transformative opportunities in mental health care, they are best positioned as augmentative tools–enhancing rather than replacing traditional psychiatric practices. AI can assist clinicians by providing faster screening, continuous patient monitoring, predictive analytics, and personalized intervention recommendations. However, critical components of mental health care, such as therapeutic alliance, clinical judgment, and ethical decision making, remain irreplaceable human elements. Therefore, future mental health systems should aim to integrate AI solutions into a clinician-guided, collaborative framework, where technology empowers professionals and improves access, accuracy, and patient outcomes without compromising empathy or professional oversight.

Reflecting on the scope of this review, its strengths lie in its comprehensive coverage of AI methodologies, practical implementations, and inclusion of assistive technologies beyond traditional machine learning. However, as a narrative review, it does not include meta-analyses or quantitative comparisons of the model performance. In addition, certain

AI subfields and psychiatric disorders that are not prominently featured in the literature may be underrepresented.

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Author contributions M.A. conducted the literature review, performed the literature search and analysis, and drafted the manuscript. M.R. provided supervision throughout the project, critically reviewed the manuscript, and offered detailed suggestions for refinement. S.K. led the conceptualization of the review, assisted in plotting and synthesizing key findings, draft the manuscript and reviewed the final manuscript for clarity and coherence. R.U. reviewed the manuscript and refined it by integrating the artificial intelligence perspective in relation to mental health conditions.

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Declarations

Conflict of interest The authors declare no Conflict of interest.

References

Acar D, Miman M, Akirmak OO (2014) Treatment of anxiety disorders patients through EEG and augmented reality. Eur Soc Sci Res J 3:18–27

Ahuja R, Banga A (2019) Mental stress detection in university students using machine learning algorithms. Procedia Comput Sci 152:349–353. https://doi.org/10.1016/j.procs.2019.05.007

Akmal M, Khalid S, Moiz M, Abbass MJ, Qureshi MF, Mushtaq Z (2022) Leveraging training strategies of artificial neural network for classification of multiday electromyography signals. In: 2022 International conference on emerging trends in electrical, control, and telecommunication engineering (ETECTE), pp 1–5. https://doi.org/10.1109/ETECTE55893.2022.10007103 . IEEE

Albakri G, Bouaziz R, Alharthi W, Kammoun S, Al-Sarem M, Saeed F, Hadwan M (2022) Phobia exposure therapy using virtual and augmented reality: a systematic review. Appl Sci 12(3):1672. https://doi.org/10.3390/app12031672

Ali SQ, Khalid S, Belhaouari SB (2019) A novel technique to diagnose sleep apnea in suspected patients using their ECG data. IEEE Access 7:35184–35194. https://doi.org/10.1109/ACCESS.2019.2904601

Alowais SA, Alghamdi SS, Alsuhebany N, Alqahtani T, Alshaya AI, Almohareb SN, Aldairem A, Alrashed M, Bin Saleh K, Badreldin HA et al (2023) Revolutionizing healthcare: the role of artificial intelligence in clinical practice. BMC Med Educ 23(1):689. https://doi.org/10.1186/s12909-023-04698-z

Al-Rayes S, Al Yaqoub FA, Alfayez A, Alsalman D, Alanezi F, Alyousef S, AlNujaidi H, Al-Saif AK, Attar R, Aljabri D et al (2022) Gaming elements, applications, and challenges of gamification in healthcare. Inf Med Unlocked 31:100974. https://doi.org/10.1016/j.imu.2022.100974

AlSamhori JF, AlSamhori ARF, Nashwan AJ (2024) Transforming depression care with artificial intelligence. Asian J Psychiatr 101:104235. https://doi.org/10.1016/j.ajp.2024.104235

Amanat A, Rizwan M, Javed AR, Abdelhaq M, Alsaqour R, Pandya S, Uddin M (2022) Deep learning for depression detection from textual data. Electronics 11(5):676. https://doi.org/10.3390/electronics11050676

Ambareen K, Meenakshi Sundaram S (2023) A survey of cyberbullying detection and performance: its impact in social media using artificial intelligence. SN Comput Sci 4(6):859. https://doi.org/10.1007/s42979-023-02301-2

Amirahmadi A, Ohlsson M, Etminani K (2023) Deep learning prediction models based on EHR trajectories: a systematic review. J Biomed Inform 144:104430. https://doi.org/10.1016/j.jbi.2023.104430

Anik IA, Kamal A, Kabir MA, Uddin S, Moni MA (2024) A robust deep-learning model to detect major depressive disorder utilising EEG signals. IEEE Trans Artif Intell. https://doi.org/10.1109/TAI.2024.3394792

Arquissandás P, Lamas D, Oliveira J (2019) Augmented reality and sensory technology for treatment of anxiety disorders. In: 2019 14th Iberian Conference on Information Systems and Technologies (CISTI), pp 1–4. https://doi.org/10.23919/CISTI.2019.8760859 . IEEE

Arshad A, Ghaffar A, Kainaat F, Siddqique MU et al (2024) The evolving landscape of user experience in AI-powered games: a multigenerational perspective. Bulletin Bus Econ (BBE) 13(2):599–604. https://doi.org/10.61506/01.00366

Bardram JE, Matic A (2020) A decade of ubiquitous computing research in mental health. IEEE Pervasive Comput 19(1):62–72. https://doi.org/10.1109/MPRV.2019.2925338

Basu M, Nath MD (2024) A study of the role of artificial intelligence in monitoring environmental and health issues in the post-covid-19 pandemic era for sustainable living. In: Artificial intelligence for multimedia information processing. CRC Press, Boca Raton, pp 132–166

Bin Heyat MB, Akhtar F, Abbas SJ, Al-Sarem M, Alqarafi A, Stalin A, Abbasi R, Muaad AY, Lai D, Wu K (2022) Wearable flexible electronics based cardiac electrode for researcher mental stress detection system using machine learning models on single lead electrocardiogram signal. Biosensors 12(6):427. https://doi.org/10.3390/bios12060427

Bloom DE, Cafiero E, Jané-Llopis E, Abrahams-Gessel S, Bloom LR, Fathima S, Feigl AB, Gaziano T, Hamandi A, Mowafi M et al (2012) The global economic burden of noncommunicable diseases. Technical report, Program on the Global Demography of Aging

Byeon H (2023) Advances in machine learning and explainable artificial intelligence for depression prediction. Int J Adv Comput Sci Appl 14(6):1–12

Calvo RA, Milne DN, Hussain MS, Christensen H (2017) Natural language processing in mental health applications using non-clinical texts. Nat Lang Eng 23(5):649–685. https://doi.org/10.1017/S1351324916000383

Cavazza M, Charles F, Aranyi G, Porteous J, Gilroy SW, Raz G, Keynan NJ, Cohen A, Jackont G, Jacob Y, et al (2014) Towards emotional regulation through neurofeedback. In: Proceedings of the 5th augmented human international conference, pp 1–8. https://doi.org/10.1145/2582051.2582093

Chen S-C, Jones C, Moyle W (2018) Social robots for depression in older adults: a systematic review. J Nurs Scholarsh 50(6):612–622. https://doi.org/10.1111/jnu.12423

Chen S-C, Moyle W, Jones C, Petsky H (2020) A social robot intervention on depression, loneliness, and quality of life for Taiwanese older adults in long-term care. Int Psychogeriatr 32(8):981–991. https://doi.org/10.1017/S1041610220000459

Cochrane K, Schiphorst T (2015) Developing design considerations for mobile and wearable technology m-health applications that can support recovery in mental health disorders. In: 2015 9th International Conference on Pervasive Computing Technologies for Healthcare (PervasiveHealth), pp 29–36. https://doi.org/10.4108/icst.pervasivehealth.2015.259151 . IEEE

Contreras LFH, Truong ND, Eshraghian JK, Xu Z, Huang Z, Nikpour A, Kavehei O (2023) Neuromorphic neuromodulation: towards the next generation of on-device AI-revolution in electroceuticals. arXiv preprint. https://doi.org/10.48550/arXiv.2307.12471

Cormack F, McCue M, Taptiklis N, Skirrow C, Glazer E, Panagopoulos E, Schaik TA, Fehnert B, King J, Barnett JH et al (2019) Wearable technology for high-frequency cognitive and mood assessment in major depressive disorder: longitudinal observational study. JMIR Mental Health 6(11):12814. https://doi.org/10.2196/12814

Day JJ (2019) Genetic and epigenetic editing in nervous system. Dialogues Clin Neurosci 21(4):359–368. https://doi.org/10.31887/DCNS.2019.21.4/jday

Debard G, De Witte N, Sels R, Mertens M, Van Daele T, Bonroy B (2020) Making wearable technology available for mental healthcare through an online platform with stress detection algorithms: the carewear project. J Sens 2020(1):8846077. https://doi.org/10.1155/2020/8846077

Deng Z-D, Luber B, Balderston NL, Velez Afanador M, Noh MM, Thomas J, Altekruse WC, Exley SL, Awasthi S, Lisanby SH (2020) Device-based modulation of neurocircuits as a therapeutic for psychiatric disorders. Annu Rev Pharmacol Toxicol 60(1):591–614. https://doi.org/10.1146/annurev-pharmtox-010919-023253

Dhelim S, Chen L, Ning H, Nugent C (2023) Artificial intelligence for suicide assessment using audiovisual cues: a review. Artif Intell Rev 56(6):5591–5618. https://doi.org/10.1007/s10462-022-10290-6

Di Loreto I, Van Dokkum L, Gouaich A, Laffont I (2011) Mixed reality as a means to strengthen post-stroke rehabilitation. In: Virtual and Mixed Reality: Systems and Applications: International Conference, Held as Part of HCI International 2011, Orlando, FL, USA, 9–14 July 2011, Proceedings, Part II. https://doi.org/10.1007/978-3-642-22024-1_2. Springer, pp 11–19

Dino F, Zandie R, Abdollahi H, Schoeder S, Mahoor MH (2019) Delivering cognitive behavioral therapy using a conversational social robot. In: 2019 IEEE/RSJ international conference on intelligent robots and systems (IROS), pp 2089–2095. https://doi.org/10.1109/IROS40897.2019.8968576. IEEE, pp 2089–2095

Djemal R, AlSharabi K, Ibrahim S, Alsuwailem A (2017) EEG-based computer aided diagnosis of autism spectrum disorder using wavelet, entropy, and ANN. Biomed Res Int 2017(1):9816591. https://doi.org/10.1155/2017/9816591

Faisal-Cury A, Ziebold C, Oliveira Rodrigues DM, Matijasevich A (2022) Depression underdiagnosis: prevalence and associated factors. a population-based study. J Psychiatr Res 151:157–165. https://doi.org/10.1016/j.jpsychires.2022.04.025

Fonseka TM, Bhat V, Kennedy SH (2019) The utility of artificial intelligence in suicide risk prediction and the management of suicidal behaviors. Aust N Zeal J Psychiatry 53(10):954–964. https://doi.org/10.1177/0004867419864428

Gao X, Yin L, Tian S, Huang Y, Ji Q (2024) Wearable technology for signal acquisition and interactive feedback in autism spectrum disorder intervention: a review. IEEE Sens J 24(9):13797–13815. https://doi.org/10.1109/JSEN.2024.3374762

Garg P, Santhosh J, Dengel A, Ishimaru S (2021) Stress detection by machine learning and wearable sensors. In: Companion publication of the 26th international conference on intelligent user interfaces, pp 43–45. https://doi.org/10.1145/3397482.3450732

Gutiérrez-Rodríguez A, Cruz-Fuentes CS, Genis-Mendoza AD, Nicolini H (2023) Crispr/cas9 genome editing approaches for psychiatric research. Braz J Psychiatry 45(2):137–145. https://doi.org/10.47626/1516-4446-2022-2913

Hanlon B (2010) Self-report questionnaire assessment of anxiety and depression amongst stroke patients in rehabilitation settings. PhD thesis, University of Glasgow

Huq SM, Maskeliūnas R, Damaševičius R (2024) Dialogue agents for artificial intelligence-based conversational systems for cognitively disabled: a systematic review. Disabil Rehabil Assist Technol 19(3):1059–1078. https://doi.org/10.1080/17483107.2022.2146768

Ienca M, Andorno R (2017) Towards new human rights in the age of neuroscience and neurotechnology. Life Sci Soc Policy 13(1):1–27. https://doi.org/10.1186/s40504-017-0050-1

Jadhav R, Chellwani V, Deshmukh S, Sachdev H (2019) Mental disorder detection: bipolar disorder scrutinization using machine learning. In: 2019 9th International conference on cloud computing, data science & engineering (confluence). https://doi.org/10.1109/CONFLUENCE.2019.8776913 . IEEE, pp 304–308

Javaid M, Haleem A, Singh RP, Suman R, Rab S (2022) Significance of machine learning in healthcare: features, pillars and applications. Int J Intell Netw 3:58–73. https://doi.org/10.1016/j.ijin.2022.05.002

Joanna Briggs Institute (JBI) (2024) JBI critical appraisal tools. https://jbi.global/critical-appraisal-tools. Accessed 12 May 2024

Johnson KB, Wei W-Q, Weeraratne D, Frisse ME, Misulis K, Rhee K, Zhao J, Snowdon JL (2021) Precision medicine, AI, and the future of personalized health care. Clin Transl Sci 14(1):86–93. https://doi.org/10.1111/cts.12884

Johnson KA, Dosenbach NU, Gordon EM, Welle CG, Wilkins KB, Bronte-Stewart HM, Voon V, Morishita T, Sakai Y, Merner AR et al (2024) Proceedings of the 11th annual deep brain stimulation think tank: pushing the forefront of neuromodulation with functional network mapping, biomarkers for adaptive DBS, bioethical dilemmas, AI-guided neuromodulation, and translational advancements. Front Hum Neurosci 18:1320806. https://doi.org/10.3389/fnhum.2024.1320806

Jung H, Lee S, Yim J, Park S, Kim J (2015) Joint fine-tuning in deep neural networks for facial expression recognition. In: Proceedings of the IEEE international conference on computer vision, pp 2983–2991. https://doi.org/10.1109/ICCV.2015.341

Karami B, Koushki R, Arabgol F, Rahmani M, Vahabie A-H (2021) Effectiveness of virtual/augmented reality-based therapeutic interventions on individuals with autism spectrum disorder: a comprehensive meta-analysis. Front Psych 12:665326. https://doi.org/10.3389/fpsyt.2021.665326

Karkosz S, Szymański R, Sanna K, Michałowski J et al (2024) Effectiveness of a web-based and mobile therapy chatbot on anxiety and depressive symptoms in subclinical young adults: randomized controlled trial. JMIR Form Res 8(1):47960. https://doi.org/10.2196/47960

Karthikeyan C (2024) AI influence for revolutionizing virtual reality (VR) therapy: an exploratory study. In: Generating entrepreneurial ideas with AI. IGI Global, Hershey, pp 217–241. https://doi.org/10.4018/979-8-3693-3498-0.ch010

Khawaja Z, Bélisle-Pipon J-C (2023) Your robot therapist is not your therapist: understanding the role of AI-powered mental health chatbots. Front Digit Health 5:1278186. https://doi.org/10.3389/fdgth.2023.1278186

Khorev V, Kurkin S, Badarin A, Antipov V, Pitsik E, Andreev A, Grubov V, Drapkina O, Kiselev A, Hramov A (2024) Review on the use of brain computer interface rehabilitation methods for treating mental and neurological conditions. J Integr Neurosci 23(7):125. https://doi.org/10.31083/j.jin2307125

Kim J, Lee J, Park E, Han J (2020) A deep learning model for detecting mental illness from user content on social media. Sci Rep 10(1):11846. https://doi.org/10.1038/s41598-020-68764-y

Kolenik T (2022) Methods in digital mental health: smartphone-based assessment and intervention for stress, anxiety, and depression. In Comito C, Forestiero A, Zumpano E (ed) Integrating artificial intelligence and IoT for advanced health informatics: AI in the healthcare sector. Springer, Cham, pp 105–128. https://doi.org/10.1007/978-3-030-91181-2_7

Kolenik T, Gams M (2021) Persuasive technology for mental health: one step closer to (mental health care) equality? IEEE Technol Soc Mag 40(1):80–86. https://doi.org/10.1109/MTS.2021.3056288

Kolenik T, Gams M (2021) Intelligent cognitive assistants for attitude and behavior change support in mental health: state-of-the-art technical review. Electronics 10(11):1250. https://doi.org/10.3390/electronics10111250

Kouroubali A, Kondylakis H, Logothetidis F, Katehakis DG (2022) Developing an AI-enabled integrated care platform for frailty. Healthcare 10:443. https://doi.org/10.3390/healthcare10030443

Lee G, Kwon M, Sri SK, Lee M (2014) Emotion recognition based on 3D fuzzy visual and EEG features in movie clips. Neurocomputing 144:560–568. https://doi.org/10.1016/j.neucom.2014.04.008

Lee EE, Torous J, De Choudhury M, Depp CA, Graham SA, Kim H-C, Paulus MP, Krystal JH, Jeste DV (2021) Artificial intelligence for mental health care: clinical applications, barriers, facilitators, and artificial wisdom. Biol Psychiatry Cogn Neurosci Neuroimaging 6(9):856–864. https://doi.org/10.1016/j.bpsc.2021.02.001

Li R, Liu Z (2020) Stress detection using deep neural networks. BMC Med Inform Decis Mak 20(1):285. https://doi.org/10.1186/s12911-020-01299-4

Li BY, Mian AS, Liu W, Krishna A (2013) Using kinect for face recognition under varying poses, expressions, illumination and disguise. In: 2013 IEEE workshop on applications of computer vision (WACV), pp 186–192. https://doi.org/10.1109/WACV.2013.6475017 . IEEE

Li M, Liu X, Lu S, Wang X, Zhong N (2017) A method of depression recognition based on visual information. J Med Imaging Health Inf 7(7):1572–1579. https://doi.org/10.1166/jmihi.2017.2168

Li Q, Wang W, Guo Q, Jiang L, Qiao K, Hu Y, Zhang X, Wang Z, Peng D, Fan Q et al (2022) Deep learning system for brain image-aided diagnosis of multiple major mental disorders. medRxiv. https://doi.org/10.1101/2022.06.01.22275855

Lin D, Nazreen T, Rutowski T, Lu Y, Harati A, Shriberg E, Chlebek P, Aratow M (2022) Feasibility of a machine learning-based smartphone application in detecting depression and anxiety in a generally senior population. Front Psychol 13:811517. https://doi.org/10.3389/fpsyg.2022.811517

Linehan MM, Wilks CR (2015) The course and evolution of dialectical behavior therapy. Am J Psychother 69(2):97–110. https://doi.org/10.1176/appi.psychotherapy.2015.69.2.97

Liu T-K, Chen Y-P, Hou Z-Y, Wang C-C, Chou J-H (2014) Noninvasive evaluation of mental stress using by a refined rough set technique based on biomedical signals. Artif Intell Med 61(2):97–103. https://doi.org/10.1016/j.artmed.2014.05.001

Liu YS, Chokka S, Cao B, Chokka PR (2021) Screening for bipolar disorder in a tertiary mental health centre using EarlyDetect: a machine learning-based pilot study. J Affect Disord Rep 6:100215. https://doi.org/10.1016/j.jadr.2021.100215

Löchner J, Carlbring P, Schuller B, Torous J, Sander L (2025) Digital interventions in mental health: an overview and future perspectives. Internet Interv 35:100824. https://doi.org/10.1016/j.invent.2025.100824

London AJ (2019) Artificial intelligence and black-box medical decisions: accuracy versus explainability. Hastings Cent Rep 49(1):15–21. https://doi.org/10.1002/hast.973

Long N, Lei Y, Peng L, Xu P, Mao P et al (2022) A scoping review on monitoring mental health using smart wearable devices. Math Biosci Eng 19(8):7899–7919. https://doi.org/10.3934/mbe.2022369

Lu E, Zhang D, Han M, Wang S, He L (2025) The application of artificial intelligence in insomnia, anxiety, and depression: a bibliometric analysis. Digital Health 11:20552076251324456. https://doi.org/10.1177/20552076251324456

Mahalil I, Rusli ME., Yusof AM, Yusof MZM, Zainudin ARR (2014) Virtual reality-based technique for stress therapy. In: 2014 4th International conference on engineering technology and technopreneuship (ICE2T). https://doi.org/10.1109/ICE2T.2014.7006265. IEEE, pp 295–300

Mahmood D, Nisar H, Tsai C-Y (2024) Exploring the efficacy of neurofeedback training in modulating alpha-frequency band and its effects on functional connectivity and band power. Expert Syst Appl 249:123415. https://doi.org/10.1016/j.eswa.2024.124415

Mantri S, Patil D, Agrawal P, Wadhai V (2015) Non invasive EEG signal processing framework for real time depression analysis. In: 2015 SAI intelligent systems conference (IntelliSys). https://doi.org/10.1109/IntelliSys.2015.7361188. IEEE, pp 518–521

Matheus K, Mamantov E, Vázquez M, Scassellati B (2023) Deep breathing phase classification with a social robot for mental health. In: Proceedings of the 25th international conference on multimodal interaction, pp 153–162. https://doi.org/10.1145/3577190.3614173

McIntosh LG, Janes S, O'Rourke S, Thomson LD (2021) Effectiveness of psychological and psychosocial interventions for forensic mental health inpatients: a meta-analysis. Aggress Violent Beh 58:101551. https://doi.org/10.1016/j.avb.2021.101551

Mittelstadt B (2019) Principles alone cannot guarantee ethical AI. Nat Mach Intell 1(11):501–507. https://doi.org/10.1038/s42256-019-0114-4

Moser MK, Ehrhart M, Resch B (2024) An explainable deep learning approach for stress detection in wearable sensor measurements. Sensors 24(16):5085. https://doi.org/10.3390/s24165085

Mumtaz W, Qayyum A (2019) A deep learning framework for automatic diagnosis of unipolar depression. Int J Med Informatics 132:103983. https://doi.org/10.1016/j.ijmedinf.2019.103983

Nashwan AJ, Gharib S, Alhadidi M, El-Ashry AM, Alamgir A, Al-Hassan M, Khedr MA, Dawood S, Abufarsakh B (2023) Harnessing artificial intelligence: strategies for mental health nurses in optimizing psychiatric patient care. Issues Ment Health Nurs 44(10):1020–1034. https://doi.org/10.1080/01612840.2023.2263579

Pan Q, Brulin D, Campo E et al (2020) Current status and future challenges of sleep monitoring systems: systematic review. JMIR Biomed Eng 5(1):20921. https://doi.org/10.2196/20921

Price WN, Cohen IG (2019) Privacy in the age of medical big data. Nat Med 25(1):37–43. https://doi.org/10.1038/s41591-018-0272-7

Prochaska JJ, Vogel EA, Chieng A, Kendra M, Baiocchi M, Pajarito S, Robinson A (2021) A therapeutic relational agent for reducing problematic substance use (woebot): development and usability study. J Med Int Res 23(3):24850. https://doi.org/10.2196/24850

Rabbitt SM, Kazdin AE, Scassellati B (2015) Integrating socially assistive robotics into mental healthcare interventions: applications and recommendations for expanded use. Clin Psychol Rev 35:35–46. https://doi.org/10.1016/j.cpr.2014.07.001

Raji ID, Smart A, White RN, Mitchell M, Gebru T, Hutchinson B, Smith-Loud J, Theron D, Barnes P (2020) Closing the AI accountability gap: defining an end-to-end framework for internal algorithmic auditing. In: Proceedings of the 2020 conference on fairness, accountability, and transparency, pp 33–44. https://doi.org/10.1145/3351095.3372873

Rammal DS, Alomar M, Palaian S et al (2024) Ai-driven pharmacy practice: Unleashing the revolutionary potential in medication management, pharmacy workflow, and patient care. Pharmacy Practice 22(2):1–11

Rasouli S, Gupta G, Nilsen E, Dautenhahn K (2022) Potential applications of social robots in robot-assisted interventions for social anxiety. Int J Soc Robot 14(5):1–32. https://doi.org/10.1007/s12369-021-00851-0

Rathnayaka P, Mills N, Burnett D, De Silva D, Alahakoon D, Gray R (2022) A mental health chatbot with cognitive skills for personalised behavioural activation and remote health monitoring. Sensors 22(10):3653. https://doi.org/10.3390/s22103653

Rehman MU, Shafique A, Khalid S, Driss M, Rubaiee S (2021) Future forecasting of covid-19: a supervised learning approach. Sensors 21(10):3322. https://doi.org/10.3390/s21103322

Rivera MJ, Teruel MA, Mate A, Trujillo J (2022) Diagnosis and prognosis of mental disorders by means of EEG and deep learning: a systematic mapping study. Artif Intell Rev 55(2):1201–1243. https://doi.org/10.1007/s10462-021-09986-y

Rohrer C, Ben Souissi S, Kurpicz-Briki M (2025) Systematic review of recent years: machine learning-based interactive therapy for people suffering from dementia. Artif Intell Rev 58(3):78. https://doi.org/10.1007/s10462-024-11084-8
Rose M, Devine J (2014) Assessment of patient-reported symptoms of anxiety. Dialogues Clin Neurosci 16(2):197–211. https://doi.org/10.31887/DCNS.2014.16.2/mrose
Rosenbacke R (2024) Errors in physician-AI collaboration: insights from a mixed-methods study of explainable AI and trust in clinical decision-making. SSRN 4773350
Russ TC, Woelbert E, Davis KA, Hafferty JD, Ibrahim Z, Inkster B, John A, Lee W, Maxwell M, McIntosh AM et al (2019) How data science can advance mental health research. Nat Hum Behav 3(1):24–32. https://doi.org/10.1038/s41562-018-0470-9
Samal P, Hashmi MF (2024) Role of machine learning and deep learning techniques in EEG-based BCI emotion recognition system: a review. Artif Intell Rev 57(3):50. https://doi.org/10.1007/s10462-023-10690-2
Sameh A, Rostami M, Oussalah M, Korpelainen R, Farrahi V (2024) Digital phenotypes and digital biomarkers for health and diseases: a systematic review of machine learning approaches utilizing passive non-invasive signals collected via wearable devices and smartphones. Artif Intell Rev 58(2):66. https://doi.org/10.1007/s10462-024-11009-5
Schönenberg M, Wiedemann E, Schneidt A, Scheeff J, Logemann A, Keune PM, Hautzinger M (2017) Neurofeedback, sham neurofeedback, and cognitive-behavioural group therapy in adults with attention-deficit hyperactivity disorder: a triple-blind, randomised, controlled trial. Lancet Psychiatry 4(9):673–684. https://doi.org/10.1016/S2215-0366(17)30291-2
Shafiei SB, Lone Z, Elsayed AS, Hussein AA, Guru KA (2020) Identifying mental health status using deep neural network trained by visual metrics. Transl Psychiatry 10(1):430. https://doi.org/10.1038/s41398-020-01117-5
Shah V (2022) Ai in mental health: predictive analytics and intervention strategies. J Environ Sci Eng Technol 1(2):55–74
Sharma M, Achuth P, Deb D, Puthankattil SD, Acharya UR (2018) An automated diagnosis of depression using three-channel bandwidth-duration localized wavelet filter bank with EEG signals. Cogn Syst Res 52:508–520. https://doi.org/10.1016/j.cogsys.2018.07.010
She WJ, Ang CS, Neimeyer RA, Burke LA, Zhang Y, Jatowt A, Kawai Y, Hu J, Rauterberg M, Prigerson HG et al (2022) Investigation of a web-based explainable AI screening for prolonged grief disorder. IEEE Access 10:41164–41185. https://doi.org/10.1109/ACCESS.2022.3163311
Shermock SB, Shermock KM, Schepel LL (2023) Closed-loop medication management with an electronic health record system in us and finnish hospitals. Int J Environ Res Public Health 20(17):6680. https://doi.org/10.3390/ijerph20176680
Shin D, Cho WI, Park CHK, Rhee SJ, Kim MJ, Lee H, Kim NS, Ahn YM (2021) Detection of minor and major depression through voice as a biomarker using machine learning. J Clin Med 10(14):3046. https://doi.org/10.3390/jcm10143046
Shivaprasad S, Chadaga K, Dias CC, Sampathila N, Prabhu S (2024) An interpretable schizophrenia diagnosis framework using machine learning and explainable artificial intelligence. Syst Sci Control Eng 12(1):2364033. https://doi.org/10.1080/21642583.2024.2364033
Siddiqi MH, Ali R, Khan AM, Kim ES, Kim GJ, Lee S (2015) Facial expression recognition using active contour-based face detection, facial movement-based feature extraction, and non-linear feature selection. Multimedia Syst 21:541–555. https://doi.org/10.1007/s00530-014-0400-2
Singh M, Agarwal V, Jindal D, Pancham P, Agarwal S, Mani S, Tiwari RK, Das K, Alghamdi BS, Abujamel TS et al (2023) Recent updates on corticosteroid-induced neuropsychiatric disorders and theranostic advancements through gene editing tools. Diagnostics 13(3):337. https://doi.org/10.3390/diagnostics13030337
Spinrad A, Taylor CB, Ruzek JI, Jefroykin S, Friedlander T, Feleke I, Lev-Ari H, Szapiro N, Sadeh-Sharvit S (2024) Action recommendations review in community-based therapy and depression and anxiety outcomes: a machine learning approach. BMC Psychiatry 24(1):133. https://doi.org/10.1186/s12888-024-05570-0
Stein MB, Nyer M (2023) Dialectical behavior therapy and cognitive behavioral therapy techniques on a general psychiatric inpatient unit. In: The Massachusetts General Hospital handbook of cognitive behavioral therapy. Springer, Cham, pp 437–453. https://doi.org/10.1007/978-3-031-29368-9_29
Stone J (2020) Extended reality therapy: the use of virtual, augmented, and mixed reality in mental health treatment. In: The video game debate 2. Routledge, New York, pp 95–106
Su C, Xu Z, Pathak J, Wang F (2020) Deep learning in mental health outcome research: a scoping review. Transl Psychiatry 10(1):116. https://doi.org/10.1038/s41398-020-0780-3
Sun J, Dong Q-X, Wang S-W, Zheng Y-B, Liu X-X, Lu T-S, Yuan K, Shi J, Hu B, Lu L et al (2023) Artificial intelligence in psychiatry research, diagnosis, and therapy. Asian J Psychiatr 87:103705. https://doi.org/10.1016/j.ajp.2023.103705

Syahputra M, Arisandi D, Lumbanbatu A, Kemit L, Nababan E, Sheta O (2018) Augmented reality social story for autism spectrum disorder. J Phys Conf Ser 978:012040. https://doi.org/10.1088/1742-6596/978/1/012040

Tang H, Miri Rekavandi A, Rooprai D, Dwivedi G, Sanfilippo FM, Boussaid F, Bennamoun M (2024) Analysis and evaluation of explainable artificial intelligence on suicide risk assessment. Sci Rep 14(1):6163. https://doi.org/10.1038/s41598-024-53426-0

Taye MM (2023) Understanding of machine learning with deep learning: architectures, workflow, applications and future directions. Computers 12(5):91. https://doi.org/10.3390/computers12050091

Tomasik J, Han SYS, Barton-Owen G, Mirea D-M, Martin-Key NA, Rustogi N, Lago SG, Olmert T, Cooper JD, Ozcan S et al (2021) A machine learning algorithm to differentiate bipolar disorder from major depressive disorder using an online mental health questionnaire and blood biomarker data. Transl Psychiatry 11(1):41. https://doi.org/10.1038/s41398-020-01181-x

Tozzo P, Zullo S, Caenazzo L (2020) Science runs and the debate brakes: somatic gene-editing as a new tool for gender-specific medicine in Alzheimer's disease. Brain Sci 10(7):421. https://doi.org/10.3390/brainsci10070421

Trappey A, Trappey CV, Chang C-M, Kuo RR, Lin AP, Nieh C (2020) Virtual reality exposure therapy for driving phobia disorder: system design and development. Appl Sci 10(14):4860. https://doi.org/10.3390/app10144860

Uddin MZ, Dysthe KK, Følstad A, Brandtzaeg PB (2022) Deep learning for prediction of depressive symptoms in a large textual dataset. Neural Comput Appl 34(1):721–744. https://doi.org/10.1007/s00521-021-06426-4

Wang X-W, Nie D, Lu B-L (2014) Emotional state classification from EEG data using machine learning approach. Neurocomputing 129:94–106. https://doi.org/10.1016/j.neucom.2013.06.046

Washington P, Park N, Srivastava P, Voss C, Kline A, Varma M, Tariq Q, Kalantarian H, Schwartz J, Patnaik R et al (2020) Data-driven diagnostics and the potential of mobile artificial intelligence for digital therapeutic phenotyping in computational psychiatry. Biol Psychiatry Cogn Neurosci Neuroimaging 5(8):759–769. https://doi.org/10.1016/j.bpsc.2019.11.015

Wolgast KA, Lightner CM, Berish D, Zlockie A, Badzek L (2025) Mindstrong cognitive behavioral skills building initiative to enhance wellness in nursing students at a big 10 university: lessons learned. J Radiol Nurs 44(1):40–47. https://doi.org/10.1016/j.jradnu.2024.11.004

Xiao H, Duan Y, Zhang Z, Li M (2018) Detection and estimation of mental fatigue in manual assembly process of complex products. Assem Autom 38(2):239–247. https://doi.org/10.1108/AA-03-2017-040

Yeh S-C, Li Y-Y, Zhou C, Chiu P-H, Chen J-W (2018) Effects of virtual reality and augmented reality on induced anxiety. IEEE Trans Neural Syst Rehabil Eng 26(7):1345–1352. https://doi.org/10.1109/TNSRE.2018.2844083

Zheng W-L, Lu B-L (2015) Investigating critical frequency bands and channels for EEG-based emotion recognition with deep neural networks. IEEE Trans Auton Ment Dev 7(3):162–175. https://doi.org/10.1109/TAMD.2015.2431497

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