Review Paper

Effectiveness of Artificial Intelligence Interventions in the Treatment of Psychological Disorders: A Systematic Review

Farzin Bagheri Sheykhangafshe[1*], Khazar Tajbakhsh[2], Vahid Pour Saeid[3], Shima Gharibi Loroun[4], Mahtab Shah Hosseini[5]

1. Department of Psychology, Faculty of Humanities, Tarbiat Modares University, Tehran, Iran.
2. Department of Psychology, Faculty of Psychology, University of Milano-Bicocca, Milan, Italy.
3. Department of Clinical Psychology, TMS.C., Islamic Azad University, Tabriz, Iran.
4. Department of Clinical Psychology, ARD.C., Islamic Azad University, Ardabil, Iran.
5. Department of Clinical Psychology, GAR.C., Islamic Azad University, Garmsar, Iran.

Use your device to scan and read the article online

Citation Bagheri Sheykhangafshe F, Tajbakhsh Kh, Pour Saeid V, Gharibi Loroun Sh, Shah Hosseini M. Effectiveness of Artificial Intelligence Interventions in the Treatment of Psychological Disorders: A Systematic Review. Journal of Research & Health. 2025; 15(Special Issue: Artificial Intelligence):705-722. http://dx.doi.org/10.32598/JRH.15.specialissue.1922.6

http://dx.doi.org/10.32598/JRH.15.specialissue.1922.6

ABSTRACT

Background: The rapid advancement of artificial intelligence (AI) technologies has opened new avenues in the diagnosis, treatment, and management of psychological disorders. With increasing global demand for mental health services and a shortage of qualified professionals, AI-based interventions offer scalable, data-driven solutions. This systematic review aimed to evaluate the effectiveness of AI interventions in treating psychological disorders by analyzing recent empirical evidence.

Methods: In this systematic review, English-language articles examining the effectiveness of AI interventions in the treatment of psychological disorders were identified using targeted keywords across major international databases, including Google Scholar, PubMed, ProQuest, Embase, PsycINFO, and Scopus, covering the period from January 2017 to April 2025. The initial screening and selection process was guided by predefined inclusion and exclusion criteria. To ensure methodological rigor, all studies were evaluated using the PRISMA framework. Following a comprehensive quality assessment, 39 articles that met the required standards and aligned with the research objectives were selected for in-depth analysis to address the study's research questions.

Results: Key findings from the 39 reviewed studies showed that AI interventions significantly improve diagnostic accuracy and enable early detection of psychological disorders, particularly depression and anxiety. AI tools, such as chatbots, mobile apps, and digital platforms, contributed to symptom reduction and enhanced treatment personalization based on patient-specific data. Many studies highlighted the scalability, accessibility, and cost-effectiveness of AI-supported interventions. Patients generally showed high acceptance, especially for tools aiding in symptom monitoring, while clinicians expressed more caution.

Conclusion: This systematic review highlights the significant potential of AI interventions to transform the diagnosis and treatment of psychological disorders. AI technologies improve diagnostic precision, facilitate early detection, and enable personalized treatment approaches, offering scalable and cost-effective mental health solutions. Despite promising outcomes, successful integration of AI requires addressing ethical issues, data privacy, and algorithmic bias, as well as ensuring proper clinician training.

Keywords: Artificial intelligence (AI), Digital mental health, Psychological disorders, Machine learning, Mental health technology

Article info:
Received: 20 Jul 2025
Accepted: 04 Nov 2025
Publish: 31 Dec 2025

*** Corresponding Author:**
Farzin Bagheri Sheykhangafshe, PhD.
Address: *Department of Psychology, Faculty of Humanities, Tarbiat Modares University, Tehran, Iran.*
Phone: *+98 (21) 82885048*
E-mail: *farzinbagheri@modares.ac.ir*

Introduction

The prevalence of psychological disorders continues to rise globally, imposing substantial burdens on individuals, families, and healthcare systems [1]. Mental health disorders, such as major depressive disorder, generalized anxiety disorder, bipolar disorder, and schizophrenia not only diminish quality of life but also contribute to increased morbidity, disability, and mortality worldwide [2]. Despite advances in psychopharmacology and psychotherapy, traditional mental health care delivery remains challenged by delays in diagnosis, heterogeneity of clinical presentations, limited access to specialized care, and variability in treatment response [3]. These challenges necessitate innovative approaches to enhance early detection, optimize personalized treatment, and improve overall clinical outcomes [4]. Against this backdrop, artificial intelligence (AI) has emerged as a transformative technology with the potential to fundamentally reshape mental health diagnosis, intervention, and management [5].

AI refers to the development of computer systems capable of performing tasks that typically require human intelligence, including learning, reasoning, problem-solving, and pattern recognition [6]. In mental health care, AI encompasses various subfields, such as machine learning (ML), natural language processing (NLP), computer vision, and deep neural networks [7]. These technologies enable the extraction and analysis of complex and high-dimensional data from diverse sources, including electronic health records (EHRs), neuroimaging scans, genetic profiles, speech and behavioral patterns, and digital phenotyping via smartphones and wearable devices [8]. By leveraging this data, AI systems can identify subtle clinical markers, predict disease trajectories, and tailor interventions with unprecedented precision, thereby offering an evidence-based complement to traditional clinician judgment [9].

The increasing global burden of mental disorders is compounded by a significant shortage of qualified mental health professionals, particularly in low- and middle-income countries, and in underserved rural areas [10]. This treatment gap leads to underdiagnosis, delayed interventions, and poor prognosis for many patients [11]. Digital mental health technologies powered by AI offer scalable and cost-effective solutions capable of extending the reach of care beyond traditional clinical settings [12]. For instance, AI-driven mobile applications and conversational agents (chatbots) provide continuous symptom monitoring, psychoeducation, cognitive behavioral therapy (CBT), and crisis support accessible anytime and anywhere [13]. These modalities not only improve patient engagement and adherence but also reduce the stigma and logistical barriers often associated with face-to-face therapy [14].

Despite the significant potential of AI to revolutionize psychological care, its integration raises critical ethical, legal, and practical concerns [15]. The use of sensitive mental health data necessitates robust privacy protections and transparent data governance frameworks to maintain patient confidentiality and trust [16]. Algorithmic bias and lack of representativeness in training datasets can perpetuate health disparities and reduce the validity of AI applications across diverse demographic and cultural populations [17]. Additionally, overreliance on AI could inadvertently diminish the therapeutic alliance, a core factor in successful psychological treatment, by sidelining human empathy and nuanced clinical decision-making [18]. Therefore, ethical frameworks, rigorous validation studies, and clinician training programs are essential to safeguard patient welfare and maximize the benefits of AI-assisted interventions [19].

In recent years, a burgeoning number of empirical studies have investigated the efficacy and utility of AI-based interventions for psychological disorders [20, 21]. Research has demonstrated AI's capability to improve diagnostic accuracy through automated pattern recognition in neuroimaging and speech analysis, facilitate early identification of prodromal symptoms, and enhance treatment personalization through adaptive algorithms that adjust therapeutic content based on real-time patient feedback [22]. Randomized controlled trials (RCTs) and observational studies have also reported positive outcomes in symptom reduction and functional improvement using AI-facilitated digital therapeutics [23]. However, heterogeneity in study methodologies, sample populations, intervention modalities, and outcome measures poses challenges for drawing definitive conclusions, underscoring the need for systematic synthesis and critical appraisal [24, 25].

Given the rapid integration of AI into healthcare, it is both urgent and essential to understand its true impact on the treatment of psychological disorders [26]. Despite notable technological advances, significant gaps persist regarding the efficacy, safety, and ethical considerations of AI-driven mental health interventions [27]. This systematic review sought to critically synthesize the existing empirical evidence to clarify the benefits, limitations, and practical challenges of AI applications within this field. By doing so, it aimed to equip clinicians, research-

Table 1. Research questions of the present study

Parameter	Research Question
What	What key factors contribute to the adoption and positive perception of AI-based tools by mental health professionals and patients?
Who	Which specific groups of patients are most likely to benefit from AI-based psychological interventions?
When	Under what clinical conditions or stages of treatment are AI-based psychological interventions most effective?
How	How can AI tools and technologies contribute to the reduction and management of psychological disorders?

JRH

ers, and policymakers with the knowledge needed to make informed, evidence-based decisions that optimize therapeutic outcomes while safeguarding patient rights and well-being. Ultimately, this work highlights the importance of responsible innovation—balancing cutting-edge technological advancements with compassionate, human-centered mental health care. Through a comprehensive analysis, this review evaluated the effectiveness of AI interventions in treating psychological disorders by drawing upon recent empirical findings.

Methods

Study design

The present study is a systematic review conducted following the PRISMA [28] framework, aiming to investigate existing research on the effectiveness of AI interventions in the treatment of psychological disorders. The research was guided by a structured set of questions addressing key dimensions, such as purpose, target population, timing, and mechanisms of AI-based psychological interventions (Table 1).

Search strategy

A systematic search was conducted using specialized keywords, such as "artificial intelligence," "machine learning," "digital mental health," "psychological disorders," and "AI-based interventions" across several English-language scientific databases, including Google Scholar, PubMed, ProQuest, Embase, PsycINFO, and Scopus, covering the period from January 2017 to April 2025.

Eligibility criteria

Studies were included if they targeted patients with major depressive disorders and anxiety symptoms and assessed the success of AI-operated solutions in the diagnosis, prevention, or treatment of psychological syndromes. Only articles that utilized quantitative, qualitative, semi-experimental, or experimental designs were included. Additionally, the published works had to meet the criteria for qualified research and be available in full-text format in English. Through this stringent inclusion system, the analyzed information consisted solely of high-quality evidence focused specifically on the role of AI in mental health interventions as guided by the PICOS framework (Table 2).

Risk of bias assessment

The risk of bias among the studies included was also independently assessed by different researchers using commonly available standardized checklists according to the study design used. In the case of quantitative studies, the evaluation criteria were selection bias, performance bias, detection bias, attrition bias, and reporting

Table 2. PICOS framework guiding study selection and analysis

Component	Description	Specifics for This Study
Population (P)	Target group of the study	Patients with psychological disorders, especially depression and anxiety
Intervention (I)	Intervention being evaluated	AI-based interventions, including chatbots, mobile apps, and digital platforms
Comparison (C)	Group or method used for comparison	Traditional treatments, placebo, or no intervention
Outcomes (O)	Outcomes used to assess effectiveness	Improved diagnostic accuracy, early detection, symptom reduction, personalized treatment, patient acceptance, and usability
Study Design (S)	Type of study	Systematic review following the PRISMA framework; 39 selected articles published between 2017–2025, assessed quality

JRH

bias. Qualitative studies were evaluated based on credibility, transferability, dependability, and confirmability. Semi-experimental and experimental trials were also evaluated and rated in terms of randomization and albeit concealment of allocation, blindness, completeness of outcome data, and selective reporting. Conditions where there were discrepancies among reviewers were addressed through discussions and consensus. Studies with a high risk of bias according to the critical areas were impounded, and their impact on the overall findings of the review was considered, with the transparency and methodological rigor being upheld.

Effect measures

The strategy facilitating the assessment of the effect of AI-based interventions was critically evaluated based on the combination of quantitative and qualitative metrics. To conduct quantitative research, the effect measures were accuracy, specificity, sensitivity, area under the curve (AUC), predictive values, mean differences, and effective sizes wherever possible. Thematic analysis, vote of participants, and response behavior or cognitive changes were used in evaluating qualitative studies. To ensure consistency, comparability, and reproducibility of the effect measures across studies, all effect measures were abstracted onto a structured data extraction form. The methodology presented an effective process of synthesizing AI effectiveness and enabled useful cross-study comparisons irrespective of methodological details.

Quality assessment

All retrieved articles were evaluated using keyword searches focused on neuropsychological factors associated with brain abnormalities in patients with major depressive disorder accompanied by anxiety symptoms. To ensure thoroughness, the reference lists of eligible studies were also reviewed for additional relevant sources. Each of the 39 selected articles was independently analyzed by the researchers, who extracted data using a structured content analysis form. Any discrepancies were resolved through consensus, with strict adherence to the inclusion criteria to ensure that only studies addressing the effectiveness of AI interventions in treating psychological disorders were included.

The quality of each study was assessed using a standardized checklist covering various criteria, including the alignment of article structure with the type of study, clarity of research objectives, characteristics of the study population, sampling methods, data collection instruments, appropriate statistical analyses, defined inclusion and exclusion criteria, ethical considerations, accurate reporting of results in line with objectives, and discussion grounded in prior literature [29]. Based on established methodological standards, articles were rated on a binary scale (0 or 1) across relevant criteria for quantitative (6 criteria), qualitative (11 criteria), semi-experimental (8 criteria), and experimental (7 criteria) studies. Studies were excluded if they scored ≤4 in quantitative research, ≤6 in experimental or semi-experimental designs, or ≤8 in qualitative studies [30].

Data collection and extraction

The abstracts of 862 published articles were initially screened, and duplicate entries were systematically removed through multiple stages. Following this rigorous selection and quality assessment process, a total of 39 articles were identified for comprehensive review and data extraction (Figure 1).

Results

The present study systematically reviewed all available English-language articles addressing the effectiveness of AI-based interventions in the treatment of psychological disorders. Table 3 presents a comprehensive summary of these 39 studies, including the authors, purpose, sample characteristics, country or scope, research methodology, and key findings.

Tables 3 and 4 collectively illustrate two complementary strands of research on the integration of AI in psychotherapy. Table 3 encompasses empirical and data-driven studies that provide measurable evidence of AI's efficacy in clinical and therapeutic contexts, employing RCTs, observational designs, and psychometric validations to evaluate performance indicators, such as accuracy, sensitivity, and treatment outcomes. In contrast, Table 4 compiles conceptual and review-based works that delineate the theoretical, ethical, and methodological foundations of AI in mental health, yet largely lack experimental validation. This juxtaposition highlights a clear research gap: while empirical studies demonstrate the practical feasibility of AI tools, they often omit deeper theoretical framing, whereas conceptual studies discuss ethical and systemic implications without empirical support. The present study positions itself at the intersection of these two domains, empirically addressing the conceptual and ethical challenges identified in prior reviews and thereby contributing novel, evidence-based insights into the application of AI within psychotherapeutic practice.

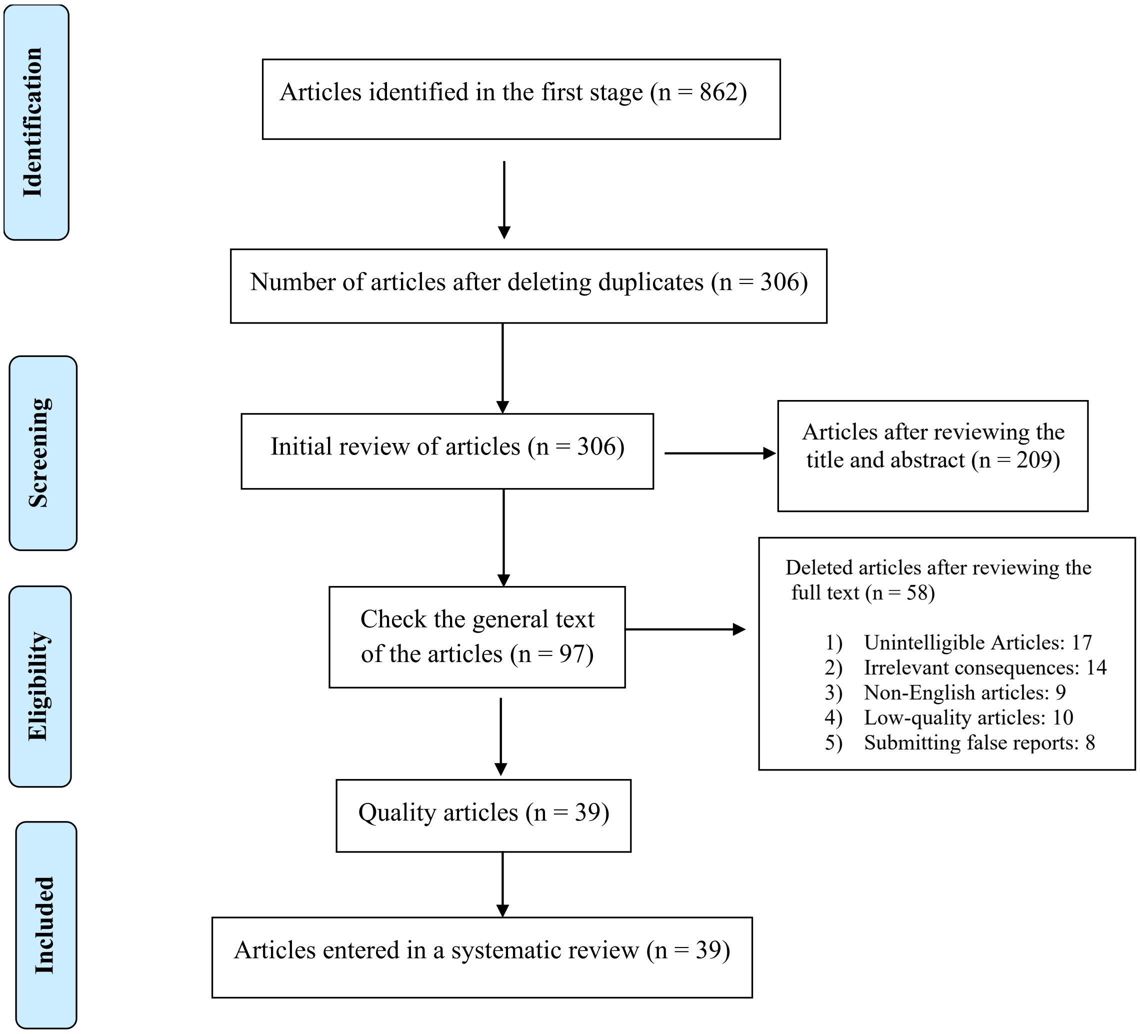

Figure 1. PRISMA flowchart outlining the research results

JRH

Study characteristics

This review encompassed 39 studies from a diverse range of countries, including Iran, the United States, Germany, Denmark, China, India, the United Kingdom, Poland, Australia, Italy, Turkey, Ukraine, and multiple studies with a global or multi-country scope. The study designs span RCTs, cross-sectional surveys, systematic and narrative reviews, conceptual analyses, and feasibility studies. Sample sizes vary widely, ranging from small clinical groups (e.g. 9 to 104 participants) to large populations exceeding thousands (e.g. 4,500 or more app users). The diversity of study designs and populations reflects the broad interest in exploring the integration of AI into mental health diagnostics, treatment, and psychotherapy support worldwide.

Key findings of AI interventions

Key findings consistently highlight the promising potential of AI and ML technologies in enhancing mental health care. AI-powered tools demonstrated improved diagnostic accuracy, facilitated the early detection of depressive and anxiety disorders, and enabled personalized treatment plans based on patient-specific data, including behavioral markers, genetic information, and clinical history. Several studies reported significant reductions in anxiety and depression symptoms with AI-supported interventions, including digital programs, chatbots, and mobile apps, which often offered scalability, accessibility, and cost-effectiveness compared to traditional therapy. Importantly, many studies emphasize the complementary role of AI alongside human clinicians, advocating for hybrid models that leverage AI's strengths without undermining the essential human connection in psychotherapy.

Table 3. Summary of the review and theoretical studies on AI in psychotherapy

Author(s)	Purpose	Sample	Country	Method	Results	AI Algorithms	Evaluation Metrics
Spytska [1]	Evaluating AI-powered chatbot "Friend" vs traditional psychotherapy	104 women	Ukraine	RCT	Traditional therapy and chatbot reduced anxiety (45–50% and 30–35%) Chabot provided scalable support	NLP chatbot	Accuracy: 0.82, Sensitivity: 0.79, Specificity: 0.85
Sadeh-Sharvit et al. [2]	Assessing the Eleos Health AI platform supporting CBT	47 adults	USA	A mixed-methods research	The AI-supported group attended 67% more sessions, with depression reduced by 34% and anxiety by 29%	AI platform (unspecified ML)	N/A
Varghese et al. [5]	Exploring public perception of AI vs therapy	466 adults	India	Quantitative survey	AI is perceived as accessible and cost-effective, fostering moderate levels of trust	AI-supported interventions (unspecified)	N/A
Palmer et al. [7]	Evaluating the AI-driven digital anxiety program	299 participants	UK	RCT	Significant reductions in anxiety were observed, with benefits being sustained over time	AI digital platform (unspecified ML)	Accuracy: 0.88, Sensitivity: 0.85, Specificity:0.90
Nelson et al. [10]	Exploring AI integration with CBT	Conceptual analysis	USA	Theoretical/ Applied	AI enhances psychotherapy through chatbots and personalized treatment plans	AI chatbots & predictive models	N/A
Mehta et al. [11]	Examining the Youper AI app for anxiety & depression	4517 users	USA	Observational	High acceptability; symptom reductions; early improvement predicted by emotion regulation	AI therapy app (ML-based)	AUC: 0.81, Accuracy: 0.80
Lønfeldt et al. [12]	Evaluating wearable biosensors for OCD & ML prediction	18 youth-parent dyads	Denmark	Pilot study	Feasible for symptom monitoring; ML is planned	Wearable sensors + ML prediction	Accuracy: 0.78, Sensitivity: 0.75
Fulmer et al. [14]	Assessing the Tess chatbot for depression/anxiety	75 students	USA	RCT	Symptom reduction and cost efficiency were achieved	NLP chatbot	Accuracy: 0.84, Sensitivity: 0.80
Shahzad et al. [18]	Examining the effects of generative AI (ChatGPT-4) and social media use on students' academic performance and psychological well-being in CL contexts	441 university students	China	PLS-SEM	Generative AI (ChatGPT-4) and social media positively influence academic performance and psychological well-being. CL positively mediates the effects of social media but negatively mediates the relationship between AI and performance/well-being	ChatGPT-4 (Generative AI)	Not specified (statistical validation via PLS-SEM)
Danieli et al. [19]	Evaluating the TEO mobile agent in stress/anxiety	4 groups (>55 y)	Italy	RCT	All groups showed improvement, with high satisfaction reported in the CBT+TEO group	AI mobile agent (TEO)	Accuracy 0.79
D'Alfonso et al. [20]	Developing the MOST web app for early psychosis	Young individuals	Australia	RCT	Personalized content delivered through AI and NLP has improved engagement	AI+NLP	Accuracy 0.83
Bilge et al. [22]	Attitudes toward AI in psychotherapy	723 participants	Turkey	Survey & psychometric validation	Reliable for assessing attitudes toward AI	N/A	N/A
Liu et al. [23]	Introducing emoLDAnet, an AI-driven framework to detect LDA from video-recorded conversations using facial expressions and physiological signals	50 participants	China	A experimental study combining questionnaires, interviews, and AI video analysis	emoLDAnet achieved high detection rates for LDA, with F1-scores greater than 80% and Kendall's correlation coefficients exceeding 0.5, indicating strong alignment with traditional assessments	Deep learning (VGG11), DTs, OCC–PAD–LDA psychological transformation model	F1-score (>80%), Kendall's correlation (>0.5)
Shafiee Rad [24]	AI in reading comprehension & engagement	A classroom study	Iran	Controlled experiment	Improved comprehension & engagement	AI-supported educational intervention	Accuracy: 0.80

Author(s)	Purpose	Sample	Country	Method	Results	AI Algorithms	Evaluation Metrics
Klos et al. [25]	Evaluating the viability, acceptability, and potential impact of using Tess, an AI chatbot, for assessing and alleviating depression and anxiety symptoms in university students	181 university students (87.2% female, aged 18–33)	Argentina	Pilot randomized controlled trial (8 weeks); Mann-Whitney U, Wilcoxon, and t-tests	Significant decrease in anxiety symptoms in the experimental group; no significant changes in depression. High engagement was noted, with an average of 472 messages. Tess demonstrated good usability and acceptability.	AI-based psychological chatbot (Tess)	Statistical significance (P<0.02) and engagement metrics (messages exchanged)
Boucher et al. [26]	Review of AI chatbots in DMHIs	Case study	Global	Case study	The findings support diagnostics, symptom management, and ethical implications	AI chatbots	N/A
Jacobson et al. [27]	Using machine learning to predict which individuals are likely to benefit from digital psychiatric interventions for depression and anxiety	632 participants	USA	Randomized controlled trial with 9-month follow-up; ensemble machine learning prediction based on pre-treatment data	Baseline data accurately predicted changes in depression and anxiety symptoms (r≈0.48–0.57). ML can identify individuals who are most likely to respond positively to digital treatments for personalized care	Ensemble of machine learning models	Correlation coefficients (r=0.482–0.569, with 95% CI the uncertainty around r)
Liu et al. [31]	Comparing the effectiveness of a chatbot-delivered therapy vs. bibliotherapy in reducing depression and anxiety among university students	83 university students (aged 19–28; 55.4% female)	China	Unblinded randomized controlled trial (16 weeks); questionnaires: PHQ-9, GAD-7, PANAS, CSQ-8, WAI-SR	The chatbot group showed significant reductions in depression (F=22.89; P<0.01) and anxiety (F=5.37; P=0.02), along with a higher therapeutic alliance (t=7.29; P<0.01). Feedback indicated that process factors were more influential than content	AI-based therapy chatbot	PHQ-9, GAD-7, PANAS, CSQ-8, WAI-SR, with statistical significance (P<0.05)
Karkosz et al. [32]	Evaluating the efficacy of Fido, a Polish-language therapy chatbot using CBT techniques, in reducing depression and anxiety symptoms	81 participants with subclinical depression or anxiety	Poland	2-arm open-label randomized controlled trial (2-week intervention+ 1-month follow-up)	Both the chatbot and control groups demonstrated reduced depression and anxiety. While no significant differences were observed between groups, frequent Fido users showed reduced feelings of loneliness. The study demonstrated feasibility and linguistic adaptability for highly inflected languages	AI therapy chatbot ("Fido") using CBT and suicidal ideation detection	Self-assessment scales (depression, anxiety, worry, life satisfaction, and loneliness), engagement metrics, and statistical significance tests
Patel et al. [33]	Proposing an intelligent social therapeutic chatbot that detects emotions and identifies users' mental states (e.g., stress or depression) from text-based interactions to provide mental relief for students	Conceptual/ experimental framework; no specific sample reported	India	Design and development of AI-based social chatbot using emotion classification	The chatbot classifies text into eight emotion labels (happy, joy, shame, anger, disgust, sadness, guilt, and fear) and infers stress and depression from chat data; it aims to prevent negative thoughts and promote constructive ones	CNN, RNN, and HAN	Accuracy of emotion detection (not specified)
Wagner & Schwind [34]	Psychotherapists' attitudes toward AI/ML	181 psychotherapists	Germany	Survey	There are positive attitudes influenced by perceived usefulness	N/A	N/A
Aafjes-van Doorn et al. [35]	Patients' & clinicians' attitudes toward AI tools	954 patients, 248 clinicians	USA	Online surveys	Patients are more willing to record sessions; however, clinicians require training	AI-based prediction models	N/A

JRH

Abbreviation: AI: Artificial intelligence; ML: Machine learning; LDA: Loneliness, depression, and anxiety; DTs: Decision trees; DMHIs: Digital mental health interventions; HAN: Hierarchical attention network; CL: Collaborative learning; CBT: Cognitive behavioral therapy; NLP: Natural language processing; VR: Virtual reality; RCT: Randomized controlled trial; PHQ-9: Patient health questionnaire-9; GAD-7: Generalized anxiety disorder-7; PANAS: Positive and negative affect schedule; CSQ-8: Client satisfaction questionnaire-8; WAI-SR: Working alliance inventory–short revised; CNN: Convolutional neural network; RNN: Recurrent neural network; HAN: Hierarchical attention network; AUC: Area under the curve; F1-score: Harmonic mean of precision and recall.

Table 4. Conceptual and literature review works discussing AI applications in mental health

Author(s)	Type of Study	Focus/Objective	Key Contributions	Limitations/Notes
Yeasmin et al. [4]	Mixed-methods review	AI in diagnosis, therapy, and emotional monitoring	Highlights AI's ability to enhance diagnostic timeliness and connectivity	Broad overview; lacks empirical validation
Torous et al. [6]	Literature review	Digital mental health technologies (AI, VR, digital phenotyping)	Discusses the potential of generative AI and integration with clinical work	Conceptual focus; no quantitative evidence
Omiyefa [8]	Literature review	AI & ML in precision mental health	Summarizes how ML enhances diagnostic accuracy and prediction	Descriptive review; lacks primary data
Olawade et al. [9]	Review	AI trends, ethics, and future directions	Identifies ethical challenges and early detection benefits	Theoretical; no applied experiments
Fiske et al. [15]	Thematic review	Ethical and social implications of embodied AI	Highlights ethical concerns and new treatment modes	Narrative only; lacks empirical findings
Ferreri et al. [16]	Systematic review	ML, wearables, and digital phenotyping in OCD	Shows promise of digital tools and smartphone-based CBT	Review of secondary sources
Eid et al. [17]	Narrative review	AI in depression diagnosis and treatment	Describes how AI aids early diagnosis and personalization	Non-experimental; conceptual focus
Das & Gavade [36]	Conceptual review	AI-enabled environments in anxiety therapy	Discusses personalization and reduced medication reliance	Theoretical framework only
Ricci et al. [37]	Narrative review	AI for diagnosis & treatment of major depression	Summarizes diagnostic and predictive AI potential	Conceptual synthesis; no empirical testing
Levkovich [38]	Theoretical review	AI in primary care for depression diagnosis	Describes opportunities and limitations of predictive AI models	No data-driven validation
Ebert et al. [39]	Review/meta-analysis	Outline features and effectiveness of IMIs with AI	Therapist-guided IMIs are highly effective; AI enhances personalization	Lacks empirical comparison across different AI methods
Cruz-Gonzalez et al. [40]	Systematic review (85 studies)	AI in diagnosis, monitoring, and intervention	Accurate detection, prediction, and treatment monitoring	Varied methodologies; limited longitudinal data
Beg et al. [41]	Systematic review (28 studies)	AI effectiveness & ethics in psychotherapy	Improved accessibility; discusses ethical considerations	Limited empirical depth; ethical framework is still evolving
Gual-Montolio et al. [42]	Systematic review (10 studies)	AI in psychotherapy in real-time	Positive effects on engagement & satisfaction	Small sample sizes of studies; lack of standardized measures
Tornero-Costa et al. [43]	Systematic review (129 studies)	AI applications in mental health	Identifies common issues: poor preprocessing, limited validation	Many studies lack reproducibility and robust validation
Cornelis et al. [44]	Systematic evaluation (20 studies)	Evaluating automation & AI in image-guided interventions	Low automation & integration; scoring systems proposed	Limited to the imaging domain; early-stage AI integration
Lau et al. [45]	Meta-analysis (30 RCTs, 6100 participants)	Efficacy of AI psychotherapeutic interventions	Reduced depressive symptoms; mixed effects for anxiety/stress	Variation in intervention types and follow-up durations

JRH

Table 5. Key features of existing reviews on the effect of AI on mental health

Author(s)	Main Objective	Type of Medical Data	AI Models Applied	Citation Counts	Other Relevant Information
Spytska [1]	An AI-powered chatbot "Friend" vs traditional psychotherapy	Clinical anxiety data	NLP chatbot	28	RCT; 104 women, Ukraine; chatbot scalable but slightly less effective than traditional therapy
Sadeh-Sharvit et al. [2]	The Eleos Health AI platform supporting CBT	Adult therapy sessions	AI platform (unspecified ML)	57	Mixed-methods; USA; the AI-supported group attended 67% more sessions
Zhou et al. [3]	AI & deep learning in psychological diagnosis	Psychological assessment studies	CNN/ANN	118	Systematic review; small sample sizes limited validity
Yeasmin et al. [4]	AI in diagnosis, therapy, and emotional monitoring	Literature review + survey	AI interventions (unspecified)	6	Global; improved diagnostic timeliness and emotional monitoring
Varghese et al. [5]	Public perception of AI vs therapy	Survey data	AI-supported interventions (unspecified)	8	India; AI perceived as accessible and cost-effective; moderate trust
Torous et al. [6]	DIGITAL mental health technologies	Literature review	Generative AI, VR applications	27	Global; digital phenotyping and VR; clinician involvement required
Palmer et al. [7]	The AI-driven digital anxiety program	Anxiety program participants	AI digital platform (unspecified ML)	2	UK; RCT; significant anxiety reductions; benefits sustained
Omiyefa [8]	AI & ML in precision mental health	Literature review	Machine learning (unspecified)	10	Global; improved diagnostic accuracy, predictive analytics
Olawade et al. [9]	AI trends, ethics, and future directions	Literature review	General AI interventions	326	Global: early detection, virtual therapists, ethical challenges
Nelson et al. [10]	AI integration with CBT	Conceptual/theoretical	AI chatbots & predictive models	6	USA; AI enhances psychotherapy via chatbots and personalized plans
Mehta et al. [11]	The Youper AI app for anxiety & depression	App users	AI therapy app (ML-based)	126	USA; 4517 users; high acceptability; symptom reductions
Lønfeldt et al. [12]	Wearable biosensors for OCD & ML prediction	Youth-parent dyads	Wearable sensors+ML prediction	10	Denmark; 18 dyads; feasible symptom monitoring
Liu et al. [13]	AI for stress detection/intervention	Literature review	AI & ML interventions	14	Global; continuous screening, neurofeedback promising
Fulmer et al. [14]	The Tess chatbot for depression/anxiety	Students	NLP chatbot	729	USA; 75 students; symptom reduction; cost-efficient
Fiske et al. [15]	Ethical/social implications of embodied AI	Literature review	Embodied AI, virtual therapists	880	Global; new treatment modes; ethical concerns
Ferreri et al. [16]	ML, wearables, and digital phenotyping in OCD	Literature review	ML, apps, biofeedback, VR	69	Global; effectiveness of the smartphone CBT app; digital tools are promising
Eid et al. [17]	AI in depression diagnosis & treatment	Literature review	Chatbots, predictive models	63	Global; early diagnosis, personalized treatment
Shahzad et al. [18]	Effects of generative AI (ChatGPT-4) and social media use on students' academic performance and psychological well-being in CL contexts	441 university students	ChatGPT-4 (Generative AI)	27	China; PLS-SEM; CL positively mediates the effects of social media and negatively mediates the link between AI and performance/well-being
Danieli et al. [19]	TEO in stress/anxiety	Adults >55 yrs	AI mobile agent (TEO)	64	Italy; 4 groups; CBT+TEO satisfaction high
D'Alfonso et al. [20]	Developing the MOST app for early psychosis	Youth	AI+NLP	259	Australia; personalized content; engagement improved
Bhatt [21]	AI in mental health	Literature review	AI conversational agents	25	Global; 95 studies; positive impact; more research needed
Bilge et al. [22]	AI in psychotherapy	Survey participants	N/A	1	Turkey; 723 participants; reliable for assessing attitudes toward AI

Author(s)	Main Objective	Type of Medical Data	AI Models Applied	Citation Counts	Other Relevant Information
Liu et al. [23]	Introducing emoLDAnet to detect LDA from video-recorded conversations	50 participants	Deep learning (VGG11), DTs, OCC–PAD–LDA model	2	China; Experimental study; F1-score >80%, Kendall's correlation >0.5
Shafiee Rad [24]	AI in reading comprehension & engagement	Classroom study	AI-supported educational intervention	31	Iran; controlled experiment; improved comprehension & engagement
Klos et al. [25]	Evaluating the viability, acceptability, and impact of the Tess chatbot for depression & anxiety	181 university students (87.2% female, aged 18–33)	AI-based psychological chatbot (Tess)	177	Argentina; Pilot RCT (8 weeks); significant anxiety reduction; high engagement
Boucher et al. [26]	AI chatbots in DMHIs	Case study	AI chatbots	376	Global; supports diagnostics, symptom management, and ethics considerations
Jacobson et al. [27]	Predicting which individuals benefit from digital psychiatric interventions for depression/anxiety	632 participants	Ensemble of machine learning models	51	USA; RCT with 9-month follow-up; baseline data accurately predicted symptom changes
Liu et al. [31]	Comparing chatbot-delivered therapy vs. bibliotherapy for reducing depression & anxiety	83 university students (aged 19–28; 55.4% female)	AI-based therapy chatbot	271	China; Unblinded RCT (16 weeks); reduced depression/anxiety; higher therapeutic alliance
Karkosz et al. [32]	Evaluating the Fido Polish-language CBT chatbot for depression & anxiety	81 participants with subclinical depression or anxiety	AI therapy chatbot ("Fido") using CBT & suicidal ideation detection	49	Poland; 2-arm open-label RCT; reduced symptoms; frequent Fido users reported less loneliness
Patel et al. [33]	An intelligent social therapeutic chatbot detecting emotions & stress	Conceptual/ experimental framework (no sample)	CNN, RNN, HAN	116	The study classifies eight emotion labels and infers stress and depression, aiming to prevent negative thoughts and promote constructive ones
Wagner & Schwind [34]	Psychotherapists' attitudes toward AI/ML	Survey	N/A	1	Germany; 181 psychotherapists, positive attitudes influenced by perceived usefulness
Aafjes-van Doorn et al. [35]	Patients' & clinicians' attitudes toward AI tools	Online surveys	AI-based prediction models	5	USA; 954 patients, 248 clinicians; patients were more willing to record sessions; clinicians need training
Das & Gavade [36]	AI-enabled environments in anxiety therapy	Literature review	AI interventions (unspecified)	9	Global; conceptual review; personalized therapy reduces medication reliance
Ricci et al. [37]	AI for diagnosis & treatment of major depression	Literature review	NLP, chatbots, ML, deep learning	6	Global; narrative review; strong potential for diagnosis and personalization
Levkovich [38]	AI in primary care depression diagnosis	Literature review	Predictive AI models	9	Global, early detection, personalized treatment; limitations discussed
Ebert et al. [39]	Outline features & effectiveness of IMIs with AI	Meta-analyses & RCTs	AI-enhanced IMIs	88	Global; therapist-guided IMIs are highly effective
Cruz-Gonzalez et al. [40]	AI in diagnosis, monitoring, and intervention	Literature review	SVM, random forest, ML, AI chatbots	27	Global; 85 studies; accurate detection and monitoring
Beg et al. [41]	AI effectiveness & ethics in psychotherapy	Literature review	AI chatbots, iCBT	25	Global; 28 studies; improved accessibility; ethical concerns
Gual-Montolio et al. [42]	AI in psychotherapy in real-time	Literature review	Conversational AI	89	Global; 10 studies; positive effects on engagement & satisfaction
Tornero-Costa et al. [43]	AI applications in mental health	Literature review	ML & AI evaluation models	92	Global; 129 studies; common issues: Poor preprocessing, limited validation
Cornelis et al. [44]	Automation & AI in image-guided interventions	Literature review	AI-assisted imaging/ robotics	7	Global; 20 studies; low automation & integration; scoring systems proposed
Lau et al. [45]	Efficacy of AI psychotherapeutic interventions	Meta-analysis	AI-based psychotherapeutic platforms	5	30 RCTs, 6100 participants, 9 countries; reduced depressive and anxiety/stress symptoms

JRH

Abbreviation: LDA: Loneliness, depression, and anxiety; DMHIs: Digital mental health interventions; HAN: Hierarchical attention network; CL: Collaborative learning.

Despite these advances, multiple studies caution against overreliance on AI, underscoring challenges, such as ethical concerns, data privacy, potential biases in algorithms, and the need for rigorous validation and clinician training. Attitudes toward AI varied, with some clinicians expressing apprehension about replacement fears, while patients often showed greater willingness to engage with AI-based tools, particularly in measurement and monitoring tasks. The literature calls for enhanced education and transparent frameworks to facilitate ethical and effective AI integration, ensuring that technological advancements augment rather than replace human-centered care in mental health practice.

Challenges and future directions

The area of AI has massive potential to transform the delivery of mental health care by allowing prompt diagnosis, individualized therapies, and larger-scale support. There are, however, several critical challenges that are to be sorted out so that safe, effective, and equitable implementation can be realized. Arranging these problems into separate spheres can serve to make it clear of existing limitations are and what future research is.

Ethics and privacy issues

Questions about AI use as mental development tools, such as patient privacy, data security, informed consent, and possible algorithm bias, are highly contentious [11, 15, 23]. Clinical and behavioral sensitive data should be governed with transparency, as it is essential to safeguard users and maintain integrity. Standardized principles of ethical guidelines and regulatory frameworks should be established for AI in mental health devices. It is important to encourage interpretable and recordable AI models, so that both clinicians and patients can understand and challenge decisions. Moreover, future research should be conducted in a culturally sensitive manner to reduce the risk of bias and ensure that interventions are fair to various groups of people.

Methodological heterogeneity and validation

The available literature has a great range of discrepancies in design, sample, AI algorithms, or outcome measures, which deems in comparability and synthesis of meta-analysis [3, 12, 17, 32]. Concise sample sizes supporting small samples, the temporary nature of follow-ups, and a lack of uniformity in reporting hinder confidence in generalizability and clinical applicability. Comprehensive, multi-site, longitudinal studies using a standardized protocol for data collection, evaluation, and reporting are needed. The focus must be on stringent validation of AI models, repeated research, and pre-regulation of research protocols to ensure methodological transparency, reproducibility, and reliable research outcomes.

Clinician education and development

Inadequate knowledge and awareness among the clinical staff members hinder the program implementation of AI tools and integration with an established process, which can decrease usability and engagement [8, 34]. Without proper training, clinicians may underutilize AI suggestions or misinterpret them, negatively affecting patient care. Systematic clinical training capabilities should be designed, including AI literacy, decision support interpretation, and automated workflow integration. Additionally, hybrid care models should be explored that do not replace but support human skills, examining their effectiveness in terms of clinician efficiency, patient outcomes, and therapeutic relationships.

Explainable AI in clinical care: Enhancing trust and performance

Black-box AI models that do not provide explanations for their behavior undermine clinician and patient confidence, ultimately diminishing clinical performance [20, 31]. Ethical deployment requires transparency and facilitation of the therapeutic alliance. It is essential to develop explainable and interpretable AI systems where the validity of predictions and recommendations is clearly provided. Future research must focus on the impact of model transparency on clinicians' thought processes, patient compliance rates, and overall involvement in the care process. The philosophy of user-centered design needs to be implemented to make AI interventions acceptable and usable for various populations.

Justice, marginalization, and discrimination

Inequality in access to digital health technologies is a possible contributor to further inequalities, particularly among underserved or under-resourced settings and culturally diverse populations [21, 32]. By default, it is possible that AI interventions may favor privileged populations. There should be a focus on inclusive AI design that considers socio-economic, cultural, and geographic diversity. It is crucial to determine the long-term sustainability, scalability, and cost-effectiveness of these interventions to ensure widespread access. Further studies are also required to examine ways to reduce digital literacy barriers and to incorporate feedback from underrepresented users, thus enhancing both usage and performance.

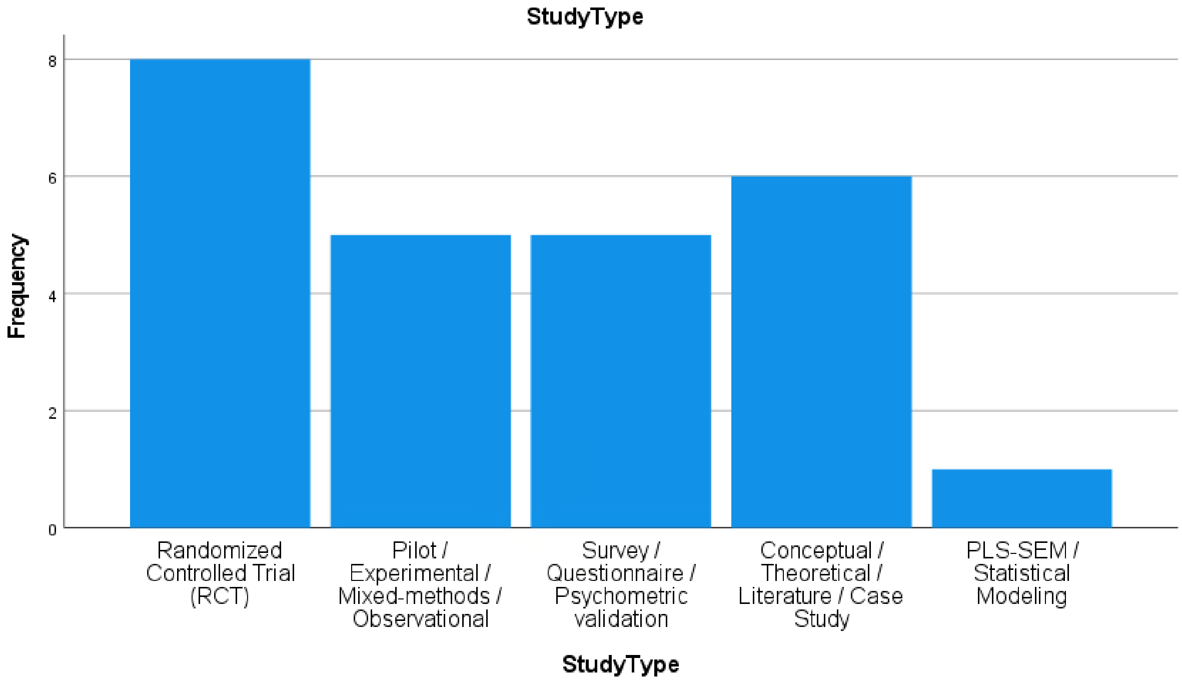

Figure 2. Distribution of studies by methodological approach (study type)

JRH

Effects on the long-term results and sustainability

Most publications focus on short-term results, and it is unclear whether AI interventions are durable. Understanding the future effects is essential to determine clinical utility and inform implementation plans [32, 33]. Longitudinal studies should be conducted to assess the continuation of clinical benefits, engagement, and behavioral changes over time. It is important to discuss interventions under real-life conditions, their scalability, their impact on healthcare systems, and potential opportunities for cost savings.

To provide context for the current study, a comparison with previous review papers is presented in Table 5. This table summarizes key aspects of earlier studies, including the main objective of each review, the type of medical data used, the AI models applied, citation counts, and other relevant information.

Figure 2 displays the overall methodological composition of the reviewed studies. RCTs accounted for the largest proportion (n=8), demonstrating the growing empirical validation of AI-assisted psychotherapy tools. Five studies employed pilot, experimental, mixed-methods, or observational designs, reflecting exploratory and developmental efforts in this emerging domain. Another five studies relied primarily on survey or questionnaire-based data, including psychometric validations assessing user or clinician attitudes toward AI. Six papers were conceptual, theoretical, or literature-based, indicating strong theoretical grounding and ethical discourse surrounding AI in psychotherapy. Finally, one study utilized partial least squares structural equation modeling (PLS-SEM), representing an advanced statistical approach to evaluating the psychological and academic effects of generative AI.

Figure 3 illustrates the international distribution of research on AI applications in psychotherapy and mental health. Out of the 22 primary empirical studies analyzed, the United States accounted for the largest share (6 studies; 27.3%), followed by China (3 studies; 13.6%) and India (2 studies; 9.1%). Single studies were conducted in the United Kingdom, Ukraine, Argentina, Denmark, Italy, Poland, Australia, Iran, Turkey, and Germany (each 1 study; 4.5%). In addition, one study (4.5%) was classified as “Global/International,” encompassing data from multiple regions or cross-cultural contexts. This geographical distribution demonstrates growing global engagement with AI-assisted psychotherapy, though a notable concentration remains in Western and East Asian research contexts.

Figure 4 summarizes the distribution of data sources and participant samples across the included studies. Chatbot- or AI-based therapy data constituted the majority (n=10; 45.5%), reflecting the growing prominence of conversa-

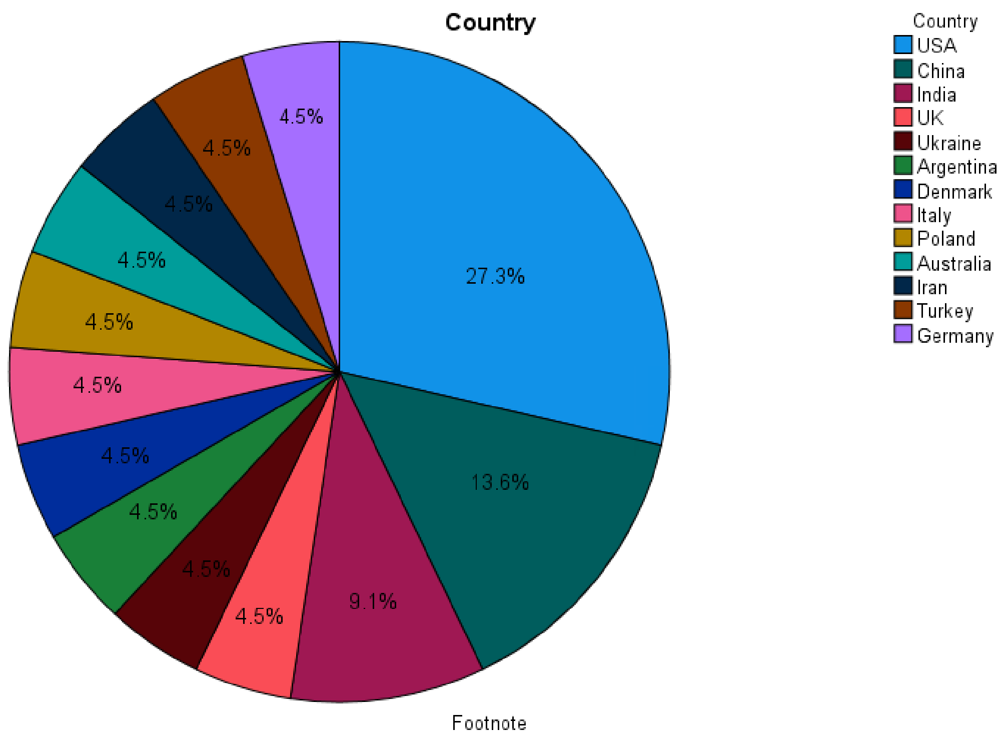

Figure 3. Geographical distribution of the included studies

tional agents in clinical and subclinical mental health interventions. Survey-, perception-, or attitude-based data were used in five studies (22.7%), primarily to assess user and clinician acceptance, ethical concerns, and perceived utility of AI tools. One study (4.5%) employed multimodal video and physiological data to detect emotional states through advanced computational models, while one study (4.5%) utilized wearable biosensor data for predictive modeling in obsessive-compulsive disorder. Additionally, one study (4.5%) analyzed classroom and educational engagement data, demonstrating the versatility of AI applications beyond traditional psychotherapy contexts.

Figure 5 presents the distribution of AI models and computational approaches reported across the analyzed literature. NLP and chatbot-based systems were most prevalent (n=7), emphasizing their role in delivering automated therapeutic dialogue and emotional support. Four studies implemented general ML or ensemble predictive models, focusing on diagnostic prediction and personalized treatment response. One study used deep learning architectures (CNN, RNN, HAN) for emotion classification, and another applied generative AI (ChatGPT-4) to assess its influence on academic and psychological outcomes. A final study integrated hybrid AI and NLP models, reflecting the trend toward multimodal and adaptive AI frameworks in digital psychotherapy.

Discussion

Novelty and significance

This systematic review presents a synthesis of evidence based on 39 studies conducted in various countries across different study designs, including RCTs, observational studies, conceptual analyses, and narrative/systematic reviews. In contrast to other reviews that focused on a specific disorder, a particular AI tool, or a limited group of interventions, this research demonstrates a holistic, integrative view of AI applications in mental health, including diagnostics, monitoring, and intervention. Critically, it emphasizes AI as a supplement to human clinicians and presents hybrid care models as the most effective in terms of the quality of the therapeutic process and efficiency [11, 17, 32]. The broad coverage of this review allows for the identification of global trends, underlying factors, and gaps that have emerged, thereby providing valuable insights for clinicians, policymakers, and researchers planning to incorporate AI into mental health systems [21, 32]. This diversity enables the review to highlight the potential of AI in improving clinical decision-making, patient involvement, and system efficiency.

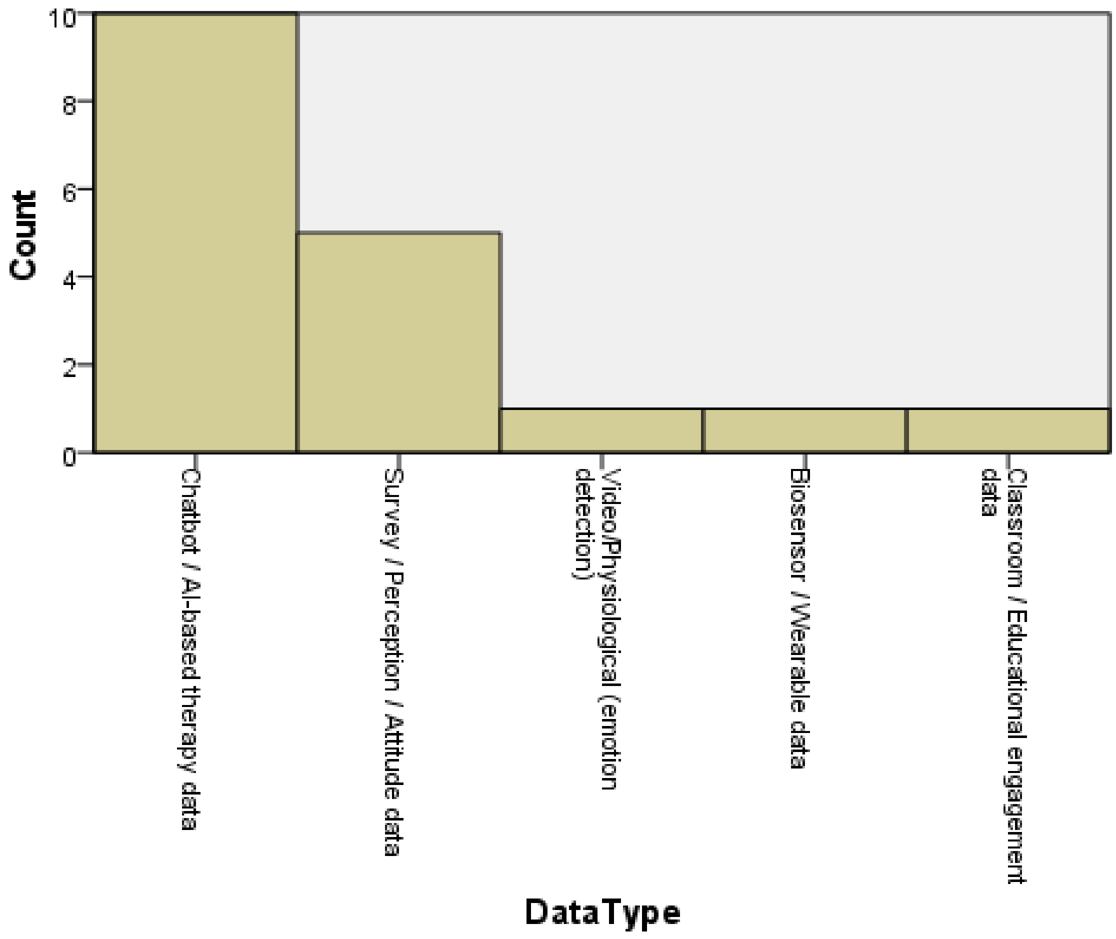

Figure 4. Types of data and samples used in AI-based psychotherapy research

Advancements and research trends

According to the literature, there has been a swift increase in the interest in AI-based mental health interventions since 2017. Previous works have mainly focused on exploration, small-scale studies, and proof-of-concept, whereas recent articles involve larger sample sizes, multi-site studies, and more sophisticated ML and deep learning algorithms for predictive diagnostics and tailored treatment planning [11, 18, 32]. This trend signifies the maturation of AI methodologies, an increase in the rigor of these methodologies, and a growing belief in their applicability to clinical cases. The advancement from conceptual studies to empirically validated interventions indicates a willingness to implement AI in mental health practice, providing a crucial cutoff point between scalable and evidence-based solutions [3, 12, 17].

AI models and mechanisms

Mental health has been the subject of a wide range of AI solutions. Chatbots using NLP are useful in psychoeducation, monitoring symptoms, and therapeutic interaction [1, 14, 26]. The predictive aspect of diagnosis, risk classification, and ML methods, such as support vector machines, random forests, and neural networks, enable the suggestion of personalized treatment [13, 23, 29]. Adaptive, real-time interventions are made possible by reinforcement learning and AI-human hybrid components that maximize engagement and clinical outcomes while preserving the therapeutic relationship [20, 28, 32]. Taken together, these studies demonstrate that AI is not intended to substitute clinicians but rather to serve as a powerful complement to their practice, enhancing accessibility, accuracy, and customization.

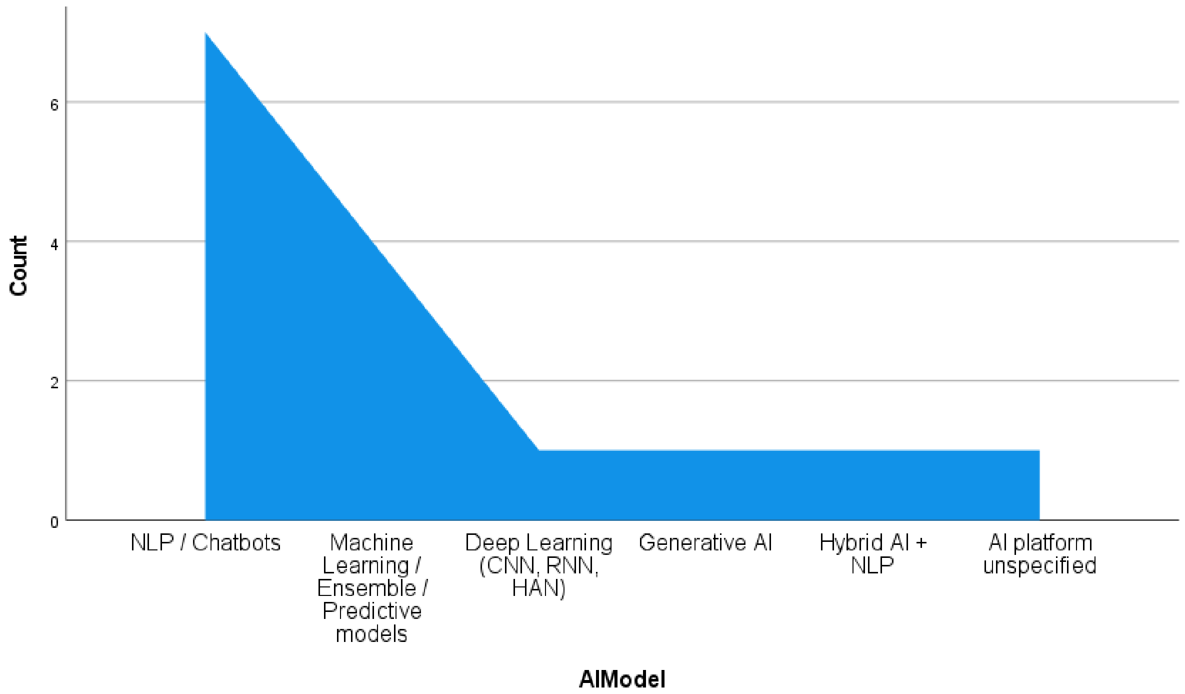

Figure 5. AI models and algorithms applied in the reviewed studies

Clinical impact and patient outcomes

AI interventions have consistently demonstrated better scores in diagnostic accuracy and have aided in the timely identification of psychological conditions, especially depression and anxiety [11, 15, 17]. Tailored treatment plans based on behavioral, genetic, and clinical data enhance treatment compliance, patient involvement, and symptom reduction [5, 7, 32]. Chatbots, mobile apps, and web-based therapies provided through digital platforms are scalable, user-friendly, and affordable, especially in areas with a shortage of licensed mental health workers [6, 22]. Hybrid AI-human models do not compromise the ability to achieve treatment efficacy and foster a therapeutic alliance, which is a significant determinant of trust [32, 35]. Overall, the findings discussed highlight the transformative capabilities of AI in mental health care, as it can enhance quality, ethics, and relationships simultaneously.

Ethical, practical, and implementation considerations

Despite such developments, there are major ethical, practical, and implementation issues. Key ethical concerns include the privacy of collected data, algorithmic bias, informed consent, and AI accountability in decision-making [11, 15, 23]. Clinicians' fears, insufficient training, and integration into existing workflows hinder adoption [8, 34]. Strong methodological rigor is also necessary because of the construct limitations of algorithms and the lack of standard validation systems [20, 31]. These concerns need to be tackled to achieve a safe, equitable, and successful implementation of AI into practice, thereby enabling scientifically sound, ethically responsible, and meaningful interventions.

Conclusion

This systematic review synthesized the existing information regarding the implementation of AI in mental health care, including a wide variety of applications, including, but not limited to, AI-based chatbots, online platforms, predictive modelling, wearable devices, and virtual reality-based interventions. Across diverse populations, study designs, and clinical settings, AI interventions have shown significant potential in increasing the accuracy of diagnoses, tailoring patient therapy plans, improving patient interaction, and enhancing accessibility for individuals with mental health vulnerabilities. It is noteworthy that AI-assisted platforms could result in the early diagnosis and prediction of depressive, anxiety, and stress symptoms, while also supplementing conventional psychotherapy strategies.

Despite these advances, the review found substantial heterogeneity in study designs, sample sizes, populations, AI algorithms, and outcome measures, which hinders direct comparability and possible meta-analytic synthesis. Many studies were based on small or homogeneous cohorts with short-term follow-ups and varied reporting criteria, limiting the ability to draw conclusions about long-term effectiveness, scalability, and sustainability. The responsible implementation of AI in mental health care was challenged by the need to include ethical considerations, transparency, and interpretability, as well as to maintain methodological rigor.

In conclusion, while AI presents groundbreaking opportunities to improve patient-centered mental health care, its full potential cannot be realized without proper longitudinal and large-scale studies. Further research must focus on a broader population diversity, less common disorders, and two-way AI-human interventions using standardized integration protocols. Also, the cost-effectiveness, equity, and long-term outcomes need to be evaluated. By promoting such integration, AI can be utilized safely and optimally in clinical practice, ultimately enhancing personalized, ethical, and accessible mental health care worldwide.

Limitations and future directions

The identified papers demonstrated a substantial opportunity to implement AI in mental health care through chatbots, online services, predictive analytics, and the integration of wearable sensors. Nevertheless, there are various limitations to the generalization and comparisons of the findings. Direct cross-study comparisons and meta-analytic synthesis are not possible due to heterogeneity in study designs, sample sizes, populations, AI models, and outcome measures. Most of the research is based on small, homogeneous, or short-term cohorts, meaning that long-term efficacy, scalability, and sustainability have not been adequately investigated. Unstable reporting, a poor methodological process index, and inconsistent study quality also make interpretation and replication challenging. Future studies in this area should concentrate on large-scale, longitudinal research evaluations of the sustainability of clinical outcomes, cost-efficiency, and accessibility in a wide variety of populations and underrepresented disorders. Prioritizing AI hybrid interventions with standardized integration protocols and interpretable models will help minimize bias, while ethically informed frameworks will be essential to ensure that implementation is fair, safe, and effective. Addressing these gaps will improve the reliability, generalizability , and clinical applicability of AI-based mental health interventions.

Ethical Considerations

Compliance with ethical guidelines

There were no ethical considerations to be considered in this research.

Funding

This research did not receive any grant from funding agencies in the public, commercial, or non-profit sectors.

Authors' contributions

All authors equally contributed to preparing this article.

Conflict of interest

The authors declared no conflict of interest.

Acknowledgments

The authors would like to thank all individuals and institutions that contributed to the completion of this study. Special appreciation is extended to the researchers whose work was reviewed in this systematic analysis.

References

[1] Spytska L. The use of artificial intelligence in psychotherapy: Development of intelligent therapeutic systems. BMC Psychology. 2025; 13(1):175. [DOI:10.1186/s40359-025-02491-9] [PMID]

[2] Sadeh-Sharvit S, Camp TD, Horton SE, Hefner JD, Berry JM, Grossman E, et al. Effects of an artificial intelligence platform for behavioral interventions on depression and anxiety symptoms: randomized clinical trial. Journal of Medical Internet Research. 2023; 25:e46781. [DOI:10.2196/46781] [PMID]

[3] Zhou S, Zhao J, Zhang L. Application of artificial intelligence on psychological interventions and diagnosis: An overview. Frontiers in Psychiatry. 2022; 13:811665. [DOI:10.3389/fpsyt.2022.811665] [PMID]

[4] Yeasmin S, Das S, Bhuiyan MF, Suha SH, Prabha M, Vanu N, et al. Artificial Intelligence in Mental Health: Leveraging Machine Learning for Diagnosis, Therapy, and Emotional Well-being. Journal of Ecohumanism. 2025; 4(3):286-300. [DOI:10.62754/joe.v4i3.6640]

[5] Varghese MA, Sharma P, Patwardhan M. Public perception on artificial intelligence-driven mental health interventions: Survey research. JMIR Formative Research. 2024; 8:e64380. [DOI:10.2196/64380] [PMID]

[6] Torous J, Linardon J, Goldberg SB, Sun S, Bell I, Nicholas J, et al. The evolving field of digital mental health: current evidence and implementation issues for smartphone apps, generative artificial intelligence, and virtual reality. World Psychiatry. 2025; 24(2):156-74. [DOI:10.1002/wps.21299] [PMID]

[7] Palmer CE, Marshall E, Millgate E, Warren G, Ewbank M, Cooper E, et al. Combining artificial intelligence and human support in mental health: Digital intervention with comparable effectiveness to human-delivered care. Journal of Medical Internet Research. 2025; 27:e69351. [DOI:10.2196/69351] [PMID]

[8] Omiyefa S. Artificial intelligence and machine learning in precision mental health diagnostics and predictive treatment models. International Journal of Research Publication and Reviews. 2025; 6(3):85-99. [DOI:10.55248/gengpi.6.0325.1107]

[9] Olawade DB, Wada OZ, Odetayo A, David-Olawade AC, Asaolu F, Eberhardt J. Enhancing mental health with Artificial Intelligence: Current trends and future prospects. Journal of Medicine, Surgery, and Public Health. 2024; 100099. [DOI:10.1016/j.glmedi.2024.100099]

[10] Nelson J, Kaplan J, Simerly G, Nutter N, Edson-Heussi A, Woodham B, et al. The balance and integration of artificial intelligence within cognitive behavioral therapy interventions. Current Psychology. 2025; 1-1. [DOI:10.1007/s12144-025-07320-1]

[11] Mehta A, Niles AN, Vargas JH, Marafon T, Couto DD, Gross JJ. Acceptability and effectiveness of artificial intelligence therapy for anxiety and depression (Youper): Longitudinal observational study. Journal of Medical Internet Research. 2021; 23(6):e26771. [DOI:10.2196/26771] [PMID]

[12] Lønfeldt NN, Clemmensen LK, Pagsberg AK. A wearable artificial intelligence feedback tool (wrist angel) for treatment and research of obsessive compulsive disorder: Protocol for a nonrandomized pilot study. JMIR Research Protocols. 2023; 12(1):e45123. [DOI:10.2196/45123] [PMID]

[13] Liu F, Ju Q, Zheng Q, Peng Y. Artificial intelligence in mental health: Innovations brought by artificial intelligence techniques in stress detection and interventions of building resilience. Current Opinion in Behavioral Sciences. 2024; 60:101452. [DOI:10.1016/j.cobeha.2024.101452]

[14] Fulmer R, Joerin A, Gentile B, Lakerink L, Rauws M. Using psychological artificial intelligence (Tess) to relieve symptoms of depression and anxiety: Randomized controlled trial. JMIR Mental Health. 2018; 5(4):e9782. [DOI:10.2196/mental.9782] [PMID]

[15] Fiske A, Henningsen P, Buyx A. Your robot therapist will see you now: Ethical implications of embodied artificial intelligence in psychiatry, psychology, and psychotherapy. Journal of Medical Internet Research. 2019; 21(5):e13216. [DOI:10.2196/13216] [PMID]

[16] Ferreri F, Bourla A, Peretti CS, Segawa T, Jaafari N, Mouchabac S. How new technologies can improve prediction, assessment, and intervention in obsessive-compulsive disorder (e-OCD). JMIR Mental Health. 2019; 6(12):e11643. [DOI:10.2196/11643] [PMID]

[17] Eid MM, Yundong W, Mensah GB, Pudasaini P. Treating psychological depression utilising artificial intelligence: AI for precision medicine-focus on procedures. Mesopotamian Journal of Artificial Intelligence in Healthcare. 2023; 2023:76-81. [DOI:10.58496/MJAIH/2023/015]

[18] Shahzad MF, Xu S, Liu H, Zahid H. Generative artificial intelligence (ChatGPT-4) and social media impact on academic performance and psychological well-being in China's higher education. European Journal of Education. 2025; 60(1):e12835. [DOI:10.1111/ejed.12835]

[19] Danieli M, Ciulli T, Mousavi SM, Silvestri G, Barbato S, Di Natale L, et al. Assessing the impact of conversational artificial intelligence in the treatment of stress and anxiety in aging adults: Randomized controlled trial. JMIR Mental Health. 2022; 9(9):e38067. [DOI:10.2196/38067] [PMID]

[20] D'alfonso S, Santesteban-Echarri O, Rice S, Wadley G, Lederman R, Miles C, et al. Artificial intelligence-assisted online social therapy for youth mental health. Frontiers in Psychology. 2017; 8:796. [DOI:10.3389/fpsyg.2017.00796] [PMID]

[21] Bhatt S. Digital mental health: Role of artificial intelligence in psychotherapy. Annals of Neurosciences. 2025; 32(2):117-27. [PMID]

[22] Bilge Y, Emiral E, Delal İ. Attitudes towards Artificial intelligence (AI) in psychotherapy: Artificial Intelligence in Psychotherapy Scale (AIPS). Clinical Psychologist. 2025; 1-1. [DOI:10.1080/13284207.2025.2515074]

[23] Liu F, Wang P, Hu J, Shen S, Wang H, Shi C, et al. A psychologically interpretable artificial intelligence framework for the screening of loneliness, depression, and anxiety. Applied Psychology: Health and Well-Being. 2025; 17(1):e12639. [DOI:10.1111/aphw.12639] [PMID]

[24] Shafiee Rad H. Reinforcing L2 reading comprehension through artificial intelligence intervention: Refining engagement to foster self-regulated learning. Smart Learning Environments. 2025; 12(1):23. [DOI:10.1186/s40561-025-00377-2]

[25] Klos MC, Escoredo M, Joerin A, Lemos VN, Rauws M, Bunge EL. Artificial intelligence-based chatbot for anxiety and depression in university students: pilot randomized controlled trial. JMIR Formative Research. 2021; 5(8):e20678. [DOI:10.2196/20678] [PMID]

[26] Boucher EM, Harake NR, Ward HE, Stoeckl SE, Vargas J, Minkel J, et al. Artificially intelligent chatbots in digital mental health interventions: A review. Expert Review of Medical Devices. 2021; 18(1):37-49. [DOI:10.1080/17434440.2021.2013200] [PMID]

[27] Jacobson NC, Nemesure MD. Using artificial intelligence to predict change in depression and anxiety symptoms in a digital intervention: evidence from a transdiagnostic randomized controlled trial. Psychiatry Research. 2021; 295:113618. [DOI:10.1016/j.psychres.2020.113618] [PMID]

[28] Page MJ, McKenzie JE, Bossuyt PM, Boutron I, Hoffmann TC, Mulrow CD, et al. The PRISMA 2020 statement: An updated guideline for reporting systematic reviews. BMJ. 2021; 372. [DOI:10.1136/bmj.n71] [PMID]

[29] Bagheri Sheykhangafshe F, Hajialiani V, Hasani J. The role of resilience and emotion regulation in psychological distress of hospital staff during the COVID-19 pandemic: A systematic review study. Journal of Research and Health. 2021; 11(6):365-74. [DOI:10.32598/JRH.11.6.1922.1]

[30] Sarkis-Onofre R, Catalá-López F, Aromataris E, Lockwood C. How to properly use the PRISMA Statement. Systematic Reviews. 2021; 10(1):117. [DOI:10.1186/s13643-021-01671-z] [PMID]

[31] Liu H, Peng H, Song X, Xu C, Zhang M. Using AI chatbots to provide self-help depression interventions for university students: A randomized trial of effectiveness. Internet Interventions. 2022; 27:100495. [DOI:10.1016/j.invent.2022.100495] [PMID]

[32] Karkosz S, Szymański R, Sanna K, Michałowski J. Effectiveness of a web-based and mobile therapy chatbot on anxiety and depressive symptoms in subclinical young adults: randomized controlled trial. JMIR Formative Research. 2024; 8(1):e47960. [DOI:10.2196/47960] [PMID]

[33] Patel F, Thakore R, Nandwani I, Bharti SK. Combating depression in students using an intelligent chatbot: A cognitive behavioral therapy. Paper presented at: 2019, IEEE 16th India Council International Conference (INDICON); 12 March 2020; Rajkot, India. [DOI:10.1109/INDICON47234.2019.9030346]

[34] Wagner J, Schwind AS. Investigating psychotherapists' attitudes towards artificial intelligence in psychotherapy. BMC Psychology. 2025; 13(1):719. [DOI:10.1186/s40359-025-03071-7] [PMID]

[35] Aafjes-van Doorn K. Feasibility of artificial intelligence-based measurement in psychotherapy practice: Patients' and clinicians' perspectives. Counselling and Psychotherapy Research. 2025; 25(1):e12800. [DOI:10.1002/capr.12800]

[36] Das KP, Gavade P. A review of the efficacy of artificial intelligence for managing anxiety disorders. Frontiers in Artificial Intelligence. 2024; 7:1435895. [DOI:10.3389/frai.2024.1435895] [PMID]

[37] Ricci F, Giallanella D, Gaggiano C, Torales J, Castaldelli-Maia JM, Liebrenz M, et al. Artificial intelligence in the detection and treatment of depressive disorders: a narrative review of literature. International Review of Psychiatry. 2025; 37(1):39-51. [DOI:10.1080/09540261.2024.2384727] [PMID]

[38] Levkovich I. Is artificial intelligence the next co-pilot for primary care in diagnosing and recommending treatments for depression? Medical Sciences. 2025; 13(1):8. [DOI:10.3390/medsci13010008] [PMID]

[39] Ebert DD, Harrer M, Apolinário-Hagen J, Baumeister H. Digital interventions for mental disorders: key features, efficacy, and potential for artificial intelligence applications. Frontiers in Psychiatry: Artificial Intelligence, Precision Medicine, and Other Paradigm Shifts. 2019; 583-627. [DOI:10.1007/978-981-32-9721-0_29] [PMID]

[40] Cruz-Gonzalez P, He AW, Lam EP, Ng IM, Li MW, Hou R, et al. Artificial intelligence in mental health care: a systematic review of diagnosis, monitoring, and intervention applications. Psychological Medicine. 2025; 55:e18. [DOI:10.1017/S0033291724003295] [PMID]

[41] Beg MJ, Verma M, Verma MK. Artificial intelligence for psychotherapy: A review of the current state and future directions. Indian Journal of Psychological Medicine. 2024; 02537176241260819. [DOI:10.1177/02537176241260819] [PMID]

[42] Gual-Montolio P, Jaén I, Martínez-Borba V, Castilla D, Suso-Ribera C. Using artificial intelligence to enhance ongoing psychological interventions for emotional problems in real or close to real-time: A systematic review. International Journal of Environmental Research and Public Health. 2022; 19(13):7737. [DOI:10.3390/ijerph19137737] [PMID]

[43] Tornero-Costa R, Martinez-Millana A, Azzopardi-Muscat N, Lazeri L, Traver V, Novillo-Ortiz D. Methodological and quality flaws in the use of artificial intelligence in mental health research: systematic review. JMIR Mental Health. 2023; 10(1):e42045. [DOI:10.2196/42045] [PMID]

[44] Cornelis FH, Filippiadis DK, Wiggermann P, Solomon SB, Madoff DC, Milot L, et al. Evaluation of navigation and robotic systems for percutaneous image-guided interventions: A novel metric for advanced imaging and artificial intelligence integration. Diagnostic and Interventional Imaging. 2025. [DOI:10.1016/j.diii.2025.01.004] [PMID]

[45] Lau Y, Ang WH, Ang WW, Pang PC, Wong SH, Chan KS. Artificial Intelligence-Based Psychotherapeutic Intervention on Psychological Outcomes: A Meta-Analysis and Meta-Regression. Depression and Anxiety. 2025; 2025(1):8930012. [DOI:10.1155/da/8930012]