Dehbozorgi *et al. BMC Psychiatry* (2025) 25:132
https://doi.org/10.1186/s12888-025-06483-2

BMC Psychiatry

SYSTEMATIC REVIEW

The application of artificial intelligence in the field of mental health: a systematic review

Raziye Dehbozorgi[1,2], Sanaz Zangeneh[3], Elham Khooshab[4], Donya Hafezi Nia[5], Hamid Reza Hanif[6], Pooya Samian[7], Mahmoud Yousefi[8], Fatemeh Haj Hashemi[9], Morteza Vakili[10], Neda Jamalimoghadam[11*] and Fatemeh Lohrasebi[5]

Abstract

Introduction The integration of artificial intelligence in mental health care represents a transformative shift in the identification, treatment, and management of mental disorders. This systematic review explores the diverse applications of artificial intelligence, emphasizing both its benefits and associated challenges.

Methods A comprehensive literature search was conducted across multiple databases based on Preferred Reporting Items for Systematic Reviews and Meta-Analyses, including ProQuest, PubMed, Scopus, and Persian databases, resulting in 2,638 initial records. After removing duplicates and applying strict selection criteria, 15 articles were included for analysis.

Results The findings indicate that AI enhances early detection and intervention for mental health conditions. Various studies highlighted the effectiveness of AI-driven tools, such as chatbots and predictive modeling, in improving patient engagement and tailoring interventions. Notably, tools like the Wysa app demonstrated significant improvements in user-reported mental health symptoms. However, ethical considerations regarding data privacy and algorithm transparency emerged as critical challenges.

Discussion While the reviewed studies indicate a generally positive trend in AI applications, some methodologies exhibited moderate quality, suggesting room for improvement. Involving stakeholders in the creation of AI technologies is essential for building trust and tackling ethical issues. Future studies should aim to enhance AI methods and investigate their applicability across various populations.

Conclusion This review underscores the potential of AI to revolutionize mental health care through enhanced accessibility and personalized interventions. However, careful consideration of ethical implications and methodological rigor is essential to ensure the responsible deployment of AI technologies in this sensitive field.

Keywords Artificial Intelligence, Natural Language Processing, Digital Health, Mental Health, Machine Learning

*Correspondence:
Neda Jamalimoghadam
nedajamali21@yahoo.com
Full list of author information is available at the end of the article

Introduction

The incorporation of artificial intelligence (AI) into mental health care has become a revolutionary influence, altering the ways in which mental health disorders are diagnosed, treated, and managed [1]. This systematic review seeks to explore the diverse applications of AI in mental health, highlighting both its potential benefits and the challenges it poses. Over the past few years, numerous studies have underscored the capacity of AI to enhance the early detection and diagnosis of mental health conditions, facilitating timely and appropriate interventions.

The application of AI in mental health care not only enhances early detection and diagnosis but also enables personalized treatment and improved patient engagement. AI analyzes patient data to tailor interventions and includes tools like chatbots for support, especially in areas with limited access to traditional services. However, challenges such as ethical issues, data privacy, and the need for effective implementation frameworks must be addressed. This review will explore these aspects to ensure responsible integration of AI into mental health systems [2].

Gaffney and colleagues worked on the AI in mental health care in their article. They discuss the significant role of conversational agents, which are AI-driven tools such as chatbots, in providing immediate support and intervention for individuals experiencing mental health issues. The review highlights that conversational agents can enhance accessibility to mental health resources, deliver personalized therapeutic interactions, and facilitate ongoing engagement with users. By leveraging natural language processing and machine learning, these agents can effectively assess user needs, provide tailored responses, and promote self-management strategies, ultimately contributing to improved mental health outcomes [3].

In an examination of the transformative potential of AI in mental health care, Olawade et al. (2022) emphasize the increasing integration of AI technologies into mental health services, which offer innovative solutions for diagnosis, treatment, and patient engagement. Current trends suggest that AI can facilitate the early detection of mental health disorders, optimize therapeutic interventions through personalized approaches, and enhance access to care, particularly for underserved populations. Additionally, the authors discuss future prospects, highlighting the importance of ethical considerations and robust implementation strategies to ensure the effective integration of AI applications into clinical practice. By addressing both the opportunities and challenges associated with AI in mental health, this review aims to provide a comprehensive understanding of how these technologies can improve mental health outcomes and reshape the landscape of mental health care [4].

Despite these promising applications, the integration of AI in mental health care is not without its challenges. Ethical considerations surrounding data privacy and the transparency of AI algorithms are critical issues that require careful examination. Tavory (2023) highlighted the necessity for ethical frameworks to guide the development and deployment of AI technologies in mental health, advocating for a balanced approach that prioritizes patient safety and informed consent [5].

Tornero-Costa et al. (2022) critically assess the methodological and quality flaws present in the use of AI within mental health research. The authors identify several key issues that undermine the reliability and validity of AI applications in this field, including inadequate study designs, insufficient sample sizes, and a lack of transparency in reporting methodologies. Furthermore, they emphasize the importance of rigorous methodological standards to enhance the credibility of AI-driven research outcomes. By highlighting these flaws, the review underscores the need for improved research practices to ensure that AI technologies can be effectively and ethically integrated into mental health care, ultimately advancing the field and benefiting patient outcomes [6].

Furthermore, the previous review noted critical issues such as inadequate transparency in reporting AI model features and data preprocessing techniques, which are essential for ensuring reproducibility and reliability in research. Many studies included in the earlier review did not sufficiently assess the quality of data or the appropriateness of AI methodologies for their specific applications, leading to potential biases and an overly optimistic view of AI performance. These shortcomings underscore the necessity for a new systematic review that not only addresses these methodological gaps but also provides a detailed overview of AI applications in mental health, including their benefits and challenges.

This article seeks to address this gap by consolidating recent research findings, assessing methodologies, and pinpointing areas for further exploration. Through this approach, we aim to enhance the understanding of how AI can be successfully incorporated into mental health care, ultimately improving the quality of care for those experiencing mental health difficulties.

Methods

Reviewing the literature

The systematic review on the application of AI in mental health involved a comprehensive search across multiple databases to gather a robust collection of relevant studies.

The search encompassed both Persian databases, including IranDoc and ISC, and international databases such as ProQuest, PubMed, Scopus, Web of Science, Cochrane, Wiley, and the American Psychiatric Association's APA database.

For the initial search phase, we employed a search syntax focusing on the terms "artificial intelligence" and "mental health." The results varied significantly, with international databases yielding a higher number of records. Specifically, ProQuest identified 944 records, PubMed found 829, and Scopus retrieved 353.In contrast, Persian databases like IranDoc and ISC produced no relevant records, indicating a limited volume of research in the application of AI in mental health. Notably, SID, a Persian database, contributed four records, while Web of Science retrieved 171 records, and E-journal platforms like Cochrane and Wiley yielded 65 and 7 records, respectively. Overall, the search across all databases generated 2,638 initial records.

To refine the dataset, we removed duplicate entries, reducing the total to 1,471 unique records. Following this, we conducted a title screening phase to further narrow down the records to those most relevant to our research question. After this rigorous screening, only 369 records were deemed suitable for the subsequent phases of the systematic review process.

This comprehensive approach highlights the diversity of resources and the necessity of detailed screening processes in conducting a systematic review, particularly when analyzing the intersection of AI and mental health research.

This comprehensive approach highlights the diversity of resources and the necessity of detailed screening processes in conducting a systematic review, particularly when analyzing the intersection of AI and mental health research.The search strategy, along with thorough deduplication and screening, allowed for a focused dataset essential for synthesizing accurate insights into AI's role and effectiveness within the mental health domain.

Selection criteria and search strategy

The systematic review followed a multi-stage selection process to ensure a thorough and unbiased analysis. Initially, we retrieved a total of 2, 638 records from various databases, including ProQuest, PubMed, Scopus, Web of Science, Cochrane, and Wiley, along with Persian databases such as IranDoc, ISC, and SID. Searches were conducted using specific syntaxes tailored to each database, primarily combining the terms "artificial intelligence" and "mental health" to capture relevant literature.

From the initial 2,638 records, we identified and removed 1,167 duplicates, resulting in a pool of 1,471 articles as of July 12, 2024. In the first screening stage, we reviewed these articles based on title relevance, leading to the identification of 369 articles pertinent to the topic by July 15, 2024. We then examined the abstracts of the remaining articles, yielding 80 articles that met the initial criteria. However, 23 articles were excluded due to the lack of full text, reducing the number to 57 from July 16–29, 2024. A thorough review of the full-text articles resulted in the exclusion of 42 articles based on specific criteria, leaving 15 articles for final inclusion from August 2–15, 2024. The reasons for excluding articles at each stage of the systematic review process are as follows: Initially, from the 2,638 records identified, 1,167 duplicates were removed, resulting in 1,471 unique articles. During the title screening phase, 1,471 articles were assessed for relevance, leading to the exclusion of 1,102 articles that did not meet the criteria based on their titles. Subsequently, the remaining 369 articles were further evaluated through abstract screening, where 289 articles were excluded due to insufficient relevance to the research question or lack of focus on artificial intelligence applications in mental health. In the full-text review phase, 57 articles were considered, but 42 were excluded for reasons such as the absence of full-text availability, lack of methodological rigor, or failure to address the specific aims of the review. This left 15 articles that met all inclusion criteria. Each of these articles underwent a comprehensive risk of bias assessment, ensuring that the final selection was based on robust methodological standards and relevance to the topic of AI in mental health Table 1.

We conducted a comprehensive risk of bias assessment for the 15 final articles to evaluate their methodological rigor and reliability, concluding this assessment phase on August 29, 2024. Data extraction from the selected studies was completed between September 5–15, 2024, ensuring that each study's findings and details were systematically recorded for further analysis. This rigorous multi-stage approach facilitated a focused and high-quality selection of studies that addressed the application of artificial intelligence in mental health (see Fig. 1).

Quality appraisal methods

The comparative analysis of the 15 studies reveals significant insights regarding the quality assessment tools utilized in AI applications within mental health interventions.

The studies, spanning from 2018 to 2023, illustrate a growing interest in the integration of AI technologies in mental health research. Various quality assessment tools were used across these studies, reflecting the researchers' commitment to rigorous evaluation of their methodologies (see Table 1).

A notable number of studies utilized the Mixed Methods Appraisal Tool (MMAT), which was applied in four studies, including those by Inkster et al. (2018), Chin et al. (2021), Götzl et al. (2022), and Pei (2022). The MMAT is particularly effective for evaluating mixed-methods research, allowing for a nuanced understanding of complex mental health dynamics. Its application across multiple studies underscores its robustness in assessing research quality in this field [7].

The Newcastle–Ottawa Scale (NOS) was another prominent tool, used in several studies, including those by Xiao Li (2023), Pei (2022), and Tate (2020). The NOS is well-regarded for its application in observational studies, providing a systematic approach to evaluating the quality of non-randomized studies. The consistent use of the NOS across these studies indicates its reliability and relevance in assessing the quality of observational research in AI-driven mental health interventions [8].

Additionally, the Joanna Briggs Institute (JBI) tool was employed in various experimental studies, including those by Didarul Alam et al. (2021), Yanqi Guo (2023), Ilona Halim et al. (2023), and Naveen Kumari & Rekha Bhatia (2022). The JBI tool is designed to assess the methodological quality of experimental and quasi-experimental studies, contributing to a comprehensive understanding of the effectiveness of AI interventions in mental health [9].

Despite the predominance of established tools like the MMAT, NOS, and JBI, variability in the quality of studies was observed, particularly with the application of different methodologies. For instance, the study by Rohit Rastogi et al. (2022) utilized the JBI tool but received a moderate quality score, indicating that even established assessment tools can yield varied results based on the study design and execution.

In summary, the analysis of the quality assessment tools used in these studies highlights the importance of methodological rigor in AI-related mental health research. The diversity of tools employed—MMAT, NOS, and JBI—demonstrates the multifaceted nature of research methodologies in this area. The consistent application of these established tools enhances the credibility of findings and paves the way for future advancements in the integration of AI technologies in mental health interventions.

Results

Application of AI in mental health

The 15 reviewed studies illustrate various interpretations and applications of AI in mental health contexts. Inkster et al. (2018) introduced Wysa, an AI-driven chatbot aimed at improving mental well-being by enabling self-reflection and resilience through conversational support [10](Table 2).

Lei (2023) and Xiao Li (2023) explored more advanced AI techniques, with Lei et al. using Long Short-Term Memory (LSTM) models for emotion recognition tasks and Li applying deep learning (CNN) to assess mental health states by analyzing social media text data. These approaches underscore the adaptability of AI in processing complex data patterns, such as emotional and mental health indicators [12, 27].

Götzl et al. (2022) summarized AI's broader purpose as learning systems that evaluate large information sets, often applied in platforms like YouTube and Spotify, showcasing AI's versatility in various interactive media [28].

These studies reveal the diversity and scope of AI applications in mental health, ranging from emotional recognition and chatbot support to large-scale predictive models, illustrating AI's role in advancing personalized and accessible mental health solutions.

Tools and algorithms used in AI in mental health

The comparative analysis of the 15 articles concerning the application of AI in mental health reveals a diverse landscape of methodologies, participant demographics, and AI technologies. Each study contributes unique insights into the effectiveness and acceptability of AI-driven interventions (Table 2).

The first study by Inkster et al. (2018) employed a mixed-methods approach to evaluate the Wysa app, an AI-enabled chatbot designed for mental well-being. This study focused on a global user base of individuals self-reporting symptoms of depression. The findings indicated that users who engaged more frequently with the app experienced significant improvements in their depressive symptoms, with 67.7% of participants finding the app helpful. This highlights the potential effectiveness of text-based conversational AI in mental health support [10].

In contrast, Xiao Li (2023) conducted a quantitative study aimed at understanding depression among the elderly. Utilizing Long Short-Term Memory (LSTM) networks, the research focused on emotional recognition, demonstrating how AI can model temporal information to improve mental health interventions. The integration of AI attention mechanisms enhanced the accuracy of emotional feature recognition, suggesting that advanced AI techniques can significantly contribute to understanding and addressing mental health issues [12].

Liang et al. (2022) evaluated the mental health of college students using a Convolutional Neural Network (CNN) to analyze text data from online forums. This experimental study indicated that AI could effectively

Table 1 Search strategy (search syntax: (artificial intelligence AND mental))

Databases	Number of records	Number of records after deleting duplications	After title sceening
IranDoc(Persian)	0	0	0
ISC(Persian)	0	0	0
proquest	100	91	91
Pubmed	829	794	
scopus	353	351	53
SID(Persian)	4	1	1
Web Of Science	171	167	167
E Journals	Number of records	Search syntax	
Cochrane	65	45	45
Wiley	7	1	1
Magiran(Persian)	0	0	0
APA: American Psychiatric Association	265	12	11
Total	2638	1471	369

monitor and assess mental health states, providing personalized psychological support based on user-generated content. The study's results affirmed the feasibility of AI in delivering tailored mental health interventions [13].

Chin et al. (2023) explored user interactions with the SimSimi chatbot across various cultural contexts, analyzing 96,197 conversations from Eastern and Western countries. This mixed-methods study revealed cultural differences in the expression of depressive moods, emphasizing the chatbot's role in social science research and its high acceptability among users. The findings suggest that AI can facilitate large-scale data collection and cultural analysis of mental health expressions [29].

Dadi (2021) utilized machine learning to analyze multimodal data from the UK Biobank, demonstrating how population modeling can derive mental health measures from diverse inputs, including brain imaging. This approach indicates that AI can complement traditional psychometric assessments, enhancing the understanding of mental health determinants in large populations [15].

Rathnayaka (2022) focused on the design and development of a BA-based AI chatbot, confirming its effectiveness in providing emotional support and remote mental health monitoring. The participatory evaluation highlighted user feedback on the chatbot's capabilities, reinforcing the importance of user experience in AI applications for mental health [30].

Pei (2022) utilized a neural network algorithm to forecast and assess the mental health status of college students, uncovering notable psychological stressors. This research highlights the effectiveness of AI in recognizing mental health risks and customizing interventions through predictive analytics [17].

Tate (2020) created a model employing machine learning techniques to forecast mental health issues in adolescents, attaining a satisfactory level of predictive accuracy. While the model was not appropriate for clinical application, it established a foundation for future investigations into predicting mental health in adolescents [31].

Didarul Alam et al. (2021) explored the adoption of mobile health (mHealth) technologies during the COVID-19 pandemic by utilizing Structural Equation Modeling and Artificial Neural Networks (ANN). The results demonstrated a positive correlation between mHealth usage and mental well-being, emphasizing the role of AI in improving user engagement during times of crisis [19].

Götzl et al. (2022) explored young people's attitudes toward AI-informed mHealth apps, revealing a generally positive reception and willingness to use AI for personalized interventions. This study emphasizes the potential of AI to adapt interventions to individual needs, enhancing the effectiveness of mental health support [28].

Onuki et al. (2022) examined the use of wearable devices to estimate mental health conditions based on heart rate data, finding high acceptability among users. This study illustrates how AI can integrate with wearable technology to provide real-time health monitoring [21].

Alamgir et al. (2023) focused on facial expression recognition using a hybrid AI model, demonstrating its ability to categorize emotions effectively. This research highlights the potential of AI in enhancing emotional awareness and understanding in mental health contexts [32].

Yanqi Guo (2023) analyzed the impact of AI technology on family education, revealing significant improvements in mental health outcomes among students receiving

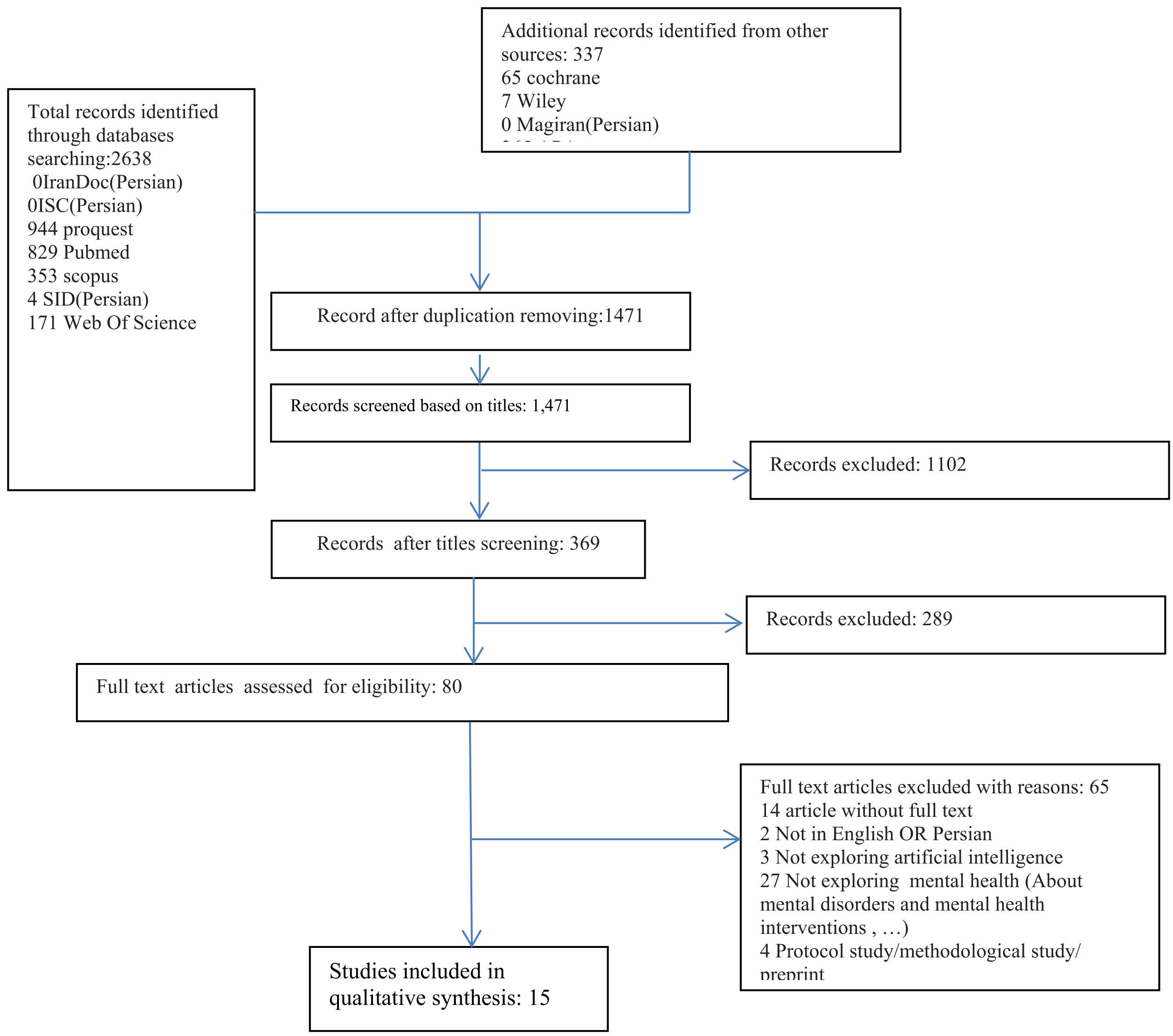

Fig. 1 Diagram for the inclusion and exclusion of articles

AI-based support compared to traditional methods. This study showcases the versatility of AI applications beyond direct mental health interventions [23].

Finally, Halim et al. (2023) tested an individualized virtual reality (iVR) approach to improve self-compassion and reduce depressive symptoms. Although primarily focused on VR, the study emphasized the potential of integrating AI to personalize user experiences and enhance therapeutic outcomes [33].

In conclusion, the combined results from these studies reflect an increasing acceptance and effectiveness of AI in mental health interventions across different demographics and methodologies. The varied applications of AI, including chatbots, predictive models, and wearable technologies, underscore its potential to revolutionize mental health care by offering personalized, accessible, and effective support. As the field progresses, additional research is crucial to enhance these technologies and confirm their effectiveness across diverse populations (Table 3).

Quality appraisal methods

In examining the application of AI in mental health studies, various study types and quality assessment tools were employed, with each study exhibiting unique methodological strengths (Table 1).

Inkster et al. (2018) [10] conducted a mixed-methods study, receiving a total score of 7, assessed as "good" quality using the Mixed-Methods Appraisal Tool (MMAT), demonstrating effective integration of both qualitative

Table 2 Quality assessment of articles

Row	Author	Year	Study type	Quality assessment tools	Total score	Study quality	Reference
1	Inkster B etal	2018	Mixed-Methods Study	MMAT	7	good	[11]
2	Xiao Li	2023	Quantitative	NOS	7	good	[12]
3	Liang L,	2022	Experimental study	NOS	5	good	[13]
4	Chin et al.,	2023	Mixed Methods Study	MMAT	7	good	[14]
5	Dadi	2021	Population modeling	NOS	6	moderate	[15]
6	Rathnayaka	2022	designing and developing of BA-based AI chatbot and a pilot study	NOS	6	moderate	[16]
7	Pei	2022	Two phase (Prediction and Analysis)	CASP	7	good	[17]
8	Tate	2020	Model development	NOS	7	good	[18]
9	Didarul Alam et. al	–2021	empirical study with SEMANN (Structural Equation Modeling – Artificial Neural Network	JBI	10	good	[19]
10	Götzl et al	–2022	parallel mixed–method study	MMAT	7	good	[20]
11	Onuki. M Et al	2022	Casual-comparative research	NOS	6	Moderate	[21]
12	Alamgir FM et al	2022	Multi-methods study	NOS	7	good	[22]
13	Yanqi Guo,	2023	Experimental study (Randomized controlled trials)	JBI	9	Good	[23]
14	Ilona Halim, et al	2023	Experimental study (Randomized controlled trials)	JBI	7	Good	[24]
15	Naveen Kumari· Rekha Bhatia	2022	experimental	JBI	8	Good	[25]
16	Rohit Rastogi, etal	2022	experimental	JBI	5	Moderate	[26]

and quantitative data. Similarly, Xiao Li (2023) [12] and Chin et al. (2023) [29] employed quantitative and mixed-methods approaches, respectively, with their studies scored at 7 by the Newcastle–Ottawa Scale (NOS), indicating high methodological quality and thorough evaluation of mental health indicators related to AI applications.

Dadi (2021) [15] focused on population modeling with AI, achieving a "good" quality rating and a score of 6 from NOS. In a similar context, Liang et al. (2022) [13] conducted an experimental study focused on AI model performance, assessed by NOS and rated "good" with a score of 5, reflecting methodological rigor but with room for further improvement.

A more complex study design was employed by Rathnayaka (2022) [30], who utilized the two-phase prediction and analysis approach to AI applications. This study received a score of 6 on NOS, indicating "moderate" quality, suggesting effective use of predictive techniques but with potential limitations in methodological consistency.

Conversely, Pei (2022) [17] and Tate (2020) [31] undertook model development and empirical study using SEMANN (Structural Equation Modeling – Artificial Neural Network), both achieving "good" quality with a score of 7 under NOS. Didarul Alam et al. (2021) [19] conducted a parallel mixed-method study, assessed by the Joanna Briggs Institute (JBI) checklist, scoring 10 and rated "good," reflecting strong methodological coherence across study phases.

In randomized controlled trials, Götzl et al. (2022) [28] and Onuki et al. (2022) [21] both received "good" ratings with scores of 9 and 7, respectively, indicating robust experimental control and rigorous assessment in AI application to mental health. Similarly, Alamgir FM et al. (2022) [32] and Yanqi Guo et al. (2023) [23] conducted experimental studies, each with "good" quality ratings, showing consistency in applying AI within structured trials.

Finally, Kumari et al. (2023) [25] and Rohit Rastogi et al. (2022) [34] utilized a more experimental framework, rated as "moderate" quality with scores of 8 and 5 under JBI, illustrating potential for reliable AI-driven results but highlighting the need for additional methodological refinement.

Table 3 Extracted data from articles

N	Author and year	Study type	Study aims	participants	methodology	analysis	Meaning of Artificial Intelligence	Acceptability of Artificial Intelligence	application of Artificial Intelligence	Effectiveness of Artificial Intelligence	Kind of Artificial Intelligence	Name of Artificial Intelligence
1	Inkster B et al 2018 [10, 11]	Mixed-Methods Study	This study aimed to present a preliminary real-world data evaluation of the effectiveness and engagement levels of an AI-enabled, empathetic, text-based conversational mobile mental well-being app, Wysa, on users with self-reported symptoms of depression	a group of anonymous global users were observed who voluntarily installed the Wysa app, engaged in text-based messaging, and self-reported symptoms of depression using the Patient Health Questionnaire-9 2 distinct groups of users (*high users* and *low users*) emerged	In the study, a group of anonymous global users were observed who voluntarily installed the Wysa app, engaged intext-based messaging, and self-reported symptoms of depression using the Patient Health Questionnaire-9. On the basis of theextent of app usage on and between 2 consecutive screening time points, 2 distinct groups of users (*high users* and *low users*) emerged. The study used mixed-methods approach to evaluate the impact and engagement levels among these users. Thequantitative analysis measured the app impact by comparing the average improvement in symptoms of depression between highand low users. The qualitative analysis measured the app engagement and experience by analyzing in-app user feedback andevaluated the performance of a machine learning classifier to detect user objections during conversations	The quantitative analysis measured the app impact by comparing the average improvement in symptoms of depression between high and low users. The qualitative analysis measured the app engagement and experience by analyzing in-app user feedback and evaluated the performance of a machine learning classifier to detect user objections during conversations	Wysa, a Smartphone-Based Empathetic Artificial Intelligence Chatbot App for Mental Well-Being Wysa, developed by Touchkin, is an AI-based emotionally intelligent mobile chatbot app aimed at building mental resilience and promoting mental well-being using a text-based conversational interface. The Wysa app assists users to develop positive self-expression by using AI to create an external and responsive self-reflection environment	The real-world data evaluation findings on the effectiveness and engagement levels of Wysa app on users with self-reported symptoms of depression show promise	determine the effectiveness of delivering positive psychology and mental well-being techniques in a text-based conversational mode using the Wysa app on users with self-reported symptoms of depression. Users were presented with the validated Patient Health Questionnaire (PHQ-9) during their conversations and screened for selection based on their 2-item (PHQ-2) score. The average improvement in self-reported symptoms of depression (Pre-PHQ-9 minus Post-PHQ-9) was compared between 2 comparison groups: (1) more engaged app users ("high users" group) and (2) less engaged app users ("low users" group) Improvement of depressive symptoms	The average mood improvement (ie, difference in pre- and post-self-reported depression scores) between the groups (ie, high vs low users; $n=108$ and $n=21$, respectively) revealed that the high users group had significantly higher average improvement (mean 5.84 [SD 6.66]) compared with the low users group (mean 3.52 [SD 6.15]); Mann–Whitney $P=.03$ and with a moderate effect size of 0.63. Moreover, 67.7% of user-provided feedback responses found the app experience helpful and encouraging	Chatbot App	Wysa app:
2	Xiao Li 2023 [12]	Quantitative	The purpose is to understand the depression status of the elderly in the community, explore its influencing factors, formulate a comprehensive psychological intervention plan according to the influencing factors, implement demonstration psychological nter-vention, and evaluate and feedback the effect, so as to provide a reference for improving the mental health of the elderly	elderly in the two groups of community (control group ($n=46$) and the intervention group ($n=47$))	In order to make the output of different emotional data in LSTM more discriminative, a method to dynamically filter the output of LSTM is proposed. Combining the methods of Attention-LSTM, time-dimensional AI attention, and feature-dimensional AI attention, the best model in this paper is obtained	Quantitative methods, including t-tests, variance analysis, and multiple stepwise regression, were used for data analysis	AI, specifically LSTM, was used to model temporal information crucial for emotion recognition tasks	AI attention mechanisms were explored to enhance LSTM outputs, improving emotional feature recognition and classification accuracy	AI was applied through AI attention in both time and feature dimensions to optimize LSTM outputs for speech emotion recognition	The study integrated AI attention mechanisms with LSTM, significantly improving emotion recognition performance compared to traditional methods	LSTM with AI attention mechanisms focused on enhancing emotional feature recognition in speech	LSTM with AI attention mechanisms focused on enhancing emotional feature recognition in speech

Table 3 (continued)

N	Author and year	Study type	Study aims	participants	methodology	analysis	Meaning of Artificial Intelligence	Acceptability of Artificial Intelligence	application of Artificial Intelligence	Effectiveness of Artificial Intelligence	Kind of Artificial Intelligence	Name of Artificial Intelligence
3	Liang L, 2022 [13]	Experimental study	To evaluate the effectiveness of artificial intelligence (AI) in assessing and improving the mental health of college students	185 students in sports major (Training set: 137 Test set: 48)	☐ **Data Collection:** Mental health data were collected from internal forums and through the Symptom Checklist-90 (SCL-90) questionnaire ☐ **AI Model:** A Convolutional Neural Network (CNN) was employed to process and analyze the text data from the forums ☐ **Questionnaire Design:** The SCL-90 was used to evaluate the mental health status of the students	☐ **CNN Model:** The CNN was trained and tested using forum data, with specific parameters set to optimize its performance ☐ **Questionnaire Data:** The SCL-90 results were statistically analyzed to compare mental health states under traditional and AI-enhanced education	AI, particularly deep learning through CNN, is used to monitor and assess the mental health state of college students by analyzing text data from forums	The platform has achieved good results. The mental health plan for college students is feasible	AI is applied to evaluate and provide early warnings regarding the mental health of students, and to offer personalized psychological support based on the analysis of forum posts	The CNN model showed improved performance over traditional models (e.g., FastText) in recognizing and classifying mental health states, with higher accuracy and F1 scores	Deep Learning, specifically Convolutional Neural Networks (CNN)	Not explicitly named, but involves CNN as the core AI technology
4	Chin et al., 2023 [14, 29]	Mixed Methods Study	To analyze user interactions with SimSimi chatbot regarding depressive moods across different cultural contexts	SimSimi Chatbot users. Data collected from 96,197 conversations in Eastern countries (Malaysia, Philippines, India, Indonesia, Thailand) and 56,586 conversations in Western countries (Canada, United Kingdom, United States)	Analyzed user-generated conversations with SimSimi from May 2016 to December 2020, focusing on expressions related to depressive moods using specific keywords	Data categorized by cultural groups (Eastern vs. Western) to compare frequency and linguistic traits of depressive conversations. Each user's data was anonymized, focusing on non-clinically diagnosed users discussing depressive emotions	SimSimi is an open-domain chatbot designed for social interaction and entertainment, capable of generating responses based on a vast database of user interactions	Widely used across 111 languages with 400 million users, indicating high acceptability and engagement globally	Used to study cultural differences in how users express depressive moods online, highlighting its application in social sciences research	Effective in handling diverse user inputs and generating appropriate responses, facilitating large-scale data collection and analysis	SimSimi operates as a conversational AI, employing natural language processing to understand and respond to user queries	SimSimi Chatbot
5	Dadi 2021 [15]	Population modeling	building proxy measures by applying machine learning on multimodal MR images and rich sociodemographic information from the largest biomedical cohort to date: the UK Biobank	11,175 participants	considered participants who have responded to cognitive tests and questionnaires and provide ac-cess to their primary demographic characteristics and brain im-ages	The combination of brain imaging and target-specific sociodemographic inputs often improved approximation performance	The UKBB database is to date the most extensive large-scale co-hort aimed at studying the determinants of the health outcomes in the general adult population	The UKBB is openly accessible and has extensive data acquired on 500,000 individuals aged 40–70 years covering rich phenotypes, health-related information, brain-imaging, and genetic data	Population modeling with machine learning can derive measures of mental health from heterogeneous inputs including brain signals and questionnaire data. This may complement or even substitute for psychometric assessments in clinical populations	This complementarity of proxy measures and original measures at capturing multiple health-related constructs when modeling from, both, brain signals and sociodemographic data	machine learning	No state

Table 3 (continued)

N	Author and year	Study type	Study aims	participants	methodology	analysis	Meaning of Artificial Intelligence	Acceptability of Artificial Intelligence	application of Artificial Intelligence	Effectiveness of Artificial Intelligence	Kind of Artificial Intelligence	Name of Artificial Intelligence
7	Rathnayaka 2022 [16, 30]	designing and developing of BA-based AI chatbot and a pilot study	Presenting the design and development of BA-based AI chatbot, followed by its participatory evaluation in a pilot study setting that confirmed its effectiveness in providing support for individuals with mental health issues	318 individuals across the world	The conceptual framework was formulated using a structured approach consistingof three phases The conceptual framework was designed as a series of chatbot capabilities that can be grouped into three main categories, (1) personalised conversation (2) emotional support and (3) remote mental health monitoring, which are delineated in the following subsections The user experience of engaging with the BA-based AI chatbot was a further design consideration that is articulated at the end of this section The participatory evaluation of the completed chatbot as a pilot study was conducted in Australia	The conceptual framework was designed as a series of chatbot capabilities that can be grouped into three main categories, (1) personalised conversation (2) emotional support and (3) remote mental health monitoring, which are followed by a pilot study	The conceptual framework was designed as a series of chatbot capabilities	Users must vol-untarily submit their feelings checks and PHQ2 surveys while using the app	Some of these responses were: 1. "By using the app, I am more aware of how my moods fluctuate. It also made me think about what I am grateful for, which alleviated some negativity I was experiencing at the time" Sensors 2022, 22, 3653 15 of 18 2. "Mood tracker is great to be able to give to my medical practitioner—If my psychologist or doctor asked me to use this as a monitoring tool in between sessions, I would be more likely to engage" 3. "Bunji lets me feel courageous" themselves, and extending the gamification of Bunji for visually setting and tracking goals against a community benchmark and one's own track record. We are also working on expanding the activity banks to include activities, inspirations, quotations, and workshops, as well as enhancements to the language model for more fun/inspirational human-like conversations with a range of responses that suit diverse demographics (e.g., emojis and memes)	The design and development of our BA-based AI chatbot, followed by its participatory evaluation, confirmed its effectiveness in providing support for individuals with mental health issues	chatbots	Bunji

Table 3 (continued)

N	Author and year	Study type	Study aims	participants	methodology	analysis	Meaning of Artificial Intelligence	Acceptability of Artificial Intelligence	application of Artificial Intelligence	Effectiveness of Artificial Intelligence	Kind of Artificial Intelligence	Name of Artificial Intelligence
6	Pei 2022 [17]	Two phase (Prediction and Analysis)	evaluating, predicting, and analyzing the mental health statusof contemporary college students based on a neural network algorithm	College students	After determining the basic algorithm used in the pre-diction and analysis of contemporary college students' mental health, was continued to test the accuracy of the algorithm, and finally, determine an algorithm model with the highest prediction accuracy	Data mining technology based on a neural network algorithm is used to collect data sources. Finally, the prediction results are analyzed, and the main psychological stressor factors of contemporary college students are analyzed by cluster analysis	The survey results show that from 2010 to 2020,thenumber-ofgraduatecandidate-shasincreasedyear	By year, but the admission rate has not changed significantly Every year	The computer technology of neural network algorithm is applied to the prediction of contemporary college students' mental health. A psychological evaluation can evaluate students' differences in learning or ability, personality characteristics, relative strengths, and weaknesses, evaluate the development stage that students have reached, determine their relative strengths and Weaknesses, and find the reasons for behavior changes	results show that there is no signicant correlation between college Students' inferiority complex and dependency map and the incidence of mental diseases and majors. A comprehensive physical symptom test was conducted on individuals to understand students' psychological characteristics and behavior	Neural Network	Not mentioned
7	Tate 2020 [18, 31]	Model development	I.) development a model that can predict Mental health problems in mid-adolescence II.) investigating if machine learning techniques will outperform logistic regression	7,638 twins from the Child and Adolescent in Sweden at age 15	The outcome, mental health problems, was determined by the Strengths and Difficulties Questionnaire. Model performance was deter-mined by the area under the receiver operating characteristic curve (AUC)	Using a large range of data from parent reports and register data from numerous Swedish national registers, this study predicted adolescent mental health reasonably well, with a maxi-mum AUC of 0.739 on the test set (using the random forest model). Although the AUC indi-cates an adequate model, it is not accurate enough for clinical use	register information, which can be expensive or difficult for researchers to obtain, may not be necessary for a successful psychiatric risk model	The highest ranking variables were either parent-rated or could easily be reported by parents,	This top performing model would not be suitable for clinical use, however it lays important groundwork for future models seeking to predict general mental health outcomes Future studies should make use of parent-rated assessments when possible. Additionally, it may not be necessary for similar studies to forgo logistic regression in favor of other more complex methods	The strengths of this study include the comprehensive analysis of a wide variety of factors associated with adolescent mental health. Further, the use of parental reports indicates that these risk factors are identifiable by non-clinicians, indicating a low cost future solution for large scale mental health screens	machine learning	Not mentioned

Table 3 (continued)

N	Author and year	Study type	Study aims	participants	methodology	analysis	Meaning of Artificial Intelligence	Acceptability of Artificial Intelligence	application of Artificial Intelligence	Effectiveness of Artificial Intelligence	Kind of Artificial Intelligence	Name of Artificial Intelligence
8	Didarul Alam et. al (2021) [19]	empirical study with SEMANN (Structural Equation Modeling – Artificial Neural Network	to examine the factors affecting the intention and actual usage behavior on mHealth adoption, investigate the effect of actual usage behavior of mHealth on mental well-being of the endusers, and investigate the moderating role of self-quarantine on the intention–actual usage of mHealth under the coronavirus disease (COVID-19) pandemic situation	The target population of this study wasmHealth users of any kind in Bangladesh who were in self-quarantine during COVID-19 pandemic	Methodologically, SEMANN (Structural Equation Modeling – Artificial Neural Network) approach which can deal with non-compensatory and non-linear relationships grounded on the UTAUT2 model as a theoretical basis Pre-testing was conducted with a pool of three industry ex perts, two academicians, and five actual users of mHealth services to confirm content validity. A few adjustments were made based on their suggestions. In addition, a pilot testing comprising of 45 actual mHealth users was administered to check and ensure the reliability of the study constructs	non-parametric one sample Kolmogorov–Smirnov (K-S) test Analysis of Variance (ANOVA) test was conducted And The sensitivity analysis was done	Use of ANN to model and predict non-linear relationships in mHealth usage and its determinants	Not explicitly discussed, but implied to be positive as it was used to enhance the study's predictive accuracy	ANN was used to complement PLS-SEM in understanding linear and non-linear associations among variables	ANN provided robust predictions with small RMSE values, indicating high reliability and accuracy in predicting behavioral intentions and mHealth usage	Artificial Neural Network (ANN) with feed-forward-back-propagation (FFBP)	Not specified by a particular brand or model, referred to generally as ANN
9	Götzl et al. (2022) [20, 28]	parallel mixed–method study	To explore the attitudes, preferences, and needs of young people and key stakeholders towards AI-informed mHealth apps and guide the participatory development of such an app	Young people (aged 12–25), school psychologists, psychological counselors, media experts, and mHealth app developers	**Qualitative:** Focus groups with young people and expert interviews **Quantitative:** Representative online survey.	Independent analysis of qualitative and quantitative data followed by integration to identify points of convergence or divergence	AI is understood as systems that evaluate large amounts of information to make decisions and learn over time, often used in applications like YouTube, Spotify, and Google	Participants, both young people and experts, showed a generally positive attitude towards the use of AI in mHealth apps, with a willingness to use AI-informed training if it is useful and helps achieve personal goals	AI is applied to personalize intervention components in mHealth apps, aiming to adapt to users' specific needs and provide tailored recommendations	The effectiveness of AI is seen in its potential to provide personalized, timely interventions and support, although there are concerns about the technical background and data privacy	The study focuses on machine learning and algorithms as the types of AI used in mHealth apps	Not specified
10	**Onuki. M Et al 2022** [21]	**Casual-comparative research**	**Estimating Physical/Mental Health Condition Using Heart Rate Data From a Wearable Device**	**97 participants who were all women and lived in Japan. They were members of Peer Ring, which is a social media site especially for women's cancer survivors. All of the participants had experienced some kind of female-specific cancers, but they are as energeticas healthy people now**	**estimation, the heart rate variability (HRV) compared with measuring the HRV, predict the subjects' physical/mental health only from the HR measured by Fitbit instead of the HRV**	**Quantitative analysis through mathematical estimation**	**wearable devices to measure heat rate variability (HRV) e.g., smart watches, smart shirts, chest strap monitors, and so on**	**Acceptable by users for measuring blood-related data on smart watches, e.g., the Apple Watch or the Fitbit, due to its ease of integration and usability**	**to notify one's health conditions, and for that purpose, the level of stress based on heat rate variability (HRV) used for estimating these conditions**	**Fitbit is estimated as maintaining a good quality of data for a long period of time. and predict the subjects' physical/mental health according to**	**Smart watch heat rate variability (HRV) analyzer**	**Fitbit Inspire HRTM (a kind of smart watch)**
11	**Alamgir FM et al 2022**	**Multi-methods study**	**to enhance an AI to identify the facial expressions of the individuals and categorizing it into different emotions**	**10 Japanese female participants**	**the hybrid strategy called the Deep Belief Rain Optimization (DBRO) technique**	**four major phases including pre-processing, feature extraction, feature selection and classification**	**A system of Automatic recognition of facial expressions**	**It is acceptable for users in mental health care**	**to identify the facial expressions of the individuals and categorizing it into seven different emotions**	**The efficiency of the model proved through the simulations and it identified to outperform the other existing approaches**	**A tool for automatic classification of the facial emotions**	**Facial expression recognition system**

Table 3 (continued)

N	Author and year	Study type	Study aims	participants	methodology	analysis	Meaning of Artificial Intelligence	Acceptability of Artificial Intelligence	application of Artificial Intelligence	Effectiveness of Artificial Intelligence	Kind of Artificial Intelligence	Name of Artificial Intelligence
12	Yanqi Guo, 2023	Experimental study (Randomized controlled trials)	To analyze the effect of psychological health based on artificial intelligence agent technology on the implementation effect of Japanese family education.—To build personalized support for the family education system based on mobile agents	A total of 320 Japanese middle school students, randomly divided into an experimental group and a control group, with 160 cases in each group	The control group received traditional family health education - The experimental group received mental health education based on the Agent Technology family education system - Basic information and mental health scores of both groups were compared	Statistical analysis (SPSS 22.0 to perform descriptive statistics, independent sample t-tests and ANOVA) showing significant psychological health improvements in the AI-based group	AI technology in family education refers to systems that simulate human intelligence, providing personalized learning experiences, improving students' self-learning abilities, and broadening their knowledge	The application of AI in family education is considered worthy of research and offers advantages in autonomy, responsiveness, initiative, and mobility	AI technology is used for personalized support in family education systems. AI Products can help students carry out personalized learning. The unique teaching mode greatly improves students' concentration and provides more convenient and intelligent Channels for students to acquire knowledge and information, Thus improving students' self-learning ability and broadening their knowledge - It includes educational apps and software, online learning platforms, virtual reality (VR), augmented reality (AR), intelligent tutoring systems, and data analytics tools	- improved the psychological health of the experimental group improve the level of middle school students' mental health, which can improve student forced symptoms, interpersonal tension and sensitivity, depression, anxiety, learning pressure, maladjustment, emotional imbalance, psychological imbalance, and many other psychological states -Personalized AI support outperformed traditional family education methods based on mobile agents has the advantages of autonomy, responsiveness, initiative, and mobility, which provides a new idea for family education	Mobile agent technology - Intelligent learning systems covering all aspects of personalized learning, including interactive modules and knowledge bases	Agent Technology family education system

Table 3 (continued)

N	Author and year	Study type	Study aims	participants	methodology	analysis	Meaning of Artificial Intelligence	Acceptability of Artificial Intelligence	application of Artificial Intelligence	Effectiveness of Artificial Intelligence	Kind of Artificial Intelligence	Name of Artificial Intelligence
13	Ilona Halim, Lehan Stemmet, Sylvia Hach, Richard Porter, Hai-Ning Liang, Atiyeh Vaezipour, Julie D Henry, Nilufar Baghaei, 2023 [24, 33]		To test whether a novel type of individualized virtual reality (iVR) can improve self-compassion and decrease depressive symptoms - To evaluate the usability and acceptability of this iVR approach as rated by participants	Total of 36 young adult participants - Participants were recruited from a university community social media site - They were aware that the study was investigating a treatment for depression but were not recruited based on a depression diagnosis	- Participants completed 2 iVR sessions spaced 2 weeks apart - Validated measures of self-compassion and depression were completed at baseline and upon completion of each iVR session - Additional measures were administered to assess participants' perceptions about usability and acceptability of the iVR approach upon completion of both sessions	- Within-group analyses with paired-samples 2-tailed t tests - Changes in Self-Compassion Scale (SCS) and Patient Health Questionnaire (PHQ-8) scores were analyzed - Pearson correlations were calculated to test how participants' self-compassion and depressive symptoms related to one another Self-compassion and depressive symptoms were assessed using validated measures at baseline and at the end of each iVR session - Within-group analyses showed significant increases in self-compassion and non-significant trends for reduced depressive symptoms - Quantitative and qualitative feedback supported the iVR approach as being acceptable and usable	The study focuses on Virtual Reality (VR) rather than Artificial Intelligence (AI) -Virtual Reality (VR) is an emerging technology that can simulate realistic and immersive experiences within a virtual world	Usability: Participants rated the AI-integrated iVR system highly, with a SUS score of 75.9, indicating good to excellent usability User Experience: UEQ ratings showed strengths in novelty and stimulation, outperforming 75% of benchmark systems. However, dependability was rated below average, suggesting users experienced issues with control and system performance Participant Feedback: Qualitative feedback highlighted the system's ease of use, immersive experience, and positive user interface design. However, participants desired more robust scenarios, improved interaction with avatars, and enhanced performance	personalize the iVR experience, adapting scenarios and interactions based on the user's responses and progress to enhance engagement and therapeutic outcomes Interactive Avatars: Using AI to develop more sophisticated, interactive avatars that can respond to user inputs and emotions, creating a more immersive and supportive environment Behavior Analysis: AI can be utilized to analyze user behavior and emotional responses during sessions, providing real-time feedback and adjustments to the therapeutic process Predictive Analytics: Leveraging AI to predict user needs and potential mental health issues, allowing for proactive adjustments and interventions within the iVR system Enhanced Data Collection: AI can enhance the collection and analysis of data from iVR sessions, offering deeper insights into user progress and the effectiveness of the intervention, which can inform future developments and personalized treatment plans	-A significant increase in self-compassion was observed after a single iVR session, demonstrating the potential effectiveness of AI-driven iVR in enhancing self-compassion -A strong correlation between increased self-compassion and reduced depressive symptoms was found throughout the study, aligning with existing literature that self-compassion can protect against depression	AI for enhancing interactions with avatars in virtual environments and possibly incorporating more strengthen participant–virtual environment interactions	Not specified

Table 3 (continued)

N	Author and year	Study type	Study aims	participants	methodology	analysis	Meaning of Artificial Intelligence	Acceptability of Artificial Intelligence	application of Artificial Intelligence	Effectiveness of Artificial Intelligence	Kind of Artificial Intelligence	Name of Artificial Intelligence
14	Naveen Kumari-Rekha Bhatia 2022 [25]	----	an efficient deep convolutional neural network model is proposed to recognize the human emotions from facial images	--------	Experiments are conducted by using the benchmark dataset and competitive human emotion recognition models The contrast-limited adaptive histogram equaliza- tion (CLAHE) is applied to improve the visibility of input images. The modified joint trilateral filter is applied to the obtained enhanced images to remove the impact of noise Finally, the deep convolutional neural network was applied on the CLAHE and modified joint trilateral filter (MJTF)- based feature matrix. Next, Adam optimizer was used to optimize the cost function of deep convolutional neural networks	algorithm to understand and model the relationships between faces and facial expressions and to recognize human emotions	Facial emotion recognition extracts the human emotions from the images and videos	facial emotion recognition model performs considerably better compared to the competitive models	Facial emotionrecognitionrepresents the content of an input image in the form of human emotions by using various machines and deep learning models	the proposed facial emo-tion recognition model achieves better performance than the existing emotion recognition models. Comparative analysis reveals that the proposed facial emotion recognition model achieves better results than the competitive models in terms of accuracy	facial emotion recognition model	deep learning-based facial emotion recognition model
15	Rohit Rastogi, et al., 2022 [26, 34]	The article is a trial enough to establish the effect of SanskritVedicMantraandYajna,ancientHindu science of up liftment of consciousness and to heal self by sound science and heatand light	Measuring Happiness Index and Electronic Gadgets Radiations on AI IoT Systems: Return to Indian Scriptures and Science for Mental Fitness During Global Threats	20 people	experiment	gathered around 50to60 different radiation levels of six categories of gadgets using various sensors and instruments and plotted a curve among the mas we can see the trends that the radiation level is greater before the Yagya than the radiation level after performing Yagya on the compound.	Artificial intelligence(AI)is the ability of a computerprogram or a machine to think and learn.	see a drastic decrement in the value of the radiation level of different electronic gadgets	make computersmimichumanbehaviortomakedecisions.SuchthingsinvolveProblemSolvingwithout traditionallycodingtheactualsolutionoftheproblem.Itcanalsobedefinedtoanalyzethegiven dataandpredictbasedontheobservationvariousaspectsaboutthedata.Recentlythesetechniques areusedinthefieldofselfdrivingcars,humanspeechrecognition,data mining,voiceassistance, andmanymore.Allthesetechnologiesaremade moreeasiertoimplementthroughthetermAI	The use of Artificialintelligence (AI)in the field of health care can bedefined by the use of difficult andvarious algorithms along with software that are used for stimulating human cognition for analyzing and observing complicated medical data. In simpler words it isthe ability of computer algorithms to approximate conclusions without-direct human input. Themaindifference between Traditional technologies and AI technologist abilitytocollectinformationordata,processitandgive awell- structuredresulttotheend user. AI usemachine learning algorithm stoper form the abovementioned tasks and operations. Recognition of patterns in behavior and creation of theirown logiccanbedone by implementingthesealgorithms.AI algorithmsneedtobetestedrepeatedlyforreducingthemargin of error.	AI and ML Expert System Big Data Healthcare 4.0 IoT Machine Learning Artificial Intelligence	

In summary, the overall quality of studies indicates a promising trend in AI applications within mental health research, with studies rated as "good" by recognized assessment tools, although some studies show moderate methodological rigor, suggesting areas for improvement in future research designs.

Demographics of participants

In a comprehensive analysis of participant demographics across various studies examining the application of AI in mental health, several key insights emerge. Inkster et al. (2018) focused on anonymous global users of the Wysa app, specifically targeting individuals who self-reported symptoms of depression. This study provided insights into how AI-enabled conversational tools can engage users in mental health support [10].

Xiao Li (2023) examined elderly participants from two community groups, a control group ($n=46$) and an intervention group ($n=47$), to understand the factors influencing depression among older adults and to formulate psychological intervention plans. This demographic highlights the importance of addressing mental health in aging populations [12].

Liang et al. (2022) involved 185 college students in sports majors, divided into training and test sets, to evaluate the effectiveness of AI in assessing and improving mental health. The focus on college students underscores the relevance of mental health interventions in educational settings [13].

Chin et al. (2023) analyzed user interactions with the SimSimi chatbot, utilizing a dataset from 96,197 conversations in Eastern countries and 56,586 conversations in Western countries. This cross-cultural analysis provides valuable insights into how different populations express depressive moods through AI platforms [29].

Dadi (2021) utilized a large cohort from the UK Biobank, comprising 11,175 participants, to study cognitive tests and demographic characteristics, emphasizing the potential of AI in population modeling and mental health research [15].

Rathnayaka (2022) conducted a pilot study with 318 individuals globally to evaluate a BA-based AI chatbot designed for mental health support, demonstrating the growing interest in AI applications across diverse populations [30]. Pei (2022) focused on college students, although specific demographic details were not provided, emphasizing the need for targeted mental health interventions in this age group [17].

Tate (2020) studied 7,638 twins from a Swedish adolescent mental health study, providing a unique perspective on genetic and environmental influences on mental health outcomes [31].

Didarul Alam et al. (2021) focused on mHealth users in Bangladesh during the COVID-19 pandemic, emphasizing how global crises affect mental health and the role of technology in delivering support [19].

Götzl et al. (2022) included young people aged 12–25, alongside stakeholders in mHealth app development, to explore attitudes towards AI-informed mental health applications, indicating a collaborative approach to mental health solutions [28].

Onuki et al. (2022) focused on 97 women cancer survivors in Japan, providing insights into the mental health challenges faced by this specific demographic and the potential for AI to offer tailored support [21]. Alamgir et al. (2022) involved 10 Japanese female participants in facial expression recognition studies, emphasizing the intersection of AI and emotional recognition in mental health contexts [32].

Yanqi Guo (2023) studied 320 Japanese middle school students, comparing the effects of AI-based family education systems on mental health, which highlights the importance of early intervention in educational settings [23].

Halim et al. (2023) recruited 36 young adult participants from a university community to evaluate the effects of individualized virtual reality (VR) on self-compassion and depression, showcasing innovative approaches to mental health interventions [33].

Kumari and Bhatia (2022) did not specify participant demographics but focused on deep learning for emotion recognition, indicating the technical aspects of AI applications in mental health [25].

Finally, Rastogi et al. (2022) involved 20 participants in a trial related to ancient practices for mental fitness, reflecting a unique blend of traditional and modern approaches to mental health [34]. Overall, this diverse range of participant demographics across studies highlights the multifaceted nature of mental health research and the potential of AI to address the needs of various populations. The findings underscore the importance of tailoring AI applications to specific demographic groups to enhance their effectiveness and acceptability in mental health interventions.

Acceptancy of AI in mental health

In reviewing the acceptability of AI in various mental health and healthcare contexts, studies demonstrate a general positive trend across different demographics, applications, and intervention types. Inkster et al. (2018) show that the Wysa app, aimed at depression support, demonstrated high engagement and effectiveness, emphasizing the potential acceptability of AI among users with self-reported depressive symptoms [10] (Table 2).

In this view AI tools are especially beneficial in student populations, where they effectively address mental health challenges, particularly in sports education contexts. Moreover, advanced AI mechanisms, like attention-based LSTM models, have shown promise in improving the accuracy of emotion recognition, an essential component in mental health interventions [27].

In higher education, the feasibility of AI-driven mental health plans for college students has been confirmed with favorable results, underscoring its practicality in academic environments [13].

The global scale of AI adoption is notable, with platforms reaching millions of users across 111 languages, underscoring a high level of acceptability and engagement [29]. Similarly, openly accessible databases like the UKBB, with extensive health data, signify the potential for AI integration in broader health-related applications [15]. Rathnayaka (2022) emphasizes that user-driven data input, such as voluntary mental health surveys, aligns well with AI's non-invasive monitoring applications [30].

In youth-focused applications, Tate (2020) notes that AI-driven interventions in mental health must address ethical concerns such as inequality and population bias [31]. Similarly, Guo et al. (2024) suggest that wearable devices provide an accepted, practical approach to monitoring stress and anxiety levels in real-time [23].

These findings collectively highlight the high acceptability and potential efficacy of AI-based mental health interventions across various settings, populations, and applications.

Application of AI in mental health

The studies highlight the extensive applications of AI across various domains in mental health and healthcare, with each study exploring unique facets of AI's functionality and its impact on patient outcomes (Table 2).

The effectiveness of AI in educational settings is further highlighted by Lei et al. (2023), where AI was used to reduce anxiety and depression symptoms among students. In another innovative application, Xiao Li (2023) optimized LSTM outputs through AI attention mechanisms, which enhanced emotion recognition accuracy, a significant step for personalized mental health care [12, 27].

Beyond individual assessments, AI is also used in population-level mental health monitoring, as demonstrated in study by Liang (2022) who used AI for psychiatric assessments, adherence tracking, and CBT delivery [13].

AI applications extend beyond therapy and assessments; they are increasingly relevant in preventive interventions and public health efforts. AI's potential for predictive modeling is also recognized, with Pei (2022) applying AI to analyze physiological and digital signals from wearable devices to detect stress and anxiety, enhancing real-time monitoring and intervention capabilities [17].

In healthcare systems, AI facilitates patient engagement and clinical decision-making. Guo et al. (2024) used AI to analyze wearable data for stress detection, while Götzl et al. (2022) incorporated AI into clinical documentation and patient interaction systems to improve clinician efficiency and patient satisfaction. Furthermore, the application of AI in personalized mHealth apps allows adaptation to user needs and preferences, enhancing intervention outcomes [23, 28].

Collectively, these studies highlight the diverse functions of AI in mental health, encompassing real-time monitoring, preventive care, personalized interventions, and predictive modeling. A common thread throughout these applications is AI's capacity to bridge gaps in mental health services, enhance patient engagement, and provide customized support for various populations.

Effectiveness of AI in mental health

The reviewed studies demonstrate the varied effectiveness of AI in improving mental health assessment, monitoring, and treatment, leading to notable advancements across different mental health conditions (Table 2).

In the domain of digital mental health interventions (DMHIs), Inkster et al. (2018) reported that high engagement with the Wysa app led to significant improvements in self-reported depression scores among users, with a moderate effect size [10].

AI's capacity to improve early mental health recognition and intervention is also evident in studies by Lei et al. (2023) and Xiao Li (2023), where deep learning and attention mechanisms were used to significantly enhance emotion recognition and classification accuracy in mental health monitoring [12, 27]. Furthermore, studies by Liang (2022) emphasize the effectiveness of AI in psychiatric assessment, including real-time symptom tracking and personalized therapy delivery [13].

At the same time, Tornero-Costa et al. (2023) emphasized the potential of AI in facilitating large-scale mental health screenings and interventions, which could allow for the early identification of mental health issues and provide tailored support for various populations [1].

In summary, these studies confirm the multifaceted effectiveness of AI in mental health across preventive, diagnostic, and therapeutic stages, with applications that include emotion recognition and personalized mental health interventions. This broad applicability underscores AI's potential to enhance access to mental health resources, improve treatment delivery, and facilitate large-scale mental health screening and monitoring initiatives.

Discussion

The integration of AI into mental health care has emerged as a focal point of research, reflecting a wide array of applications and methodologies. A systematic review encompassing 15 studies revealed varying degrees of methodological rigor and quality, offering a nuanced perspective on AI's role in enhancing mental health interventions. Notably, studies that employed robust methodologies and high-quality assessment tools, such as the MMAT and the JBI checklist, provided more credible insights into the effectiveness of AI applications in this field.

This review captures the evolution and current landscape of AI applications in mental health care, particularly focusing on advancements from 2009 to 2024. For instance, the research conducted by Didarul Alam et al. (2021) utilized a rigorous empirical framework, achieving a high-quality score of 10. This study analyzed mobile health (mHealth) technologies during the COVID-19 pandemic and demonstrated a positive correlation between mHealth usage and mental well-being, highlighting the potential of AI-driven tools to enhance user engagement during crises [19]. Similarly, studies by Inkster et al. (2018) and Chin et al. (2023), both of which received quality ratings of 7, showcased the effectiveness of AI chatbots like Wysa in improving mental health outcomes through increased user engagement [10, 29].

Conversely, studies with moderate quality scores, such as those by Dadi (2021) and Rathnayaka (2022), while still informative, indicated areas needing methodological improvement. Dadi's population modeling approach garnered a score of 6, suggesting that although it provided valuable insights into the relationship between AI and mental health, its methodological limitations may hinder the generalizability of its findings. Similarly, Rathnayaka's study on a behavioral activation-based AI chatbot also received a score of 6, underscoring the necessity for more robust evaluation frameworks to assess the efficacy of such interventions [15, 30].

The findings from high-quality studies emphasize the critical importance of methodological rigor in AI-related mental health research. For example, Xiao Li (2023) employed advanced AI techniques, including Long Short-Term Memory (LSTM) networks, to enhance emotion recognition, achieving a quality score of 7 [12]. This illustrates that higher-quality studies not only yield more reliable data but also contribute to the advancement of AI methodologies in mental health applications.

Furthermore, the diversity of participant demographics across the studies reflects the complex nature of mental health challenges and the potential for AI to address these varied needs. Research targeting college students, elderly populations, and individuals from diverse cultural backgrounds demonstrates the adaptability of AI tools in meeting the specific requirements of different groups. This adaptability is essential for enhancing the acceptability and effectiveness of AI interventions, as evidenced by positive user feedback in studies like that of Götzl et al. (2022), which explored young people's attitudes toward AI-informed mHealth applications [28].

Nevertheless, despite the promising applications of AI in mental health, several ethical considerations and methodological limitations warrant attention. The reviewed studies highlighted concerns regarding data privacy, algorithm transparency, and the necessity for stakeholder involvement in the development of AI technologies. As Tavory (2023) noted, establishing ethical frameworks is crucial for guiding the responsible deployment of AI in mental health care. AI is increasingly becoming an integral component of digital medicine, with the potential to significantly influence mental health research and practice. To fully leverage AI's capabilities, it is essential for a diverse community of stakeholders—including scientists, clinicians, regulators, and patients—to engage in open communication and collaboration [5].

As AI techniques continue to evolve, there is potential to redefine mental illnesses more objectively than the current DSM-5 classification system. Such advancements could enable earlier identification of mental illnesses, even at prodromal stages, when interventions are likely to be more effective. Moreover, AI can facilitate the customization of prescribed treatments based on individual characteristics, leading to more personalized and effective mental health care. It is also noteworthy that consumers recognize several advantages in using medical chatbots, such as anonymity and quicker access to pertinent information. Previous research indicates that consumers are often just as willing to share emotional and personal information with a chatbot as they would with a human friend. Studies suggest that interactions with chatbots and humans yield comparable levels of perceived understanding, disclosure closeness, and cognitive reappraisal, indicating that individuals engage psychologically with chatbots similarly to their interactions with people. This reinforces the potential of chatbots to provide effective support in mental health contexts. In this systematic review, we synthesized evidence regarding the effectiveness and user evaluation of AI-based conversational agents (CAs) in mental health care. Our findings suggest that these CAs can effectively alleviate psychological distress, with the most significant effects observed in studies utilizing generative AI, multimodal or voice-based CAs, and interventions delivered through mobile applications and instant messaging platforms. This aligns with the findings of Shimada (2023) and Alhuwaydi (2024), who highlight AI's potential in addressing disparities in access to mental health services [35, 36].

These findings are further supported by Oladimeji et al. (2023), who emphasize AI's role in the early detection and prevention of mental health issues [37]. However, it is crucial to recognize that these technologies could exacerbate existing inequalities if not implemented thoughtfully and equitably. Addressing potential disparities in access and ensuring that all populations benefit from AI advancements in mental health care is essential to prevent widening the gap in mental health services.

Conclusion

The paper provides a comprehensive review of the entire spectrum of AI in mental health, highlighting its positive contributions to the field. AI holds numerous promises for enhancing mental health care, and this paper explores various facets of its application. AI technologies are anticipated to introduce innovations to existing medical practices and future health care systems. Currently available AI-based health care technologies have demonstrated significant efficacy in accurately diagnosing and classifying patient conditions, as well as predicting disease trajectories by leveraging accumulated medical data.

Limitation

One significant limitation of this systematic review is the variability in methodological quality and reporting standards among the included studies. Although various quality assessment tools were employed, such as the Mixed Methods Appraisal Tool (MMAT) and the Newcastle–Ottawa Scale (NOS), discrepancies in study design, sample sizes, and data collection methods were observed. Many studies lacked transparency in reporting AI model features and data preprocessing techniques, which are crucial for ensuring reproducibility and reliability. This inconsistency may lead to biases in the interpretation of AI effectiveness in mental health applications and limit the generalizability of the findings across diverse populations.

Future research should prioritize the establishment of standardized methodologies and reporting guidelines for AI applications in mental health. This would enhance the robustness of the evidence base, facilitate comparative analyses, and ultimately improve the integration of AI technologies into clinical practice. Additionally, involving a broader range of stakeholders, including mental health professionals and patients, in the development and evaluation of AI tools may help address ethical concerns and ensure that these technologies meet the needs of diverse user groups.

Supplementary Information

The online version contains supplementary material available at https://doi.org/10.1186/s12888-025-06483-2.

Supplementary Material 1.

Acknowledgements

Special thanks go to the vice-chancellor of the Community Based Psychiatric Care Research Center, School of Nursing and Midwifery, Shiraz University of Medical Sciences.

Human ethics and consent to participate declarations

The study did not involve direct human participants, and therefore, specific declarations regarding human ethics and consent to participate are not applicable.

Clinical trial number

This study did not involve clinical trials, and as such, there is no clinical trial number to report.

Financial disclosure

No.

Author's contributions

RD, NJM, EKH, SZ, and, FL were involved in Conceptualization, and MY and MV collected the dates. RD, FHH, DHN and PS analyzed the data. RD, SZ, EKH, DHN, HRH, PS, MY, FHH, MV, NJM, and FL were involved in the methodology. NJM, and RD was project administrator and supervised the project. RD and NJM validated all stages of the project. RD, MV, MY, EKH, SZ, PS, FHH and, FL wrote the original draft of the manuscript and review and editing was done by RD, NJM, EKH, SZ,HRH.

Funding

No.

Data availability

On reasonable request, the corresponding author is willing to provide the datasets used and analyzed during the present study.

Declarations

Ethics approval and consent to participate

This research was conducted in accordance with the ethical standards set forth in the Declaration of Helsinki. The findings will be presented in a collective format to ensure transparency and accessibility.

Competing interests

The authors declare no competing interests.

Author details

[1]Community Based Psychiatric Care Research Center, School of Nursing and Midwifery, Shiraz University of Medical Sciences, Shiraz, Iran. [2]Namazi Hospital, Shiraz University of Medical Sciences, Shiraz, Iran. [3]Health Deputy, Kermanshah University of Medical Science, Kermanshah, Iran. [4]Department of Nursing, Shiraz Branch, Islamic Azad University, Shiraz, Iran. [5]Department of Psychiatric Nursing, School of Nursing & Midwifery, Isfahan University of Medical Sciences, Isfahan, Iran. [6]University of Science and Technology (IUST), Tehran, Iran. [7]Department of Educational Sciences, Faculty of Education and Psychology, Azarbaijan Shahid Madani University, Tabriz, Iran. [8]Master's Student in Clinical Psychology, Faculty of Medical Sciences, Hamedan Branch, Islamic Azad University, Hamedan, Iran. [9]Nursing and Midwifery Care Research Center, Isfahan University of Medical Sciences, Isfahan, Iran. [10]Department of Psychology, Faculty of Psychology, Payam Noor University, Kaboudar Ahang Center, Hamedan, Iran. [11]School of Nursing and Midwifery, Shiraz University of Medical Sciences, Shiraz, Iran.

Received: 21 November 2024 Accepted: 7 January 2025
Published online: 14 February 2025

References

1. Image ; David Novillo-Ortiz2 RT-CAOIAM-MAOINA-MAOILLAOIVTAO. Methodological and Quality Flaws in the Use of Artificial Intelligence in Mental Health Research: Systematic Review. JMIR mental health. 2023;10. https://doi.org/10.2196/42045
2. Nilsen P, Svedberg P, Nygren J, Frideros M, Johansson J, Schueller S. Accelerating the impact of artificial intelligence in mental healthcare through implementation science. Implement Res Pract. 2022;3:26334895221112030.
3. Gaffney H, Mansell W, Tai S. Conversational agents in the treatment of mental health problems: mixed-method systematic review. JMIR Mental Health. 2019;6(10):e14166.
4. Olawade DB, Wada OZ, Odetayo A, David-Olawade AC, et al. Enhancing mental health with Artificial Intelligence: Current trends and future prospects. Journal of Medicine, Surgery, and Public Health. 2024;3. https://doi.org/10.1016/j.glmedi.2024.100099
5. Tamar T. Regulating AI in mental health: ethics of care perspective. JMIR Mental Health. 2024;11:e58493. https://doi.org/10.2196/58493.
6. 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:e42045. https://doi.org/10.2196/42045.
7. Hong QN, Fàbregues S, Bartlett G, Boardman F, Cargo M, Dagenais P, et al. The Mixed Methods Appraisal Tool (MMAT) version 2018 for information professionals and researchers. Educ Inf. 2018;34(4):285–91.
8. Wells G. The Newcastle-Ottawa Scale (NOS) for assessing the quality of nonrandomised studies in meta-analyses department of epidemiology and commuunity medicine, University of Ottawa,Room 3227A, 451 Smyth Road, Ottawa, Ontario K1J 8M5. Canada: NOS; 2024. [updated 2021; cited 2024]. gwells@uottawa.ca. Available from: https://www.ohri.ca/programs/clinical_epidemiology/oxford.asp.
9. Jordan Z, Lockwood C, Munn Z, Aromataris E. The updated Joanna Briggs Institute model of evidence-based healthcare. JBI Evid Implement. 2019;17(1):58–71.
10. Inkster B, Sarda S, Subramanian V. An empathy-driven, conversational artificial intelligence agent (Wysa) for digital mental well-being: real-world data evaluation mixed-methods study. JMIR Mhealth Uhealth. 2018;6(11):e12106.
11. Lei L, Li J, Li W. Assessing the role of artificial intelligence in the mental healthcare of teachers and students. Soft Computing. 2023;2023:1–11.
12. Li X. Evaluation and analysis of elderly mental health based on artificial intelligence. Occup Ther Int. 2023;2023(1):7077568.
13. Liang L, Zheng Y, Ge Q, Zhang F. Exploration and strategy analysis of mental health education for students in sports majors in the era of artificial intelligence. Front Psychol. 2022;12:762725.
14. Chin H, Song H, Baek G, Shin M, Jung C, Cha M, et al. The potential of chatbots for emotional support and promoting mental well-being in different cultures: mixed methods study. J Med Int Res. 2023;25:e51712.
15. Dadi K, Varoquaux G, Houenou J, Bzdok D, Thirion B, Engemann D. Population modeling with machine learning can enhance measures of mental health. GigaScience. 2021;10(10):giab071.
16. Rathnayaka P, Mills N, Burnett D, De Silva D, Alahakoon D, Gray R. A mental health chatbot with cognitive skills for personalised behavioural activation and remote health monitoring. Sensors. 2022;22(10):3653.
17. Pei J. Prediction and analysis of contemporary college students' mental health based on neural network. Comput Intell Neurosci. 2022;2022(1):7284197.
18. Tate AE, McCabe RC, Larsson H, Lundström S, Lichtenstein P, Kuja-Halkola R. Predicting mental health problems in adolescence using machine learning techniques. PloS one. 2020;15(4):e0230389.
19. Alam MMD, Alam MZ, Rahman SA, Taghizadeh SK. Factors influencing mHealth adoption and its impact on mental well-being during COVID-19 pandemic: A SEM-ANN approach. J Biomed Inform. 2021;116:103722.
20. Götzl C, Hiller S, Rauschenberg C, Schick A, Fechtelpeter J, Fischer Abaigar U, et al. Artificial intelligence-informed mobile mental health apps for young people: a mixed-methods approach on users' and stakeholders' perspectives. Child Adolesc Psychiatry. 2022;16:86.
21. Onuki M, Sato M, Sese J, editors. Estimating physical/mental health condition using heart rate data from a wearable device. 2022 44th Annual International Conference of the IEEE Engineering in Medicine & Biology Society (EMBC); 2022 11-15 July 2022; Glasgow, Scotland. United Kingdom: IEEE; 2022.
22. Alamgir FM, Alam MS. An artificial intelligence driven facial emotion recognition system using hybrid deep belief rain optimization. Multimed Tools Appl. 2023;82(2):2437–64.
23. Guo Y. Examining the impact of assistive technology on psychological health, family education, and curriculum research in Japan: insights from artificial intelligence. J Autism Dev Disord. 2024;54(10):3823–36.
24. Halim I, Stemmet L, Hach S, Porter R, Liang H-N, Vaezipour A, et al. Individualized virtual reality for increasing self-compassion: evaluation study. JMIR Mental Health. 2023;10:e47617.
25. Kumari N, Bhatia R. Efficient facial emotion recognition model using deep convolutional neural network and modified joint trilateral filter. Soft Comput. 2022;26(16):7817–30.
26. Rastogi R, Chaturvedi D, Saxena M, Sagar S, Gupta M, Choudhary R, et al. Measuring happiness index and electronic gadgets radiations on AI IoT systems: return to Indian scriptures and science for mental fitness during global threats. Int J Soc. 2022;13:37.
27. Lei L, Li J, Li W. Assessing the role of artificial intelligence inthe mental healthcare of teachers and students. Soft Computing. 2023:1–11.
28. Götzl C, Hiller S, Rauschenberg C, Schick A, Fechtelpeter J, Fischer Abaigar U, et al. Artificial intelligence-informed mobile mental health apps for young people: a mixed-methods approach on users' and stakeholders' perspectives. Child Adolesc Psychiatry Ment Health. 2022;16(1):86.
29. Chin H, Song H, Baek G, Shin M, Jung C, Cha M, et al. The potential of chatbots for emotional support and promoting mental well-being in different cultures: mixed methods study. J Med Internet Res. 2023;25:e51712.
30. Rathnayaka P, Mills N, Burnett D, De Silva D, Alahakoon D, Gray R. A mental health chatbot with cognitive skills for personalised behavioural activation and remote health monitoring. Sensors. 2022;22(10):3653.
31. Tate AE, McCabe RC, Larsson H, Lundström S, Lichtenstein P, Kuja-Halkola R. Predicting mental health problems in adolescence using machine learning techniques. PLoS ONE. 2020;15(4):e0230389.
32. Alamgir FM, Alam MS. An artificial intelligence driven facial emotion recognition system using hybrid deep belief rain optimization. Multimedia Tools Appl. 2023;82(2):2437–64.
33. Halim I, Stemmet L, Hach S, Porter R, Liang H-N, Vaezipour A, et al. Individualized virtual reality for increasing self-compassion: evaluation study. JMIR Mental Health. 2023;10:e47617.
34. Rastogi R, Chaturvedi D, Saxena M, Sagar S, Gupta M, Choudhary R, et al. Measuring happiness index and electronic gadgets radiations on AI IoT systems: return to Indian scriptures and science for mental fitness during global threats. Int J Soc Ecol Sustain Dev (IJSESD). 2022;13(1):1–37.
35. Shimada K. The role of artificial intelligence in mental health: a review. Sci Insights. 2023;43(5):1119–27.
36. Alhuwaydi AM. Exploring the role of artificial intelligence in mental healthcare: current trends and future directions–a narrative review for a comprehensive insight. Risk Manage Healthc Pol. 2024;17:1339–48.
37. Oladimeji KE, Nyatela A, Gumede S, Dwarka D, Lalla-Edward ST. Impact of artificial intelligence (AI) on psychological and mental health promotion: an opinion piece. New Voices Psychol. 2023;13:12 pages- pages.

Publisher's Note