

## The Role of Artificial Intelligence (AI) in Mental Health: A Systematic Review

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### ABSTRACT

This research aims to explore the role of Artificial Intelligence (AI) in mental health by addressing the central research question: How does AI play a role in mental health? To answer this, the study conducts a systematic literature review of 80 peer-reviewed articles, examining how AI contributes to key areas of mental health care, including the identification of mental health issues and the provision of support, and its influence on overall mental health outcomes. The review categorizes studies into two core themes: (1) AI for detecting mental health conditions and (2) AI for providing support. Techniques applied across the studies range from machine learning and deep learning to large language models and behavior-sensing technologies. Methodologically, the reviewed literature demonstrates a strong reliance on empirical approaches such as surveys, laboratory experiments, secondary data analysis, and mathematical modeling. In contrast, design science and qualitative methods, which offer real-world insight and user-centered innovation, remain underutilized. The findings underscore the flexibility of AI in mental health applications while highlighting the need for broader methodological diversity. This paper contributes to the growing discourse on AI in mental health and offers guidance for future research, particularly in developing practical, scalable, and user-centered AI tools that enhance access to mental health care and promote early intervention and well-being.

*Keywords:* Artificial intelligence (AI), mental health, AI and mental health issue detection, AI and mental health support, AI-powered interventions, mental health diagnosis

### INTRODUCTION

Mental health disorders affect millions of individuals globally GBD 2019 Mental Disorders Collaborators (2022). The Australian Bureau of Statistics (2020-2022) reported that approximately 20% of Australian residents, around 5 million had been diagnosed with a mental disorder and exhibited related symptoms (Branley & Goloubeva, 2023). In some cases, untreated mental health issues may become a silent but deadly force, ultimately contributing to fatal outcomes. A well-known example was Leslie Cheung, one of Hong Kong's influential singers and actors, who suffered from clinical depression and died by suicide in April 2003 (BBC, 2003). More recent global cases include Robin Williams, Amy Winehouse, and Ellen Loo (Lam, 2018; VolunteerFDIP, 2024). Despite the growing recognition of mental health challenges, access to timely and effective mental health support remains limited. Traditional care systems often face resource shortages and long waiting times, deterring individuals from seeking or receiving adequate support (Fernando, 2024; QFCC, 2025). This has become a pressing issue, as it may lead to burnout of mental health workers. In April 2024, more than 500 Australian psychiatrists signed an open letter to the federal health minister urging the government to address workforce shortages (Forsberg, 2024). In some situations, mental health support resources are entirely unavailable. Moreover, beyond resource constraints, stigma and a lack of awareness may also prevent individuals from accessing these services (QFCC, 2025).

In contrast, the rapid proliferation of artificial intelligence (AI) has transformed daily life across domains (Wang *et al.*, 2022). Particularly, the emergence of generative AI applications has enhanced public access and usability (Nah *et al.*, 2023). For instance, ChatGPT's chatbot design and its ability to quickly generate personalized content have made it easy for internet users to engage with it similarly to instant messaging platforms. As a result, by August 2024, ChatGPT had reached over 200 million weekly users, doubling its user base in less than a year (Roth, 2024). When individuals need mental health support but face barriers such as limited resources or stigma, AI applications may offer a viable alternative. By eliminating the need for direct disclosure to others and reducing wait times, AI tools can provide quicker, more personalized responses, often without significant financial costs (Vaidyam *et al.*, 2019). In this way, AI not only supports individuals in mental health issues but may also alleviate the burden on mental health professionals.

Some scholars have highlighted the potential role of AI in facilitating mental health (e.g., D'Alfonso, 2020), yet the current literature remains relatively fragmented and lacks a unified direction. Therefore, a systematic literature review is needed to consolidate existing findings, highlight methodological and theoretical gaps, and guide future research and implementation.

To address this, our study poses the central research question: How does AI contribute to mental health care? Specifically, the review examines two key dimensions:

- (1) How is AI being used to detect and classify mental health issues?
- (2) How is AI being applied to provide mental health support?

By synthesizing current research insights, this paper seeks to provide a comprehensive overview of AI's applications in mental health. The findings will offer guidance for policymakers, practitioners, and researchers on how AI can be strategically leveraged to create a more inclusive, accessible, and effective mental health ecosystem.

## METHODS

In this section, we describe the method of conducting a systematic literature review using the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) framework developed by Moher *et al.* (2009) and updated in 2021 (Page *et al.*, 2021). PRISMA provides a structured methodology for identifying, screening, and including relevant studies, ensuring reproducibility and reducing selection bias. By applying this framework, the study aims to synthesize existing knowledge effectively and highlight gaps in AI-driven mental health interventions (Liberati *et al.*, 2009).

### Search Strategy

To conduct a systematic and comprehensive literature review on Artificial Intelligence (AI) in mental health, this study follows a structured search strategy using Scopus.com as the primary database to identify relevant peer-reviewed journal articles. The search term "AI in mental health" was used to specifically target studies addressing the application of AI methodologies, frameworks, and interventions within mental health contexts. The search process, including article identification, screening, and inclusion, will be documented thoroughly to ensure transparency and consistency throughout the review.

### Inclusion and Exclusion Criteria

To ensure the selection of high-quality and relevant studies on AI applications in mental health, a structured set of inclusion and exclusion criteria was applied in this review. Peer-reviewed journal articles published between 2015 and 2025 were included to capture recent advancements. Studies focusing on AI methodologies, frameworks, and applications related to mental health were considered, while only articles published in English were included to maintain consistency. Relevant subject areas, including Computer Science, Decision Sciences, Medicine, Psychology, and Health Professions, were selected to ensure a broad understanding of AI's impact. Only studies in the final publication stage were included to ensure fully peer-reviewed and validated research.

To refine the scope of the review, non-research publications such as review articles, expert opinions, and editorials were excluded. Studies unrelated to AI or mental health were also excluded to maintain relevance. Additionally, unavailable full-text articles were excluded after all reasonable efforts to access them were made.

### Article Selection Process

The article selection process followed the PRISMA diagram and involved at least two authors independently cross-checking the screening and exclusion aspects to ensure consistency and accuracy. Following a title and abstract screening of 123 articles, 43 articles were excluded - 41 due to being unrelated to AI and mental health, and 2 for being published in a language other than English. This process resulted in 80 studies being included in the final review, ensuring that the selected literature was both relevant and aligned with the search objectives. Figure 1 illustrates the steps undertaken during the screening and selection process.

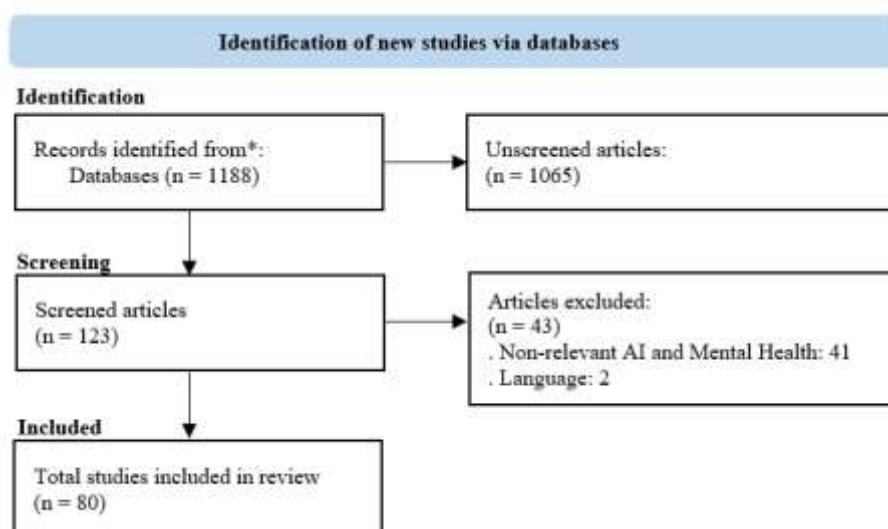


Figure 1: Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) for AI in mental health

### Methodology Classification Framework

In this study, we employed the research methodology classification framework proposed by Palvia *et al.* (2003) as later modified by Palvia *et al.* (2015). Following their recommendations, each selected study was categorized into at least one methodological type, as outlined in Table 1. By examining the methodologies used in AI-based mental health studies, we can better understand how AI is transforming mental health care delivery, improving diagnosis, and providing personalized supportive treatment.

Table 1: Methodology Classification Based on Palvia's Framework

1	Speculation/commentary	8	Field experiment
2	Frameworks and conceptual model	9	Laboratory experiment
3	Literature review	10	Design science
4	Literature analysis	11	Mathematical modeling
5	Case study	12	Qualitative research
6	Survey	13	Secondary data
7	Field research	14	Content analysis

### Theoretical Framework Classification

In addition to analyzing the methodology of the articles, it is crucial to also check the theoretical background of the research. A theoretical framework is essential in research as it provides a foundational structure that guides the study's design and analysis (Lederman & Lederman, 2015). It clarifies the relationships between variables, offers explanations for observed phenomena, and grounds the research in existing knowledge (Grant & Osanloo, 2015). For example, Self-Determination Theory can be applied to understand how AI tools, like chatbots or virtual therapists, impact mental health outcomes such as emotional regulation and user engagement.

## FINDINGS

### Summary of Research Methods and Theoretical Foundations

According to the review of the 80 articles, the following table summarizes the five most commonly adopted research methods and theoretical foundations. For articles which adopted a mixed-method or multi-method approach, we counted towards both methods.

Table 2: Top 5 Research Methods and Theoretical Foundations Adopted in AI and Mental Health Studies

Top 5 research methods adopted	Top 5 theoretical foundation adopted
1. Secondary Data ( $n=19$ )	1. None ( $n=57$ )
2. Laboratory Experiment ( $n=17$ )	2. Cognitive Theory ( $n=3$ )
3. Mathematical Modeling ( $n=16$ )	Only a small number of studies adopted a specific theory, such as: . Self-Determination Theory . Transactional Theory of Stress and Coping . Privacy Calculus & CASA theory . And a few other isolated cases
4. Survey ( $n=15$ )	
5. Literature Review / Qualitative Research / Content Analysis ( $n=7$ )	

As seen in the findings, secondary data analysis, laboratory experiment, mathematical modeling and survey were the most commonly used research methods, reflecting a strong emphasis on empirical and data-driven approaches in AI and mental health research. These methods reflect the field's focus on measuring, modeling, and predicting mental health conditions using quantitative techniques. However, qualitative research, literature review, and content analysis were used far less frequently, ranking jointly as the fifth most common approaches, highlighting limited but present engagement with exploratory and interpretive perspectives. Furthermore, most studies lacked a clear theoretical foundation, with only a small number referencing cognitive or psychological theories.

### Central Themes in Literature

Our preliminary findings suggested that existing literature related to the role of AI on mental health are trying to answer at least two questions, including (1) How does AI help identify mental health issues? (2) How does AI support mental health?

### AI and mental health issues detection

We identified 41 papers that explore how AI technologies help detect, classify, or predict mental health conditions. These studies utilized advanced AI techniques such as machine learning, deep learning, and natural language processing to analyze a wide range of data including speech, text, behavioral patterns, and physiological signals. Table 3 presents representative examples of these approaches across different mental health issues.

Table 3: Examples of AI Techniques for Mental Health Issue Detection

Mental Health Issues	Inputs	AI Techniques and Algorithms	Outputs	Examples of Reference
Depression	<ul style="list-style-type: none"> <li>Behavioural risk factor surveillance system data</li> <li>Sociodemographic and clinical features (age, income, employment, comorbidities)</li> </ul>	<ul style="list-style-type: none"> <li>Machine Learning Algorithm (e.g., Extreme Gradient Boosting, XGBoost)</li> <li>Explainable AI method (e.g., SHapley Additive exPlanations, SHAP)</li> </ul>	<ul style="list-style-type: none"> <li>Health status of patients with coronary heart disease (CHD) and depression.</li> <li>The role of features (e.g., employment status, physical activity) in the model's prediction.</li> </ul>	(Kaushik <i>et al.</i> , 2025; Li <i>et al.</i> , 2025)
Suicidal Ideation / Risk	<ul style="list-style-type: none"> <li>Culturally adapted vignettes</li> </ul>	<ul style="list-style-type: none"> <li>Large Language Models (e.g., ChatGPT-4)</li> </ul>	<ul style="list-style-type: none"> <li>Estimated likelihood of suicidal thoughts, attempts and mortality</li> <li>Cultural and gender sensitivity assessment in risk evaluations</li> </ul>	(Levkovich <i>et al.</i> , 2024; Meter <i>et al.</i> , 2025)
Attention Deficit Hyperactivity Disorder (ADHD)	Electroencephalogram (EEG) signals	Deep learning algorithms, such as, <ul style="list-style-type: none"> <li>Convolutional Neural Network (CNN)</li> <li>Modified Residual Neural Network (ResNet)</li> </ul>	<ul style="list-style-type: none"> <li>Improved diagnostic accuracy and progress</li> </ul>	(Jahani & Safaei, 2024)
Child/Youth Mental Health	Narrative clinical notes from psychiatric emergency department visits (children and adolescents)	<ul style="list-style-type: none"> <li>Large Language Models (e.g., ChatGPT-4)</li> <li>Natural Language Processing: RDoC framework)</li> </ul>	<ul style="list-style-type: none"> <li>Dimensional scores for six Research Domain Criteria (RDoC)</li> <li>Associations with hospital admission likelihood and emergency department length of stay</li> </ul>	(Jr. & Perlis, 2024; Wan & Zou, 2025)
Emotion & Stress Classification	<ul style="list-style-type: none"> <li>EEG signals</li> <li>Physiological Signals</li> </ul>	<ul style="list-style-type: none"> <li>Deep Learning: AlexNet + DenseNet for feature extraction</li> <li>Dimensionality Reduction: Principal Component Analysis (PCA)</li> <li>Classifier: Multi-class SVM deep learning</li> </ul>	<ul style="list-style-type: none"> <li>Emotional states (positive, negative, neutral; valence and arousal) classification</li> <li>Enhanced classification performance using hybrid feature extraction and reduction</li> </ul>	(Pichandi <i>et al.</i> , 2024; Zhang & Chen, 2025)
Obsessive-Compulsive Disorder (OCD)	<ul style="list-style-type: none"> <li>Clinical vignettes with symptom presentations (e.g., harm, contamination, religious obsessions)</li> </ul>	<ul style="list-style-type: none"> <li>Large Language Models (e.g., ChatGPT-4, Gemini Pro, LLaMA 3)</li> </ul>	<ul style="list-style-type: none"> <li>OCD Diagnosis with accuracy comparison against human professionals</li> </ul>	(Chen <i>et al.</i> , 2024; Kim <i>et al.</i> , 2024)
Childhood Abuse Detection	<ul style="list-style-type: none"> <li>Minnesota Personality Inventory Adolescent Version (MMPI-A) scores</li> <li>Sociodemographic features from adolescent psychiatric inpatients</li> </ul>	Machine Learning Algorithms, such as <ul style="list-style-type: none"> <li>K-nearest neighbor (kNN)</li> <li>Support Vector Machine (SVM)</li> <li>Random Forests (RF)</li> <li>Gaussian I Bayes (NB)</li> <li>Multi-layer Perceptron (MLP)</li> <li>Indicators involved:</li> <li>Information Gain</li> <li>GINI Index</li> </ul>	<ul style="list-style-type: none"> <li>Trait-based abuse history classification</li> <li>Identifications of unique MMPI-A "fingerprints" associated with each abuse type</li> </ul>	(Sadeghpour <i>et al.</i> , 2024; Zhang <i>et al.</i> , 2025)

These examples illustrates the diverse ways AI is being applied across mental health domains, revealing several key insights. First, AI models are being used with structured inputs, such as sociodemographic data, psychometric scores, and clinical histories, to support diagnosis in conditions like depression, OCD, and childhood trauma (Li *et al.*, 2025; Sadeghpour *et al.*, 2024). These

applications enhance diagnostic workflows and enable more targeted patient classification. Second, deep learning models applied to physiological data (e.g., EEG) show strong potential in supplementing traditional assessments for disorders like ADHD and emotional dysregulation, offering real-time, scalable analysis (Jahani & Safaei, 2024; Pichandi *et al.*, 2024). Third, large language models such as ChatGPT-4 enable the interpretation of unstructured text, including clinical notes and vignettes, making them useful for suicide risk triage, child psychiatry, and culturally sensitive evaluations (Jr. & Perlis, 2024; Kim *et al.*, 2024; Levkovich *et al.*, 2024). Additionally, several studies incorporate explainable AI methods (e.g., SHAP) and hybrid architectures to enhance model transparency and build user trust, critical factors for implementation in mental health care settings (Chen *et al.*, 2024; Pichandi *et al.*, 2024). Overall, these trends suggest that AI-enabled mental health systems are evolving beyond technical feasibility toward practical, user-aligned solutions that complement human expertise and address critical gaps in access, efficiency, and personalization.

### AI and mental health support

In addition, we identified 33 papers that focused on how AI supports mental health through therapeutic interventions, psychoeducation, and emotional regulation. These studies involved the use of mental health chatbots, AI-driven journaling tools, and conversational agents. Table 4. presents representative examples of AI-based applications that support mental health through various interventions and tools.

Table 4: Examples of AI-Based Applications Supporting Mental Health

Type of Support	Input	AI Approaches/ Applications	Outcomes	Examples of Reference
Personalised Therapeutic and problem-exploration support	<ul style="list-style-type: none"> <li>Users' sharing of situations and problems</li> </ul>	<ul style="list-style-type: none"> <li>Chatbots (e.g., "Pi" and ChatGPT) with active listening and empathetic responding, enabled by prompt engineering, with anthropomorphic features (e.g., natural language, human-like interface)</li> </ul>	<ul style="list-style-type: none"> <li>Support for early-stage problem exploration and emotional/social needs</li> <li>Partial replication of human counsellor roles</li> <li>Delivery of real-time, 24/7 emotional support and personalized CBT-based interventions</li> </ul>	(Kuhail <i>et al.</i> , 2024; Manole <i>et al.</i> , 2024; Peng <i>et al.</i> , 2024)
Self-help Psycho-educational support	<ul style="list-style-type: none"> <li>Psycho-educational prompts</li> </ul>	<ul style="list-style-type: none"> <li>Chatbot (e.g., ChatGPT)</li> </ul>	<ul style="list-style-type: none"> <li>Delivery of accurate information</li> <li>Empathetic responses to users</li> <li>Increased accessibility of psychoeducation</li> </ul>	(Maurya <i>et al.</i> , 2024; Sohaib Alam <i>et al.</i> , 2024)
Family-based psychological and educational support	<ul style="list-style-type: none"> <li>Situation encountered</li> </ul>	<ul style="list-style-type: none"> <li>Mobile agent-based AI education system</li> <li>Animated emotional agents with NLP, fuzzy logic, and user profiling</li> </ul>	Support on: <ul style="list-style-type: none"> <li>Emotional regulation through agent-based feedback</li> <li>Improved concentration</li> <li>Parent-child engagement</li> </ul>	(Guo, 2023)
Multi-domain support for neurodivergent users (with symptoms such as Autism, ADHD, Dyslexia, Social anxiety)	<ul style="list-style-type: none"> <li>Users' sharing of symptoms, dissatisfaction with human counsellors, personal challenges and other situations</li> </ul>	<ul style="list-style-type: none"> <li>Large Language Models (e.g., ChatGPT)</li> </ul>	Support on <ul style="list-style-type: none"> <li>Therapy preparation</li> <li>Emotional self-regulation</li> <li>Social cue interpretation</li> <li>Tone refinement</li> </ul>	(Carik <i>et al.</i> , 2025)

The examples in Table 4 reveal emerging patterns in how AI supports mental health across various domains. A key trend is the shift from diagnostic to interactive support, with AI increasingly positioned not as a tool for classification but as an active participant in emotional dialogue, psychoeducation, and behaviour regulation (Kuhail *et al.*, 2024; Manole *et al.*, 2024; Peng *et al.*, 2024). Many systems leverage natural language processing to personalise responses and simulate human-like empathy, reflecting a growing emphasis on emotional resonance and user engagement (Maurya *et al.*, 2024; Sohaib Alam *et al.*, 2024). Another pattern is the use of adaptive interfaces, such as animated agents or mobile platforms, to deliver interventions in context-sensitive, age-appropriate formats, particularly in youth and family settings (Guo, 2023). Additionally, AI support is becoming more functionally integrated, with tools addressing not just emotional regulation but also social interaction and cognitive scaffolding, especially for neurodivergent users (Carik *et al.*, 2025). Collectively, these applications show how AI supports mental health not only through diagnosis, but by enabling emotional reflection, education, social connection, behavioural coaching, and cognitive skill-building, extending the accessibility and responsiveness of mental health support systems.

## DISCUSSION AND CONCLUDING REMARKS

This review of 80 peer-reviewed articles offers critical insights into the dual role of artificial intelligence (AI) in mental health, focusing on both detection and support. While the field is expanding, several methodological and theoretical gaps remain.

The literature remains heavily focused on quantitative methods such as surveys, lab experiments, secondary data analysis, and modeling. While effective for prediction and diagnosis, these approaches often neglect human factors like trust and user experience. Underused but essential methods—such as field experiments, case studies, and qualitative research—can provide deeper insight into real-world AI adoption. Likewise, design science research, found in only a few studies ( $n=5$ ), holds strong potential for developing practical, user-centered AI tools. Future work should integrate design science research mixed or participatory methods to enhance both technical relevance and user engagement. Another critical gap lies in the limited use of theoretical frameworks. Of the 80 studies reviewed, 57 did not reference any guiding theory. The consistent use of psychological and information systems theories can enhance methodological justification and connect results to broader scholarly conversations (Corley & Gioia, 2011).

In addition to the core themes, six complementary studies offered valuable yet tangential perspectives. These include analyses of public perceptions of AI in therapy (Jagemann *et al.*, 2024), AI-supported research mapping (Amirian *et al.*, 2024), and applications in cognitive neuroscience (Taghilou *et al.*, 2024). Others addressed ethical considerations and trend analysis in AI psychology research (Gao & Lou, 2024). While not directly answering the central research questions, these works underscore the interdisciplinary and rapidly expanding nature of AI in mental health.

Moving forward, we advocate for more interdisciplinary research that combines technical development with human-centered design and theory-driven inquiry. Such efforts will not only advance academic understanding but also guide the creation of intelligent, empathetic, and accessible AI tools that meaningfully support individuals experiencing psychological distress. In the next stage of our research, we plan to conduct a meta-analysis of selected high-quality studies from this review to quantitatively assess the effectiveness of AI-driven interventions. Additionally, we aim to develop a conceptual framework that integrates psychological theories and information systems models to guide the design of future AI-based mental health tools. This framework will inform the development and evaluation of a prototype system that provides personalized support, which we intend to pilot in real-world environments such as educational or clinical settings.

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