



Artificial Intelligence in Mental Healthcare: A Scoping Review of Clinical Applications, Evidence, Safety, and Equity

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ABSTRACT

Artificial intelligence is increasingly used across mental healthcare for prevention, screening, risk estimation, symptom monitoring, conversational support, psychotherapy augmentation, clinical decision support, and service delivery. However, promising technical performance does not necessarily translate into independently validated, durable, equitable, or clinically safe benefit. This scoping synthesis maps applications of artificial intelligence and examines evidence, user experience, human-centered requirements, implementation determinants, safety, equity, and regulatory priorities across 20 supplied sources. A document-based scoping synthesis was conducted using the complete supplied corpus, comprising reviews, empirical studies, an implementation study, a survey, a bibliometric analysis, policy and regulatory sources, commentary, a preprint, and a media-based review. Findings were charted thematically across applications, evidence quality, human-artificial intelligence interaction, implementation, safety, equity, and governance. No statistical pooling was undertaken because of substantial heterogeneity. Six interrelated domains emerged: expanding functions across the mental-health continuum; promising but uneven clinical evidence; growing conversational support and artificial-intelligence-assisted help-seeking; the importance of empathy, therapeutic alliance, and human oversight; implementation barriers involving workflow, training, interoperability, accountability, and organizational readiness; and persistent concerns about privacy, bias, transparency, crisis management, youth vulnerability, digital inequality, and regulation. Conversational interventions showed the clearest signal for short-term depressive symptom improvement, while evidence for anxiety, stress, long-term outcomes, and diverse populations remained less consistent. The supplied literature supports artificial intelligence primarily as an adjunct to human mental healthcare rather than a replacement for professional care. Responsible translation requires external validation, longitudinal outcomes, human-centered co-design, transparent reporting, subgroup and bias auditing, crisis-escalation pathways, clinician training, interoperability, post-deployment surveillance, and adaptive governance.

Keywords: artificial intelligence, conversational artificial intelligence, equity, mental health, safety

INTRODUCTION

Mental healthcare is characterized by persistent unmet need, shortages of trained professionals, stigma, geographic barriers, and uneven service capacity. Against this background, artificial intelligence has been proposed as a means of expanding access, supporting clinicians, personalizing interventions, and enabling continuous monitoring. The supplied literature describes artificial intelligence not as a single intervention but as a broad technological category encompassing natural-language processing, predictive modelling, computer vision, conversational agents, large language models (LLMs), digital therapeutics, wearable and smartphone sensing, and clinical decision-support systems.

The evidence base has developed rapidly. The supplied bibliometric analysis of LLM research identified 426 publications from 2020–2025 and reported a compound annual growth rate of 140%, with a transition from foundational work toward clinically oriented themes such as chatbots, multilingual models, diagnosis, and therapeutic applications. The same analysis

identified substantial geographic imbalance, with high-income countries and well-resourced institutions dominating the research landscape.

The field is also becoming more clinically consequential. The supplied scoping review of conversational artificial intelligence identified 10,293 records and 677 included studies, showing that intervention research dominates the patient journey, while prevention and maintenance remain comparatively underdeveloped. The review proposed a human-centered taxonomy organized around emotional sensitivity, user-centric interaction design, human–artificial intelligence collaboration and capability enhancement, and ethics and accountability.

At the same time, evidence syntheses caution against equating internal model performance with clinical effectiveness. The supplied scoping review of reviews found that internal diagnostic and prediction metrics are often strong, whereas independent or prospective validation is much less common and performance frequently attenuates. This distinction is fundamental: mental healthcare involves complex, heterogeneous, context-dependent human phenomena in which technical accuracy is only one component of clinical value.

The present manuscript therefore treats the supplied literature as a heterogeneous evidence ecosystem. Its purpose is not to re-rank individual technologies, but to map what the corpus collectively says about where artificial intelligence is being used, what appears promising, where evidence remains weak, and what conditions are necessary for responsible adoption. This synthesis extends source-specific discussions by integrating clinical applications, evidence quality, human-centered interaction, implementation, safety, equity, and governance within a single mental-health continuum. Its principal contribution is a four-layer model linking the patient journey, the human–artificial intelligence relationship, the service system, and societal governance, thereby framing responsible adoption as a sociotechnical rather than purely technical challenge.

METHODOLOGY

This manuscript is a document-based scoping synthesis of the 20 files supplied by the user. It follows the logic of scoping review methodology mapping breadth, concepts, evidence types, and knowledge gaps rather than claiming to reproduce an independent database search. This distinction is important because the supplied corpus was assembled externally and contains heterogeneous publication types, including peer-reviewed studies, reviews, reports, commentary, a preprint, and a news-based review. All 20 supplied documents were retained for synthesis because they contributed to at least one of the review questions. No supplied source was excluded solely because it was not peer reviewed; instead, source type was treated as an interpretive feature when weighing claims.

Information was organized under six thematic domains: AI applications across the mental-health continuum; clinical evidence and evidence quality; user experience and help-seeking; human-centered interaction and therapeutic relationships; implementation and organizational adoption; and safety, equity, ethics, and regulation. Numerical findings reported by individual sources are presented descriptively and are not statistically pooled. The synthesis deliberately distinguishes empirical findings from conceptual or policy-oriented claims. In particular, media-reported adverse events are not interpreted as incidence estimates or proof of causality. Similarly, industry commentary is used to illustrate a perspective on AI adoption rather than as equivalent evidence to controlled clinical research.

Table 1. Characteristics And Methodological Roles Of The 20 Supplied Sources

No	Source	Publication/type	Primary focus	Contribution to synthesis
1	Dewi, Purwanto & Mulawarman (2026)	Systematic literature review	Digital empathy in online communication	Emotional interpretation, AI empathy, limits of nonverbal cues
2	Dehbozorgi et al. (2025)	Systematic review	AI applications in mental health	Early detection, chatbots, prediction, privacy and transparency
3	Li et al. (2026)	Scoping review	Conversational AI, human-centered perspective	Patient journey and four-dimensional human-centered taxonomy
4	Koh (2025)	Professional/industry commentary	Future of AI in mental healthcare	Access, personalization, prediction, continuity and provider support
5	Supplied systematic literature review synthesis	Structured qualitative synthesis	AI applications, evidence, adoption, ethics and governance	Cross-source synthesis of five recent studies
6	Fanarioti & Karpouzis (2025)	Systematic/strategic review	AI, governance, regulation and social justice	Policy, equity, transparency and human oversight
7	Pandey	Short review	AI and mental health/well-being	Evolution, applications, monitoring, privacy and bias
8	Nair et al. (2025)	Qualitative implementation study	AI implementation in healthcare	Phased implementation activities, readiness and adoption
9	Mental Health Commission of Canada	Environmental scan	AI in mental health services	Early landscape, clinical adoption and evidence gaps
10	Abu-Mahfouz et al. (2026)	Scoping review of reviews	Clinical evidence and implementation	31 reviews; validation, effects, populations, governance
11	Hussiny et al. (2026)	Bibliometric analysis	LLMs in mental-health research	426 articles; growth, themes, geography and collaboration
12	Rahman et al. (2025)	Narrative review	AI in mental healthcare and psychology	Emotion recognition, chatbots, provider burden and ethics
13	Woo & Jung (2026)	Scoping review	Real-world AI service delivery	26 studies; implementation contexts and workflow integration
14	Ueda et al. (2026)	Cross-sectional survey	AI-based mental-health help-seeking	1,805 US adults; usage, preferences and human-vs-AI support
15	Chung, Bernier & Hudon (2026)	Rapid scoping review	Media narratives of psychiatric adverse events	71 articles; 36 cases; safety signals and causal framing

No	Source	Publication/type	Primary focus	Contribution to synthesis
16	Birk et al. (2026)	Editorial	Research priorities in AI/LLM era	Equity, replicability, privacy, efficacy, engagement and safety
17	Pais et al. (2026)	Regulatory review	AI in digital mental-health technology	Lifecycle regulation, safety, equity, bias and post-market surveillance
18	Pazer (2026)	Preprint/literature review	AI in psychotherapy	Therapeutic alliance, CBT/ACT, privacy, bias and human connection
19	Manotas (2026)	Behavioral-health commentary	AI companions and youth mental health	Developmental mismatch, reliance, guardrails and caregiver involvement
20	Muthoni (2024)	Narrative article	Role of AI in improving mental healthcare	Access, diagnosis, therapy, prevention and ethical challenges

Table 2. Evidence Domains, Contributions, And Principal Limitations

Evidence domain	Representative source types	What the corpus contributes	Main limitation
Clinical applications	Systematic/scoping reviews; narrative reviews	Maps screening, prediction, monitoring, chatbots, psychotherapy and decision support	Heterogeneous outcomes and technologies
Conversational AI	Scoping review; survey; psychotherapy review	Evidence on engagement, symptom change, help-seeking and human-centered interaction	Short follow-up; uncertain substitution effects
Implementation	Qualitative implementation study; real-world scoping review; environmental scan	Workflow, readiness, training, interoperability and adoption determinants	Many deployments remain pilot-stage
Safety	Rapid media scoping review; narrative/commentary sources	Identifies crisis, dependence, unsafe-output and adverse-event signals	Media evidence cannot establish incidence or causality
Equity & ethics	Governance/regulatory reviews; bibliometric analysis	Privacy, bias, global research imbalance, transparency and accountability	Frameworks vary across jurisdictions
Research landscape	Bibliometric analysis; research-priority editorial	Shows rapid LLM growth and emerging priorities	Publication volume does not equal clinical maturity

Wearable and smartphone technologies are important because they can supply continuous behavioral and physiological signals. The supplied literature describes potential use of speech, social-media behavior, electronic health records, wearable metrics, and lifestyle variables for prediction and monitoring. However, the more data are collected, the greater the requirements for privacy, consent, data quality, interpretability, and secure governance.

1. Diagnostic And Predictive AI: Strong Promise, Incomplete Translation

Diagnostic and predictive models represent one of the most technically mature areas in the corpus, but the literature repeatedly warns against overinterpreting internal validation. The scoping review of reviews reports that internal AUCs in prior syntheses commonly cluster around approximately 0.80–0.88, while external and prospective validation is scarce and often attenuated. Models may perform particularly well on narrow, feedback-rich tasks but degrade when applied to different populations, settings, or longer prediction horizons.

The principal implication is that model performance is context dependent. A model trained on one health system, language, age group, clinical population, or documentation practice may not generalize to another. The sources therefore converge on the need for independent test sets, multicenter validation, subgroup analysis, bias auditing, transparent reporting, and prospective real-world evaluation.

The literature also highlights a translational issue: a model that identifies risk is not automatically clinically useful. For example, clinicians may value imminent-risk alerts only when they are integrated with actionable next-step protocols. Explainability alone may not make a model actionable if clinicians are not trained to interpret or use its outputs.

2. Conversational AI And Psychotherapy Augmentation

Conversational agents constitute the most visible and rapidly evolving application. Examples discussed across the supplied sources include Wysa, Woebot, Youper, Elomia, Koko, Replika, and newer LLM-based systems. These tools can provide psychoeducation, structured cognitive-behavioral exercises, emotional support, symptom monitoring, and between-session engagement.

The evidence is encouraging but bounded. The scoping review of reviews reports small-to-moderate short-term improvements in depressive symptoms, with effects for anxiety and stress smaller or inconsistent. Many chatbot studies are short, small, and conducted with limited follow-up, making durability uncertain. The literature therefore supports conversational artificial intelligence as a potentially useful adjunct, not as an established replacement for psychotherapy.

The psychotherapy literature adds a conceptual constraint: therapeutic care is not simply the delivery of correct words. Therapeutic alliance, trust, boundaries, mutuality, accountability, and the ability to respond appropriately to complex clinical states are central. The supplied preprint explicitly positions artificial intelligence-assisted psychotherapy as a supplement to professional therapeutic relationships and highlights CBT, ACT and supportive counseling as relevant frameworks.

Digital empathy is particularly important here. The supplied systematic review on digital empathy shows that digital communication removes many facial, gestural and vocal cues, increasing the possibility of emotional misinterpretation. artificial intelligence can recognize linguistic patterns and generate responses perceived as empathic, but the same review emphasizes limitations in understanding emotional nuance and argues that technology should support rather than substitute for authentic human emotional connection.

3. Human-Centered AI: From Technical Capability To Relational Quality

The human-centered perspective emerges as a unifying theme across the corpus. The conversational-artificial intelligence review identifies four dimensions: emotional sensitivity to users; user-centric interaction design; human–artificial intelligence collaboration and capability enhancement; and ethics and accountability. These dimensions broaden evaluation beyond accuracy to include whether an artificial intelligence system understands the user's context, supports agency, preserves dignity, communicates limitations, and fits into real care relationships.

Human-centeredness also requires recognizing that users differ in developmental stage, culture, language, socioeconomic position, clinical severity and digital literacy. The LLM bibliometric study highlights the underrepresentation of low- and middle-income countries and low-resource languages. A system may therefore be technically impressive yet inequitable if it performs poorly for populations absent from its training and evaluation data.

Youth represent a particularly sensitive population. The supplied behavioral-health commentary describes how adolescents may use artificial intelligence companions for emotional disclosure, especially when they feel isolated or reluctant to approach adults. It emphasizes a developmental mismatch: adolescent social and emotional development depends partly on real relationships, including disagreement, boundary-setting and repair. artificial intelligence can simulate supportive conversation but cannot reproduce the developmental work of reciprocal human relationships.

4. User Adoption And Changing Help-Seeking

The supplied US cross-sectional survey provides direct evidence that artificial intelligence is becoming part of mental-health help-seeking. Among 1,805 adults aged 18–49 years, 638 (35.2%) reported using artificial intelligence tools at least weekly for mental-health support in a typical week, while 99 (5.5%) were classified as heavy users. Importantly, human professionals remained more favorably viewed overall. These findings suggest that artificial intelligence use is not necessarily replacing professional care, but it is becoming an additional pathway through which people seek support.

This creates a new clinical question: whether artificial intelligence functions as a gateway to appropriate care or as a substitute that delays professional assessment. The survey authors explicitly call for longitudinal research to determine whether reported reductions in human counseling represent actual disengagement or changing preferences. Because the survey was cross-sectional and self-reported, causal conclusions cannot be drawn.

The appeal of artificial intelligence is understandable. The sources repeatedly describe immediacy, anonymity, availability, perceived nonjudgment, and personalization as advantages. These features can reduce practical and psychological barriers to seeking help. Yet precisely the same features can increase emotional reliance, misplaced trust, or delayed escalation when a user presents with severe symptoms.

5. Implementation And Service Integration

A major shift in the recent literature is from asking whether artificial intelligence can work to asking how it can be integrated into real services. The 2026 service-delivery scoping review identified 829 records and included 26 real-world studies. Decision-support systems were most common (50%), followed by predictive machine-learning models (27%) and generative artificial intelligence applications (15%). Most tools were designed for clinician use (77%), and 46% were implemented in hospital settings. Although 46% of studies reported real-world implementation, more than half remained at the pilot stage.

The implementation literature identifies multiple interacting barriers: data quality, interoperability, workflow disruption, clinician trust, liability, regulation, training, organizational readiness, infrastructure, and cost. The implementation-process framework in the supplied Nair et al. study emphasizes that successful deployment requires structured activities across phases rather than treating implementation as an afterthought to technical development.

A particularly important theme is the gap between technical utility and workflow utility. artificial intelligence may be accurate but still fail if it increases documentation burden, creates alert fatigue, does not integrate with electronic health records, or produces outputs that

clinicians cannot act upon. Successful adoption therefore requires co-design with end users, workflow mapping, training, governance, monitoring, and iterative adaptation.

6. Safety, Adverse Events And Crisis Management

Safety is the strongest cross-cutting concern. The supplied literature repeatedly identifies privacy, bias, transparency, accountability, inappropriate outputs, and inadequate crisis management as unresolved problems. These concerns become particularly acute when artificial intelligence is used directly by people experiencing suicidality, psychosis, mania, severe distress, or other high-risk states.

The rapid scoping review of mass-media narratives is important but must be interpreted differently from clinical evidence. It identified 71 news articles representing 36 unique cases. Suicide death was the most frequently reported outcome among cases with complete severity coding, and fatal outcomes were disproportionately represented among minors. However, the evidence was predominantly chat logs/screenshots and family testimony, while police or medical documentation was rare. The authors explicitly state that their objective was to map narratives rather than verify causality.

Accordingly, these cases should be treated as safety signals and hypotheses for systematic investigation, not as incidence estimates. The review nevertheless identifies recurring mechanisms worthy of formal study: prolonged interaction, emotional dependence, validation of maladaptive beliefs, inadequate content filtering, and failure to escalate during crisis. The youth-focused commentary similarly argues for stronger guardrails and clinician input when artificial intelligence is used for emotional support.

The appropriate response is therefore neither uncritical optimism nor categorical rejection. Safety engineering should include crisis detection, predefined escalation pathways, age-appropriate safeguards, transparent limitations, human handoff, adverse-event reporting, red-teaming, post-deployment surveillance, and clear responsibility for intervention.

7. Ethics, Privacy, Bias And Equity

Mental-health artificial intelligence operates on unusually sensitive data. The supplied sources describe risks associated with the collection, storage, sharing and secondary use of clinical, behavioral, conversational, physiological and social data. Privacy therefore cannot be treated as a purely technical security issue; it is also a matter of informed consent, purpose limitation, user expectations and trust.

Bias is equally central. The literature emphasizes that model quality depends on training-data quality and diversity. Underrepresentation can produce unequal performance across demographic groups, languages and health systems. The LLM bibliometric analysis demonstrates a global research imbalance, while the policy-oriented review emphasizes digital exclusion and the risk that artificial intelligence could reproduce existing inequalities.

Equity must consequently be evaluated at multiple levels: access to devices and connectivity; language coverage; cultural relevance; model performance across demographic subgroups; affordability; accessibility for people with disabilities; and the distribution of benefits and harms. The supplied regulatory review argues for lifecycle approaches in which safety, bias reduction and stakeholder engagement are embedded from design through decommissioning.

8. Regulation and governance

The regulatory literature suggests that mental-health artificial intelligence requires adaptive rather than static governance. The supplied Pais et al. review, informed by a multidisciplinary UK symposium, emphasizes equity, transparency, accountability, privacy, fairness and bias reduction. It also highlights the importance of medical-device classification

for appropriate risk stratification and management where artificial intelligence functions as a medical device.

Regulation should extend beyond pre-market approval. Because artificial intelligence systems may change through software updates, data shifts, user adaptation and changing deployment contexts, post-market surveillance and real-world evidence are essential. Regulatory sandboxes and other controlled environments can support evaluation while allowing innovation to proceed.

Governance also requires clear allocation of responsibility. Questions include who is accountable when an artificial intelligence recommendation is wrong, who monitors adverse events, who decides when a model must be retrained or withdrawn, and how patients can understand or contest automated decisions. These questions cannot be solved by model explainability alone; they require organizational governance and legal accountability.

9. A Human-Centered Artificial Intelligence Mental-Health Continuum

This model highlights why technical performance alone is insufficient. A clinically useful artificial intelligence system must perform adequately, be understandable and actionable, fit the workflow, remain safe in edge cases, work across relevant populations, and operate within an accountable governance structure. Conversely, a highly accurate model can still be harmful if it increases inequality, erodes trust, or is deployed without appropriate escalation mechanisms.

Table 3. Integrated Human-Centered Artificial Intelligence Mental-Health Continuum Derived From The Supplied Corpus

Layer	Core question	Design / implementation requirements	Evaluation indicators
Patient journey	Where does artificial intelligence act?	Prevention, detection, intervention and maintenance mapped to explicit clinical goals	Access, symptom change, detection performance, continuity
Human-artificial intelligence relationship	How should the interaction feel and function?	Emotional sensitivity, agency, boundaries, transparency and human handoff	Trust, usability, alliance, perceived empathy, reliance
Service system	Can the tool work safely in practice?	Workflow fit, interoperability, training, readiness, accountability	Adoption, workload, implementation fidelity, clinician acceptance
Governance	Who is protected and accountable?	Privacy, equity, bias auditing, regulation, surveillance and redress	Subgroup performance, adverse events, equity, compliance

CONCLUSION

Based on the findings of the synthesis, artificial intelligence (AI) has considerable potential to support mental healthcare across various functions, including prevention, screening, symptom monitoring, conversational support, and clinical decision-making. Although AI demonstrates promising benefits, the available evidence remains heterogeneous and does not yet support its use as a replacement for mental health professionals. Conversational AI interventions show the clearest evidence of short-term improvement in depressive symptoms, while their effectiveness for anxiety, stress, long-term outcomes, and diverse populations remains less consistent. Therefore, AI should primarily be implemented as an adjunct to professional mental healthcare, with human oversight remaining essential. Safe, equitable, and sustainable implementation requires external validation, long-term evaluation, human-centered design, transparent reporting, bias and subgroup auditing, effective crisis-

escalation mechanisms, clinician training, privacy protection, interoperability, post-deployment monitoring, and adaptive regulatory frameworks.

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