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Artificial Intelligence for Mental Health in Sub-Saharan Africa: A Systematic Review of Current Trends, Techniques, Research Gaps, and Global Evidence

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Abstract

Background: Artificial intelligence (AI) is increasingly integrated into digital mental health systems to improve detection and management of psychiatric conditions, yet disparities persist in low-resource regions such as Sub-Saharan Africa (SSA).

Objective: To examine empirical AI applications in mental health, focusing on methodological trends, application domains, and implementation gaps in SSA relative to global evidence.

Methods: This systematic review was conducted in accordance with the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) 2020 statement. Four databases (PubMed, IEEE Xplore, Google Scholar, and Semantic Scholar) were searched for studies published between 2010 and 2025. Included studies comprised SSA-based research and selected global evidence considered transferable to SSA using predefined relevance criteria. Evidence was synthesized through structured thematic narrative synthesis guided by predefined research questions and a coding framework.

Results: Thirty-three studies (14 SSA-specific, 19 global) revealed four patterns: machine learning dominated (54.5%), while chatbot use was relatively higher in SSA; depression and general mental health predominated globally, whereas SSA studies emphasized trauma, post-traumatic stress disorder (PTSD), and HIV-related distress; prediction/classification applications dominated (60.6%), with only one randomized trial; and major gaps remained in geographic coverage, linguistic diversity, and implementation research.

Conclusions: AI mental health research in SSA is emerging, with gradual growth over time. Addressing geographic, linguistic, and methodological gaps is critical to support equitable AI-enabled mental health innovation in the region.

Keywords: Artificial Intelligence; Mental Health; Machine Learning; Deep Learning; Natural Language Processing; Digital Mental Health; Sub-Saharan Africa; Systematic Review; Global Health.

Introduction

Mental health disorders represent one of the most pressing public health challenges of the twenty-first century. The World Health Organization (WHO) estimates that approximately one in eight people globally—nearly one billion individuals—lives with a mental health condition, with depression and anxiety disorders among the most prevalent [1]. These conditions impose a disproportionate burden on individuals, families, and health systems: they account for approximately 13% of the global burden of disease and are the leading cause of disability worldwide [2]. The burden is particularly acute among adolescents and young adults, for whom mental disorders represent the leading cause of disability and a major contributor to premature mortality through suicide [1]. The COVID-19 pandemic further amplified these trends, triggering a 25% increase in the global prevalence of anxiety and depression in 2020 alone, with effects that continue to reverberate across health systems [2]. Despite this enormous burden, access to mental health care remains severely limited. Globally, more than 70% of people with mental health conditions receive no treatment—a figure that rises to over 90% in low- and middle-income countries (LMICs) [3]. Structural barriers compound the treatment gap: mental health services are chronically underfunded, accounting for less than 2% of national health budgets in most LMICs [3]. Social stigma remains a pervasive deterrent to help-seeking, particularly at early stages of illness [4]. The global shortage of mental health professionals—estimated at over 1.18 million workers worldwide—is most acute in resource-constrained settings, where the ratio of psychiatrists to population can be as low as 0.06 per 100,000 compared to over 10 per 100,000 in high-income countries [5] Traditional, face-to-face care models are not only expensive but structurally incapable of scaling to meet rising demand [[6]

Artificial Intelligence as a Transformative Opportunity

In response to these systemic challenges, artificial intelligence (AI) has emerged as a promising modality for augmenting mental health service delivery. AI refers broadly to the capacity of computational systems to perform tasks that typically require human intelligence, including pattern recognition, natural language understanding, and decision-making [7]. In the mental health domain, AI technologies offer several distinct capabilities: early identification of at-risk individuals, enhancement of diagnostic accuracy, personalisation of treatment pathways, and facilitation of continuous monitoring outside clinical settings [8], [9], [10]]. A conceptual taxonomy of AI applications in mental health is essential for interpreting the research landscape. Four principal technique categories can be distinguished: (1) Machine Learning (ML), encompassing supervised and unsupervised algorithms—such as Support Vector Machines, Random Forests, and logistic regression—applied to structured clinical, behavioural, or physiological data; (2) Deep Learning (DL), including convolutional neural networks (CNNs) and recurrent architectures (e.g., LSTM), suited to complex, high-dimensional inputs such as neuroimaging, speech, and facial expressions; (3) Natural Language Processing (NLP), enabling computational analysis of text and speech for sentiment classification, symptom extraction, and clinical note mining; and (4) Conversational AI and Chatbots, which deploy rule-based or generative dialogue systems to deliver psychoeducation, cognitive-behavioural therapy (CBT) exercises, and emotional support at scale[9]],[10]0][11]1]. These techniques are applied across four functional domains: prediction (identifying individuals at risk of developing or relapsing into mental illness), diagnosis (supporting clinical classification of disorders), intervention (delivering therapeutic content or facilitating behavior change), and monitoring (tracking symptom trajectories and treatment adherence over time[10]10[12]12]. Understanding this taxonomy is critical for contextualizing the research reviewed in this study and for identifying where evidence is concentrated or abse[7][7].

The Sub-Saharan African Context: A Region of Unmet Need

The challenges of mental health service delivery are nowhere more pronounced than in Sub-Saharan Africa (SSA). The region carries a substantial and growing mental health burden: depression, anxiety, post-traumatic stress disorder (PTSD), and substance use disorders are among the leading contributors to disability-adjusted life years (DALYs) in SSA, compounded by high rates of trauma exposure, gender-based violence, HIV-related psychological distress, and perinatal mental health conditions [13]. Yet the treatment gap in SSA is among the widest globally: fewer than 10% of individuals with mental health disorders receive any form of treatment, and in some countries this figure falls below 1% [[3], [14]].

The mental health workforce crisis in SSA is severe. The WHO Mental Health Atlas (2020) reports a median of 0.1 psychiatrists per 100,000 population in low-income African countries, compared to a global median of 1.3—a more than tenfold disparity [5] Psychologists, psychiatric nurses, and community mental health workers are similarly scarce. The vast majority of mental health care in SSA is therefore delivered by non-specialist primary care workers or community health workers (CHWs), often without access to structured protocols or decision-support tools. Paradoxically, SSA's rapidly expanding digital infrastructure offers a potential pathway for AI-assisted mental health delivery. Mobile phone penetration across SSA reached approximately 46% of the population in 2023 and is projected to exceed 50% by 2025, with mobile internet subscriptions growing at an annual rate of over 10% [[15]In several SSA countries—including Kenya, Nigeria, Ghana, and South Africa—mobile money, telemedicine, and mHealth platforms have already demonstrated feasibility and uptake at scale. However, significant inequities persist: smartphone ownership remains lower than feature phone use in many rural areas; internet connectivity is unreliable and expensive in large parts of the region; and electricity access—a prerequisite for device charging and connectivity—remains unavailable to approximately 600 million SSA residents [1[15] 1[16].

Cultural and linguistic dimensions further complicate the deployment of AI mental health tools in SSA. The region encompasses over 2,000 languages, yet the vast majority of AI mental health systems are developed and validated in English, French, or other colonial languages [17].

Culturally specific idioms of distress—ways in which psychological suffering is expressed and understood within particular communities—are rarely captured by standardised assessment instruments developed in Western contexts. The risk of imposing culturally inappropriate diagnostic frameworks or therapeutic approaches through AI systems is therefore substantial and underappreciated in current research [[17], [18]].

Prior Systematic Reviews and Identified Gaps

Several systematic and scoping reviews have examined AI applications in mental health, providing an important foundation for the present work. Laranjo et al. (2018) conducted a landmark systematic review of conversational agents for health behaviour change, finding preliminary evidence of effectiveness but noting significant methodological limitations, including small sample sizes, short follow-up periods, and a near-complete absence of studies from low-resource settings [19]. Bendig et al. (2019) conducted a scoping review specifically focused on chatbots and mental health, identifying 13 eligible studies and concluding that while chatbots showed promise for symptom reduction and psychoeducation, evidence remained sparse and geographically concentrated in high-income countries [20]. More recent reviews—including Abu-mahfouz et al. (2026), Cruz-González et al. (2025), and Malgaroli et al. (2023)—have extended coverage to machine learning and NLP applications, consistently reporting strong predictive performance in controlled settings but limited evidence of real-world implementation, particularly in LMICs [[9], [10]0].

A critical gap across these reviews is the near-complete absence of SSA-focused analysis. Existing reviews either aggregate findings globally without geographic disaggregation, or restrict their scope to high-income country settings. None has systematically compared SSA-specific research with globally applicable evidence, nor examined the methodological and technological adaptations required for effective AI deployment in SSA contexts. Alaran et al. (2025) highlighted the broader challenges of AI adoption in African health systems—including data scarcity, infrastructure constraints, and regulatory gaps—but did not conduct a systematic review of empirical AI mental health applications [21]. This absence represents a significant gap in the literature, given SSA's disproportionate mental health burden and the growing body of region-specific AI research.

Rationale and Aims of the Present Review

Against this backdrop, a systematic review specifically examining AI applications in mental health within and relevant to SSA is both timely and necessary. Such a review serves three distinct purposes: first, to map the current state of SSA-specific AI mental health research and identify which conditions, techniques, and application domains have received attention; second, to

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identify globally applicable AI evidence that meets defined criteria for transferability to SSA contexts, enabling evidence-informed adaptation rather than wholesale importation of high-income country solutions; and third, to identify the methodological, geographic, linguistic, and ethical gaps that must be addressed to advance equitable AI contributions to closing SSA's mental health treatment gap.

The present review therefore addresses four research questions: (1) What AI techniques have been applied in mental health care, and how are they specifically utilised within the SSA context? (2) Which mental health conditions have attracted the greatest research attention, and how do SSA priorities differ from global trends? (3) What patterns characterise study design and research objectives across the reviewed literature? (4) Where do the critical research gaps lie, particularly in resource-limited and infrastructure-constrained settings such as SSA? By systematically synthesising both SSA-conducted research and globally applicable evidence through a comparative lens, this review aims to provide a rigorous and actionable evidence base for researchers, policymakers, technology developers, and funders committed to advancing equitable AI-driven mental health care in Sub-Saharan Africa.

Methods

Study Design

This study adopted a systematic literature review (SLR) to examine applications of artificial intelligence (AI) in mental health care, with particular emphasis on Sub-Saharan Africa (SSA). The review was conducted in accordance with the PRISMA 2020 statement to ensure transparency, methodological rigor, and reproducibility.

Research Questions

The review was guided by four predefined research questions, which informed the search strategy, study selection, data extraction, and thematic synthesis:

RQ1. What AI techniques have been applied in mental health care, and how are they utilized within the Sub-Saharan African context?

RQ2. Which mental health conditions have attracted the greatest research attention, and how do SSA priorities differ from global trends?

RQ3. What patterns characterize study design and research objectives across the reviewed literature?

RQ4. Where do the critical research gaps lie, particularly in resource-limited and infrastructure-constrained settings such as SSA?

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Search Strategy

A structured search strategy was developed based on three core conceptual components: artificial intelligence, mental health, and geographic context. Relevant synonyms within each component were combined using the Boolean operator OR, and the three components were linked using AND to retrieve studies addressing all themes.The search was conducted across four databases: PubMed, IEEE Xplore, Google Scholar, and Semantic Scholar. A total of 205 records were initially identified across the four databases. Following deduplication and preliminary filtering, 195 records were retained for screening, distributed as follows: PubMed (n = 31), IEEE Xplore (n = 74), Google Scholar (n = 60), and Semantic Scholar (n = 30).

Inclusion and Exclusion Criteria

To ensure the relevance, quality, and consistency of the retrieved studies, a set of predefined inclusion and exclusion criteria was established prior to the screening process.

Inclusion Criteria

Studies were considered eligible for inclusion if they satisfied all of the following conditions:

1. Published between 2010 and 2025
2. Written in English
3. Published as peer-reviewed journal articles or conference papers
4. Available in full text
5. Addressed the application of artificial intelligence in the context of mental health care.
6. Studies were included if they met one of two predefined inclusion pathways, based on pre-defined operational criteria:

Category A — SSA-Conducted Studies (Primary SSA Evidence)

(A1) Primary data collected from participants in one or more SSA countries;

(A2) Study led or co-led by researchers affiliated with SSA institutions;

(A3) AI model developed, trained, or validated using SSA-based datasets;

(A4) Study explicitly states SSA country focus in objectives or methods.

Studies meeting at least one of A1–A4 were classified as SSA-Conducted.

Category B — SSA-Relevant Global Studies (Applicable Global Evidence)

(B1) The study explicitly reports deployment or intended use on mobile or low-bandwidth platforms;

(B2) The study addresses mental health conditions with a documented high burden in SSA (e.g., depression, anxiety, PTSD, substance use, perinatal disorders), based on WHO or global burden reports;

(B3) The study design is applicable to primary care or task-shifting contexts;

(B4) The study explicitly discusses applicability to low-resource or LMIC settings;

(B5) The study describes the AI model as lightweight or suitable for deployment without high-performance infrastructure.

Studies meeting at least two of B1–B5 were classified as SSA-Relevant Global. Studies not meeting Category A or B criteria were excluded. Conducted outside SSA and did not address conditions, populations, or resource constraints comparable to SSA, nor provide insights applicable to the SSA implementation context.

Exclusion Criteria

Studies were excluded from the review if they met any of the following conditions:

1. Published before 2010 or after 2025
2. Written in a language other than English
3. Classified as books, theses, dissertations, or grey literature
4. Available in abstract only, without access to the full text
5. Did not address AI applications in the field of mental health
6. Lacked a clear focus on or relevance to the mental health domain
7. Conducted outside SSA and did not address conditions, populations, or resource constraints comparable to SSA, nor provide insights applicable to the SSA implementation context

With respect to Google Scholar specifically, additional filters were applied to exclude books, theses, and dissertations, with the aim of minimizing grey literature and enhancing the overall quality and scientific credibility of the retrieved records.

Study Selection

All records were screened at the title and abstract level, followed by full-text assessment based on predefined inclusion and exclusion criteria. Screening was conducted independently by two reviewers to enhance methodological rigor and reduce selection bias. Inter-reviewer agreement was assessed, and discrepancies were resolved through discussion and consensus.

Of the 195 records identified, 141 were excluded during title and abstract screening. The remaining 54 reports were assessed for full-text eligibility. Following detailed evaluation, 21 reports were excluded for not meeting the predefined inclusion criteria, resulting in 33 studies included in the final synthesis. Study classification based on these criteria is provided in Multimedia Appendix 1, and the reasons for full-text exclusion are summarized below.

Data Extraction and Classification

A standardized data extraction framework was developed to systematically classify studies according to mental health focus, AI technique, data type, and application domain. Mental health outcomes were categorized into: (1) specific clinical conditions (e.g., depression, anxiety, PTSD, schizophrenia, substance use disorders), and (2) general mental health and well-being.

Data extraction and study classification were conducted independently by two reviewers using predefined coding rules. Inter-reviewer agreement was assessed, and discrepancies were resolved through consensus. Where necessary, classifications were refined through iterative re-review of full-text articles in accordance with predefined criteria (Table 1).

Table 1. Reasons for Exclusion During Full-Text Screening

Reason for Exclusion	n
No empirical evidence	4
Not relevant to SSA	5
No AI method described	3
Not mental health related	2
Prototype without evaluation	2
Physical health only	2
Emotion recognition only	1
Editorial or non-peer reviewed	1
Technology adoption only	1
Total	21

Assessing Study Quality

The methodological quality of the included studies was assessed using the Mixed Methods Appraisal Tool (MMAT), version 2018. The MMAT was selected because the review included heterogeneous study designs, including quantitative prediction studies, intervention studies, qualitative studies, and mixed-methods studies. Studies were first categorised according to design type, and the corresponding MMAT criteria were applied using design-specific appraisal questions.

Given the AI-specific focus of this review, a supplementary appraisal matrix was used to capture methodological dimensions that general critical appraisal tools do not fully address. This supplementary matrix considered five domains: model validation, external validation, adequacy of evaluation metrics, dataset relevance and representativeness, and implementation feasibility. These criteria were applied only to empirical AI studies where relevant.

Quality appraisal was conducted independently by two reviewers using predefined decision rules. This approach was implemented to enhance methodological rigor and ensure consistency in the assessment process. Inter-reviewer agreement was assessed, and any discrepancies were resolved through discussion and consensus. Where necessary, classifications were refined through iterative review of the full text. Quality appraisal findings were not used as exclusion criteria but were employed to contextualize the strength of evidence and inform the interpretation of findings.

Ethical Considerations

This review is based entirely on previously published studies and does not involve human participants, identifiable data, or primary data collection. Formal ethics approval was therefore not required.

Results

A total of 33 studies published between 2010 and 2025 met the inclusion criteria (Figure 1). Of these, 14 studies (42.4%) were conducted specifically within SSA, while the remaining 19 studies (57.6%) were global in scope but provided insights applicable to SSA contexts. The studies spanned multiple AI paradigms, mental health conditions, and research designs, as detailed below across the four research questions (RQ1–RQ4). The full list of included studies, along with their key characteristics, is presented in Table 2. A complete summary of all included studies, including full bibliographic details and classification, is provided in Multimedia Appendix 5.

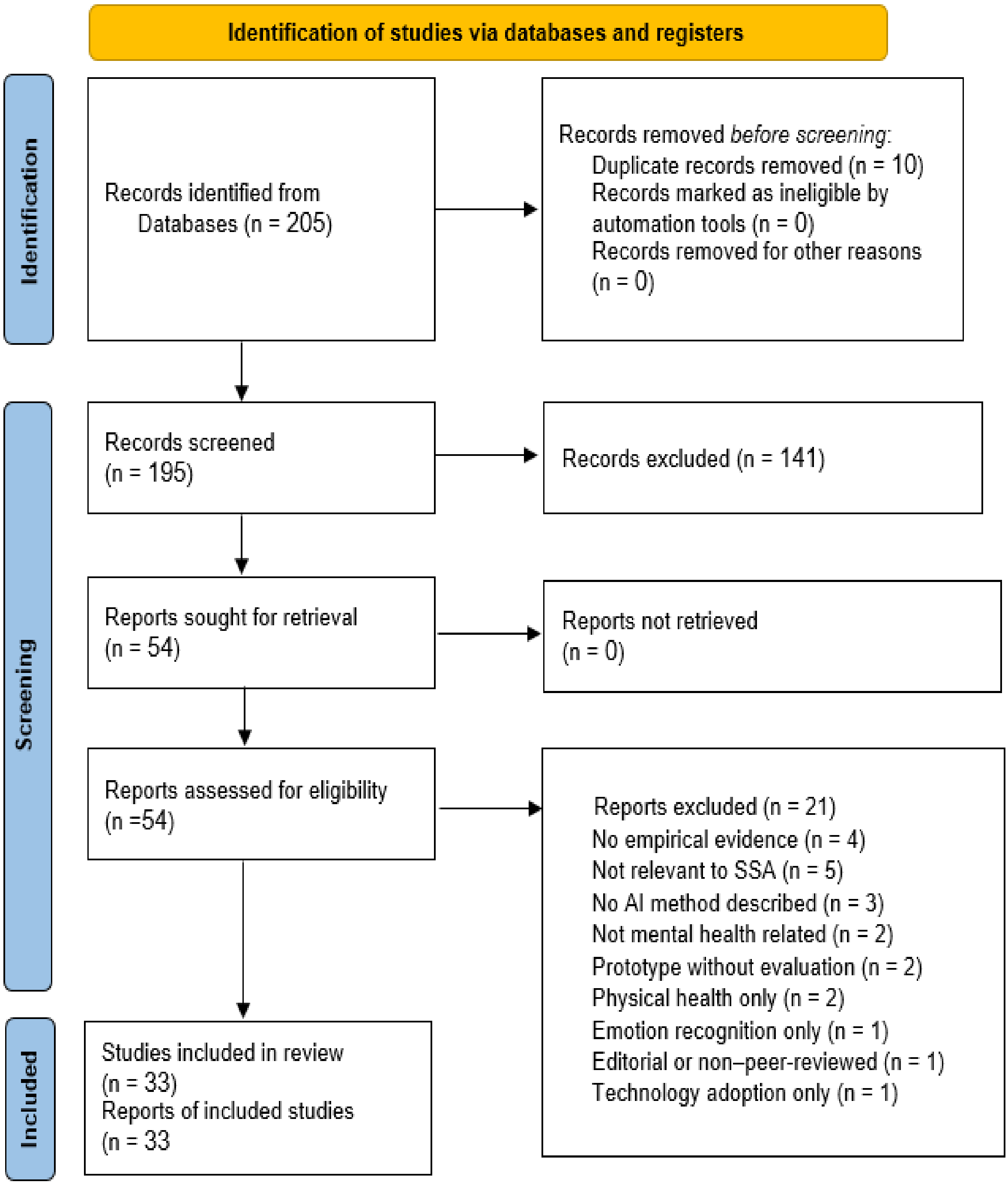

Figure 1. PRISMA 2020 flow diagram of the study selection process

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Table 2. Characteristics of Included Studies — Representative Examples (N = 33; see Multimedia Appendix 5 for full table)

#	Study Name	Year	Country	Region (SSA/Global)	AI Technique	Application Type	Mental Health Focus
1	A Bi-Lingual Counselling Chatbot for GBV Victims in Kenya[22]	2024	Kenya	SSA	Chatbot	Intervention	GBV / Trauma
2	An AI-based Decision Support System for Predicting Mental Health Disorders [27]	2023	USA	Global	Expert Systems / DSS	Prediction	General Mental Health
3	An Expert System for Diagnosis and Treatment of Mental Ailment [28]	2020	Nigeria	SSA	Expert Systems / DSS	Diagnosis	General Mental Health
4	Analyzing the Impact of Digital Transformation on Mental Health of IT Professionals Using Machine Learning [29]	2025	Not specified	Global	Machine Learning	Prediction	General Mental Health
5	Automated Classification of Depression Severity Using Speech [30]	2020	Germany	Global	Machine Learning	Prediction / Classification	Depression
6	Predicting Posttraumatic Stress Disorder Risk: A Machine Learning Approach [31]	2019	USA	Global	Machine Learning	Prediction	PTSD
7	Classifying Severity Level of Psychiatric Symptoms on Twitter Data [32]	2021	Ethiopia	SSA	NLP / Text Mining	Prediction / Classification	General Mental Health
8	Cross-trial Prediction of Treatment Outcome in Depression: A ML Approach[24]	2016	Global	Global	Machine Learning	Prediction	Depression
9	Early Detection of Depression from Social Media Data Using Machine Learning [33]	2020	India	Global	Machine Learning	Prediction / Classification	Depression

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10	Effectiveness of a Chatbot in Improv-ing Mental Wellbeing of Health Workers in Malawi (RCT)[23]	2024	Malawi	SSA	Chatbot	RCT	Mental well-being
11	Enhanced Labeling Technique for Reddit Text and Fine-tuned Longformer Models for Classifying Depression Severity in English and Luganda [34]	2023	Uganda	SSA	NLP / Text Mining	Prediction / Classification	Depression
12	Ensemble Machine Learning Classifier with Multi-feature Selection to Predict Disability in Mental Health Disor-ders [35]	2025	Ghana	SSA	Ensemble ML	Prediction / Classification	General Mental Health
13	Fusion of Momentary Moods in Major De-pression with Fuzzy Recurrence Analysis and Tensor Decompo-sition [36]	2021	South Africa	SSA	Machine Learning	Prediction / Classification	Depression
14	How Well Can PTSD Be Predicted from Pre-trauma Risk Factors? (WHO Mental Health Surveys)[26]	2014	Multiple	SSA/Global	Machine Learning	Prediction	PTSD
15	Identifying Predictors of Problematic Substance Use Among Youth Liv-ing with HIV in Uganda [37]	2025	Uganda	SSA	Machine Learning	Prediction / Classification	Substance Use
16	Identifying Schizophre-nia Using fMRI With a Deep Learning Algo-rithm[25]	2025	Not specified	Global	Deep Learning	Diagnosis	Schizophrenia
17	Improving Mental Dis-order Predictions Using Feature-based Ma-chine Learning Tech-niques [38]	2023	Multiple	Global	Machine Learning	Prediction / Classification	General Mental Health

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18	Lab Tests Can Be Used to Predict High-risk Alcohol Use Among People with HIV: A Machine Learning Proof-of-Concept [39]	2025	South Africa	SSA	Machine Learning	Prediction / Classification	Substance Use
19	Machine Learning Algorithm for Predicting Mood Disturbances [40]	2024	Nigeria	SSA	Machine Learning	Prediction / Classification	Depression
20	Machine Learning-based Detection of Stress Levels in Students with Social Media Addiction [41]	2025	Not specified	Global	Machine Learning	Prediction / Classification	Anxiety / Stress
21	Machine Learning-based Predictive Modelling of Mental Health in Rwandan Youth [42]	2025	Rwanda	SSA	Machine Learning	Prediction / Classification	General Mental Health
22	Mental Health Chatbot Using Deep Learning and Natural Language Processing [43]	2024	Nigeria	SSA	Chatbot	Intervention	General Mental Health
23	Model for the Presumptive Diagnosis of Mental Disorders in Adults Applying Machine Learning [44]	2023	South Africa	SSA	Machine Learning	Diagnosis	General Mental Health
24	Neural-semantic Prediction of Prenatal EPDS Subscale 3A Categories Using Socio-demographic Features [45]	2025	Uganda	SSA	Machine Learning	Prediction / Classification	Anxiety / Stress
25	Perinatal Depression and Anxiety in Ghana: A Qualitative Study on AI-driven Interventions [46]	2025	Ghana	SSA	Qualitative / Participatory	Qualitative / Participatory	Anxiety / Stress
26	Pervasive Mental Health Self-help Based on Cognitive-Behaviour Therapy and Machine Learning [47]	2011	South Africa	SSA	Machine Learning	Intervention	General Mental Health

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27	Predicting Depression from Smartphone Behavioral Markers Using Machine Learning [48]	2021	Ghana	SSA	Machine Learning	Prediction / Classification	Depression
28	Predicting Digital Addiction Patterns with Machine Learning [49]	2025	Nigeria	SSA	Machine Learning	Prediction / Classification	Substance Use
29	Predicting Individuals' Mental Health Status in Kenya Using Machine Learning [50]	2021	Kenya	SSA	Machine Learning	Prediction / Classification	General Mental Health
30	Smartening E-therapy Using Facial Expressions and Deep Learning [51]	2020	South Africa	SSA	Deep Learning	Intervention	General Mental Health
31	The Potential of Chatbots for Emotional Support and Promoting Mental Well-being in Different Cultures [52]	2023	Multiple	Global	Chatbot	Intervention	General Mental Health
32	Using Generative AI to Co-design Digital Mental Health Interventions with Adolescents in Rural South Africa [53]	2025	South Africa	SSA	Generative AI / LLM	Qualitative / Participatory	General Mental Health
33	Wellness Buddy: An AI Mental Health Chatbot for Kenyan University Students [54]	2023	Kenya	SSA	Chatbot	Intervention	General Mental Health
34	Natural Language Processing for Mental Health Interventions: A Systematic Review and Research Framework [55]	2023	Multiple	Global	NLP / Text Mining	Analysis / Review	General Mental Health

Quality Appraisal Findings

Findings from the hybrid quality appraisal (Multimedia Appendices 3 and 4) indicated a methodologically mixed evidence base. All 33 studies contributed to the review synthesis; however, AI-specific appraisal criteria were applicable only to 2٧ empirical AI studies, whereas ٦ qualitative or review studies were considered not applicable for this component (Multimedia Appendices 3 and 4).

Most studies reported clear research objectives and used analytical approaches broadly appropriate to their aims. Recurrent limitations included small or convenience samples, limited external validation of AI models, incomplete treatment of bias or confounding, and sparse discussion of implementation feasibility. While internal model validation was commonly reported, external validation

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and implementation-oriented evaluation were uncommon across the evidence base (Table 3).

Table 3. Summary of Recurrent Methodological Limitations.

Domain	Common limitation identified
Sample adequacy	Small or convenience samples
Model and external validation	Rarely reported
Bias/confounding	Often incompletely addressed
Implementation feasibility	Limited discussion
Dataset representativeness	Often insufficient

RQ1: AI Techniques Applied in Mental Health Care

RQ1 examines what AI techniques have been applied in mental health care globally and how they are specifically utilized within the SSA context.

Global Distribution of AI Techniques

Traditional Machine Learning (ML) methods dominated the overall corpus, appearing in 18 of 33 studies (54.5%). This encompassed algorithms such as Support Vector Machines (SVM), Random Forests, logistic regression, and k-Nearest Neighbours, predominantly applied to structured clinical and survey datasets for classification and prediction tasks. Chatbot and Conversational AI systems accounted for 5 studies (15.2%), reflecting growing interest in interactive mental health support tools. Natural Language Processing (NLP) and Text Mining appeared in 3 studies (9.1%), as did Deep Learning architectures (9.1%). Expert Systems and Decision Support Systems (DSS) featured in 2 studies (6.1%), while Ensemble ML, Generative AI/LLM, and Other AI approaches each appeared in a single study (3.0%), as shown in Figure 2 (bar charts) and summarized in Table 4.

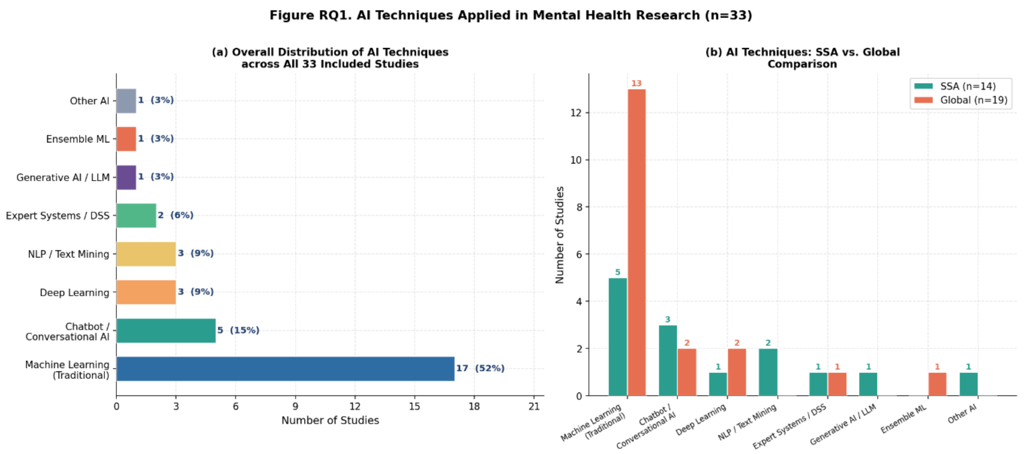

Figure 2. Distribution of AI techniques across all studies (n=33), comparing SSA-specific (n=14) and global studies (n=19).

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SSA-Specific AI Technique Utilization

Within the SSA-specific subset (n=14), the distribution of AI techniques was notably more diverse. Traditional ML remained the most common approach (5 studies, 35.7%), though its dominance was less pronounced than in the global literature (68.4%). Chatbot and Conversational AI systems were proportionally more prevalent in SSA (21.4% vs. 10.5% globally), suggesting a contextual preference for interactive, accessible tools in low-resource settings. NLP/Text Mining featured in 14.3% of SSA studies compared to 0% in the global subset. Notably, the sole Generative AI/LLM study in the entire corpus was SSA-based. No Ensemble ML studies were identified in the SSA subset.

Table 4. AI Techniques by Scope

(Machine Learning (Traditional	(54.5%) 18	(35.7%) 5	(68.4%) 13
Chatbot / Conversational AI	(15.2%) 5	(21.4%) 3	(10.5%) 2
NLP / Text Mining	(9.1%) 3	(21.4%) 3	(0.0%) 0
Deep Learning	(6.1%) 2	(0.0%) 0	(10.5%) 2
Expert Systems / DSS	(6.1%) 2	(7.1%) 1	(5.3%) 1
Ensemble ML	(3.0%) 1	(0.0%) 0	(5.3%) 1
Generative AI / LLM	(3.0%) 1	(7.1%) 1	(0.0%) 0
Other AI	(3.0%) 1	(7.1%) 1	(0.0%) 0

RQ2: Mental Health Conditions Attracting AI Research Attention

RQ2 investigates which mental health conditions have attracted the greatest attention among AI researchers, both globally and within the SSA context.

Global Condition Distribution

General Mental Health and Wellbeing represented the largest category across all 33 studies (14 studies, 42.4%), encompassing broad screening tools, wellness applications, and multi-disorder risk assessment platforms. Depression and Mood Disorders constituted the second most studied category (8 studies, 24.2%). Anxiety, PTSD, and Stress-related conditions featured in 5 studies (15.2%), while Substance Use Disorders appeared in 3 studies (9.1%). Psychotic Disorders were addressed in only 1 study (3.0%). Notably, Bipolar Disorder, Child and Adolescent Mental Health, Dementia and Neurocognitive Disorders, and Eating Disorders were entirely absent from the corpus, as illustrated in Figure 3 (donut and comparative bar charts) and detailed in Table 5.

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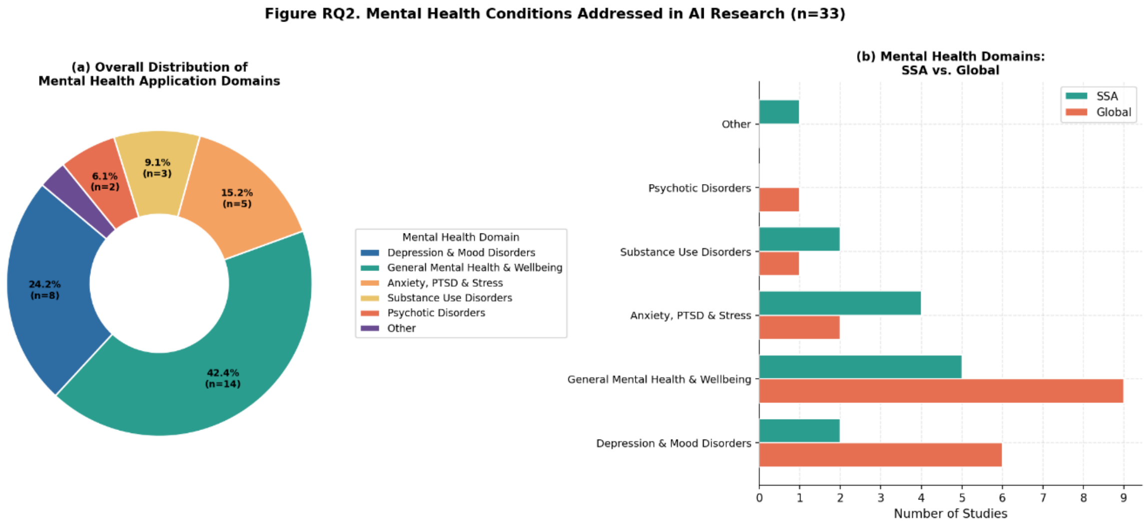

Figure 3. Distribution of mental health conditions across all studies (n=33), with SSA vs. global comparison.

SSA-Specific Condition Priorities

The SSA-specific subset (n=14) revealed a distinct epidemiological focus. Anxiety, PTSD, and Stress-related conditions were proportionally more prominent in SSA (4 studies, 28.6%) compared to the global subset (10.5%), reflecting the region's elevated burden of trauma-related disorders stemming from conflict, gender-based violence (GBV), and HIV/AIDS-related distress. Depression and Mood Disorders were comparatively underrepresented in SSA (2 studies, 14.3%) relative to global literature (31.6%). Two studies addressed perinatal mental health. Psychotic Disorders attracted no dedicated AI research in the SSA corpus.

Table 5. Mental Health Conditions by Scope

General Mental Health & Wellbeing	(42.4%) 14	(35.7%) 5	(47.4%) 9
Depression & Mood Disorders	(24.2%) 8	(14.3%) 2	(31.6%) 6
Anxiety, PTSD & Stress	(18.2%) 6	(28.6%) 4	(10.5%) 2
Substance Use Disorders	(9.1%) 3	(14.3%) 2	(5.3%) 1
Psychotic Disorders	(3.0%) 1	(0.0%) 0	(5.3%) 1
Other	(3.0%) 1	(7.1%) 1	(0.0%) 0
Bipolar Disorder	(0.0%) 0	(0.0%) 0	(0.0%) 0
Child / Adolescent Mental Health	(0.0%) 0	(0.0%) 0	(0.0%) 0
Dementia / Neurocognitive	(0.0%) 0	(0.0%) 0	(0.0%) 0

RQ3: Study Design Patterns and Research Objectives

RQ3 examines the patterns in study design and research objectives across the reviewed literature (Table 6).

Predominance of Prediction and Classification Studies

Prediction and Classification studies constituted the largest methodological category, accounting for 20 of 33 studies (60.6%). This pattern was consistent across both SSA (57.1%) and

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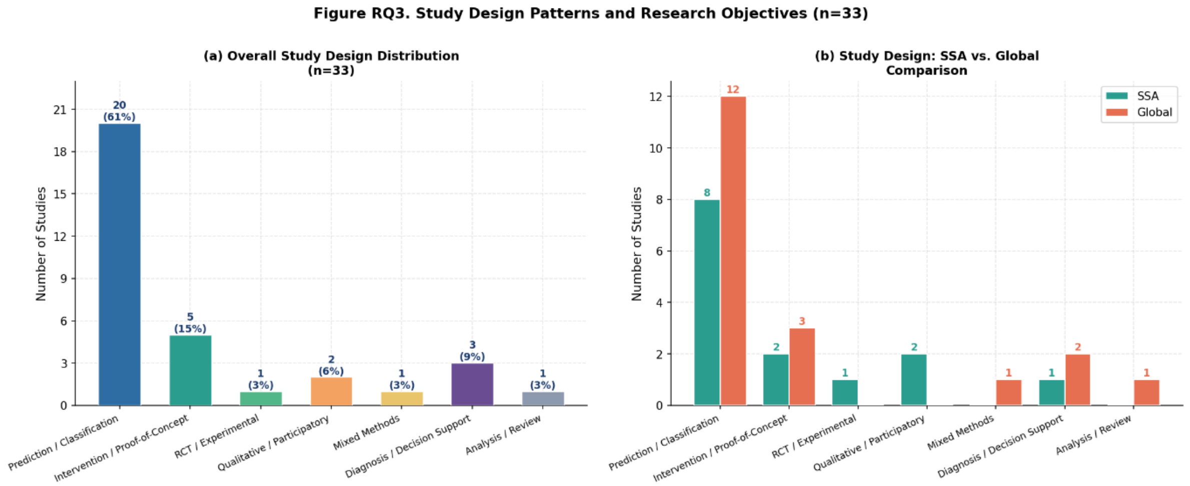

Figure 4. Study design distribution across all studies (n=33), comparing SSA-specific (n=14) and global studies (n=19).

The Prediction-to-Implementation Gap

A striking methodological imbalance emerged: 60.6% of studies focused on prediction or classification tasks, while only 15.2% described intervention-oriented research. This 'prediction-to-implementation gap' indicates that the field has invested heavily in demonstrating algorithmic feasibility but has yet to translate these capabilities into clinically deployed, patient-facing tools — particularly within SSA. Within SSA, the proportion of Qualitative/Participatory studies (14.3%) exceeded the global rate (0%), suggesting contextually sensitive research orientation.

Table 6. Study Design Patterns by Scope

Prediction / Classification	(60.6%) 20	(57.1%) 8	(63.2%) 12
Intervention / Proof-of-Concept	(15.2%) 5	(14.3%) 2	(15.8%) 3
Diagnosis / Decision Support	(9.1%) 3	(7.1%) 1	(10.5%) 2
Qualitative / Participatory	(6.1%) 2	(14.3%) 2	(0.0%) 0
RCT / Experimental	(3.0%) 1	(7.1%) 1	(0.0%) 0
Analysis / Review	(3.0%) 1	(0.0%) 0	(5.3%) 1
Mixed Methods	(3.0%) 1	(0.0%) 0	(5.3%) 1

RQ4: Research Gaps in Resource-Limited Settings

RQ4 identifies where the research gaps lie, particularly in resource-limited and infrastructure-constrained settings such as SSA.

Geographic Coverage Gaps

Of the 49 countries comprising Sub-Saharan Africa, only 8 (16.3%) were represented in the reviewed literature. East African nations dominated, accounting for 7 of 14 SSA studies (50.0%). Uganda was the most represented country (4 studies), followed by Kenya and South Africa (3 studies each). Although countries such as Nigeria, Ethiopia, Tanzania, and the DRC bear substantial mental health burdens, research representation remains poorly aligned with this burden.

Linguistic and Cultural Gaps

Of the 33 included studies, 31 (93.9%) were conducted entirely in English. Only a single study incorporated an indigenous African language (Luganda). No studies developed or validated AI tools in Swahili, Amharic, Hausa, Yoruba, Zulu, or any other major African language, repre-
sentin

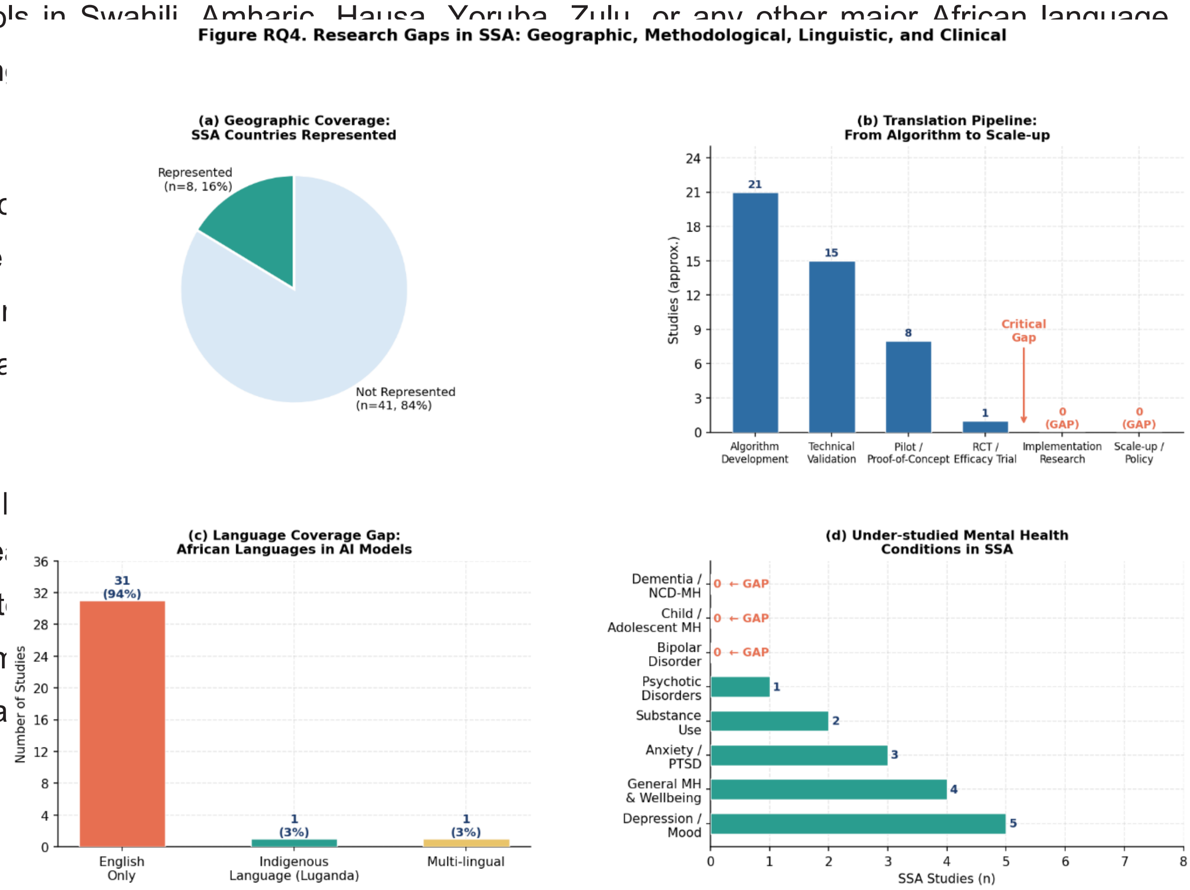

Figure 5. Research gaps in SSA: geographic coverage, linguistic diversity, methodological pipeline, and under-studied mental health conditions.

Integrative Summary

Taken together, the findings from RQ1 through RQ4 paint a coherent picture of a field in early development, characterized by technical promise but significant translational and equity gaps. The dominance of traditional ML techniques (RQ1) and prediction-oriented study designs (RQ3) suggests that the field has prioritized algorithmic feasibility over clinical deployment.

The concentration of research on depression and general mental health (RQ2) — at the expense of conditions such as psychosis, bipolar disorder, and child mental health — reflects global research priorities that may not fully align with SSA's epidemiological burden. The geographic, linguistic, and methodological gaps identified in RQ4 collectively indicate that the current evidence base is insufficient to guide equitable, context-sensitive AI deployment across the diverse and complex health systems of Sub-Saharan Africa.

Discussion

Principal Findings

This systematic review identified 33 studies examining AI applications in mental health care within and relevant to Sub-Saharan Africa, published between 2010 and 2025. The findings reveal a nascent but rapidly expanding field characterized by significant geographic concentration, methodological patterns favoring prediction over intervention, and a predominance of machine learning approaches targeting high-prevalence mental disorders. While 42.4% of studies (n=14) were conducted specifically in SSA contexts, the remaining 57.6% (n=19) represent global research with potential transferability to resource-constrained settings. The sharp acceleration in publications from 2020 onwards — particularly the concentration of 12 studies in 2025 alone — signals growing recognition of AI's potential to address the substantial mental health treatment gap in SSA.

SSA-specific research demonstrates contextual adaptation, with studies addressing locally relevant challenges including gender-based violence, HIV-related mental health, perinatal mental health in low-resource settings, and linguistic diversity through indigenous language processing. However, substantial geographic, methodological, and technological disparities persist, limiting the field's capacity to address the region's diverse mental health needs at scale. The quality appraisal findings (Multimedia Appendices 3 and 4) further suggest that these translational gaps are compounded by recurring methodological limitations, particularly weak external validation and limited implementation-oriented evaluation.

Comparison with Prior Work

Geographic Disparities and Research Capacity Gaps

The geographic distribution of SSA-specific studies reveals stark disparities in research capacity and activity. East Africa, particularly Uganda (n=4) and Kenya (n=3), accounted for 50% of SSA-specific research, while vast regions including Central Africa, most of West Africa, and significant portions of Southern Africa remain entirely unrepresented. This concentration likely reflects multiple intersecting factors: established research infrastructure and academic institutions,

availability of research funding and international collaborations, relatively advanced digital health ecosystems, and policy environments supportive of digital innovation.

The absence of research from countries with substantial mental health burdens — including the Democratic Republic of Congo, Ethiopia, Tanzania, Zimbabwe, and most West African nations — represents a critical gap. This geographic concentration risks producing AI solutions optimized for specific contexts that may not generalize to the diverse linguistic, cultural, epidemiological, and infrastructural landscapes across SSA. The limited representation from francophone and lusophone Africa is particularly concerning, as language barriers may impede both research collaboration and technology transfer.

Methodological Patterns and the Prediction-to-Implementation Gap

The overwhelming dominance of prediction and classification studies (60.6%) across the corpus reflects a broader pattern in AI health research — a focus on demonstrating algorithmic performance rather than advancing toward clinical implementation. While predictive models for mental health risk stratification are valuable, their clinical utility remains limited without rigorous evaluation of deployment feasibility, real-world effectiveness, and health system integration.

The near-absence of implementation science research and the presence of only a single RCT in the entire corpus are particularly concerning given the complexity of mental health care delivery in SSA. Implementation science frameworks — such as the Consolidated Framework for Implementation Research (CFIR) or the RE-AIM framework — are essential for understanding how AI tools can be integrated into existing health systems, adapted to local contexts, and sustained over time. The field's current trajectory suggests a significant risk of producing technically sophisticated tools that never reach the patients who need them most.

Technological Trends and Innovation Patterns

The dominance of traditional ML approaches reflects both the maturity of these techniques and the nature of available data in SSA health systems. Structured clinical data, survey responses, and physiological measurements are the primary inputs for most reviewed studies, aligning with the strengths of traditional ML algorithms. However, the limited adoption of deep learning, NLP, and advanced AI architectures in SSA contexts may reflect data scarcity, computational resource constraints, and limited local AI expertise.

The proportionally higher adoption of chatbot and conversational AI systems in SSA (21.4% vs. 10.5% globally) is a noteworthy finding. Chatbots offer particular promise in SSA contexts given their compatibility with mobile phone-based delivery, potential for asynchronous interaction, and ability to provide psychoeducation and basic support without requiring continuous professional involvement. The emergence of a Generative AI/LLM study in the SSA corpus — despite being the only such study globally — suggests early awareness of the transformative potential of large language models for mental health applications in the region.

Application Domains: Priorities and Gaps

The focus on general mental health and depression in the global literature reflects the epidemiological prominence of these conditions and the relative availability of validated assessment instruments and datasets. SSA-specific research shows a contextually appropriate shift toward trauma, PTSD, and stress-related conditions, reflecting the region's elevated burden of adversity-related mental health problems.

However, the complete absence of research on bipolar disorder, child and adolescent mental health, dementia, and eating disorders represents a critical misalignment between AI research priorities and SSA's full mental health burden. Child and adolescent mental health is of particular concern given SSA's young population demographic — with over 60% of the population under 25 in many countries — and the high rates of adversity exposure, including conflict, poverty, and orphanhood due to HIV/AIDS.

Ethical Considerations and Potential Harms

The reviewed literature demonstrates insufficient attention to the ethical dimensions of AI mental health applications in SSA. Algorithmic bias — the potential for AI systems trained predominantly on non-African data to perform poorly or inequitably for African populations — was rarely discussed. This is a critical concern given the genetic, cultural, linguistic, and socioeconomic diversity of SSA populations and the historical underrepresentation of African data in global AI training datasets.

Data privacy and security considerations, particularly relevant given the sensitivity of mental health information and the variable strength of data protection frameworks across SSA, were similarly underaddressed. The potential for AI tools to inadvertently pathologize culturally normative expressions of distress, reinforce stigma, or displace community-based and traditional healing practices requires careful consideration in future research and deployment.

Infrastructure and Implementation Challenges

The practical challenges of deploying AI mental health tools in SSA extend beyond the technical. Smartphone and internet penetration, while growing rapidly, remains uneven across the region, with significant rural-urban and gender-based disparities. Electricity reliability, a prerequisite for both device charging and server infrastructure, varies considerably. The limited availability of Electronic Health Records (EHR) constrains the availability of structured training data and the

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integration of AI tools into clinical workflows.

Community Health Worker (CHW) programmes represent a critical but underexplored deployment pathway for AI mental health tools in SSA. CHWs serve as the primary mental health touchpoint for millions of SSA residents, yet no reviewed study examined AI deployment through CHW programmes. Engaging CHWs as both data contributors and tool users could significantly expand the reach and cultural appropriateness of AI mental health interventions.

Future Research Directions

Based on the identified gaps, the following research priorities are recommended:

- Geographic expansion: Prioritise research in West Africa, Central Africa, and the Horn of Africa, with particular attention to high-burden countries currently unrepresented in the literature.
- Indigenous language integration: Develop and validate AI tools in major African languages including Swahili, Amharic, Hausa, Yoruba, and Zulu, with attention to culturally specific idioms of distress.
- Implementation science: Apply established implementation frameworks to examine how AI tools can be integrated into SSA health systems, with attention to facilitators, barriers, and sustainability.
- Randomized controlled trials: Conduct rigorous RCTs to evaluate the effectiveness of AI mental health interventions in SSA contexts, with adequate power, representative samples, and clinically meaningful outcomes.
- Under-studied conditions: Develop AI applications for bipolar disorder, child and adolescent mental health, dementia, and perinatal mental health in SSA.
- Community Health Worker integration: Explore AI deployment through CHW programmes as a scalable pathway for mental health support in resource-limited settings.
- Ethical frameworks: Develop context-specific ethical guidelines for AI mental health applications in SSA, addressing algorithmic bias, data privacy, informed consent, and cultural safety.
- Longitudinal research: Conduct longitudinal studies to examine the sustained impact of AI mental health tools on patient outcomes, health system capacity, and treatment gaps.

Limitations

This review has several limitations. First, although the search strategy was comprehensive, relevant studies may have been missed, particularly grey literature and publications in languages other than English. Second, the heterogeneity of included studies precluded meta-analysis and limited the ability to draw definitive conclusions regarding comparative effectiveness. Third, while a structured quality appraisal using the Mixed Methods Appraisal Tool (MMAT) and a supplementary AI-specific appraisal framework was undertaken, variation in study designs, reporting standards, and outcome measures limited direct comparison of methodological quality across studies. Many included studies also lacked rigorous clinical validation, external model validation, or implementation evaluation. Fourth, the rapid pace of artificial intelligence development means the evidence base may evolve faster than the publication cycle, potentially rendering some findings outdated. Fifth, categorisation of studies as SSA-specific versus globally relevant involved some interpretive judgment, particularly for multi-country studies and studies included as contextual evidence. Finally, this review focused specifically on AI applications in mental health care and may have overlooked relevant work addressing social determinants, prevention, or policy-oriented uses of AI that may indirectly influence mental health outcomes.

Conclusions

This systematic review reveals a nascent but rapidly expanding field of AI applications for mental health in Sub-Saharan Africa, characterized by promising innovations alongside substantial gaps and challenges. The sharp acceleration in research output, particularly in 2025, signals growing recognition of AI's potential to address the region's severe mental health treatment gap. SSA-specific research demonstrates important contextual adaptation, addressing locally relevant challenges including HIV-related mental health, gender-based violence, perinatal mental health, and linguistic diversity.

However, critical gaps persist. Research is geographically concentrated in a few East African countries, leaving vast regions unrepresented. Methodologically, the field remains dominated by prediction studies, with limited advancement to intervention testing and implementation research. Technologically, advanced AI techniques and indigenous language processing remain underdeveloped. Ethically, insufficient attention to algorithmic bias, clinical safety, privacy, and equity risks perpetuating mental health inequities.

Realizing the potential of AI to improve mental health care in SSA requires addressing these gaps through intentional capacity building, geographic expansion of research, advancement from prediction to implementation, development of context-appropriate technologies, establishment of ethical and regulatory frameworks, and sustained investment in interdisciplinary research. Without such efforts, AI risks becoming another technology that benefits the already advantaged while neglecting those with greatest need, ultimately widening rather than narrowing mental health inequities in the region.

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Conflicts of Interest

None declared.

Data Availability

The data supporting the findings of this study are available within the article and its supplementary materials. The full list of included studies and extraction data are available from the corresponding author upon reasonable request.

Author Contributions

Conceptualization: A.M.

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Screening and Data Extraction: A.M., A.G.M.M.

Data Analysis: A.M.

Writing – Original Draft: A.M.

Writing – Review & Editing: A.M., A.G.M.M.

Supervision: A.G.M.M.

All authors reviewed and approved the final manuscript.

Abbreviations (in order of first appearance)

AI: Artificial Intelligence

SSA: Sub-Saharan Africa

PRISMA: Preferred Reporting Items for Systematic Reviews and Meta-Analyses

ML: Machine Learning

PTSD: Post-Traumatic Stress Disorder

WHO: World Health Organization

LMICs: Low- and Middle-Income Countries

DALYs: Disability-Adjusted Life Years

DL: Deep Learning

CNN: Convolutional Neural Network

LSTM: Long Short-Term Memory

NLP: Natural Language Processing

CBT: Cognitive Behavioral Therapy

CHWs: Community Health Workers

SLR: Systematic Literature Review

MMAT: Mixed Methods Appraisal Tool

RCT: Randomized Controlled Trial

SVM: Support Vector Machine

DSS: Decision Support System

LLM: Large Language Model

GBV: Gender-Based Violence

EHR: Electronic Health Records

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