المجلة العلمية المُحكمة للأكاديمية العربية الدولية
The Scientific Journal of the International Arab Academy
رقم شهادة عضوية اتحاد الجامعات الدولي (IUU): 1102202600217 ـ رقم شهادة معامل التأثير العربي: (287)
ISSN (ONLINE): 1858 - 8441 - ISSN (PRINT): 1858 - 845X

(17)

Barriers and Enablers of AI Adoption for Mental Health Care in Sudan: A Framework-Based Analysis

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Abstract

Background: Sudan faces a severe mental health crisis driven by prolonged conflict, humanitarian emergencies, and a critically under-resourced mental health system. Artificial intelligence (AI) offers promising opportunities to expand access to mental health services in low-resource settings; however, its responsible deployment is constrained by interconnected challenges including data scarcity, privacy risks, and barriers to clinical adoption.

Objective: This study aims to develop a context-specific framework for the responsible integration of AI into mental health care in Sudan, addressing key challenges related to data availability, ethical governance, and implementation feasibility.

Methods: This study employed a structured Framework Synthesis approach informed by systematic literature searching and thematic analysis, integrating evidence from AI mental health implementations in low-resource African settings, established ethical frameworks for computational psychiatry, and Sudan-specific mental health research. Insights from these sources were synthesized to construct a structured, context-aware framework for AI deployment.

Results: We propose a three-component framework comprising: (1) data strategies to address scarcity and representational gaps through synthetic data generation, federated learning, and community-based data collection; (2) privacy-preserving mechanisms including differential privacy, anonymization, and privacy-by-design principles; and (3) a phased clinical integration model emphasizing human-in-the-loop designs and clinician copilot paradigms. The framework aligns with core ethical principles including beneficence, autonomy, justice, privacy, and transparency, while addressing Sudan-specific constraints such as linguistic diversity, stigma, infrastructure limitations, and conflict-related trauma.

Conclusions: Responsible AI deployment in Sudan requires coordinated strategies that balance innovation with ethical safeguards and contextual realities. The proposed framework provides actionable guidance for researchers, policymakers, and healthcare practitioners seeking to implement AI-enabled mental health solutions in Sudan and similar low-resource, conflict-affected settings. Future work should focus on prospective validation, long-term impact evaluation, and the development of locally grounded datasets to support sustainable and equitable AI integration.

Keywords: **Artificial Intelligence, Mental Health, Sudan, Low-Resource Settings, Digital Health, Clinical Adoption, Privacy-Preserving AI.**

1. Introduction

Mental healthcare in Sudan faces a profound and multidimensional crisis shaped by prolonged armed conflict, political instability, forced displacement, economic collapse, and severely limited mental health infrastructure. Existing evidence indicates that mental health services remain heavily concentrated in major urban centres, leaving large rural and conflict-affected populations without access to even basic mental healthcare [1, 2, 3, 4, 5, 6, 40]. Stigma surrounding mental illness further discourages help-seeking behaviours, while shortages of psychiatrists, psychologists, and trained mental health workers severely constrain service delivery capacity. [2, 3, 4]

These structural deficits are compounded by broader infrastructural limitations, including unreliable electricity, inconsistent internet connectivity, fragmented health information systems, and the near absence of electronic mental health records. Such conditions create substantial barriers to scaling conventional face-to-face psychiatric services and complicate the implementation of digital health innovations. At the same time, Sudan continues to experience high levels of conflict-related trauma, displacement, anxiety, depression, and post-traumatic stress disorder (PTSD), generating growing demand for accessible and scalable mental health support mechanisms [1, 4]. Community-based trauma initiatives and NGO-led psychosocial support programmes have attempted to address some of these gaps, demonstrating the importance of culturally adapted and community-oriented interventions in conflict-affected settings [5, 6]. [4]

Against this backdrop, artificial intelligence (AI) has emerged globally as a promising tool for expanding mental healthcare access, improving screening and monitoring, supporting clinical decision-making, and delivering scalable psychological support through digital platforms. AI technologies—including machine learning, natural language processing, conversational agents, computer vision, and expert systems—have demonstrated growing utility across multiple mental health domains worldwide. Recent implementations in African contexts further suggest that AI-enabled mental health interventions may be feasible even within resource-constrained settings. For example, emotion-aware conversational agents deployed in Ghana demonstrated strong user acceptability and encouraged professional help-seeking among users [7], while large-scale low-bandwidth interactive voice response platforms successfully reached over 700,000 users across Sub-Saharan Africa [8]. In Sudan specifically, university students reported positive perceptions of conversational chatbots for mental health support, particularly valuing their anonymity, accessibility, and convenience. However, the study also highlighted a preference for maintaining human clinical oversight, with AI systems viewed as supportive tools rather than replacements for human clinicians [9, 10].

Despite these promising developments, the adoption of AI for mental healthcare in Sudan remains extremely limited. This gap between technological potential and real-world implementation reflects a broader set of interconnected barriers extending beyond technical feasibility alone. First, Sudan faces severe data scarcity and representational limitations. Most existing AI mental health models are trained on datasets derived from high-income countries and may not adequately capture Sudanese Arabic dialects, culturally specific expressions of psychological distress, or the lived realities of conflict-affected populations. Second, privacy and ethical concerns are particularly significant in mental health contexts, where sensitive personal information may expose individuals to stigma, discrimination, or social harm in settings with limited data protection frameworks [11, 12]. Third, substantial clinical adoption barriers persist, including limited AI literacy among healthcare professionals, concerns regarding automation bias, weak digital infrastructure, workflow integration challenges, and uncertainty regarding governance and accountability [6, 13, 14, 15]

These challenges highlight a critical mismatch between the AI technologies dominating global mental health research and the contextual realities of low-resource, conflict-affected settings such as Sudan. Technologies requiring large datasets, advanced computational infrastructure, and stable digital ecosystems may have limited deployability in Sudan, whereas lower-bandwidth and human-centred approaches—such as conversational AI, clinician copilot systems, and community-integrated digital tools—may offer greater practical relevance. However, systematic frameworks guiding the responsible and contextually appropriate adoption of such technologies within Sudan's mental health system remain largely absent [6, 16].

This paper therefore examines the barriers and enablers influencing AI adoption for mental healthcare in Sudan through a framework-based analysis. Specifically, the study explores how challenges related to data scarcity, privacy protection, and clinical integration shape the feasibility of AI deployment within Sudan's mental health ecosystem. Drawing on evidence from AI mental health implementations in low-resource African settings, ethical frameworks for computational psychiatry, and Sudan-specific mental health research, the paper develops a context-aware framework for responsible AI adoption. The proposed framework integrates data strategies, privacy-preserving mechanisms, and phased clinical integration pathways tailored to Sudan's infrastructural, sociocultural, and healthcare realities [17, 18].

The remainder of this paper is organised as follows. Section 2 reviews Sudan's mental health landscape and current AI applications in mental healthcare. Section 3 examines the major barriers and contextual enablers affecting AI adoption in Sudan. Section 4 presents the proposed framework for responsible AI integration, including data strategies, privacy-preserving approaches, and clinical implementation pathways. Section 5 discusses implications for policy, practice, and future research, while Section 6 concludes with recommendations for responsible and sustainable AI deployment in Sudan's mental health system [17].

First, there is a notable lack of Sudan-specific frameworks capable of guiding AI adoption within the country's unique sociotechnical and healthcare context. While previous studies have explored digital mental health interventions in African and low-resource settings, few studies provide structured implementation frameworks tailored to Sudan's infrastructural limitations, cultural dynamics, linguistic diversity, and conflict-related mental health burden [7, 9, 10, 20]. As a result, existing AI deployment models often overlook contextual realities that strongly influence feasibility and sustainability. [20]

Second, the literature provides limited discussion of responsible AI deployment models for mental healthcare in fragile and resource-constrained environments. Although ethical concerns such as privacy, bias, transparency, and accountability are increasingly acknowledged in global AI research, these issues remain underexplored in relation to conflict-affected settings where weak governance structures, sensitive mental health data, and limited cybersecurity capacity may amplify implementation risks [6, 12, 21]. Existing studies frequently emphasize technical performance while providing insufficient attention to ethical governance, data protection, and clinically safe integration pathways.

Third, there remains an absence of integrated adoption analyses that simultaneously examine infrastructural, ethical, clinical, and cultural dimensions of AI implementation. Most prior studies focus on isolated technological applications or individual barriers without offering comprehensive frameworks capable of explaining how multiple contextual factors interact to shape AI adoption outcomes [8, 11]. Consequently, there is limited guidance for policymakers, healthcare institutions, and researchers seeking to implement AI-enabled mental health solutions in ways that are contextually appropriate, ethically grounded, and operationally feasible in Sudan.

The following section reviews the global evidence base for AI applications in mental health, with particular attention to low-resource and conflict-affected settings comparable to Sudan, establishing the opportunity landscape before examining adoption barriers.

AI Opportunities and Contextual Enablers in Sudan

Artificial intelligence (AI) technologies have increasingly emerged as promising tools for improving access to mental healthcare in low-resource settings characterized by workforce shortages, limited infrastructure, and substantial unmet mental health needs. In many low- and middle-income countries (LMICs), conventional psychiatric services remain inaccessible for large segments of the population due to shortages of specialists, weak healthcare systems, stigma, and geographic barriers [1, 22]. Within such contexts, AI-enabled mental health technologies offer opportunities for scalable, low-cost, and accessible interventions capable of supporting screening, psychoeducation, emotional support, symptom monitoring, and clinical decision-making [11].

Conversational chatbots are among the most widely discussed AI applications for digital mental health in resource-constrained environments. These systems can provide anonymous and continuously accessible mental health support while reducing barriers associated with stigma and limited service availability. Emotion-aware AI chatbots integrating conversational AI with emotion recognition models have demonstrated encouraging results in African contexts. In Ghana, users reported high levels of usability, cultural relevance, and perceived emotional support, with many indicating that the chatbot encouraged them to seek professional mental healthcare [7]. Similarly, research among Sudanese university students found that conversational chatbots were positively perceived because of their accessibility, convenience, and privacy. However, the study also highlighted a preference for maintaining human clinical oversight, with AI systems viewed as supportive tools rather than full replacements for therapists [9, 10]. The ability of chatbot systems to operate through smartphones and messaging platforms makes them particularly attractive in contexts where mental health professionals are scarce and stigma discourages traditional help-seeking behaviour.

Interactive Voice Response (IVR) systems also demonstrate significant promise for low-resource mental healthcare delivery [23, 24], especially in environments with inconsistent internet connectivity and limited smartphone penetration. Unlike many digital health interventions that require stable broadband access, IVR systems can function through standard mobile phones and low-bandwidth telecommunications infrastructure. Large-scale implementations such as the Digital MindSKILLZ platform successfully reached more than 700,000 users across six Sub-Saharan African countries, demonstrating both scalability and user acceptability for voice-based mental health interventions [8]. Such approaches are particularly relevant for rural and underserved populations where digital exclusion remains a major challenge. The broader growth of telemental health and mobile health (mHealth) platforms across Africa further illustrates the potential of low-bandwidth technologies to extend mental healthcare access beyond urban centres [6].

AI-powered screening and decision-support systems represent another important area of opportunity. Machine learning and AI-assisted assessment tools can support early identification of depression, anxiety, autism spectrum disorders, suicide risk, and other mental health conditions, particularly in settings where specialist diagnostic capacity is limited [8]. In Egypt, feasibility studies of AI-assisted autism screening tools demonstrated that AI technologies could support earlier detection and referral processes while also highlighting the importance of ethical safeguards, stakeholder trust, and alignment with healthcare system capacity [8]. Expert systems and AI-supported clinical decision tools may also strengthen task-shifting models by assisting non-specialist healthcare workers in screening and triage processes, thereby extending the reach of scarce psychiatric expertise [14, 25].

Beyond individual technologies, AI also offers broader opportunities for strengthening mental health systems through automation, personalization, and continuous monitoring. Natural language processing (NLP) systems can analyse text and speech patterns associated with emotional distress, while predictive analytics may assist clinicians in identifying high-risk patients and improving intervention planning [19, 26]. Federated learning and privacy-preserving AI approaches additionally create opportunities for developing context-sensitive mental health systems while minimizing risks associated with centralized data storage and sensitive patient information [17, 21].

Despite these promising developments, successful implementation of AI in low-resource mental healthcare depends not only on technical performance but also on contextual appropriateness, cultural adaptation, ethical governance, and sustainable clinical integration. Existing evidence suggests that AI technologies are most effective when positioned as supportive and augmentative tools that complement human clinicians rather than replace them entirely [9, 14]. Consequently, the promise of AI for mental healthcare in Sudan and similar low-resource settings lies not merely in technological innovation itself, but in the development of responsible, context-aware, and infrastructure-sensitive implementation strategies.

Having established the global potential of AI for mental health in low-resource settings, the following section examines why these opportunities have not yet translated into widespread adoption in Sudan, identifying the structural and contextual barriers that must be addressed.

The barriers to adoption extend far beyond technical availability alone. Sudan faces severe infrastructural limitations, including unreliable electricity, weak internet connectivity, fragmented digital health systems, and limited access to electronic health records. Many advanced AI models additionally depend on large, high-quality datasets and computational resources that are difficult to obtain in resource-constrained environments [8, 11]. Consequently, technologies developed and validated in high-income countries may not be directly transferable to Sudan's sociotechnical realities.

Data scarcity represents another major obstacle. Existing AI mental health models are predominantly trained on datasets derived from Western populations and often fail to capture Sudanese Arabic dialects, culturally specific expressions of psychological distress, and conflict-related mental health experiences [6, 26]. The absence of locally representative mental health datasets raises concerns regarding model bias, reduced accuracy, and inequitable performance across vulnerable populations.

Privacy and ethical concerns further complicate AI implementation in mental healthcare. Mental health information is highly sensitive, and the absence of strong data governance frameworks increases risks related to stigma, discrimination, and unauthorized data exposure [6, 12, 21]. In conflict-affected settings such as Sudan, these risks may be amplified by political instability, weak regulatory oversight, and limited cybersecurity infrastructure.

Clinical adoption barriers also remain substantial. Many healthcare professionals have limited exposure to AI technologies and may express concerns regarding reliability, accountability, workflow disruption, and automation bias [13, 14]. At the same time, patients may hesitate to engage with AI-driven systems due to cultural perceptions, trust concerns, or fear of reduced human interaction in mental healthcare delivery. Existing evidence from Sudan suggests that users generally perceive conversational AI positively when positioned as supportive tools rather than replacements for human clinicians [9].

Taken together, these challenges highlight that the central issue is not whether AI technologies for mental healthcare exist, but rather why their adoption remains difficult within Sudan's specific infrastructural, cultural, ethical, and clinical context. Understanding these barriers—and identifying the contextual enablers capable of supporting responsible implementation—is therefore essential for developing realistic and sustainable AI mental health strategies in Sudan.

1.1 Study Aim and Contribution

The paper contributes to the literature in three important ways. First, it provides one of the few Sudan-focused analyses examining AI adoption challenges in mental healthcare, addressing a major geographic and contextual gap in existing digital mental health research. Second, the study integrates technical, ethical, clinical, and sociocultural dimensions into a unified framework-based analysis rather than examining these challenges in isolation. Third, the paper proposes a context-aware framework for responsible AI adoption that incorporates privacy-preserving strategies, human-in-the-loop clinical integration, and low-resource implementation pathways tailored to Sudan's healthcare realities.

By combining insights from AI mental health literature, responsible AI frameworks, and Sudan-specific contextual evidence, this study seeks to support researchers, clinicians, policymakers, and digital health developers in designing more feasible, ethical, and sustainable AI-enabled mental healthcare systems for Sudan and similar low-resource settings.

2. Methods

Study Design

This study employed a structured Framework Synthesis approach informed by systematic literature searching and thematic analysis — a recognised methodology in public health research for developing analytical frameworks in contexts where direct empirical evidence is scarce. Framework Synthesis differs from a systematic review in that it does not seek to aggregate measurable outcomes, but rather to construct a conceptual framework grounded in available evidence. It also differs from a narrative review in that it follows a structured, transparent, and auditable analytical protocol.

Search Strategy

A systematic literature search was conducted between January and March 2026 across four databases: PubMed, IEEE Xplore, Google Scholar, and Semantic Scholar, covering the period from 2015 to 2025. Search terms were drawn from three thematic groups combined using Boolean AND operators:

Group 1 (Artificial Intelligence): artificial intelligence, machine learning, NLP, chatbot, conversational agent

Group 2 (Mental Health): mental health, psychiatry, depression, PTSD, psychological distress

Group 3 (Context): Sudan, low-resource settings, conflict-affected, Sub-Saharan Africa, LMIC

Inclusion Criteria

A study was included if it met at least one of the following criteria:

• Applies AI to mental health care in Africa, or specifically in Sudan • Addresses implementation challenges in low-resource settings • Presents an ethical framework for AI application in mental health care • Documents the mental health context in Sudan or conflict-affected countries

Exclusion Criteria

A study was excluded if it:

• Was restricted to high-income contexts without discussing transferability

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ISSN (ONLINE): 1858 - 8441 - ISSN (PRINT): 1858 - 845X

• Had no relevance to mental health or artificial intelligence

• Was published before 2015

Analytical Framework

Following evidence collection, a Thematic Framework Analysis was applied in three sequential steps:

Step 1 — Coding: Each paper was coded according to: type of barrier, type of enabler, geographic context, technology approach, and ethical framework.

Step 2 — Clustering: Similar codes were grouped into major themes: data, privacy, and clinical integration.

Step 3 — Synthesis: Themes were mapped onto the Sudanese context specifically to construct the three-layer framework. This process ensured that the resulting framework is contextually grounded rather than generically derived.

Study Selection Outcome: The systematic application of the above search strategy and inclusion/exclusion criteria yielded a final corpus of 33 studies. These were drawn from: PubMed (n = 8), IEEE Xplore (n = 6), Google Scholar (n = 12), and Semantic Scholar (n = 7). The 33 references span four evidence types: empirical studies (n = 12), systematic/scoping reviews (n = 8), theoretical/ethical frameworks (n = 7), and policy/epidemiological reports (n = 6). This corpus was deemed sufficient for Framework Synthesis given the scarcity of Sudan-specific empirical data and the primarily conceptual-analytical nature of the study.

Evidence Mapping Table

The findings of this study underscore the need for continued empirical investigation, cross-sector collaboration, and sustained policy commitment to realise the transformative potential of AI for mental health care in Sudan and comparable low-resource settings.

Table 1. Evidence Mapping: Framework Components, Evidence Types, References, and Confidence Levels

Framework Component	Evidence Type	Key References	Confidence Level
Data Strategy Layer (Federated Learning, Synthetic Data, Active Learning)	Empirical + Review	Kumar et al. (2024) [26]; Ganadily & Xia (2023) [18, 31]; Xue et al. (2023) [17]; Tayebi Arasteh et al. (2023) [32]	High
Data Strategy Layer (Community-informed Data Collection)	Theoretical + Review	Pozuelo et al. (2022) [27]; Ankomah & Turkson (2024) [7]; Barkley et al. (2023) [8]	Moderate

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Privacy & Governance Layer (Differential Privacy, Privacy-by-Design)	Empirical	Tayebi Arasteh et al. (2023) [32]; Ganadily & Xia (2023) [31]; Xue et al. (2023) [17]	High
Privacy & Governance Layer (Informed Consent, Ethical Governance)	Theoretical Framework	Bouderhem (2024) [28]; Putica et al. (2024) [12]; Albalawi et al. (2024) [37]	High
Clinical Integration Layer (Human-in-the-Loop, Clinician Copilot)	Empirical + Review	Osman et al. (2024) [9]; Yeasmin et al. (2023) [38]; Mukta & Islam (2024) [13]	Moderate–High
Clinical Integration Layer (Technology Adoption — TAM/UTAUT)	Theoretical Framework	Kalayou et al. (2020) [34]; Mensah (2023) [35]	Moderate
Sudan Mental Health Context	Review + Epidemiological	Shoib et al. (2022) [1]; Eltayeb et al. (2021) [5]; Ahmed Sango et al. (2022) [39]; Regev & Lavee (2022) [16]	High
AI in Sub-Saharan Africa / LMIC	Review + Comparative	Sone & Sone (2024) [15]; Abdelrahman et al. (2023) [6]; Roca et al. (2024) [14]	Moderate–High
Arabic NLP for Mental Health	Empirical	Mezzi et al. (2023) [10]; Fadhil & Schiavo (2019) [36]	Moderate
Responsible AI Ethics Principles	Theoretical Framework	Bouderhem (2024) [28]; Singh (2023) [19]; Graham et al. (2019) [11]	High

PRISMA-ScR Literature Flow Diagram

Figure 1. Adapted PRISMA-ScR flow diagram illustrating the literature search and selection process.

The adapted PRISMA-ScR flow is presented to enhance transparency in evidence identification and selection rather than to indicate a formal systematic or scoping review.

IDENTIFICATION	Records identified through database searching • PubMed: n = 120 • IEEE Xplore: n = 85 • Google Scholar: n = 210 • Semantic Scholar: n = 95 Total records identified: N = 510 Additional records from citation tracking: n = 18 Total after deduplication: N = 412

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SCREENING	Records screened by title and abstract: N = 412 Records excluded (title/abstract screening): n = 298 Reasons for exclusion: • High-income context only, no transferability discussion: n = 121 • No mental health relevance: n = 89 • No AI/technology component: n = 56 • Published before 2010: n = 32 Records forwarded to full-text review: N = 114
ELIGIBILITY	Full-text articles assessed for eligibility: N = 114 Full-text articles excluded: n = 81 Reasons: • Insufficient Sudan/LMIC contextual relevance: n = 34 • Focused on physical health AI only: n = 22 • Duplicate findings from same dataset: n = 15 • Conference abstracts without full methodology: n = 10 Articles meeting all inclusion criteria: N = 33
INCLUDED	Studies included in final Framework Synthesis: N = 33 Breakdown by evidence type: • Empirical studies (RCT, observational, pilot): n = 12 • Systematic/scoping reviews: n = 8 • Theoretical/ethical frameworks: n = 7 • Policy reports & epidemiological studies: n = 6 Breakdown by geographic focus: • Sudan-specific: n = 6 • Sub-Saharan Africa / LMIC: n = 18 • Global/cross-regional: n = 9

Initial title and abstract screening was conducted independently by two reviewers. Discrepancies were discussed and resolved through consensus before full-text assessment.

3. Results

3.1 Barriers to AI Adoption in Sudan

Despite the growing global use of artificial intelligence (AI) in mental healthcare, adoption in Sudan remains limited due to interconnected technical, ethical, clinical, and infrastructural challenges. These barriers significantly affect the feasibility, safety, and sustainability of AI implementation within Sudan's low-resource and conflict-affected healthcare environment [1, 5] .

Table 2. Categorized Barriers to AI Adoption for Mental Health Care in Sudan

Barrier Category	Specific Barriers	Contextual Relevance in Sudan
Data Scarcity & Representational Gaps	• Lack of labelled mental health datasets • Western-centric training data • No standardized Arabic NLP corpora	AI models trained on non-Sudanese data fail to reflect local linguistic, cultural, and clinical patterns
Privacy & Ethical Challenges	• Weak data protection legislation • Risk of re-identification • Absence of informed consent frameworks	Mental health data is highly sensitive; governance gaps increase risk of misuse and stigma
Clinical & Workforce Barriers	• Severe psychiatrist shortages • Low AI literacy among clinicians • Resistance to AI-assisted care	Limited institutional capacity to deploy, maintain, or oversee AI systems in clinical settings
Infrastructure & Digital Constraints	• Unreliable electricity and internet • No integrated health information systems • Limited device access	Fragile digital infrastructure makes deployment of bandwidth-heavy AI tools impractical
Sociocultural & Stigma Barriers	• Mental illness stigma reduces help-seeking • Distrust of digital health tools • Cultural sensitivity gaps	Stigma and cultural resistance limit uptake of AI-powered mental health applications

A major barrier to AI adoption in Sudan is the lack of high-quality and representative mental health data. Most existing AI mental health models are trained on datasets from high-income countries and may not accurately reflect Sudanese cultural contexts, Arabic dialects, or conflict-related mental health experiences [11, 26]. In addition, Sudan lacks large-scale electronic health records and digitized psychiatric databases, limiting opportunities for AI training and validation [1]. These representational gaps may reduce model accuracy and increase the risk of biased or unreliable outputs [21].

Privacy and Ethical Challenges

Mental health data are highly sensitive, making privacy and ethical governance central concerns for AI adoption. Weak digital governance frameworks, limited cybersecurity infrastructure, and the stigma associated with mental illness increase risks related to confidentiality, discrimination, and unauthorized data access [12, 27]. Ethical concerns also include algorithmic bias, limited transparency, and unclear accountability mechanisms, particularly when AI systems are developed using culturally unrepresentative datasets [21, 28].

Clinical and Workforce Barriers

Sudan faces severe shortages of psychiatrists, psychologists, and trained mental health professionals, limiting institutional readiness for AI integration [1, 29]. Many clinicians also have limited experience with AI technologies and may question their reliability, transparency, and impact on clinical decision-making [14]. At the patient level, stigma, mistrust of automated systems, and low digital literacy may further reduce acceptance of AI-supported mental healthcare [27]. Existing evidence from Sudan suggests that users generally prefer AI systems positioned as supportive tools that complement rather than replace human clinicians [9].

Infrastructure and Digital Constraints

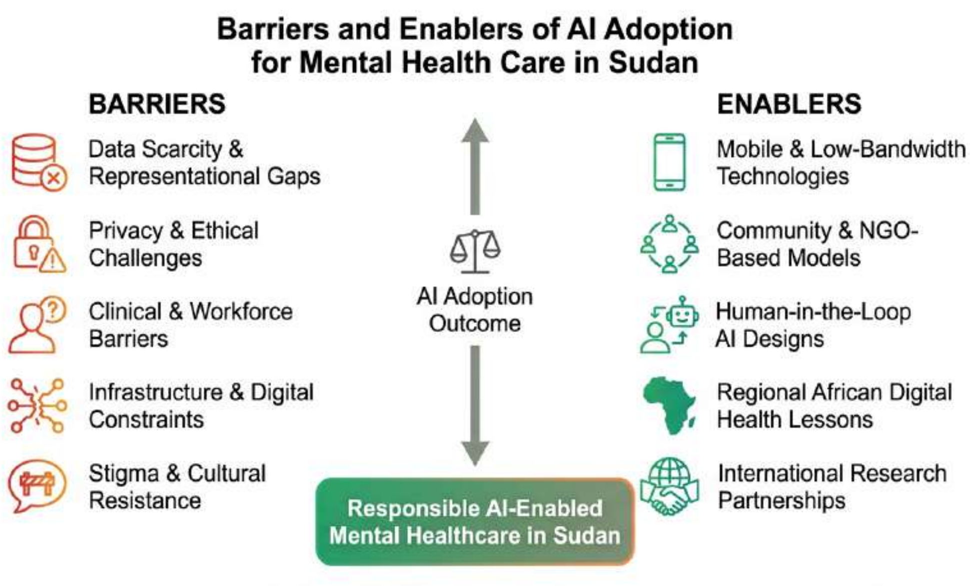
Frequent electricity interruptions, unstable internet connectivity, limited digital infrastructure, and the absence of integrated electronic health systems significantly constrain AI deployment in Sudan [1]. These challenges particularly affect AI systems that rely on continuous connectivity, cloud computing, or large computational resources [26]. Consequently, many AI technologies developed in high-resource settings remain difficult to implement sustainably within Sudan's healthcare environment [8, 11].

Understanding these barriers in their full complexity is essential for designing effective solutions. The next sub-section identifies the contextual enablers and structural opportunities that can be leveraged to overcome these challenges within Sudan's specific environment.

3.2 Enablers and Contextual Opportunities

Despite the significant barriers affecting AI adoption for mental healthcare in Sudan, several contextual enablers and emerging opportunities may support the development of feasible and scalable AI-enabled mental health interventions. These opportunities are particularly important in low-resource and conflict-affected settings where conventional mental healthcare systems remain severely constrained.

Figure 2. Summary of key barriers and enablers influencing AI adoption for mental health care in Sudan



Mobile and Low-Bandwidth Technologies

The growing penetration of mobile phones across Sudan and Sub-Saharan Africa creates important opportunities for AI-supported mental healthcare delivery [6, 11, 24, 30]. Low-bandwidth technologies such as SMS-based systems, conversational chatbots, and Interactive Voice Response (IVR) platforms can operate with limited internet connectivity and reduced computational requirements, making them more suitable for underserved and rural populations. Large-scale interventions such as Digital MindSKILLZ have demonstrated that mobile and voice-based mental health platforms can successfully reach hundreds of thousands of users in resource-constrained African settings [8, 10].These technologies provide scalable pathways for psychoeducation, emotional support, symptom monitoring, and early mental health screening. [24, 30]

Community and NGO-Based Mental Health Models

Sudan's reliance on community-based mental health initiatives and NGO-supported psychosocial services presents another important opportunity for AI integration [5]. In many low-resource settings, non-specialist healthcare workers and community mental health programmes already play central roles in mental healthcare delivery. AI-supported tools could strengthen these task-shifting approaches by assisting community workers with screening, triage, referral support, and patient follow-up. Existing NGO and humanitarian mental health programmes may also provide practical implementation environments for pilot AI interventions, particularly in conflict-affected and displaced populations.

Human-in-the-Loop and Clinician Copilot Models

Human-in-the-loop AI models offer a more contextually appropriate approach for Sudan's healthcare environment by positioning AI systems as supportive tools rather than replacements for clinicians [13, 14]. Clinician copilot systems can assist healthcare workers in documentation, screening, decision support, and patient monitoring while preserving human oversight and clinical accountability. Such models may improve clinician trust, reduce resistance to adoption, and address concerns regarding automation bias and ethical responsibility. Evidence from Sudan further suggests that users generally prefer AI technologies that complement rather than replace human mental health professionals [9].

Regional and Cross-African Digital Health Lessons

Table 3. Key Enablers and Contextual Opportunities for AI Adoption in Sudan

Enabler Category	Specific Opportunities	Implementation Potential
Mobile & Low-Bandwidth Technologies	• High mobile phone penetration • USSD/SMS-based mental health tools • Offline-capable applications	High — mobile-first AI tools can reach rural and conflict-affected populations without internet
Community & NGO-Based Models	• Established community mental health networks • NGO psychosocial support programs • Peer support integration	High — community structures provide trusted channels for AI-assisted outreach and screening
Human-in-the-Loop AI Designs	• Clinician copilot systems • AI as decision-support (not replacement) • Continuous human oversight	High — preserves clinical judgment while extending reach of limited mental health workforce
Regional African Digital Health Lessons	• Kenya, Nigeria, Ethiopia AI deployments • Cross-border federated learning • Shared Arabic-African NLP resources	Medium — lessons from comparable LMICs can accelerate Sudan-specific implementation
International Research Partnerships	• Collaboration with global AI health institutions • Open-source AI mental health tools • Capacity building grants	Medium — external partnerships can provide technical expertise, datasets, and funding

Emerging digital mental health initiatives across Africa provide valuable lessons for Sudan's future AI adoption strategies. Studies from Ghana, Nigeria, Egypt, and other African countries demonstrate growing acceptance of AI-enabled chatbots, mobile health systems, and AI-assisted screening tools within low-resource settings [7, 8, 10]. These regional experiences highlight the importance of culturally adapted design, low-bandwidth infrastructure, privacy-sensitive implementation, and integration with existing healthcare systems. Cross-African collaboration may therefore support knowledge sharing, regional dataset development, ethical governance strategies, and the adaptation of AI technologies to contexts with similar infrastructural and sociocultural challenges.

Building on the preceding analysis of barriers and enablers, the following section presents the proposed three-layer framework for responsible AI adoption, translating these contextual insights into a structured and actionable model.

3.3 Proposed Framework for Responsible AI Adoption in Sudan

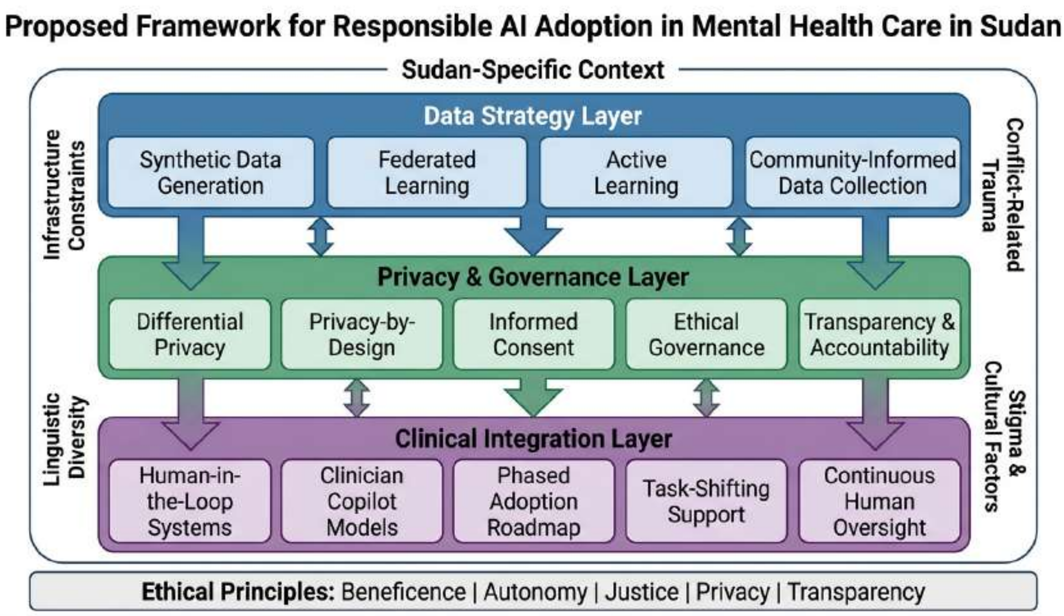
The proposed framework provides a context-aware model for supporting responsible artificial intelligence (AI) adoption in Sudan's mental healthcare system. The framework was designed in response to the interconnected barriers identified throughout this study, including data scarcity, privacy concerns, infrastructural limitations, and clinical adoption challenges. Rather than treating AI implementation as a purely technical problem, the framework integrates technological, ethical, and clinical dimensions into a unified structure tailored to Sudan's low-resource and conflict-affected healthcare environment.

The framework consists of three interconnected layers: (1) a Data Strategy Layer addressing data scarcity and representational limitations, (2) a Privacy and Governance Layer focusing on ethical safeguards and responsible AI principles, and (3) a Clinical Integration Layer supporting sustainable and human-centred implementation pathways. Together, these components aim to support scalable, contextually appropriate, and ethically grounded AI deployment for mental healthcare in Sudan.

Framework Overview

The framework positions responsible AI adoption as a multi-layered process requiring alignment between data availability, ethical governance, and clinical implementation readiness. At the foundational level, the framework addresses the challenge of limited and fragmented mental health datasets through adaptive data-generation and distributed learning strategies. The second layer incorporates governance mechanisms designed to protect sensitive mental health information and strengthen trust in AI-enabled systems. The final layer focuses on clinical integration, emphasizing human oversight, clinician support, and phased implementation models compatible with Sudan's healthcare realities. Figure 3 illustrates the proposed three-layer framework for responsible AI adoption in Sudan's mental healthcare system.

Figure 3. Proposed Framework for Responsible AI Adoption in Mental Health Care in Sudan



3.3.1 Data Strategy Layer

The Data Strategy Layer addresses one of the most significant barriers to AI adoption in Sudan: the scarcity of representative mental health data. Because existing AI models are predominantly trained on datasets derived from high-income countries, locally relevant data-generation and data-management approaches are necessary to improve contextual relevance and reduce algorithmic bias.

Synthetic data generation may help address limitations associated with small or fragmented datasets by producing artificial yet statistically representative training data while reducing direct exposure of sensitive patient information [21]. Federated learning approaches additionally offer opportunities for decentralized AI model training without requiring centralized storage of sensitive mental health records, thereby improving both privacy protection and cross-institutional collaboration [17, 31]. Active learning methods may further optimize limited annotation resources by prioritizing the most informative clinical samples during model training processes.

Community-informed and culturally sensitive data collection practices are also essential for improving representational diversity and ensuring that AI systems better reflect Sudanese linguistic, cultural, and conflict-related mental health experiences.

3.3.2 Privacy and Governance Layer

The Privacy and Governance Layer focuses on protecting sensitive mental health information while strengthening trust, accountability, and ethical AI implementation. Because mental health data are highly sensitive, privacy-preserving mechanisms are critical within Sudan's sociocultural and regulatory context.

Differential privacy techniques may reduce re-identification risks by introducing controlled statistical noise into datasets while preserving analytical utility [18, 32]. Privacy-by-design principles are incorporated throughout the framework to ensure that privacy protection is integrated during system development rather than added after deployment. The framework also emphasizes informed consent mechanisms that clearly communicate data usage, storage, and AI-supported decision-making processes to users.

Ethical governance structures involving transparency, accountability, fairness, and human oversight are integrated to reduce risks associated with algorithmic bias and opaque decision-making [12]they also raise concerns about privacy, algorithmic bias, transparency, and the erosion of clinical judgment. This article introduces the Integrated Ethical Approach for Computational Psychiatry (IEACP. These governance mechanisms are particularly important in fragile and low-resource settings where weak regulatory systems and limited cybersecurity infrastructure may increase vulnerability to misuse or unauthorized access.

3.3.3 Clinical Integration Layer

The Clinical Integration Layer focuses on sustainable and human-centred implementation pathways for AI-enabled mental healthcare. Rather than replacing clinicians, the framework positions AI systems as supportive tools designed to augment clinical decision-making and strengthen task-shifting approaches.

Human-in-the-loop models ensure that healthcare professionals remain actively involved in reviewing, interpreting, and validating AI-generated recommendations [12]. Clinician copilot systems may assist with screening, documentation, patient monitoring, and triage support while preserving human accountability and professional judgement. Such approaches may also improve clinician trust and reduce resistance toward AI adoption.

Table 4. Summary of the Three-Layer Responsible AI Adoption Framework

Framework Layer	Core Components	Primary Objective	Ethical Alignment
1. Data Strategy Layer	• Synthetic data generation • Federated learning • Active learning • Community-informed data collection	Address data scarcity and representational gaps to enable AI model training on Sudan-relevant data	Justice, Fairness, Non-maleficence
2. Privacy & Governance Layer	• Differential privacy • Privacy-by-design • Informed consent • Ethical governance • Transparency & accountability	Protect sensitive mental health data and establish governance structures for responsible AI deployment	Autonomy, Privacy, Transparency, Accountability
3. Clinical Integration Layer	• Human-in-the-loop systems • Clinician copilot models • Phased adoption roadmap • Task-shifting support • Continuous oversight	Enable sustainable, human-centred integration of AI into mental health clinical workflows	Beneficence, Human Dignity, Non-maleficence

The framework additionally proposes a phased implementation roadmap beginning with low-risk and low-bandwidth AI applications such as psychoeducational chatbots, symptom monitoring systems, and mobile screening tools before progressing toward more advanced decision-support systems. Continuous human oversight, ongoing evaluation, and clinician training are emphasized

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to ensure safe and contextually appropriate AI integration within Sudan's mental healthcare system.[25, 33].

3.4 Implementation Roadmap

To support the responsible adoption of AI-enabled mental health systems in Sudan and similar low-resource settings, this study proposes a phased implementation roadmap focused on feasibility, workforce readiness, governance, and long-term sustainability.

3.4.1 Phase 1 — Pilot

Initial implementation should begin through small-scale pilot programs in selected mental health facilities or academic hospitals. Early deployment should focus on low-risk assistive AI applications with continuous human oversight to evaluate feasibility, usability, trust, and ethical concerns within local clinical environments.

3.4.2 Phase 2 — Capacity Building

The second phase should prioritize workforce development through AI literacy training for clinicians, technicians, and health administrators. Universities, professional institutions, and NGOs can play an important role in improving digital mental health awareness and strengthening interdisciplinary collaboration between mental health and technology professionals.

3.4.3 Phase 3 — Integration

Following successful pilot evaluation, AI systems can be gradually integrated into existing clinical workflows. This phase should include the development of privacy policies, governance protocols, ethical review mechanisms, and secure data management procedures to ensure responsible implementation and patient protection.

3.4.4 Phase 4 — Scaling and Monitoring

The final phase involves expanding AI-supported mental health services across broader healthcare settings while maintaining continuous monitoring and evaluation. Long-term implementation should include performance auditing, bias assessment, clinician feedback, and ongoing ethical oversight to ensure sustainability, safety, and contextual appropriateness.

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Figure 4. Phased implementation roadmap for AI-enabled mental health care in Sudan.

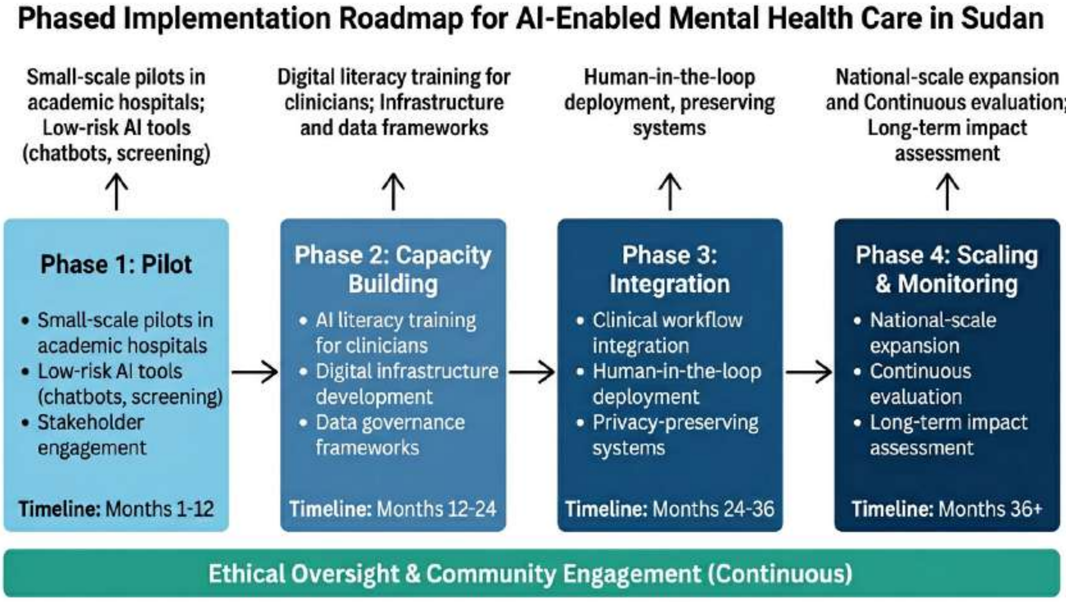

Table 5. Implementation Roadmap with Success Indicators

Note: All quantitative thresholds in this table are informed by reported benchmarks from comparable digital mental health pilot studies in Sub-Saharan Africa and other LMIC settings [7, 8, 34, 35]. They are intended as indicative targets and should be recalibrated based on local baseline assessments prior to deployment.

Implementation Phase	Key Activities	Success Indicators
Phase 1 **Pilot** **(Months 1–12)**	• Deploy low-bandwidth AI screening tools in 2–3 selected facilities • Establish IRB-approved data collection protocols • Conduct baseline workforce AI literacy assessment	• User satisfaction score □ 70% (validated survey) • Zero critical security/privacy incidents over 3 months • □ 80% data collection protocol compliance • AI screening tool sensitivity □ 75% vs. clinician baseline
Phase 2 **Capacity Building** **(Months 13–24)**	• Deliver AI literacy training to □ 50 clinicians • Establish federated learning infrastructure • Develop Arabic-language NLP modules	• □ 50 clinicians complete certified AI training • Federated node operational across □ 3 facilities • Arabic NLP module achieves F1-score □ 0.75 on local dataset • Staff AI competency assessment pass rate □ 65%

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Phase 3 Integration (Months 25–36)	• Integrate AI tools into existing clinical workflows • Implement differential privacy mechanisms • Launch community-based mental health AI pilot	• AI-assisted consultations constitute ▯ 30% of total • Privacy audit: zero data breaches over 6 months • Community uptake: ▯ 60% of eligible participants enrolled • Clinician override rate ▯ 20% (indicates appropriate AI trust)
Phase 4 Scaling & Monitoring (Month 37+)	• Expand to ▯ 10 facilities nationally • Establish national AI mental health governance board • Publish outcome data and iterate framework	• Coverage: ▯ 10 facilities across ▯ 3 states • Governance board operational with published guidelines • Patient outcome improvement: PHQ-9/GAD-7 scores improve ▯ 15% • Annual external audit compliance rate ▯ 90% • Framework cited/adopted by ▯ 1 national policy document

3.5 Comparative Analysis

Table 6. Comparative Analysis of AI Adoption Frameworks

Framework / Study	Context Sensitivity	Ethics & Governance	Data Strategy	Clinical Integration	Key Limitation	Sudan Applicability
TAM (Technology Acceptance Model)	Perceived usefulness & ease of use driving adoption	Low — designed for stable, high-income tech contexts	None	None	Indirect (behavioural intent)	Low — ignores infrastructure & conflict constraints
UTAUT (Unified Theory of Acceptance and Use of Technology)	Social influence, facilitating conditions, effort expectancy	Moderate — some LMIC applications	None	None	Indirect (facilitating conditions)	Moderate — captures workforce factors but not conflict context
DOI (Diffusion of Innovations)	Innovation spread across social systems over time	Moderate — applicable to community-level adoption	None	None	Indirect (adoption stages)	Moderate — useful for community uptake modelling
CFIR (Consolidated Framework for Implementation Research)	Multi-level implementation determinants	Moderate — designed for health system implementation	Weak — mentions ethics but no structured layer	None	Strong (inner/outer setting domains)	Moderate — applicable but not AI-specific
IEACP (Integrated Ethical AI for Computational Psychiatry)	Ethical decision-making for AI in psychiatry	Low — developed for high-income clinical settings	Strong — core ethical principles for AI psychiatry	None	Moderate (clinical ethics focus)	Low — no infrastructure or data strategy for LMICs
Proposed Framework (This Study) ▯	Responsible AI adoption: data, privacy, clinical integration	High — designed specifically for Sudan/conflict-LMIC context	Strong — Privacy & Governance Layer with differential privacy	Strong — Data Strategy Layer with federated learning	Strong — Human-in-the-loop, phased roadmap	High — context-specific, validated against Sudan literature

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Ankomah & Turkson (2024)	Sub-Saharan Africa (Ghana, Nigeria)	Moderate — privacy-by-design principles	Moderate — emotion-aware data processing	Emotion-aware chatbots for low-resource public health	Limited ethical governance; no privacy-preserving mechanisms	Integrates privacy-by-design and governance layer specific to Sudan
Sone (2024)	Nigeria, Nepal, Ecuador	Low — limited ethics governance layer	Moderate — cross-regional data pooling	AI mental health support comparative lessons	Cross-regional; not Sudan-specific; no data strategy	Sudan-specific data strategy with federated learning and synthetic data
Putica et al. (2024) (IEACP)	Global / High-income	Strong — ethical AI decision-making core	Moderate — data quality emphasis	Ethical decision-making for computational psychiatry	Not adapted for LMIC infrastructure or conflict settings	Contextualizes ethical principles within Sudan's conflict-affected environment
WHO Mental Health Atlas (2021)	Global	Strong — WHO ethics guidelines embedded	Moderate — data collection standards	Mental health service mapping and policy	No AI-specific adoption guidance; no implementation roadmap	Provides actionable phased roadmap for AI clinical integration

3.6 Illustrative Use Case: AI-Enabled Mental Health Chatbot at the University of Khartoum

Overview

To demonstrate the practical applicability of the proposed framework, this section presents a hypothetical but evidence-grounded use case: the deployment of an AI-powered mental health chatbot for students at the University of Khartoum — one of Sudan's largest higher education institutions, serving over 40,000 students in a resource-constrained and conflict-affected urban environment [9, 20].

Layer 1 — Data Strategy

Given the absence of locally labelled Arabic mental health datasets, the chatbot's NLP model would be pre-trained on multilingual corpora (English and Modern Standard Arabic) and fine-tuned using a federated learning protocol across three pilot sites: the University of Khartoum student health clinic, the Khartoum Teaching Hospital psychiatric outpatient unit, and a community mental health NGO. Active learning techniques would be used to iteratively improve the model using clinician-reviewed conversation logs, while synthetic data generation would address initial data scarcity [17, 26, 31]. All training data would remain on-site, with no raw patient data transmitted externally, ensuring compliance with Sudan's data sovereignty constraints.

Layer 2 — Privacy and Governance

The chatbot would implement differential privacy mechanisms to prevent re-identification of students from conversation logs [32]. Informed consent would be obtained via a simple Arabic-language opt-in flow at first use, with students retaining the right to delete their data at any time. An institutional ethics committee at the University of Khartoum, in consultation with the Ministry of Health, would provide oversight. Given Sudan's weak formal data protection legislation,

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the governance structure would draw on WHO ethical guidelines [2] and the IEACP principles [12] as interim standards, adapted for the Sudanese context.

Layer 3 — Clinical Integration

The chatbot would function as a clinician copilot rather than an autonomous diagnostic tool. It would conduct initial psychoeducation and PHQ-9/GAD-7 symptom screening via a low-bandwidth USSD interface accessible on basic mobile phones — critical given inconsistent campus internet connectivity [23, 24]. High-risk cases identified by the chatbot would be automatically escalated to a human counsellor within 24 hours. University counsellors would receive a weekly AI-generated summary dashboard, retaining full clinical authority over all interventions. This human-in-the-loop design directly addresses the clinical trust deficit identified as a primary adoption barrier [9, 13].

Expected Outcomes and Success Indicators

Phase 1 success would be measured by: (a) student engagement rate ≥ 60% (threshold informed by benchmarks from prior digital mental health implementation studies in low-resource settings [7, 8, 34]) among registered users over 3 months; (b) counsellor satisfaction score ≥ 70% on a validated usability scale; (c) zero privacy incidents over the pilot period; and (d) chatbot screening sensitivity ≥ 75% relative to clinician gold-standard assessment. These indicators align directly with the Implementation Roadmap success criteria (Table 5) and provide a concrete basis for prospective framework validation.

Having presented the three-layer framework and its phased implementation roadmap, the following section discusses the principal findings, theoretical contributions, and practical implications of this analysis, alongside its limitations and directions for future research.

4. Discussion

This study highlights that the adoption of AI for mental health care in Sudan is shaped not only by technological limitations, but also by cultural perceptions, institutional readiness, and trust-related concerns common in low-resource environments. Existing literature further suggests that AI adoption in mental health cannot be understood solely through technical capability, as socio-cultural beliefs, workforce readiness, ethical concerns, and infrastructural constraints collectively influence implementation feasibility. Evidence from low-resource and African contexts additionally indicates that acceptance of AI-supported mental health systems often remains conditional upon transparency, human oversight, and demonstrated clinical reliability.

4.1 Principal Findings

Existing literature suggests that AI is generally perceived as a potentially useful supportive technology rather than a replacement for clinicians. Evidence from low-resource and African contexts further indicates a preference for assistive or clinician-centered AI models in which healthcare professionals remain responsible for final clinical decisions and patient interaction. This reflects broader concerns surrounding transparency, accountability, clinical safety, and ethical responsibility in AI-supported mental healthcare. Trust in AI systems appears to be conditional rather than absolute. Existing literature suggests that willingness to use AI increases when systems are transparent, clinically validated, and supervised by healthcare professionals. Similar concerns have been reported in digital mental health and responsible AI literature, particularly in low-resource healthcare environments where institutional trust and technical literacy may vary considerably.

The study also identified infrastructure limitations as a major barrier to implementation. Limited digital infrastructure, weak data management systems, unstable internet access, and shortages of trained professionals continue to constrain the feasibility of large-scale AI deployment in Sudan. These findings align with prior studies examining digital health adoption in low- and middle-income countries (LMICs), where infrastructural readiness remains a critical determinant of successful implementation.

In addition, stigma and cultural beliefs surrounding mental illness strongly influenced attitudes toward AI adoption. Some evidence indicates that mental health remains socially sensitive, and concerns regarding privacy, confidentiality, and community perception may discourage individuals from engaging with digital mental health systems. This suggests that culturally sensitive implementation approaches are necessary for AI adoption in fragile and conservative social contexts.

4.2 Theoretical Implications

4.2.1 Responsible AI

This study contributes to the growing literature on responsible AI by demonstrating that trust, transparency, and human oversight are central requirements for AI adoption in mental health care within low-resource settings. The findings reinforce the importance of explainability and contextual governance mechanisms, particularly in sensitive healthcare domains where ethical concerns directly influence user acceptance. The study further highlights that responsible AI frameworks should account for sociocultural realities and institutional limitations rather than focusing exclusively on technical performance [34, 35]. Unlike the Integrated Ethical AI for Computational

Psychiatry (IEACP) framework [12], which was developed for high-income clinical settings and focuses primarily on ethical decision-making within established psychiatric institutions, the proposed framework explicitly addresses the structural preconditions for AI adoption that are absent in Sudan: data scarcity, federated infrastructure, and conflict-disrupted governance. Specifically, IEACP provides no guidance on data collection strategies in low-resource settings, offers no privacy-preserving technical architecture for environments lacking data protection legislation, and does not account for the workforce and connectivity constraints that define healthcare delivery in fragile states — all of which are core components of the framework proposed in this study.

4.2.2 Digital Mental Health

The findings expand current understanding of digital mental health implementation in low-resource psychiatry. The study demonstrates that culturally sensitive deployment strategies are essential in contexts where stigma, limited awareness, and resource shortages significantly shape healthcare behavior. In addition, the preference for clinician-assisted AI models supports emerging discussions around hybrid human–AI mental health systems that combine technological support with human judgment and therapeutic interaction.

4.2.3 LMIC Adoption Literature

This study also contributes to the broader literature on technology adoption in LMICs by highlighting how fragile health systems, workforce shortages, and infrastructural constraints influence AI implementation. Unlike many high-income settings where AI adoption is often driven by efficiency and optimization, existing evidence from low-resource environments emphasizes the importance of reliability, accessibility, privacy, and clinical supervision in shaping acceptance of AI-supported mental health systems. The analysis further suggests that AI adoption frameworks developed in high-income settings may not fully capture the sociotechnical realities of fragile and resource-constrained environments such as Sudan [34, 35].

4.3 Practical and Policy Implications

The findings have several practical implications for policymakers, healthcare institutions, universities, NGOs, and technology developers. Policymakers should prioritize the development of national AI governance frameworks that address data protection, ethical oversight, accountability, and responsible clinical deployment. Healthcare institutions should invest in digital infrastructure and gradually introduce AI-supported systems through supervised pilot programs.

Universities and training institutions should strengthen AI literacy and digital mental health education among clinicians, psychologists, and health informatics professionals. NGOs and international health organizations may also play an important role in supporting capacity building, digital inclusion, and infrastructure development within underserved communities.

For developers, the findings emphasize the importance of culturally aware and context-sensitive AI design. Systems intended for low-resource mental health settings should prioritize usability, transparency, low-bandwidth functionality, multilingual support, and strong privacy protections. The development of locally relevant datasets and ethically governed data collection mechanisms may further improve the contextual reliability of future AI systems.

4.4 Ethical Considerations

Existing literature highlights several ethical concerns associated with AI adoption in mental health care, including privacy risks, informed consent, stigma, algorithmic bias, and the potential misuse of sensitive patient data. Evidence from low-resource and digitally constrained environments further suggests that concerns regarding confidentiality and data protection may significantly influence trust and acceptance of AI-supported mental health systems, particularly in settings where digital governance structures remain limited.

The findings also suggest that excessive reliance on automated systems may undermine clinical judgment and patient-centered care if human oversight is not maintained. Algorithmic bias and limited local datasets may further reduce fairness and reliability when AI systems are developed primarily using data from high-income populations. These concerns reinforce the importance of transparent governance mechanisms, culturally sensitive implementation strategies, and continuous ethical monitoring.

Ethical AI deployment in mental health should prioritize patient dignity, cultural sensitivity, and contextual governance rather than purely technical performance.

5. Limitations

This study has several limitations. First, the study is based on a structured framework synthesis approach informed by systematic literature searching and thematic analysis rather than empirical field validation. Consequently, the proposed framework has not yet been prospectively evaluated within real-world clinical settings in Sudan. Second, the analysis relies on existing literature from low-resource and African contexts, which may not fully capture all regional, institutional, or sociocultural variations within Sudan's mental health system. Finally, the rapidly evolving nature

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of AI technologies, governance frameworks, and public attitudes may alter future implementation conditions beyond those considered in this study. Additionally, three references ([18], [21], [26]) are preprint manuscripts that have not undergone formal peer review; while included for their methodological relevance, their findings should be interpreted with appropriate caution.

Despite these limitations, the study provides important exploratory insights into AI adoption in a severely underexplored context.

6. Future Research Directions

Future research should investigate AI adoption in mental health through longitudinal and multi-site studies capable of examining changes in perceptions, trust, and implementation readiness over time. Additional pilot implementation studies are needed to evaluate the real-world feasibility, usability, and clinical impact of AI-supported mental health systems within low-resource healthcare environments.

Further research may also focus on the development of culturally adapted AI systems designed specifically for Arabic-speaking and African contexts. Areas such as multilingual Arabic and African natural language processing (NLP), clinician–AI collaboration models, and human-centered digital mental health interfaces remain underexplored and require additional investigation.[10, 36].

Future technical studies should also explore privacy-preserving AI architectures, federated learning approaches for low-resource settings, and secure decentralized mental health data systems capable of balancing innovation with ethical protection and contextual governance.[17, 18].

6.1 Framework Validation Strategy

To validate the proposed framework prior to empirical deployment, a three-phase validation strategy is proposed.

6.1.1 Phase A — Delphi Expert Consensus

A Delphi consensus process will engage 15–20 domain experts drawn from mental health practitioners, AI researchers, and public health policymakers in Sudan and comparable LMIC settings. Experts will rate each framework component on a 5-point Likert scale across three dimensions: contextual relevance, feasibility, and ethical appropriateness. Consensus is defined as □70% agreement; items not reaching consensus will be revised and re-evaluated in a second Delphi round.

6.1.2 Phase B — Expert Review Panel

An expert review panel of 8–10 specialists — including mental health clinicians, AI ethics researchers, and Sudan-based public health practitioners — will independently evaluate the framework's three layers using a structured scoring rubric. Each component will be assessed for clinical relevance, ethical alignment, and contextual feasibility. Feedback will be synthesised and used to refine the framework before pilot deployment.

6.1.3 Phase C — Pilot Implementation and Empirical Testing

A small-scale pilot study should deploy a low-bandwidth AI mental health tool in a university or clinical setting in Sudan over a 6-month period. Outcome measures may include user engagement, clinician acceptance, PHQ-9/GAD-7 trajectories, and privacy compliance indicators. Findings would inform iterative refinement prior to wider implementation.

7. Conclusion

This study developed a context-specific framework to support responsible AI adoption for mental health care in Sudan, integrating data strategies, ethical governance mechanisms, and clinical implementation pathways. The findings highlight that AI adoption in fragile and low-resource settings is shaped not only by technical feasibility but also by sociocultural, infrastructural, and ethical considerations. The proposed framework provides a structured roadmap for researchers, policymakers, and healthcare institutions while emphasizing the importance of privacy protection, human oversight, and contextual adaptation. Future work should focus on expert validation and empirical implementation studies to assess feasibility and long-term impact.

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