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Exploring Technological Frames of AI Adoption among Mental Health Professionals in a Resource-Constrained Context: Evidence from Sudan

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ABSTRACT: Artificial Intelligence (AI) holds transformative potential for mental health care, yet its adoption in resource-constrained, conflict-affected settings remains poorly understood. Sudan's mental health system faces severe challenges including critical specialist shortages, exclusive reliance on paper-based records, infrastructure deficits, and the compounding effects of prolonged armed conflict. These conditions create a unique and critically important context for examining how technology adoption is socially constructed and interpreted by frontline practitioners. **Aim:** This study explores how mental health stakeholders in Sudan interpret and frame AI adoption through Technological Frames Theory (TFT), examining perceptions of AI's potential value, implementation barriers, ethical concerns, and contextual adaptation requirements. **Method:** A qualitative, interpretive study using semi-structured interviews with 35 participants — 32 mental health professionals (MHP-01–MHP-32) and 3 managers and decision-makers (MGR-01–MGR-03). Data collection occurred in two phases (June 2024 and January–April 2026), interrupted by armed conflict. All participating facilities operated exclusively with paper-based patient records at the time of the study. Data were analysed thematically guided by TFT's three dimensions: nature of technology, technology in use, and technology strategy. **Findings:** Four themes emerged: (1) Perceived Value — AI viewed as a supportive efficiency tool and access enabler, not a professional replacement; (2) Implementation Challenges — paper-based systems, infrastructure gaps, limited digital literacy, and workforce shortages; (3) Ethical Concerns — privacy, confidentiality, data security in conflict contexts, and preservation of therapeutic relationships; (4) Contextual Adaptation — cultural sensitivity, linguistic localisation, stigma reduction, and post-conflict digital transformation vision. **Conclusion:** Stakeholders hold cautiously optimistic frames toward AI, contingent on foundational digital infrastructure, electronic health records, workforce capacity, and ethical safeguards. The study introduces the *Digital Readiness Gap* as a novel theoretical construct and proposes a four-phase sequential framework for AI adoption in fragile healthcare environments. Findings have implications for policymakers, technology developers, and health system planners in Sudan and comparable LMIC contexts.

Keywords: Artificial Intelligence, Mental Health, Technological Frames Theory, Sudan, Resource-Constrained Settings, Digital Health, Healthcare Technology Adoption.

1. INTRODUCTION

1.1 Background and Context

Mental health care systems worldwide face mounting pressures from increasing service demand, workforce shortages, and resource constraints . These challenges are particularly acute in low- and middle-income countries (LMICs), where mental health services remain severely underdeveloped despite high disease burdens . The global treatment gap for mental health disorders — the proportion of people with mental illness who receive no treatment — exceeds 75% in many LMICs, driven by inadequate infrastructure, insufficient funding, and persistent social stigma . Sub-Saharan Africa bears a disproportionate share of this burden, with mental health receiving less than 1% of health budgets in many countries across the region despite accounting for a significant proportion of disability-adjusted life years .

Sudan's mental health landscape reflects these broader regional challenges while being further complicated by decades of conflict, political instability, and economic hardship. The country's mental health system operates with a critical shortage of psychiatrists, psychologists, and trained mental health workers, resulting in vast underserved populations particularly in rural and remote areas . Service availability is further constrained by geographic inequities, with most specialist care concentrated in urban centres such as Khartoum and Omdurman . Post-conflict trauma, displacement, and ongoing humanitarian crises have intensified mental health needs across the population , yet service provision remains fragmented and severely under-resourced . A defining characteristic of Sudan's mental health facilities — and one of central importance to this study — is their exclusive reliance on paper-based patient records. No electronic health information system exists across the participating facilities, representing a fundamental infrastructural constraint for any digital health initiative .

The emergence of Artificial Intelligence (AI) technologies offers potential pathways to address some of these challenges. AI applications in healthcare — including natural language processing, predictive analytics, machine learning-based diagnostics, and digital therapeutic tools — have demonstrated capacity to extend service reach, improve decision support, and reduce administrative burden on overstretched health workers . In mental health specifically, AI-powered chatbots, sentiment analysis tools, and risk prediction models have shown promise in contexts with limited access to human specialists . The potential for AI to extend mental health services to underserved populations through mobile and digital platforms is particularly relevant to resource-constrained settings .

However, the adoption of AI in healthcare is not a neutral technical process. It is fundamentally shaped by how practitioners, managers, and policymakers interpret, understand, and assign meaning to these technologies within their specific organisational and societal contexts . Technologies that are technically capable may fail to be adopted if stakeholders frame them as threatening, incomprehensible, or misaligned with their values and work practices . Conversely, technologies that are imperfect or incomplete may be adopted enthusiastically if stakeholders construct positive, enabling frames around them. Understanding these interpretive processes is therefore as important as understanding the technical capabilities of AI itself.

1.2 Problem Statement

Despite growing global interest in AI-enabled mental health care, there is a critical gap in evidence from conflict-affected, resource-constrained settings such as Sudan . Most AI adoption research focuses on high-income countries with established digital infrastructure, leaving a significant knowledge gap about contexts where even basic electronic records are absent . The exclusive reliance on paper-based records in Sudan's mental health facilities represents not merely a technological gap but a fundamental *Digital Readiness Gap* — a structural prerequisite deficit that must be addressed before meaningful AI adoption can occur.

Furthermore, existing AI adoption frameworks — including the Technology Acceptance Model (TAM) and Diffusion of Innovations theory — were largely developed and validated in digitally mature environments . Their applicability to settings where the foundational digital infrastructure does not yet exist remains untested. Technological Frames Theory (TFT) offers a more contextually flexible framework, capable of capturing the interpretive dimensions of technology adoption without assuming pre-existing digital infrastructure . This study addresses the dual gap in empirical evidence and theoretical application by examining AI adoption frames in Sudan's mental health sector — one of the most under-researched and critically important healthcare contexts globally.

The outbreak of armed conflict in Sudan in April 2023 further complicates the adoption landscape, disrupting health services, displacing health workers, and creating unprecedented levels of trauma and mental health need simultaneously with the destruction of health infrastructure. This paradox — of heightened need coinciding with reduced capacity — makes the question of AI adoption both more urgent and more complex.

1.3 Research Objectives and Questions

This study aims to explore how mental health professionals and managers in Sudan interpret and frame AI adoption through the lens of Technological Frames Theory. The specific research questions are:

1. How do mental health professionals and managers in Sudan frame the potential value of AI in mental health care?
2. What implementation challenges do stakeholders identify as barriers to AI adoption?
3. What ethical and human-centred concerns shape stakeholder frames regarding AI?
4. How do stakeholders envision contextually appropriate AI adoption given Sudan's unique constraints?

1.4 Significance of the Study

This study makes several important contributions to the literature. First, it extends TFT application to a fragile, post-conflict healthcare context in sub-Saharan Africa — a region significantly underrepresented in health informatics and digital health research . Second, it introduces the *Digital Readiness Gap* as a novel theoretical construct applicable to other LMICs facing similar infrastructural deficits, providing a conceptual tool for analysing AI adoption prerequisites in pre-digital health systems. Third, it provides empirically grounded recommendations for policymakers, practitioners, and technology developers seeking to support AI adoption in resource-constrained settings .

The study also contributes to a growing body of scholarship on the social and organisational dimensions of digital health transformation. By foregrounding the perspectives of frontline mental health professionals and managers — rather than technology developers or external policymakers — it centres the voices of those who will ultimately determine whether AI tools are adopted, adapted, or rejected in practice. In a context where external technology actors increasingly target LMICs as markets for digital health solutions, this grounded, stakeholder-centred perspective is both timely and necessary. The findings have direct relevance for international organisations, governments, and NGOs working on health system strengthening in Sudan and comparable fragile state contexts.

2. Literature Review

2.1 AI in Healthcare: Global Trends

AI technologies are increasingly integrated into healthcare systems worldwide, demonstrating potential across diagnostics, treatment planning, administrative automation, and patient monitoring . Machine learning algorithms have shown diagnostic accuracy comparable to specialists in domains including radiology, dermatology, pathology, and ophthalmology . Natural language processing enables automated clinical documentation, reducing administrative burden on healthcare workers and freeing time for direct patient care . Predictive analytics support early identification of at-risk patients, resource allocation optimisation, and hospital readmission prevention . Robotic process automation is streamlining administrative workflows in healthcare organisations, reducing costs and error rates .

Despite these advances, AI adoption remains uneven across healthcare contexts, with significant disparities between high-income and low-income settings . In high-income countries, AI adoption is accelerating, supported by robust digital infrastructure, large annotated datasets, regulatory frameworks, and investment capital. In LMICs, the same technologies face formidable barriers including limited infrastructure, data scarcity, regulatory gaps, and workforce capacity constraints . The risk of a widening AI health divide — where AI amplifies existing inequities in healthcare access and quality — has been identified as a major concern in global health discourse .

2.2 AI in Mental Health Care

In mental health, AI applications span a broad spectrum: chatbots and conversational agents for psychological support and psychoeducation; sentiment analysis and natural language processing for mood monitoring and crisis detection; machine learning models for suicide risk prediction and early intervention; clinical decision-support systems for diagnosis and treatment planning; and digital therapeutic platforms delivering evidence-based interventions at scale . Digital mental health interventions, including AI-powered tools, have demonstrated efficacy in reducing symptoms of depression and anxiety in randomised controlled trials, particularly in contexts with limited access to human specialists .

AI-powered tools can extend reach to underserved populations through mobile platforms, potentially bridging service gaps in LMICs . The potential for AI to serve as a first point of contact for individuals who would not otherwise seek help — due to stigma, geographic barriers, or cost — is a particularly significant opportunity in resource-constrained settings . However, concerns persist about the quality and safety of AI-mediated mental health support, including risks of algorithmic bias in risk prediction, data privacy violations, the erosion of therapeutic alliance, and the potential for AI to substitute for rather than supplement human care . These concerns are amplified in contexts where regulatory oversight and professional accountability mechanisms are weak.

2.3 AI Adoption in Low-Resource and Developing Countries

AI adoption in LMICs faces distinct challenges that differ qualitatively from those in high-income settings. Infrastructure limitations — including unreliable electricity, limited internet connectivity, and absence of digital health systems — create foundational barriers that precede questions of AI readiness .

Low digital literacy among health workers, patients, and communities limits the usability and uptake of digital health tools. Inadequate data governance frameworks leave patient data vulnerable to misuse, breaches, and exploitation by commercial actors . Resource constraints limit the capacity for AI system maintenance, updates, and technical support — creating sustainability challenges for even well-implemented AI deployments.

Studies from sub-Saharan Africa highlight the importance of contextualising AI tools to local languages, cultural norms, and health system structures . Community health worker integration and mobile-first design have emerged as promising strategies for AI deployment in low-resource settings, leveraging existing community trust and the widespread availability of mobile phones . Evidence from Kenya, Nigeria, Ethiopia, and other African countries demonstrates both the feasibility and complexity of digital health implementation in contexts with fragile infrastructure , . Successful implementations share common features: strong community engagement, local co-design, phased rollout, and sustained investment in training and support.

2.4 Mental Health Services in Sudan and Sub-Saharan Africa

Sub-Saharan Africa bears a disproportionate burden of mental health disorders while having the lowest density of mental health professionals globally . The treatment gap for mental disorders in the region exceeds 90% in many countries, driven by extreme workforce shortages, inadequate infrastructure, and insufficient funding . Sudan's mental health system is characterised by extreme specialist shortages, geographic inequity, and near-total absence of community-based mental health services . The country has fewer than 100 psychiatrists serving a population of over 45 million, with services almost entirely concentrated in Khartoum and a handful of other urban centres .

The outbreak of armed conflict in April 2023 has further devastated Sudan's health infrastructure. Hospitals have been attacked, health workers displaced, and supply chains disrupted across the country . The mental health consequences of the conflict — including post-traumatic stress disorder, depression, anxiety, and grief — are occurring on a massive scale, while the capacity to respond is simultaneously being destroyed. Previous studies from the Horn of Africa document severe shortfalls in mental health service capacity and the urgent need for innovative service delivery models that can function in fragile, conflict-affected environments , . The intersection of extreme need and extreme resource constraint makes Sudan a uniquely important — and uniquely challenging — context for digital health innovation.

2.5 Ethical and Human-Centred Considerations in AI Healthcare

Ethical frameworks for AI in healthcare emphasise transparency, accountability, fairness, non-maleficence, and human oversight as core principles . In mental health specifically, concerns about AI replacing human therapeutic relationships, compromising patient confidentiality, perpetuating inequities in care access, and operating without adequate clinical oversight are particularly salient . The therapeutic relationship — the alliance between clinician and patient — is widely recognised as one of the most powerful determinants of mental health treatment outcomes, and any AI deployment that undermines this relationship risks reducing treatment effectiveness .

Human-centred design approaches that involve clinicians and patients in AI development and implementation have been advocated as essential for ethical and effective adoption . In resource-constrained contexts, ethical considerations are compounded by governance gaps, limited regulatory capacity, and the vulnerability of service populations — many of whom have experienced trauma, displacement, and institutional distrust. The application of standard data governance principles — developed in the context of stable, high-income democracies — to conflict-affected settings requires significant adaptation . Health data in conflict zones carries particular risks of weaponisation, and any AI health system must be designed with these context-specific threats explicitly in mind.

2.6 Summary and Research Gap

While the literature documents AI's potential for mental health care and highlights adoption challenges in LMICs, there remains a significant gap in empirical studies from conflict-affected settings with pre-digital health infrastructure. Existing research on AI adoption in LMICs largely focuses on settings with at least partial digital infrastructure — electronic records, mobile health platforms, or internet connectivity. Sudan presents a qualitatively different case: a country with urgent mental health needs, zero digital health infrastructure, active conflict, and a health workforce that has never worked with electronic records. Applying TFT to this context allows for a theoretically grounded examination of how stakeholders make sense of AI in the complete absence of the digital prerequisites that most adoption frameworks assume. This study directly addresses this gap.

3. Theoretical Framework

3.1 Technological Frames Theory (TFT)

Technological Frames Theory, developed by Orlikowski and Gash , provides a social constructivist lens for understanding how individuals and groups interpret technologies within organisational contexts. Drawing on cognitive science and organisational theory, TFT posits that people develop cognitive frames — shared assumptions, expectations, and knowledge — about technology that shape their attitudes toward adoption, use, and outcomes. These frames are not simply individual beliefs; they are socially constructed through interaction, shared experience, organisational culture, and professional identity .

TFT was originally developed to explain why IT implementations in organisations frequently fail to achieve their intended outcomes, even when the technology is technically sound. Orlikowski and Gash demonstrated that misalignment between the technological frames of different stakeholder groups — for example, IT developers and end users — is a primary predictor of adoption failure . When stakeholders hold incompatible assumptions about what a technology is, how it should be used, and what goals it serves, implementation conflicts, resistance, and workarounds are predictable outcomes. Conversely, when frames are aligned — or when deliberate processes of frame alignment are pursued — adoption is smoother and outcomes are more likely to meet expectations.

TFT has been applied across diverse organisational and national contexts, including IT adoption in Brazilian organisations , e-government projects in Japan , knowledge management systems , and IoT workplace digitisation . Its utility lies in revealing frame congruence or incongruence between stakeholder groups — divergent frames predict adoption difficulties, while aligned frames facilitate implementation. In healthcare settings, TFT has been used to analyse clinician resistance to electronic health records, clinical decision-support systems, and telemedicine platforms .

3.2 Core Dimensions: Nature of Technology, Technology in Use, and Technology Strategy

TFT comprises three analytical dimensions that together capture the full scope of stakeholder interpretations of technology :

1. **Nature of Technology**: Stakeholders' understandings of what AI is, what it can do, and what its fundamental characteristics are. This includes beliefs about AI's capabilities, limitations, and identity — whether it is understood as a tool, an agent, a threat, or an opportunity. In the context of this study, this dimension captures how mental health stakeholders conceptualise AI: as a clinical assistant, an efficiency tool, a replacement for human care, or something else entirely.

1. **Technology in Use**: Stakeholders' expectations about how AI will be used in practice — including anticipated workflows, interactions with existing processes, impacts on professional roles and responsibilities, and effects on patient care. This dimension is particularly important in the Sudanese context, where the absence of electronic records means that any AI application would require a fundamental transformation of existing work practices.

1. **Technology Strategy**: Stakeholders' understandings of why AI is being adopted, who drives adoption, and what organisational and policy goals it serves. This dimension captures the political and strategic dimensions of technology adoption — including questions of power, resource allocation, and institutional priorities. In a resource-constrained context, technology strategy frames are likely to be shaped by urgent practical needs, donor priorities, and governance challenges.

3.3 Application of TFT to This Study

This study applies TFT to analyse how mental health professionals (MHP) and managers/decision-makers (MGR) in Sudan construct frames about AI adoption. The two stakeholder groups are expected to hold partially divergent frames given their different professional roles, responsibilities, and relationships with technology. MHPs are likely to frame AI through the lens of clinical practice, patient welfare, and therapeutic relationships, while MGRs may emphasise organisational efficiency, resource management, and strategic planning .

The application of TFT to a pre-digital, conflict-affected context extends the theory beyond its original organisational IT settings. In this study, TFT is used not only to analyse existing frames but to understand how frames are formed in the absence of direct technology experience — that is, how stakeholders construct interpretations of a technology they have not yet encountered in practice. This prospective dimension of TFT application — examining anticipated rather than experienced frames — represents a novel theoretical contribution.

3.4 Conceptual Framework

The study's conceptual framework integrates TFT with the Digital Readiness Gap concept. While TFT explains how stakeholders interpret AI, the Digital Readiness Gap — defined as the structural deficit in digital infrastructure, electronic records, and digital literacy that must be bridged before AI adoption is feasible — adds a contextual layer specific to pre-digital healthcare environments. The Digital Readiness Gap is not simply a technological deficit; it is also a cognitive and organisational one, shaping the frames through which stakeholders interpret AI by limiting their reference points and experiential basis for evaluation.

Together, these constructs provide a comprehensive analytical lens for understanding AI adoption readiness in fragile, resource-constrained settings. The framework suggests that addressing the Digital Readiness Gap is not merely a technical prerequisite for AI adoption but a necessary condition for the development of informed, realistic, and aligned technological frames among stakeholders.

4. Methodology

4.1 Research Design

This study employs a qualitative, interpretive design appropriate for exploring stakeholder perceptions and meaning-making processes . Semi-structured interviews were selected as the primary data collection method to elicit rich, contextualised narratives about AI adoption. The interpretive paradigm aligns with TFT's social constructivist epistemological foundations, recognising that participants' frames are co-constructed through language, experience, and social interaction. A qualitative approach was deemed most appropriate given the exploratory nature of the research questions and the near-total absence of prior empirical studies on AI adoption frames in Sudan's mental health sector. This design enabled the researcher to capture the complexity, nuance, and contextual specificity of stakeholder interpretations that quantitative methods would be unable to access.

The study is positioned within the broader tradition of interpretive information systems research, which prioritises understanding the subjective meanings that actors assign to technologies and organisational processes . This tradition has produced influential insights into technology adoption, resistance, and adaptation across diverse organisational and national contexts, and provides a well-established methodological home for TFT-based research.

4.2 Participants

A total of 35 participants were recruited through purposive sampling from mental health facilities in Sudan. Participants were selected to represent diverse professional roles, institutional contexts, facility types, and geographic locations within accessible areas of the country. The sampling strategy was guided by the principle of maximum variation , seeking to capture a broad range of perspectives across the two stakeholder groups of interest.

Table 1: Participant Characteristics (N=35)

Code	Role	Facility Type	Experience (yrs)	Location
MHP-01	Psychiatrist	Public Hospital	15	Khartoum
MHP-02	Clinical Psychologist	NGO Clinic	8	Khartoum
MHP-03	Mental Health Nurse	Public Hospital	12	Khartoum
MHP-04	Psychiatrist	Teaching Hospital	20	Khartoum
MHP-05	Psychologist	Community Centre	6	Omdurman
MHP-06	Mental Health Worker	NGO	4	Omdurman

MHP-07	Psychiatrist	Private Clinic	18	Khartoum
MHP-08	Clinical Psychologist	Public Hospital	10	Khartoum North
MHP-09	Mental Health Nurse	Community Centre	7	Omdurman
MHP-10	Psychologist	Teaching Hospital	9	Khartoum
MHP-11	Mental Health Worker	NGO Clinic	3	Khartoum
MHP-12	Psychiatrist	Public Hospital	22	Khartoum
MHP-13	Clinical Psychologist	NGO	5	Omdurman
MHP-14	Mental Health Nurse	Public Hospital	11	Khartoum North
MHP-15	Psychiatrist	Public Hospital	9	Khartoum
MHP-16	Clinical Psychologist	Community Centre	7	Omdurman
MHP-17	Mental Health Nurse	NGO Clinic	5	Khartoum
MHP-18	Psychologist	Teaching Hospital	13	Khartoum
MHP-19	Mental Health Worker	Public Hospital	2	Khartoum North
MHP-20	Psychiatrist	NGO	17	Omdurman
MHP-21	Clinical Psychologist	Public Hospital	6	Khartoum
MHP-22	Mental Health Nurse	Community Centre	10	Omdurman
MHP-23	Psychologist	NGO Clinic	8	Khartoum
MHP-24	Mental Health Worker	Teaching Hospital	4	Khartoum
MHP-25	Psychiatrist	Public Hospital	19	Khartoum North
MHP-26	Clinical Psychologist	Private Clinic	11	Khartoum
MHP-27	Mental Health Nurse	Public Hospital	14	Omdurman
MHP-28	Psychologist	NGO	3	Khartoum
MHP-29	Mental Health Worker	Community Centre	6	Omdurman
MHP-30	Psychiatrist	Teaching Hospital	24	Khartoum
MHP-31	Clinical Psychologist	Public Hospital	9	Khartoum North
MHP-32	Mental Health Nurse	NGO Clinic	7	Omdurman
MGR-01	Programme Manager	Ministry of Health	14	Khartoum
MGR-02	Administrative Director	Teaching Hospital	16	Khartoum
MGR-03	Institutional Director	NGO	12	Omdurman

All 35 facilities represented in the sample operated exclusively with paper-based patient records at the time of the study. No electronic health information systems, digital record-keeping tools, or clinical software were in use at any participating facility. Participants ranged in professional experience from 2 to

24 years, providing perspectives across career stages. The sample included participants from public hospitals, teaching hospitals, private clinics, community centres, and NGO facilities, ensuring institutional diversity.

One additional participant (from an administrative records unit) was approached but excluded from the final sample, as their role was limited to administrative staff records management and did not involve mental health service delivery or clinical decision-making. Their exclusion ensures that all participants have direct relevance to the research questions regarding AI adoption in mental health care.

4.3 Data Collection

Data collection occurred in two phases due to the outbreak of armed conflict in Sudan in April 2023. Phase 1 (June 2024) involved initial interviews with 18 participants, conducted after a period of relative stabilisation in Khartoum and Omdurman. Fieldwork was subsequently suspended when renewed conflict escalation made safe access impossible. Phase 2 (January–April 2026) resumed data collection with the remaining 17 participants following further partial stabilisation of conditions in accessible areas. The two-phase approach, while necessitated by circumstances beyond the researcher's control, provided an unplanned opportunity to observe whether participant frames had shifted over the 18-month interval — a dimension addressed in the analysis.

All interviews were conducted in Arabic, audio-recorded with participant consent, and professionally transcribed. Interview duration ranged from 45 to 90 minutes, with most interviews lasting approximately 60 minutes. Interview guides were structured around TFT's three dimensions, with questions exploring participants' understanding of AI, anticipated uses in mental health care, perceived benefits and risks, implementation challenges, ethical concerns, and contextual adaptation requirements. Probing questions were used to elicit specific examples, elaborations, and clarifications. Interviews were conducted in-person where safe and feasible, and via secure video call for participants in areas with access constraints.

4.4 Data Analysis

Transcripts were translated into English by a professional translator with mental health terminology expertise, and cross-checked by the researcher for accuracy. Data were analysed using reflexive thematic analysis guided by TFT's three dimensions as an organising framework. Analysis proceeded through six phases: (1) familiarisation with the data through repeated reading and note-taking; (2) systematic generation of initial codes across the entire dataset; (3) searching for themes by collating codes into candidate theme groups; (4) reviewing and refining themes against the coded data and the full dataset; (5) defining and naming themes with clear boundaries and internal coherence; and (6) producing the analytical write-up integrating data extracts, analytical commentary, and theoretical interpretation.

NVivo software (version 14) was used to manage coding and facilitate systematic retrieval of coded segments. Themes were developed inductively from participant narratives while being interpreted deductively through TFT's analytical dimensions, reflecting the dual inductive-deductive approach recommended for theory-guided qualitative analysis . Member checking was conducted with eight participants — five MHPs and three MGRs — to validate the interpretive accuracy of the emerging themes. Participants confirmed the resonance of the themes with their experience, with minor clarifications incorporated into the final analysis.

The analytical process involved multiple cycles of reading and re-reading transcripts to develop deep familiarity with the data. Initial codes were generated freely, capturing both semantic content and latent meanings in participant accounts. Candidate themes were developed by grouping codes according to shared conceptual content and TFT dimensional relevance. Theme boundaries were refined through ongoing comparison between coded data and the broader dataset. The final thematic structure was reviewed against the original research questions to ensure analytical coherence and completeness.

4.5 Rigour and Trustworthiness

Rigour was established through multiple strategies aligned with Lincoln and Guba's criteria for trustworthiness in qualitative research . Credibility was supported through prolonged engagement with the research context, member checking with six participants, and reflexive journaling throughout the analytical process. Transferability is supported through thick description of the research context, participant characteristics, and analytical process, enabling readers to assess the applicability of findings to comparable settings. Dependability was ensured through a comprehensive audit trail of analytical decisions, including documentation of coding decisions, theme development rationale, and analytical memos. Confirmability was maintained through reflexive documentation of researcher positionality — including the researcher's professional background, cultural identity, and assumptions — and their potential influence on data collection and interpretation.

4.6 Ethical Considerations

Ethical approval was obtained from the relevant institutional review board prior to data collection. All participants provided written informed consent, with the consent process conducted in Arabic to ensure full comprehension. Anonymity was maintained through participant coding (MHP-01–MHP-32; MGR-01–MGR-03), with no identifying information retained in transcripts or analytical files. Given the conflict context, additional safeguards were implemented including encrypted data storage on secure servers, flexible interview scheduling to accommodate security conditions, and explicit participant withdrawal rights without consequence or explanation required. The sensitivity of mental health topics was acknowledged in the interview approach, with participants offered the option to pause or end interviews at any point. No financial incentives were provided to avoid coercion, given the economic vulnerability of participants in the conflict context.

5. Findings

Four major themes emerged from the analysis, each reflecting distinct dimensions of participants' technological frames regarding AI adoption in Sudan's mental health context. Table 2 presents the thematic structure with corresponding TFT dimensions.

Table 2: Themes and Sub-Themes

Theme	Sub-Themes	TFT Dimension
1. Perceived Value	Efficiency gains; Access expansion; Professional support tool	Nature of Technology
2. Implementation Challenges	Paper-based records; Infrastructure deficits; Digital literacy; Workforce capacity	Technology in Use
3. Ethical Concerns	Privacy and confidentiality; Therapeutic relationship; Data security in conflict	Technology in Use
4. Contextual Adaptation	Cultural and linguistic localisation; Stigma reduction; Post-conflict vision	Technology Strategy

5.1 Introduction to Findings

Table 3: Research Questions, Themes, and Representative Quotes

Research Question	Theme	Representative Quote
Perceived value of AI	Theme 1	*"AI could help us see more patients and reduce the waiting time"* (MHP-04)
Implementation barriers	Theme 2	*"We still use paper files. We don't even have a computer in every room"* (MHP-01)
Ethical concerns	Theme 3	*"The patient must trust that what they say stays private"* (MHP-07)
Contextual adaptation	Theme 4	*"Any AI system must understand our culture, our language, our trauma"* (MGR-01)

The four themes are analytically distinct but empirically interconnected. Participants' enthusiasm for AI's potential value (Theme 1) was consistently qualified by acute awareness of implementation barriers (Theme 2) and ethical imperatives (Theme 3). Contextual adaptation (Theme 4) emerged as a cross-cutting concern that shaped all other themes — participants consistently emphasised that AI adoption in Sudan cannot be a simple transfer of technologies developed elsewhere but must be a contextually grounded, locally driven process.

5.2 Theme 1: Perceived Value and Role of AI

Participants across both groups expressed cautiously optimistic frames regarding AI's potential value, consistently framing AI as a *supportive tool* rather than a replacement for human professionals. This framing was remarkably consistent across professional roles, facility types, and experience levels, suggesting a shared cultural frame about the primacy of human care in mental health.

Mental health professionals emphasised AI's potential to address the overwhelming patient-to-provider ratio. MHP-04 stated: *"We have hundreds of patients and not enough staff. AI could help us see more patients and reduce the waiting time — not replace us, but help us manage the load."* MHP-12 echoed this framing: *"I see AI as an assistant. Like having a very knowledgeable colleague who never sleeps and can remind you of things you might miss."* MHP-02 added a specific clinical application: *"Imagine an AI that could screen patients before they see me — ask about symptoms, history, current functioning — so that when the patient arrives, I already have a baseline. That would save enormous time."*

Managers framed AI primarily through an organisational efficiency and strategic access lens. MGR-01 articulated a vision of AI as a tool for geographic reach: *"The potential is enormous. We could reach people in Darfur, in the displaced camps, who will never see a psychiatrist in their lives. AI could be that first contact."* MGR-03 emphasised decision-support value for non-specialist staff: *"For our staff who are not specialists — community workers, nurses — AI could guide them on what to do, when to refer, what is an emergency. This could save lives."* MGR-02 highlighted documentation and administrative efficiency: *"So much of our time is spent on paperwork, record-keeping, reporting. If AI could automate even part of this, our staff could focus on patients."*

A consistent sub-theme across both groups was the framing of AI as *complementary* to human care, preserving the centrality of the therapeutic relationship. MHP-07 articulated this clearly: *"AI is a tool. The healing comes from the human connection. AI can support that connection, prepare for it, follow up after it — but it cannot replace it."* MHP-10 reinforced this: *"In psychiatry, we treat the person, not the diagnosis. AI can help with the diagnosis, with the data, with the follow-up. But the relationship — that is ours."*

5.3 Theme 2: Implementation Challenges

The most prominent theme across all 35 interviews concerned the fundamental implementation barriers facing AI adoption in Sudan's mental health context. The exclusive reliance on paper-based records emerged as the most critical structural barrier, framed by participants as a prerequisite challenge that must be resolved before any AI application can be considered.

MHP-01 described the baseline reality with striking directness: *"We still use paper files. We don't even have a computer in every room. How can we talk about AI when we don't have basic digital infrastructure?"* MHP-08 elaborated on the implications: *"Every patient record is a physical file. If the file is lost, the information is gone. There is no backup, no system. Before AI, we need electronic records."* MHP-03 connected the paper records issue to data quality: *"Our records are incomplete, inconsistent, sometimes illegible. AI needs data — clean, structured, accessible data. We don't have that."*

Participants identified a cascading set of infrastructure challenges beyond records. Unreliable electricity was identified by 27 of 35 participants as a fundamental barrier: *"We have power cuts every day. Sometimes for hours. Any digital system needs reliable power. Without that, nothing works"* (MHP-09). Limited internet connectivity was cited by 31 participants as a constraint on cloud-based AI applications. MGR-02 noted the maintenance challenge: *"Even if we get the technology, who maintains it? We don't have IT staff. When something breaks, it stays broken."* MHP-14 raised the issue of physical security: *"During the conflict, equipment was stolen or destroyed. Investing in digital infrastructure in an active conflict zone carries enormous risk."*

Digital literacy was identified as a significant barrier at both individual and organisational levels. MHP-06 acknowledged: *"I know how to use a phone, but I have never used clinical software. Training would take time, and we are already stretched."* MHP-11 noted generational variation: *"Younger staff are more comfortable with technology. But the senior clinicians who make decisions — many of them have never used a computer for clinical work."* MGR-03 framed this as a systemic challenge: *"The problem is not just one person learning. The whole system needs to change — documentation, workflows, supervision, reporting. That takes years, not weeks."*

Workforce shortages further compounded implementation challenges. MHP-11 observed: *"We are so few. Adding a new technology means adding new tasks — learning, maintaining, troubleshooting. Without more staff, AI could actually increase the burden on existing workers."* MGR-01 raised the issue of staff turnover: *"We train people, then they leave — for better* *salaries, for safety, for other countries. Any investment in digital capacity faces this constant drain."*

5.4 Theme 3: Ethical and Human-Centred Concerns

Participants articulated strong ethical frames centred on privacy, confidentiality, data security, and the preservation of therapeutic relationships — concerns particularly heightened by Sudan's conflict and post-conflict context. These ethical concerns were not abstract; they were grounded in specific, lived experiences of institutional distrust and data vulnerability.

Privacy and confidentiality concerns were universal across all 35 participants. MHP-07 stated: *"The patient must trust that what they say stays private. If they think the government, or anyone, can access their mental health records, they will not come. In Sudan, with everything that has happened, this fear is very real."* MHP-03 connected data security to the conflict context: *"During the war, patient records were destroyed or taken. People are afraid. Digital records could be hacked or seized. We need very strong protections."* MHP-13 raised the specific vulnerability of mental health data: *"Mental health records are the most sensitive. A diagnosis of depression, of trauma, of psychosis — in the wrong hands, this can be used against a person. We must be extremely careful."*

The therapeutic relationship was framed as inviolable across all MHP interviews. MHP-04 articulated: *"Mental health is different from other medicine. The relationship between the therapist and the patient is itself the treatment. AI cannot replicate that. It must never try to."* MHP-12 added nuance: *"AI could help me prepare better, document better, follow up better — but the moment of connection, the empathy, the presence — that is human."* MHP-05 raised the cultural dimension of therapeutic relationships in Sudan: *"Trust is built slowly here, through community, through family, through shared experience. An AI cannot build that kind of trust. It can only support a relationship that humans have already built."*

Managers raised governance and accountability concerns that extended beyond individual clinical ethics. MGR-01 questioned liability: *"If AI gives wrong advice and a patient is harmed, who is responsible? The doctor? The hospital? The company that made the AI? We need clear rules before we start."* MGR-02 raised the issue of informed consent: *"Do patients understand what AI is? Do they consent to their data being processed by an algorithm? These are not simple questions."* MGR-03 expressed concern about commercial exploitation: *"Technology companies come to developing countries because the regulations are weak. We must protect our patients from being used as data sources for systems that will be sold elsewhere."*

5.5 Theme 4: Contextual Adaptation and Future Vision

Participants consistently emphasised that any AI system deployed in Sudan must be deeply adapted to local cultural, linguistic, and contextual realities. Generic AI tools designed for other populations were viewed as inadequate and potentially harmful. This theme combined critical realism about current constraints with genuine aspirational vision for a digitally transformed future.

Cultural and linguistic adaptation was identified as non-negotiable by all participants. MHP-13 stated: *"Arabic is not enough — we speak Sudanese Arabic, with our own expressions for distress, for illness, for healing. An AI trained on Egyptian or Saudi data will not understand us."* MHP-05 elaborated: *"Mental health concepts are expressed differently here. Trauma is described through the body, through spiritual language. AI must learn this language."* MHP-02 raised the challenge of culturally specific diagnostic categories: *"Some of what we see clinically does not map onto Western diagnostic categories. An AI trained on DSM criteria may miss important presentations that are specific to our context."*

Stigma reduction emerged as a potential AI benefit within this theme. MGR-03 noted: *"Sometimes people are ashamed to talk to a human about mental illness. An AI — if it is private and trusted — might be the first step. It could reduce the barrier of shame."* MHP-09 agreed: *"Young people especially might be more comfortable talking to a screen than to a person about mental health. If AI can be that first contact — that anonymous, safe space — it could bring people into care who would never come otherwise."*

Despite current infrastructure deficits, participants articulated an aspirational future vision for AI integration that was both specific and grounded. MGR-01 offered: *"I imagine a Sudan where community health workers use AI on their phones to screen for depression, to refer to specialists, to follow up. This is possible. But first, we need peace, we need infrastructure, we need training."* MHP-04 concluded with a phrase that captures the study's central tension: *"The technology will come. The question is whether we are ready for it — and whether it is* *ready for us."* MHP-08 expressed a conditional optimism: *"If the conditions are right — if we have the infrastructure, the training, the governance — I am excited about what AI could do for our patients. The potential is real."*

5.6 Summary of Findings

The four themes collectively reveal a stakeholder landscape characterised by genuine enthusiasm for AI's potential value, tempered by acute awareness of structural barriers and ethical imperatives. TFT analysis reveals frame alignment between MHPs and MGRs on core values — AI as supportive, not replacement; ethical safeguards as non-negotiable; cultural adaptation as essential — but divergence in emphasis: MHPs prioritise clinical ethics and therapeutic relationships, while MGRs emphasise organisational strategy, governance, and resource management. The Digital Readiness Gap emerges as the foundational challenge that must be addressed before any AI adoption can be meaningfully pursued. Crucially, participants did not frame this gap as a reason to abandon AI ambitions, but as a sequencing challenge — a set of prerequisites to be addressed systematically before AI adoption can begin.

6. Discussion

6.1 Interpreting AI Through TFT

The application of TFT to Sudan's mental health context reveals that stakeholders have constructed coherent, contextually grounded frames about AI adoption despite having no direct experience with AI systems in clinical practice. This finding is itself theoretically significant: it demonstrates that TFT frames can be prospective as well as retrospective — formed through professional experience, cultural context, and abstract knowledge of technology rather than through direct use. Across TFT's three dimensions, distinct patterns emerge that both align with and extend existing literature.

Table 4: Comparison of TFT Frames — MHP vs. MGR

TFT Dimension	MHP Frame	MGR Frame
Nature of Technology	AI as clinical support tool; assistant not replacement; ethically bounded	AI as efficiency and access enabler; strategic asset; organisational transformer
Technology in Use	Clinical workflow integration; patient safety; therapeutic relationship preservation; cultural fit	Organisational process change; staff training; infrastructure development; governance
Technology Strategy	Bottom-up, clinician-led adoption; ethics-first; community trust building	Top-down, policy-driven; infrastructure investment priority; regulatory framework development

Regarding the *nature of technology*, both groups frame AI as fundamentally assistive rather than autonomous — consistent with findings from healthcare AI adoption studies in other LMICs . This frame contrasts with techno-optimist narratives common in high-income country research, where AI is sometimes framed as potentially replacing clinical roles . The Sudanese context appears to produce more pragmatic, human-centred frames, likely shaped by the lived experience of working in resource-constrained environments where human connection is the primary — and often only — therapeutic resource. The consistent framing of AI as a tool that supports rather than supplants human care reflects both a professional identity claim and a realistic assessment of AI's current limitations.

Regarding *technology in use*, the universal emphasis on paper-based records as a foundational barrier is a distinctive finding that sets this study apart from most AI adoption literature. Unlike studies in contexts with partial digital infrastructure, Sudanese stakeholders frame AI adoption as requiring a complete digital transformation of health records systems before any AI application is feasible. This represents a qualitatively different adoption challenge — not incremental digital enhancement but wholesale infrastructure creation . The TFT lens reveals that this framing is not simply a practical concern but an interpretive one: stakeholders understand AI as a technology that requires a specific kind of digital ecosystem, and they correctly identify the absence of that ecosystem as the primary barrier.

Regarding *technology strategy*, the divergence between MHP and MGR frames is analytically significant. MHPs emphasise a bottom-up, ethics-first approach to adoption, while MGRs favour top-down, policy-driven strategies. This frame incongruence, identified by TFT as predictive of adoption difficulties , suggests that successful AI implementation will require deliberate alignment mechanisms — participatory design processes, joint governance structures, and shared decision-making frameworks that bring clinical and managerial perspectives into productive dialogue.

6.2 The Digital Readiness Gap

The most significant theoretical contribution of this study is the articulation of the *Digital Readiness Gap* as a distinct construct for understanding AI adoption in pre-digital healthcare environments. Unlike the *digital divide* — which describes differential access to technology across populations — the Digital Readiness Gap describes the structural prerequisite deficit that exists when a healthcare system lacks the foundational digital infrastructure (electronic records, reliable connectivity, digital literacy, IT support capacity) upon which AI applications depend.

Sudan's mental health system exemplifies this gap in its most extreme form: 100% paper-based records, no electronic health information systems, limited IT infrastructure, unreliable power and connectivity, and a workforce with minimal digital experience. In this context, AI adoption is not merely challenging — it is structurally premature. Addressing the Digital Readiness Gap requires sequential investment: first in electronic records and basic digital infrastructure, then in digital literacy and workforce capacity, and only then in AI applications . Attempting to skip phases — deploying AI before electronic records exist, or investing in digital literacy before infrastructure is in place — is likely to result in failed implementations, wasted resources, and stakeholder disillusionment.

The Digital Readiness Gap concept has broader applicability beyond Sudan. Many countries in sub-Saharan Africa, South Asia, and fragile state contexts share similar characteristics: health systems that are predominantly or entirely paper-based, with limited digital infrastructure and workforce capacity. For these contexts, the Digital Readiness Gap provides a diagnostic framework for assessing AI adoption readiness and a planning

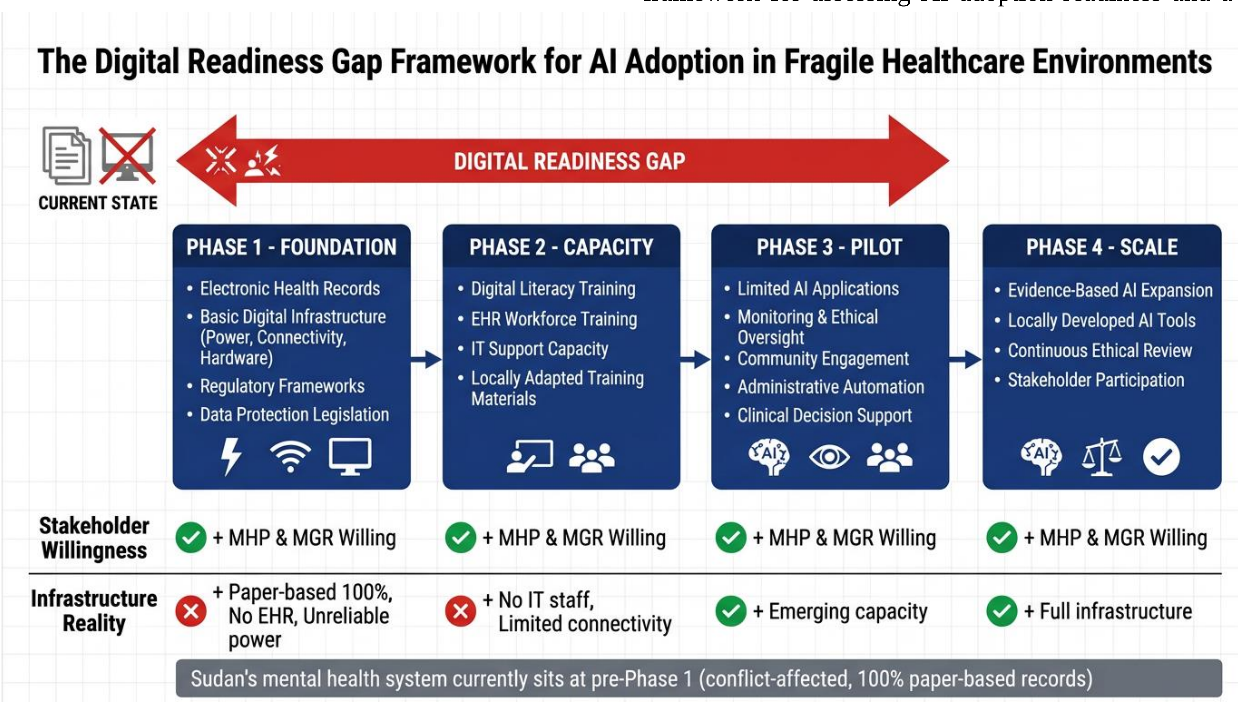

Figure 1:The Digital Readiness Gap Framework for AI Adoption in Fragile Healthcare Environments

tool for sequencing the investments required to close it. International organisations and donors investing in AI health solutions in LMICs would benefit from incorporating Digital Readiness Gap assessment as a standard component of implementation planning.

Figure 1. The Digital Readiness Gap Framework illustrates the four sequential phases required for AI adoption in fragile healthcare environments. The red double-headed arrow represents the gap between Sudan's current pre-digital state (100% paper-based records, conflict-affected infrastructure) and AI-readiness. Notably, stakeholder willingness (MHP and MGR) is uniformly positive across all phases, while infrastructure reality presents critical barriers in Phases 1 and 2 that must be systematically addressed before AI applications can be responsibly piloted.

6.3 Electronic Records and Data Infrastructure

Participants' unanimous identification of paper-based records as the primary barrier reflects a fundamental infrastructural reality that distinguishes Sudan's context from most AI adoption literature. Electronic Health Record (EHR) systems are typically assumed as a baseline in AI healthcare research . In Sudan, the absence of EHRs represents not a gap in AI readiness but a gap in basic health informatics infrastructure that predates any AI consideration.

The implications for AI adoption strategy are significant and sequential. Any AI implementation roadmap for Sudan must begin with EHR development and deployment — a multi-year undertaking requiring substantial investment, training, and change management. Attempting to implement AI applications on a paper-based foundation would be technically infeasible and clinically unsafe . The transition from paper-based to electronic records is itself a complex organisational change requiring careful attention to workflow redesign, staff training, data migration, and sustained post-implementation support. International experience from EHR implementation in LMICs highlights the importance of phased approaches, local customisation, and community engagement . Sudan's mental health sector would benefit from learning these lessons before embarking on AI adoption — and from positioning EHR implementation as Phase 1 of a longer digital transformation journey.

6.4 Ethical Considerations and Human-Centred Care

The strong ethical frames articulated by participants — particularly around privacy, confidentiality, and therapeutic relationships — reflect both universal principles of healthcare ethics and context-specific concerns shaped by Sudan's conflict experience. The fear that digital health records could be accessed, seized, or weaponised by conflict parties is not hypothetical in Sudan's context; health data has been instrumentalised in conflict settings globally, and the risks are acute in a country where state actors, armed groups, and external parties have all demonstrated willingness to exploit civilian vulnerabilities .

These findings reinforce calls for human-centred AI design in healthcare , , and extend them to conflict-affected contexts where standard data governance assumptions may not hold. Robust data security, community-controlled governance structures, and explicit protections against conflict-related data access must be built into any AI health system deployed in fragile states. The therapeutic relationship — consistently foregrounded by MHP participants — represents a non-negotiable boundary that AI systems must be designed to support rather than supplant. This aligns with emerging ethical frameworks for AI in mental health that position human oversight and relational care as inviolable principles , .

The governance concerns raised by MGR participants — regarding liability, informed consent, and commercial exploitation — point to the need for regulatory frameworks that are specifically adapted to the Sudanese context. Generic AI ethics guidelines developed in high-income countries are unlikely to adequately address the specific vulnerabilities and power dynamics of fragile state healthcare systems. Context-specific regulatory development, involving Sudanese health authorities, civil society organisations, and community representatives, is an essential prerequisite for ethical AI adoption.

6.5 Cultural Context, Stigma, and Post-Conflict Realities

The emphasis on cultural and linguistic adaptation reflects a well-documented challenge in global digital health — the tendency for AI systems to be developed in high-income contexts and deployed without adequate localisation . For Sudan, this challenge is compounded by the diversity of Arabic dialects, the cultural specificity of mental health expression, the absence of validated Sudanese mental health assessment tools in digital formats, and the profound impact of conflict-related trauma on how distress is experienced and expressed. An AI system trained on data from other Arabic-speaking populations — or, worse, translated from English-language training data — would lack the cultural and linguistic competence to be clinically useful or safe in the Sudanese context.

The paradoxical potential of AI for stigma reduction — identified by several participants — is a noteworthy finding with important implications for service design. In contexts where mental health stigma is severe and deeply embedded in social and cultural norms, the perceived anonymity of AI-mediated interactions may lower barriers to help-seeking. This aligns with emerging evidence from other LMIC contexts where chatbot-mediated mental health support has shown promise precisely because it offers a stigma-free, private entry point to care , . However, this potential must be approached cautiously: the same anonymity that reduces stigma barriers may also reduce the safety net of human clinical oversight, particularly for individuals at acute risk. Careful system design, with clear pathways from AI-mediated first contact to human clinical assessment, is essential.

Post-conflict realities add a further layer of complexity. Participants' aspirational visions of AI-enabled mental health care must be understood against the backdrop of a health system that has been severely damaged by conflict, with many facilities destroyed, staff displaced, and supply chains disrupted. The reconstruction of health infrastructure in post-conflict settings is itself a multi-decade undertaking, and AI adoption must be situated within — rather than ahead of — this broader reconstruction agenda. International actors investing in Sudan's health system recovery should consider digital infrastructure development, including EHR systems, as an integral component of health system reconstruction rather than a later-stage add-on.

6.6 Proposed Conceptual Framework for AI Adoption in Fragile Healthcare Environments

Based on the findings and TFT analysis, this study proposes a sequential framework for AI adoption in fragile, resource-constrained healthcare environments comprising four phases:

1. **Foundation Phase**: Establish electronic health records, basic digital infrastructure (reliable power, connectivity, hardware), and regulatory frameworks for health data governance. Develop context-specific data protection legislation and conflict-sensitive data security protocols. This phase addresses the Digital Readiness Gap at its most fundamental level.

1. **Capacity Phase**: Develop digital literacy among health workers at all levels, from community health workers to senior clinicians. Train workforce in EHR use and digital documentation. Build IT maintenance and technical support capacity within health facilities and the broader health system. Develop locally adapted training materials in Sudanese Arabic.

1. **Pilot Phase**: Implement limited, well-governed AI applications in selected facilities with robust monitoring, community engagement, and ethical oversight mechanisms. Prioritise applications with the highest potential impact and lowest risk — such as administrative automation, appointment scheduling, and clinical decision support for non-specialist staff. Conduct rigorous evaluation of pilot outcomes, including unintended consequences.

1. **Scale Phase**: Expand evidence-based AI applications based on pilot learning, with continuous ethical review, stakeholder participation, and adaptive management. Invest in locally developed AI tools trained on Sudanese clinical data and adapted to Sudanese cultural and linguistic contexts. Establish ongoing governance mechanisms for AI oversight.

This framework explicitly incorporates the Digital Readiness Gap concept, positioning AI adoption as the culmination of a broader digital transformation process rather than its starting point. It also reflects the TFT insight that frame alignment between stakeholder groups — achieved through participatory processes in the Foundation and Capacity phases — is a prerequisite for successful AI adoption in the Pilot and Scale phases. The framework is intended as a flexible guide rather than a rigid prescription, recognising that the pace and sequencing of phases will vary depending on local conditions, available resources, and evolving conflict dynamics.

7. Conclusion

7.1 Summary of Key Contributions

This study makes four principal contributions to the literature on AI adoption in healthcare and digital health in fragile states:

1. **Empirical evidence from a conflict-affected, pre-digital context**: The study provides rare qualitative data on AI adoption frames from Sudan's mental health sector — a context almost entirely absent from health informatics and digital health research. The findings document a stakeholder community that is thoughtful, ethically engaged, and cautiously optimistic about AI's potential, while acutely aware of the structural prerequisites that must be met before adoption can begin.

1. **Extension of TFT to fragile healthcare environments**: The application of TFT to a pre-digital, conflict-affected setting extends the theory's scope and demonstrates its utility for analysing prospective adoption frames — frames formed in the absence of direct technology experience. This extension enriches TFT's theoretical toolkit and opens new avenues for its application in global health contexts.

1. **The Digital Readiness Gap construct**: This study introduces and theorises the Digital Readiness Gap as a distinct analytical concept for understanding AI adoption prerequisites in pre-digital health systems. The construct provides a diagnostic and planning tool applicable beyond Sudan to other LMICs and fragile states facing similar infrastructural deficits.

1. **A sequential adoption framework**: The proposed four-phase framework provides a structured, evidence-based roadmap for AI adoption in fragile healthcare environments, addressing both technical and human-centred dimensions and explicitly incorporating the Digital Readiness Gap as a foundational challenge to be systematically addressed.

7.2 Practical Recommendations

Based on the findings, the following recommendations are offered for policymakers, health system managers, and technology developers:

1. **Prioritise EHR infrastructure** as the foundational prerequisite for any AI health initiative in Sudan. International donors and development partners should include digital infrastructure development as a core component of health system reconstruction funding.

2. **Invest in digital literacy** programmes for mental health workers at all levels before introducing AI tools. Training should be contextually adapted, practically oriented, and sustained over time.

3. **Develop culturally adapted AI tools** in Sudanese Arabic, co-designed with local mental health professionals, patients, and communities.

4. **Establish robust data governance** frameworks with explicit conflict-context protections, including community-controlled data governance structures and conflict-sensitive data security protocols.

5. **Adopt participatory design** approaches that bring MHP and MGR frames into alignment, reducing the adoption incongruence identified in this study.

6. **Integrate stigma-reduction** potential of AI into mental health access strategies, while maintaining human clinical oversight for individuals at acute risk.

7.3 Limitations

Several limitations should be acknowledged. The conflict context constrained sampling, limiting geographic diversity and potentially excluding perspectives from the most conflict-affected areas — particularly Darfur, South Kordofan, and Blue Nile state, where mental health needs are most acute. While the expanded sample of 35 participants provides greater depth than smaller qualitative studies, the concentration of participants in Khartoum and Omdurman reflects access constraints rather than a deliberate geographic focus. The two-phase data collection, separated by 18 months of conflict, may have introduced temporal variation in participant frames, though member checking and cross-phase analytical comparison suggested reasonable consistency in core themes. The study is limited to Sudan and caution is warranted in generalising findings to other LMIC contexts, though the Digital Readiness Gap construct and the sequential adoption framework may have broader applicability. All interviews were conducted in Arabic and translated to English, with potential for nuance loss despite professional translation and member checking. The absence of patient and community perspectives represents a significant gap that future research should address — the perspectives of those who would ultimately use or be affected by AI mental health tools are essential for a complete picture of adoption dynamics. Finally, as a qualitative study, the findings are not intended to be statistically representative but to provide deep, contextually grounded insights that can inform theory development and practice.

7.4 Future Research Directions

Future research should examine patient and community perspectives on AI in mental health care in conflict-affected settings, providing the demand-side complement to this study's supply-side analysis. Longitudinal studies tracking frame evolution as digital infrastructure develops in Sudan — potentially over a decade or more — would provide valuable insights into how adoption frames change as the Digital Readiness Gap is progressively closed. Comparative studies across sub-Saharan African countries at different stages of digital health development would test the generalisability of the Digital Readiness Gap construct and the sequential adoption framework across diverse LMIC contexts. Implementation science studies examining EHR deployment in fragile states would provide the foundational evidence base needed to support Phase 1 of the proposed framework, drawing lessons from comparable implementations in post-conflict settings. Research examining the specific design requirements for culturally adapted AI mental health tools in Arabic-speaking, post-conflict contexts — including participatory design studies with Sudanese clinicians and patients — would directly support the practical recommendations of this study. Finally, mixed-methods studies combining TFT frame analysis with quantitative adoption intention measures could provide more comprehensive evidence for AI health adoption policy in LMICs, bridging the gap between interpretive and positivist research traditions.

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