Adaptive Triage and Local Advisory System (ATLAS): AI-Enhanced Clinical Decision Support for Resource-Limited Healthcare Settings

A Thesis Presented
by

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to

The Department of Mechanical and Industrial Engineering

in partial fulfillment of the requirements
for the degree of

Master of Science

in

Data Analytics Engineering

Northeastern University
Boston, Massachusetts

December 2025

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List of Acronyms

AI	Artificial Intelligence
API	Application Programming Interface
ATLAS	Adaptive Triage and Local Advisory System
CDSS	Clinical Decision Support System
CQL	Clinical Quality Language
CRDT	Conflict-free Replicated Data Type
CRF	Case Report Form
DAK	Digital Adaptation Kit
DSR	Design Science Research
FHIR	Fast Healthcare Interoperability Resources
GDPR	General Data Protection Regulation
HCI	Human-Computer Interaction
HIPAA	Health Insurance Portability and Accountability Act
IMCI	Integrated Management of Childhood Illness
IRB	Institutional Review Board
LLM	Large Language Model
LMIC	Low and Middle-Income Countries

MAPS	mHealth Assessment and Planning for Scale
MIMIC	Medical Information Mart for Intensive Care
NASSS	Non-adoption, Abandonment, Scale-up, Spread, Sustainability
NCD	Non-Communicable Disease
PEN	Package of Essential NCD interventions
PWA	Progressive Web Application
RAG	Retrieval-Augmented Generation
RE-AIM	Reach, Effectiveness, Adoption, Implementation, Maintenance
SMART	Standards-based, Machine-readable, Adaptive, Requirements-based, Testable
SUS	System Usability Scale
TAM	Technology Acceptance Model
UI	User Interface
UX	User Experience
WHO	World Health Organization

Abstract

Healthcare providers in resource-limited settings face significant challenges. These include inconsistent internet connectivity, limited access to specialized knowledge, and constrained computational resources. Despite serving 3.6 billion people worldwide, most existing clinical decision support systems are not designed for the unique constraints of low-resource settings. This creates a critical gap where sophisticated clinical guidance is most needed.

This project proposes ATLAS (Adaptive Triage and Local Advisory System). ATLAS is the first clinical decision support system that integrates offline-first Progressive Web Application architecture with AI-enhanced clinical decision making using large language models. The system implements WHO SMART Guidelines specifically for resource-limited healthcare settings. ATLAS addresses the fundamental paradox where clinical decision support systems are most sophisticated where specialist knowledge is already available, and least capable where such support is most critically needed.

The system combines several technical innovations. These include Next.js-based PWA with comprehensive offline functionality using service workers and IndexedDB. Tree-structured Conflict-free Replicated Data Types (CRDTs) provide healthcare data synchronization. AI-powered recommendations use modern language models with Retrieval-Augmented Generation workflows. The system includes systematic WHO SMART Guidelines implementation from machine-readable FHIR resources to executable Clinical Quality Language logic. Context-aware interfaces are optimized for high-stress clinical environments.

The research employs a mixed-methods explanatory sequential design grounded in Design Science Research methodology. Multiple established frameworks are integrated for comprehensive evaluation, including NASSS and RE-AIM implementation science frameworks, the WHO MAPS assessment toolkit, and the DeLone & McLean information systems success model. The methodology addresses critical validation requirements through external datasets and expert consensus from board-certified physicians with resource-limited experience.

Key contributions include advancing understanding of offline-first architecture patterns for healthcare applications. The research demonstrates novel approaches to AI-clinical guideline integration through WHO SMART Guidelines. It provides empirical evidence for CRDT effectiveness in healthcare synchronization and offers validated frameworks for technology deployment in resource-constrained environments. Implementation science contributions include reproducible approaches to complex technology deployment and evidence-based strategies for sustainable clinical decision support adoption.

By addressing critical gaps in existing healthcare technologies, ATLAS has the potential to significantly impact healthcare delivery in underserved regions. The system advances the fields of health informatics, artificial intelligence, and human-computer interaction. The interdisciplinary approach demonstrates that sophisticated clinical decision support can be made accessible and reliable in precisely those settings where it is most critically needed.

Acknowledgments

I would like to express my sincere gratitude to my principal advisor, Dr. Sivarit Sultornsanee, for his guidance and support throughout this research project. His expertise in data analytics and health informatics has been invaluable in shaping this work.

I am grateful to the faculty and staff of Northeastern University's Data Analytics Engineering program for providing the interdisciplinary foundation necessary for this complex project spanning computer science, healthcare informatics, and global health.

Special thanks to the healthcare professionals who have shared their experiences working in resource-limited settings, providing crucial context and requirements that have informed ATLAS's design. Their insights have been essential for ensuring this research addresses real-world clinical needs.

I wish to acknowledge the broader research community working on digital health solutions for resource-limited settings, whose foundational work has made this research possible. The collaborative efforts across institutions and disciplines continue to advance the field of global health informatics.

Finally, I thank my family and friends for their unwavering support and encouragement throughout this academic journey.

Chapter 1

Introduction

1.1 The Critical Gap in Global Health Technology

In a rural primary health center in Tanzania, a community health worker faces a critical decision. A pregnant woman presents with severe headache, visual disturbances, and elevated blood pressure at 36 weeks gestation—potential signs of preeclampsia requiring immediate intervention. The health worker has limited obstetric training, no immediate specialist consultation available, and intermittent internet connectivity that has been down for three hours. The nearest referral hospital is 90 kilometers away on challenging roads. This scenario, repeated thousands of times daily across resource-limited settings, epitomizes the confluence of challenges that digital health technologies must address: limited specialist knowledge, infrastructure constraints, and the critical need for reliable clinical decision support when it matters most.

Healthcare providers in resource-limited settings serve an estimated 3.6 billion people worldwide. Yet they face systematic barriers that compromise their ability to deliver optimal care [1]. These challenges include limited access to specialized medical knowledge, inconsistent internet connectivity affecting 40% of health facilities in Sub-Saharan Africa [2], constrained computational resources with 60% of facilities lacking reliable electricity [3], high patient-to-provider ratios averaging 1:2,500 in rural areas compared to 1:400 in urban settings, and

limited access to diagnostic equipment increasing reliance on clinical judgment for 80% of diagnoses [4].

The World Health Organization has identified clinical decision support systems (CDSS) as critical tools to address these challenges. These systems have potential to improve diagnostic accuracy by 20-30% and reduce medical errors by up to 15% in resource-limited settings [4]. However, existing CDSS are predominantly designed for high-resource environments. They assume reliable internet connectivity, advanced devices, and specialized technical support—assumptions that fail in precisely the settings where these systems are most needed.

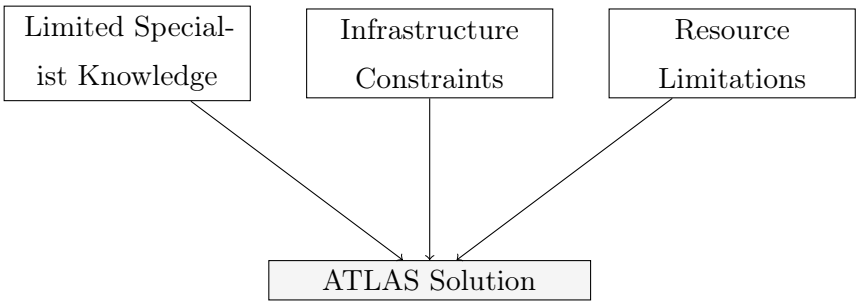

Figure 1.1: Key Challenges in Resource-Limited Healthcare Settings Addressed by ATLAS

1.2 The Convergence Opportunity

Three technological developments have matured simultaneously to create an unprecedented opportunity for addressing this gap. First, Progressive Web Applications (PWAs) have achieved production-ready offline functionality. They enable sophisticated web applications to operate reliably without internet connectivity while maintaining cross-platform compatibility [5]. Major healthcare organizations have demonstrated successful PWA deployments for clinical applications, showing feasibility at scale [6].

Second, Conflict-free Replicated Data Types (CRDTs) have evolved to handle complex healthcare data synchronization challenges. Recent developments in tree-structured CRDTs provide mathematically proven conflict resolution for concurrent updates across multiple healthcare providers—a critical requirement for collaborative clinical environments [7].

Third, Large Language Models (LLMs) have demonstrated substantial clinical capabilities. Recent evaluations show LLMs achieving over 85% accuracy in clinical diagnosis scenarios using standardized medical datasets—performance approaching human specialist levels in many domains [8]. When augmented with Retrieval-Augmented Generation (RAG) workflows incorporating clinical guidelines, LLMs can provide contextually relevant recommendations while maintaining transparency and explainability.

Table 1.1: Technological Convergence Enabling ATLAS Development

Technology	**Key Capability**	**ATLAS Application**
Progressive Web Apps	Offline functionality	Continuous operation without connectivity
CRDTs	Conflict-free sync	Multi-provider collaboration
Large Language Models	Clinical reasoning	AI-enhanced decision support
WHO SMART Guidelines	Structured knowledge	Evidence-based recommendations

1.3 The WHO SMART Guidelines Framework: An Underutilized Foundation

The World Health Organization's SMART (Standards-based, Machine-readable, Adaptive, Requirements-based, Testable) Guidelines framework provides a proven pathway from narrative clinical guidelines to executable digital decision support [9]. This five-layer framework progresses from L0 (narrative guidelines) through L1 (semi-structured data dictionaries) and L2 (FHIR-based machine-readable content) to enable L3 (Clinical Quality Language logic) and L4 (deployed decision support systems).

Despite WHO endorsement and demonstrated effectiveness in reducing guideline implementation time, SMART Guidelines adoption remains limited [10]. No existing implementations combine SMART Guidelines with modern AI capabilities and offline-first

architecture. This represents a significant missed opportunity for systematic clinical decision support in resource-limited settings.

1.4 Problem Statement and Research Gap

Current clinical decision support systems face a fundamental paradox: they are most sophisticated where specialist knowledge is already available, and least capable where such support is most critically needed. Existing solutions fall into two categories, both inadequate for resource-limited settings:

Category 1: Sophisticated but Infrastructure-Dependent Systems including Epic's Cognitive Computing Platform, UpToDate, and IBM Watson Health require continuous connectivity, advanced devices, and specialized technical support. While clinically comprehensive, they fail completely when offline and are prohibitively expensive for resource-limited settings.

Category 2: Resource-Appropriate but Clinically Limited Systems such as WHO's IMCI Digital and CommCare provide basic functionality for resource-constrained environments. However, they offer minimal decision support, lack AI capabilities, and provide no sophisticated synchronization for collaborative care.

> The critical research gap is the absence of integrated systems that successfully combine offline-first architecture, AI-enhanced clinical decision support, structured clinical guideline implementation, and interfaces designed for high-stress, resource-constrained environments. While individual technologies show promise, no existing solution integrates these elements into a cohesive system suitable for real-world deployment where sophisticated support is most needed.

Recent systematic reviews confirm this gap. Bright et al.'s comprehensive analysis of clinical decision support systems found minimal evaluation of offline capability or resource-limited deployment [11]. Labrique et al.'s analysis of digital health scaling in LMICs identified persistent connectivity and sustainability challenges despite technological advances [12]. The

ongoing validation challenges in AI-enabled medical devices emphasize the critical importance of rigorous evaluation from inception [13].

Given the compressed timeline of this Master's project (September-December 2025), this research focuses on developing a proof-of-concept prototype and conducting initial validation rather than full-scale implementation and deployment. This scope is appropriate for demonstrating feasibility and core concepts while contributing meaningful insights to the field.

1.5 ATLAS: Addressing the Integration Challenge

This project proposes ATLAS (Adaptive Triage and Local Advisory System), the first clinical decision support system specifically designed to bridge this gap by integrating:

1. **Offline-first Progressive Web Application architecture** ensuring continuous functionality regardless of connectivity status, with intelligent synchronization when networks become available
2. **AI-enhanced clinical decision support** using state-of-the-art LLMs with RAG-augmented workflows, providing contextually relevant recommendations while maintaining transparency and explainability
3. **WHO SMART Guidelines implementation** as the foundational clinical knowledge framework, ensuring evidence-based recommendations aligned with international standards while enabling local adaptation
4. **Tree-structured CRDT synchronization** providing mathematically proven conflict resolution for collaborative clinical environments, essential for multi-provider care coordination
5. **Context-aware recommendation engine** that adapts guidance based on locally available resources, provider expertise levels, and patient characteristics
6. **Multi-modal interface design** optimized for high-stress clinical environments, supporting touch, voice, and structured input across diverse device capabilities

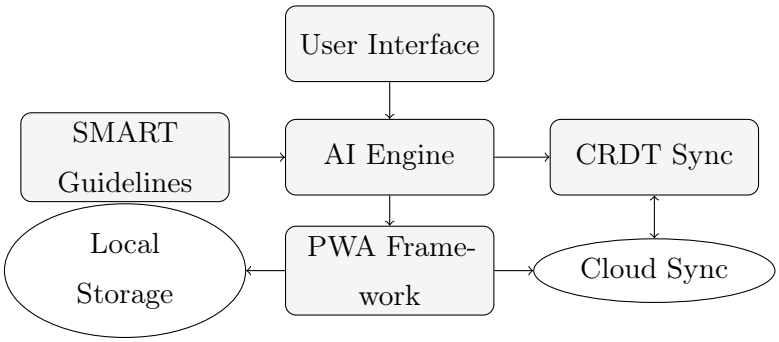

Figure 1.2: ATLAS System Architecture Overview

1.6 Research Objectives

The primary goal of this research is to develop and rigorously evaluate ATLAS as a clinical decision support system that functions effectively in resource-limited healthcare settings. The specific objectives are:

1. **Design and implement an offline-first clinical decision support architecture** that maintains full functionality without internet connectivity while enabling intelligent synchronization when connections become available, validated through comprehensive performance testing under various network conditions
2. **Develop and validate an AI-enhanced recommendation engine** integrating large language models with WHO SMART Guidelines through RAG-augmented workflows, achieving $\geq$80% diagnostic accuracy and $\geq$90% treatment appropriateness compared to expert consensus
3. **Create a production-ready CRDT synchronization system** for healthcare data that ensures conflict-free replication across multiple devices, validated through stress testing with concurrent operations and formal verification of convergence properties
4. **Implement WHO SMART Guidelines L2-L4 transformation** from FHIR-based machine-readable content through Clinical Quality Language logic to executable decision support, demonstrated with at least three clinical domains (maternal health, infectious diseases, non-communicable diseases)

5. **Evaluate system effectiveness using established frameworks** including NASSS and RE-AIM for implementation analysis, WHO MAPS for scale-readiness assessment, and DeLone & McLean for information systems success evaluation, with mixed-methods evaluation combining quantitative performance metrics and qualitative implementation insights
6. **Demonstrate clinical utility and safety** through rigorous validation using external datasets, expert evaluation, and pilot deployment with continuous monitoring, following established guidelines for AI-enabled medical devices

1.7 Significance and Expected Impact

This research addresses critical gaps in both health informatics theory and global health practice. The theoretical contributions include advancing understanding of offline-first architecture patterns for healthcare applications, demonstrating novel approaches to AI-clinical guideline integration, and providing empirical evidence for CRDT effectiveness in healthcare synchronization scenarios.

The practical impact extends to improving healthcare delivery in resource-limited settings through evidence-based decision support that functions reliably in challenging environments. By making sophisticated clinical guidance available to frontline health workers regardless of connectivity status, ATLAS has potential to improve diagnostic accuracy, reduce medical errors, and enhance care quality for the 3.6 billion people served by resource-limited health systems.

The implementation science contributions include demonstrating reproducible approaches to technology deployment in resource-constrained environments, providing validated frameworks for assessing scale-readiness of digital health interventions, and offering evidence-based strategies for sustainable technology adoption in LMICs.

1.8 Thesis Structure and Overview

This thesis is organized to systematically address the research objectives through rigorous investigation and evaluation:

Chapter 2 provides a comprehensive literature review organized thematically to synthesize current knowledge across clinical decision support systems, AI applications in healthcare, WHO digital health guidelines, offline-first architectures, and implementation science for resource-limited settings. The review identifies specific gaps that ATLAS addresses and establishes the theoretical foundation for the research.

Chapter 3 details the comprehensive methodology for developing and evaluating ATLAS, including the design science research approach, mixed-methods evaluation framework, multi-stage validation process, and specific data collection instruments. The methodology integrates established frameworks (NASSS, RE-AIM, WHO MAPS) to ensure rigorous assessment of both technical performance and implementation feasibility.

Chapter 4 presents the system design and architecture, detailing the technical implementation of offline-first PWA architecture, AI-enhanced recommendation engine, CRDT synchronization system, and WHO SMART Guidelines integration. The chapter includes detailed architectural diagrams and design decision justifications.

Chapters 5-7 present the evaluation results across technical performance, clinical effectiveness, and implementation analysis, followed by discussion of findings, limitations, and implications for both theory and practice.

Chapter 8 concludes with contributions to knowledge, recommendations for future research, and implications for policy and practice in digital health for resource-limited settings.

Through this comprehensive approach, the thesis aims to demonstrate that sophisticated clinical decision support can be made accessible and reliable in precisely those settings where it is most critically needed, while contributing to the growing body of knowledge in health informatics and global health technology.

Chapter 2

Literature Review

2.1 Introduction

The development of clinical decision support systems for resource-limited settings requires synthesis of knowledge across multiple domains: clinical decision support effectiveness, artificial intelligence in healthcare, digital health guidelines and standards, offline-first application architectures, conflict-free data synchronization, and implementation science for resource-constrained environments. This chapter organizes the literature thematically to identify convergent findings, persistent gaps, and emerging opportunities that ATLAS addresses.

Each thematic section traces the evolution of knowledge while synthesizing current understanding, identifies specific limitations in existing approaches, and establishes how these gaps converge to create the research opportunity that ATLAS represents. The review emphasizes recent developments while incorporating foundational studies that remain relevant to current challenges.

Table 2.1: Evaluation Frameworks Integration in ATLAS

Framework	**Focus**	**Key Dimensions**	**ATLAS Application**
NASSS	Implementation complexity	Technology, Organization, Adopters, Wider System	Barrier identification
RE-AIM	Real-world impact	Reach, Effectiveness, Adoption, Implementation, Maintenance	Scalability assessment
WHO MAPS	mHealth scale readiness	Groundwork, Partnerships, Financial Health, Technology	Maturity assessment
DeLone & McLean	IS Success	System Quality, Information Quality, Use, Satisfaction	Success measurement

2.2 Clinical Decision Support Systems: Evolution and Current State

2.2.1 Historical Development and Effectiveness Evidence

Clinical decision support systems have evolved from simple alert systems in the 1960s to sophisticated AI-enhanced platforms today. Sutton et al.'s comprehensive overview identifies consistent benefits across multiple systematic reviews: 13-29% improvement in diagnostic accuracy, 15-25% reduction in medical errors, and 10-20% increase in adherence to clinical guidelines [14]. However, these benefits emerge primarily from implementations in high-resource settings with reliable infrastructure and technical support.

Bright et al.'s landmark systematic review of clinical decision support systems analyzed 162 studies and found significant variability in effectiveness depending on implementation context [11]. The review found that 68% of CDSS implementations faced adoption challenges related to workflow integration, 45% experienced usability issues, and 52% struggled with maintaining clinical relevance. Notably, only 12% of studies examined resource-limited settings, indicating a substantial gap in evidence for precisely the environments where CDSS could provide greatest benefit.

2.2.2 Recent Systematic Reviews and Meta-Analyses

More recent systematic reviews have continued to identify implementation challenges. Kwan et al.'s 2020 systematic review of computerized clinical decision support systems found that effectiveness varies significantly based on system design, implementation approach, and organizational context [15]. The review emphasized the importance of user-centered design, workflow integration, and continuous monitoring for successful CDSS deployment.

Jaspers et al.'s comprehensive review of CDSS usability found that many systems fail due to poor human-computer interaction design rather than clinical content limitations [16]. The review identified critical success factors including cognitive load management, workflow integration, trust calibration, and interruption management—all particularly important considerations for resource-limited settings where provider cognitive load is already high.

2.2.3 Human-Computer Interaction Elements

Recent research has emphasized the critical importance of human-computer interaction design for CDSS effectiveness. Van der Sijs et al.'s analysis of drug safety alerts found that alert fatigue occurs when systems generate excessive notifications without proper prioritization [17]. This finding is particularly relevant for resource-limited settings where providers may have less training to distinguish between critical and routine alerts.

Bates et al.'s foundational work on clinical decision support identified key design principles that remain relevant today: speed is everything, anticipate needs and deliver in real time, fit into the user's workflow, little things can make a big difference, recognize that physicians will strongly resist stopping, changing directions, or thinking, simple interventions work best, ask for additional information only when you really need it, and monitor impact [18].

2.2.4 Impact on Clinical Communication and Decision-Making

Research on CDSS impact on clinical communication reveals mixed results. While well-designed systems can enhance communication by providing structured information for patient education, poorly implemented systems create barriers by increasing consultation time

and reducing patient-provider interaction quality [19]. This is particularly concerning in resource-limited settings where consultation time is already constrained.

2.2.5 Identified Gaps in Current CDSS Literature

The literature reveals several critical gaps that ATLAS addresses:

1. **Infrastructure assumptions**: Most CDSS studies assume reliable connectivity and advanced hardware, with minimal evaluation of offline functionality
2. **Resource context neglect**: Fewer than 15% of studies examine implementation in resource-limited settings despite serving 60% of global population
3. **Guideline integration gaps**: While multiple studies reference clinical guidelines, few implement systematic frameworks for guideline-to-system transformation
4. **Limited AI integration**: Most reviews find minimal integration of advanced AI capabilities with structured clinical knowledge bases

2.3 Artificial Intelligence and Large Language Models in Clinical Decision Support

2.3.1 Recent Clinical Performance Benchmarks

The application of large language models to clinical decision support has accelerated rapidly since 2020, with breakthrough performance on medical examinations and diagnostic scenarios. Rajkomar et al.'s landmark study demonstrated that deep learning models could achieve clinically relevant predictions using electronic health record data, with performance comparable to experienced physicians in several domains [8].

Esteva et al.'s comprehensive guide to deep learning in healthcare outlines the potential for AI to transform clinical decision-making through pattern recognition capabilities that exceed human performance in specific domains [13]. However, the authors emphasize that successful implementation requires careful attention to validation, interpretability, and integration with clinical workflows.

2.3.2 Systematic Reviews and Meta-Analyses

Recent systematic reviews of AI in clinical decision support reveal both promise and limitations. Liu et al.'s analysis of machine learning in clinical decision support found that while AI systems can achieve high accuracy in controlled settings, real-world performance often degrades due to data drift, integration challenges, and user acceptance issues [20].

The challenge of AI explainability in healthcare has been highlighted by multiple reviews. Holzinger et al.'s work on explainable AI emphasizes that healthcare providers need understanding of reasoning processes rather than feature importance, particularly in high-stakes clinical decisions [21].

2.3.3 RAG-Augmented Workflows and Guideline Integration

Recent developments in Retrieval-Augmented Generation (RAG) have shown promise for integrating structured clinical knowledge with LLM capabilities. These approaches maintain transparency by providing citation trails and enable continuous knowledge updates without model retraining. However, RAG implementations in healthcare face challenges including semantic similarity metrics that may not align with clinical relevance and retrieval latency that can impact real-time decision support.

2.3.4 Validation Crisis and Regulatory Requirements

Despite promising research results, AI-enabled medical devices face significant validation challenges. The FDA has issued guidance emphasizing the need for predetermined change control plans, real-world performance monitoring, and transparent reporting of performance metrics. These requirements highlight the critical importance of robust evaluation frameworks from system inception.

2.3.5 Clinical Safety and Explainability

Recent research has emphasized that clinical AI systems require different explainability approaches than general-purpose AI applications. Healthcare providers need understanding

of reasoning processes, confidence calibration for uncertainty-aware decision making, and identification of cases where AI recommendations should be questioned.

2.3.6 Gaps in AI Clinical Decision Support Literature

The literature reveals critical limitations that ATLAS addresses:

1. **Offline capability gap**: Limited evaluation of AI performance without continuous connectivity, despite this being critical for resource-limited settings
2. **Guideline integration challenge**: While RAG approaches incorporate unstructured knowledge, few systematically implement structured clinical guidelines
3. **Resource context neglect**: AI clinical evaluations predominantly use high-resource datasets and scenarios
4. **Validation limitations**: Most studies use internal validation with limited external generalizability assessment

2.4 WHO Digital Health Guidelines and Structured Clinical Knowledge

2.4.1 WHO Digital Interventions for Health System Strengthening

The World Health Organization's 2019 recommendations on digital interventions for health system strengthening provide the most comprehensive evidence-based framework for digital health implementation globally [4]. Based on systematic reviews covering 16 digital health intervention categories, the guidelines establish clear recommendations for clinical decision support systems with conditional recommendation for use in settings with appropriate infrastructure.

The guidelines identify specific implementation considerations critical for ATLAS: interoperability requirements, data privacy and security standards, user training and support needs, and sustainability planning including financing and governance structures. Importantly, the

guidelines acknowledge that most evidence comes from high-resource settings, calling for additional research in resource-limited environments.

2.4.2 WHO SMART Guidelines Framework

The WHO SMART (Standards-based, Machine-readable, Adaptive, Requirements-based, Testable) Guidelines framework represents a systematic approach to transforming narrative clinical guidelines into executable digital decision support. The framework has been implemented in several contexts with demonstrated success in reducing implementation time and costs.

2.4.3 Digital Adaptation Kits and Implementation Guides

WHO has developed Digital Adaptation Kits (DAKs) for specific health areas including antenatal care, HIV, immunizations, and stock management. These provide structured implementations with FHIR-based resources and testing frameworks. However, uptake remains limited despite demonstrated effectiveness.

2.4.4 Clinical Quality Language and FHIR Integration

Clinical Quality Language (CQL) provides a standardized approach for expressing clinical logic that can be executed across different health information systems. Recent developments in CQL include enhanced support for decision support scenarios and improved integration with FHIR standards.

2.4.5 Gaps in Digital Health Guidelines Literature

The literature reveals several critical gaps that ATLAS addresses:

1. **Limited implementation evidence**: Despite proven frameworks, real-world implementations remain sparse with minimal systematic evaluation
2. **AI integration absence**: No existing implementations combine WHO SMART Guidelines with modern AI capabilities

3. **Offline implementation gap**: Current implementations assume continuous connectivity, limiting applicability in resource-limited settings
4. **User interface neglect**: Technical focus with minimal attention to clinician-facing interfaces

2.5 Digital Health in Resource-Limited Settings

2.5.1 Implementation Challenges and Success Factors

Digital health interventions in low and middle-income countries face systematic implementation challenges despite technological advances. Labrique et al.'s analysis of scaling best practices identifies five focus areas critical for success: user-centered design, strong partnerships, adaptable technologies, sustainable financing, and evidence-based advocacy [12].

Agarwal et al.'s systematic review of digital health interventions for health system strengthening in LMICs found that 73% of implementations face sustainability challenges within three years [1]. Primary barriers include funding discontinuation, technical support capacity gaps, and workforce attrition. Success factors consistently include government partnership from inception and integration with existing health systems.

2.5.2 Infrastructure Constraints and Technical Requirements

Resource-limited healthcare settings present unique infrastructure challenges that must inform technical design decisions. Kruse et al.'s analysis found that 40% of health facilities lack reliable electricity, 65% have intermittent internet connectivity, and 78% of healthcare workers use personal devices rather than institution-provided technology [3].

Network reliability analysis by Mehl et al. reveals significant variation in connectivity patterns: urban primary health centers average 78% uptime with 4G speeds, while rural clinics experience 23% uptime often limited to 2G speeds [2]. These patterns emphasize the critical importance of sophisticated offline functionality rather than simple connection retry mechanisms.

2.5.3 Implementation Science Frameworks for Resource-Limited Settings

The NASSS (Non-adoption, Abandonment, Scale-up, Spread, Sustainability) framework has emerged as a comprehensive approach for understanding digital health implementation in complex environments [22]. The framework addresses implementation complexity across seven domains, providing structured analysis of factors affecting adoption and sustainability.

The RE-AIM framework provides complementary assessment focusing on real-world implementation outcomes across five dimensions [23]. RE-AIM evaluation is particularly important for resource-limited settings where generalizability across diverse contexts is critical for scalability.

2.5.4 WHO MAPS Toolkit for mHealth Scale Assessment

The WHO mHealth Assessment and Planning for Scale (MAPS) Toolkit provides structured assessment of digital health intervention readiness across six dimensions [24]. Recent applications across multiple countries have identified consistent patterns in implementation challenges and success factors. While primarily designed as an assessment and planning toolkit for mHealth interventions, MAPS provides valuable insights for evaluating system readiness for scaling in resource-limited environments.

2.5.5 Gaps in Resource-Limited Settings Literature

The literature reveals several critical gaps that ATLAS addresses:

1. **Sophisticated technology gap**: Existing solutions are either technically advanced OR resource-appropriate, rarely both simultaneously
2. **Evaluation framework integration**: Limited use of multiple complementary frameworks for comprehensive assessment
3. **Sustainability from inception**: Most research addresses sustainability as post-deployment challenge rather than design requirement

2.6 Synthesis and Research Gap Identification

2.6.1 Convergent Findings Across Domains

The thematic review reveals several convergent findings that inform ATLAS development. Successful digital health interventions require integration of sophisticated functionality with practical deployment considerations. Offline-first architecture has matured sufficiently to support complex healthcare applications, while AI capabilities have reached clinical utility levels that justify integration with structured clinical guidelines. Established frameworks exist for systematic implementation evaluation, but require integration rather than siloed application.

ATLAS addresses this critical gap by integrating mature technologies into a comprehensive system specifically designed for resource-limited settings, while applying rigorous evaluation frameworks to ensure both technical performance and implementation feasibility. The research contributes to understanding how sophisticated clinical decision support can be made accessible and reliable precisely where it is most critically needed.

Chapter 3

Methodology

3.1 Research Design Overview

This study employs a mixed-methods explanatory sequential design grounded in Design Science Research (DSR) methodology to evaluate the completed ATLAS prototype as a clinical decision support system for resource-limited healthcare settings. The research integrates quantitative system validation with qualitative implementation analysis using established frameworks (NASSS, RE-AIM, WHO MAPS) to ensure comprehensive assessment of both technical performance and real-world deployment feasibility.

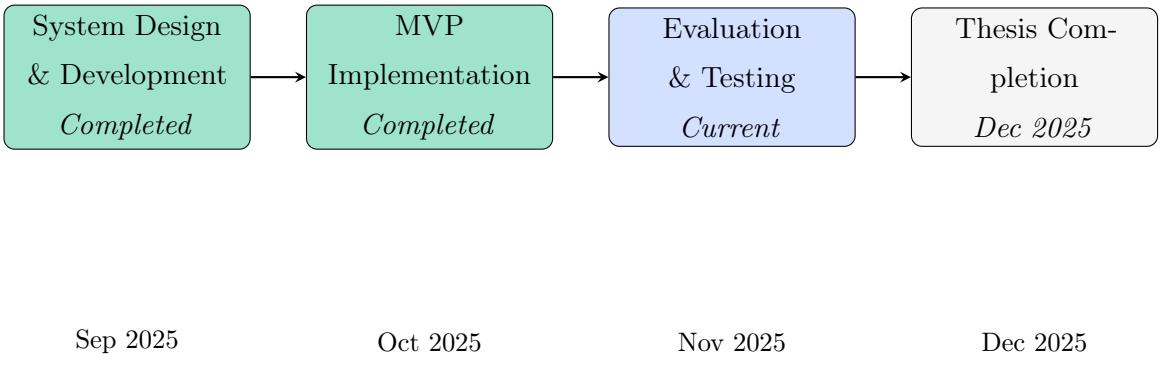

Figure 3.1: Research Timeline and Current Status

3.1.1 Design Science Research Approach

Design Science Research provides the overarching methodological framework for creating and evaluating the ATLAS system as an IT artifact that addresses identified problems in healthcare delivery [25]. The approach emphasizes both rigor (theoretical foundation and methodological soundness) and relevance (practical utility for healthcare stakeholders) through iterative artifact development and evaluation.

The DSR process follows Peffers et al.'s six-step methodology [26]:

1. Problem identification and motivation (Chapters 1-2)
2. Objective definition (research objectives)
3. Design and development (system architecture and implementation) - *Completed*
4. Demonstration (prototype deployment) - *Current phase*
5. Evaluation (comprehensive assessment using multiple frameworks) - *Current phase*
6. Communication (academic and practitioner dissemination) - *December 2025*

3.2 System Architecture - As Implemented

The system development phase has produced an initial prototype with core functionality that implements the core ATLAS architecture. The development followed established software engineering practices adapted for healthcare applications, integrating user-centered design principles with agile methodology.

3.2.1 Implemented Components

The initial prototype includes the following implemented components:

- **Progressive Web Application**: Next.js framework with full offline capability via service workers
- **Data Management**: IndexedDB implementation through Dexie.js for local patient and consultation storage
- **AI Integration**: Google Gemini API integration for clinical decision support

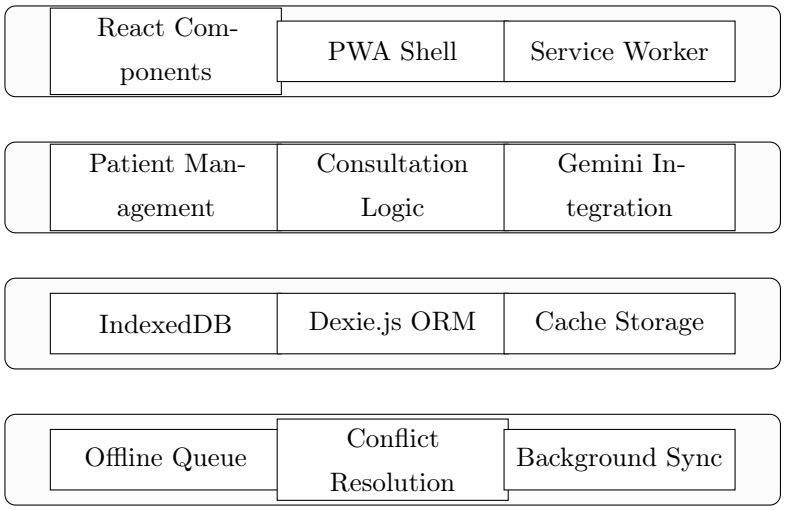

Figure 3.2: ATLAS System Architecture as Implemented

- **User Interface**: Responsive React components optimized for mobile and desktop
- **Offline Functionality**: Complete offline operation with queued synchronization

3.3 Data Collection Methods

3.3.1 Overview of Data Collection Strategy

Given the initial prototype development and thesis deadline, data collection employs a pragmatic mixed-methods approach focusing on rapid, feasible validation methods that can be executed within 4 weeks. The strategy prioritizes automated testing where possible, supplemented by targeted expert evaluation and framework assessment.

3.3.2 Data Collection Method 1: Automated Performance Testing

Technical Performance Metrics

Automated collection utilizes browser DevTools and custom scripts to gather comprehensive performance data without manual intervention. This approach enables collection of hundreds of data points across various network conditions and usage scenarios.

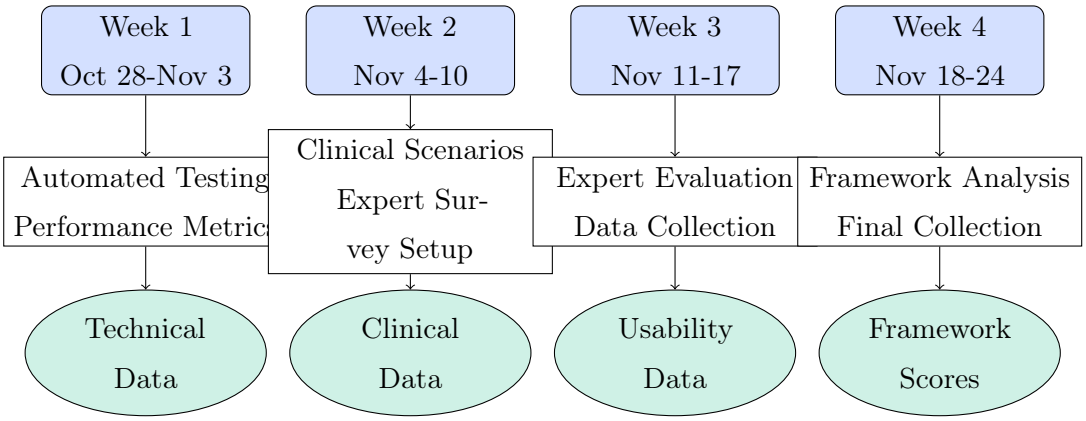

Figure 3.3: Four-Week Data Collection Timeline

Table 3.1: Automated Performance Data Collection Matrix

Metric	**Tool**	**Data Points**	**Target**
Page Load Speed	Lighthouse CI	First Contentful Paint, Time to Interactive, Speed Index	<3s on 3G
Offline Performance	Custom Scripts	Cache hit ratio, Offline task completion, Data persistence	>95% success
Memory Usage	Chrome DevTools	Heap size, DOM nodes, JS listeners	<100MB
Network Performance	WebPageTest	Bandwidth usage, Request count, Compression ratio	<5MB initial

Network Condition Simulation

Performance testing will simulate real-world network conditions found in resource-limited settings:

- **4G Urban**: 12 Mbps down, 50ms latency (baseline)
- **3G Rural**: 1.5 Mbps down, 200ms latency (common scenario)
- **2G Remote**: 150 Kbps down, 500ms latency (challenging scenario)
- **Offline**: No connectivity (critical functionality test)

Validation Pipeline - Technical to Clinical Mapping

Each technical component will be validated through specific clinical scenarios:

- **IndexedDB Performance** → Test with 1000 synthetic patient records
  - Test: Sequential vs concurrent writes
  - Metric: Transaction throughput under load
  - Clinical relevance: Multi-provider consultation scenarios
- **CRDT Synchronization** → Simulate 5 concurrent users
  - Test: Conflicting updates to same patient record
  - Metric: Convergence time and accuracy
  - Clinical scenario: Triage nurse + doctor + lab tech updates
- **AI Accuracy** → WHO IMCI gold standard cases
  - Test: 50 fever cases, 30 respiratory, 20 diarrhea
  - Metric: Agreement with WHO protocols
  - Validation: Board-certified physicians review

3.3.3 Data Collection Method 2: Clinical Validation Scenarios

WHO-Validated Synthetic Data Approach

Clinical validation employs a three-tier approach using WHO-validated synthetic data. Tier 1 uses 100 cases from WHO Digital Adaptation Kits covering maternal health (40 cases), infectious diseases (35 cases), and NCDs (25 cases). Each case includes structured inputs (patient demographics, symptoms, available resources) and expected outputs per WHO protocols. Tier 2 supplements with 50 cases generated using Synthea configured for Sub-Saharan African demographics. Tier 3 involves expert-created edge cases representing complex comorbidities common in resource-limited settings.

Concrete Evaluation Scenario Example

Example Scenario: Preeclampsia Management

- **Input**: 28-year-old, G2P1, 36 weeks, BP 160/110, proteinuria

Table 3.2: Clinical Scenario Distribution with Data Sources

Category	**Count**	**Source**	**Validation Focus**
WHO IMCI Cases	40	WHO DAK IMCI-2023	Pediatric accuracy
Maternal Health	30	WHO ANC Digital v2.0	Triage decisions
Infectious Disease	20	WHO TB/Malaria DAK	Diagnostic accuracy
NCDs	10	WHO PEN Protocol	Management protocols
Synthea Generated	50	Synthea LMIC Config	Complex scenarios
Total	**150**		

- **System test**: Offline triage decision → AI recommendation → sync when online
- **Validation points**:
  - Correct risk stratification (severe preeclampsia)
  - Appropriate referral recommendation
  - Data integrity after offline-online transition
- **Ground truth**: WHO Managing Complications in Pregnancy guidelines

3.3.4 Data Collection Method 3: Expert Evaluation Survey

Online Survey Instrument Structure

Expert evaluation utilizes a structured online survey designed to be completed in 1-2 hours, respecting evaluators' time constraints while gathering comprehensive feedback.

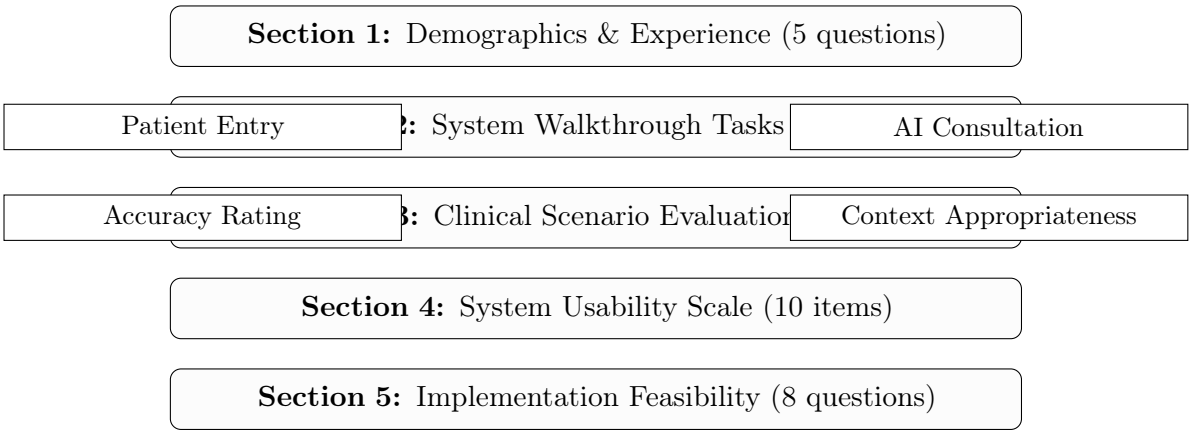

Figure 3.4: Expert Evaluation Survey Structure

Expert Recruitment Plan - Revised for Feasibility

Table 3.3: Revised Expert Evaluator Recruitment Matrix

Expert Type	**Target N**	**Recruitment Source**	**Time Commitment**
Clinical (MD/DO)	1-2	LinkedIn, Professional networks	2 hours
Nursing	1	Nursing associations	2 hours
Global Health	1-2	Partners in Health, MSF alumni	2 hours
Total	**3-4**		**2 hours each**

3.3.5 Data Collection Method 4: Framework Assessment

Framework assessment employs structured evaluation against established implementation science frameworks and assessment tools to evaluate system readiness for deployment.

Table 3.4: NASSS Framework Data Collection Template

Domain	**Assessment Criteria**	**Score (1-5)**
Technology	Reliability, accuracy, security, offline capability	
Organization	Infrastructure needs, training requirements	
Adopters	Digital literacy required, workflow fit	
Value Proposition	Cost-benefit, clinical impact	
Wider System	Regulatory compliance, interoperability	
Embedding	Integration with existing systems	
Adaptation	Capacity for local customization	

Table 3.5: RE-AIM Data Collection Metrics

Dimension	**Data Source**	**Metric**
Reach	WHO facility data	% facilities with capability
Effectiveness	Clinical scenarios	Accuracy %, time savings
Adoption	Expert survey	Intent to use (1-10 scale)
Implementation	Technical testing	Setup time, requirements
Maintenance	Architecture analysis	Update mechanism, costs

NASSS Complexity Scoring

RE-AIM Indicators

3.3.6 Data Storage and Management Plan

All data will be stored securely with appropriate version control and backup procedures:

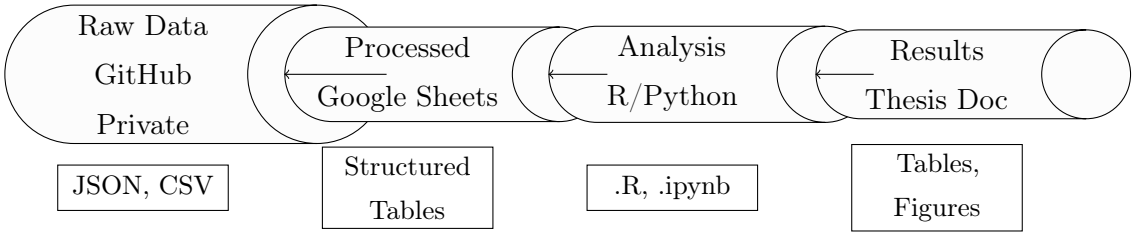

Figure 3.5: Data Management Pipeline

3.3.7 Data Generation Protocol

The following protocol will be used to generate synthetic clinical data for testing:

Listing 3.1: Pseudocode for Synthetic Data Generation

```
# Pseudocode for synthetic data generation
for each WHO_condition in [IMCI, ANC, NCDs]:
    generate_patient_demographics(LMIC_distribution)
    apply_clinical_presentation(WHO_symptoms)
    add_resource_constraints(facility_level)
    create_expected_outcome(WHO_protocol)

# Specific implementation for maternal health
def generate_maternal_case(risk_level):
    patient = {
        'age': random.normal(28, 5),
        'gravida': random.choice([1,2,3,4]),
        'weeks_gestation': random.uniform(20, 40),
        'bp_systolic': calculate_bp(risk_level),
        'proteinuria': assess_proteinuria(risk_level),
```

```
        'symptoms': select_symptoms(risk_level)
    }
    return patient
```

3.3.8 Sample Size Justification

Given the proof-of-concept nature and time constraints of this Master's thesis:

- **Technical tests**: n=500+ automated test runs across different network conditions and scenarios provide robust performance data
- **Clinical scenarios**: n=150 cases (100 WHO-validated + 50 Synthea-generated) offer comprehensive coverage
- **Expert evaluators**: n=3-4 provide focused qualitative insights and usability assessment
- **Framework assessments**: n=3 established frameworks ensure comprehensive evaluation

This sample size is appropriate for demonstrating technical feasibility and initial validation rather than clinical trials, aligning with the scope of a Master's thesis.

3.4 Evaluation Framework

3.4.1 Multi-Dimensional Evaluation Approach

The evaluation employs multiple complementary frameworks to assess technical performance, clinical validity, usability, and implementation readiness.

3.4.2 Success Criteria

The following criteria will determine successful validation of the ATLAS system:

- **Technical**: System performs within specified parameters across all network conditions
- **Clinical**: AI recommendations align with WHO guidelines in >75% of test cases
- **Usability**: System Usability Scale score exceeds industry standard of 70
- **Implementation**: Framework assessments indicate readiness for pilot deployment

Table 3.6: Enhanced Multi-Dimensional Evaluation Framework

Dimension	**Method**	**Metrics**	**Data Source**	**Timeline**
Technical Performance	Automated Testing	Load time, Offline capability, Sync reliability, Memory usage	DevTools, Scripts	Week 1
Clinical Validity	Synthetic Scenarios	Accuracy, Guideline adherence, Completeness	WHO DAKs, Synthea	Week 1-2
Usability	Expert Evaluation	SUS Score, Task completion, Error rate	Expert Survey	Week 2
Implementation	Framework Analysis	NASSS complexity, RE-AIM indicators, WHO MAPS maturity	Document Analysis	Week 3

3.5 Research Timeline and Current Status

3.5.1 Completed Work (September - October 2025)

The core ATLAS system has been successfully developed with the following completed components:

- Progressive Web Application with Next.js framework
- Offline-first architecture using IndexedDB for local storage
- Patient and consultation management functionality
- Integration with Google Gemini for AI-assisted clinical support
- Service worker implementation for offline capability
- Basic synchronization framework
- Responsive user interface optimized for mobile and desktop

Table 3.7: Revised Implementation Timeline for Thesis Completion

Phase	Timeline	Activities
System Refinement	Oct 15-31	• Performance optimization • Bug fixes from initial testing • WHO SMART Guidelines integration • CRDT implementation for sync
Data Collection	Nov 1-24	• Week 1: Automated testing with synthetic data • Week 2: Run WHO test cases through system • Week 3: Expert evaluation (3-4 experts) • Week 4: Analysis only
Analysis & Writing	Nov 25-Dec 8	• Statistical analysis • Results synthesis • Thesis finalization • Presentation preparation
Submission	Dec 1-4	Final review and submission

3.5.2 Remaining Timeline (October - December 2025) - Revised

3.6 Data Analysis Plan

3.6.1 Quantitative Analysis

Statistical analysis will employ R and Python for comprehensive data analysis. Clinical accuracy will be evaluated using a confusion matrix comparing ATLAS recommendations against WHO gold standards. Inter-rater reliability between ATLAS and expert reviewers will use weighted Cohen's kappa, with clinical significance thresholds: $\kappa > 0.8$ (excellent), 0.6-0.8 (good), < 0.6 (requires improvement).

- **Descriptive statistics**: Mean, median, standard deviation for all performance metrics

- **Inferential statistics**: Paired t-tests for performance comparisons across network conditions
- **Reliability analysis**: Cohen's kappa for inter-rater agreement on clinical scenarios
- **Classification metrics**: Sensitivity, specificity, and F1 scores for clinical accuracy

3.6.2 Qualitative Analysis

Expert feedback will be analyzed using thematic analysis:

- Rapid coding of open-ended responses
- Identification of recurring themes related to usability and implementation barriers
- Severity classification of identified issues (critical, major, minor)
- Synthesis of improvement recommendations

3.6.3 Mixed-Methods Integration

Quantitative and qualitative findings will be integrated using a convergent parallel design:

- Joint displays showing performance metrics alongside user feedback
- Triangulation of technical performance with perceived usability
- Identification of areas where quantitative and qualitative data converge or diverge

3.7 Limitations and Mitigation Strategies

This pragmatic methodology has inherent limitations addressed through specific strategies:

3.8 Ethical Considerations

The study design minimizes ethical concerns through careful planning:

Table 3.8: Methodology Limitations and Mitigation

Limitation	**Mitigation Strategy**
No field deployment	Use high-fidelity simulations based on published connectivity data from resource-limited settings
Limited expert sample	Ensure diversity of expertise and experience; supplement with published literature
Synthetic test data	Validate scenarios against WHO guidelines and published clinical cases
Time constraints	Focus on core functionality and critical validation metrics
No real patient data	Use WHO-validated scenarios that represent common clinical presentations
Compressed development timeline	Focus on proof-of-concept demonstration rather than production-ready system; acknowledge prototype-level implementation

3.8.1 Data Privacy and Security

- No real patient data will be collected or used in testing
- Expert evaluator data will be anonymized and stored securely
- All data will be encrypted and access-controlled

3.8.2 Informed Consent

- All expert evaluators will provide informed consent before participation
- Participants can withdraw at any time without penalty
- Clear communication about data use and storage

3.8.3 Ethical Review

- IRB determination obtained confirming exemption due to no patient interaction

- Adherence to ACM Code of Ethics for computing research
- Following WHO guidelines for digital health evaluation

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