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

August 2025

Contents

List of Figures

List of Tables

List of Acronyms

AI	Artificial Intelligence
ATLAS	Adaptive Triage and Local Advisory System
CDSS	Clinical Decision Support System
CRDT	Conflict-free Replicated Data Type
FHIR	Fast Healthcare Interoperability Resources
GDPR	General Data Protection Regulation
HIPAA	Health Insurance Portability and Accountability Act
LLM	Large Language Model
PWA	Progressive Web Application
UI	User Interface
WHO	World Health Organization

Abstract

This project proposes the development of ATLAS (Adaptive Triage and Local Advisory System), an innovative clinical decision support system designed specifically for healthcare providers working in resource-limited settings. The system combines an offline-first architecture, AI-assisted clinical decision making, and an intuitive user interface optimized for various devices, including low-end tablets and smartphones.

By addressing the critical challenges of intermittent connectivity, limited computational resources, and specialized clinical knowledge, ATLAS aims to support healthcare providers in delivering quality care in underserved regions. The system will implement a progressive web application architecture that functions reliably without internet connectivity while providing intelligent synchronization when connections are available [1].

Key features include offline-first data architecture with robust local storage, AI-powered clinical decision support using pre-trained models, context-aware clinical guidelines based on WHO protocols [2], a responsive interface designed for high-stress environments, multi-modal input options including voice recognition, and intelligent synchronization with conflict resolution.

This project addresses a critical gap in global health informatics by creating technology specifically designed for challenging environments where standard cloud-based solutions fail [3]. The interdisciplinary approach integrates data science, artificial intelligence, and human-computer interaction to create a solution with the potential for significant real-world impact.

Chapter 1

Introduction

1.1 Background and Motivation

Healthcare providers in resource-limited settings face significant challenges that impact their ability to deliver optimal care:

- **Limited access to specialized medical knowledge** and up-to-date clinical guidelines
- **Inconsistent internet connectivity**, preventing reliable use of cloud-based resources
- **Constrained computational resources** and device availability
- **High patient-to-provider ratios**, necessitating efficient workflows
- **Limited access to diagnostic equipment**, increasing reliance on clinical judgment

The World Health Organization and other global health entities have identified clinical decision support systems as a critical tool to improve healthcare quality in underserved regions [2]. However, most existing systems are designed for high-resource settings, requiring continuous internet connectivity and advanced devices.

Research Gap: Most clinical decision support systems assume consistent connectivity and advanced infrastructure.
This project addresses the need for systems specifically designed for resource-constrained environments.

Figure 1.1: The research gap addressed by ATLAS

1.2 Problem Statement

Despite the potential for digital health technologies to improve healthcare delivery in resource-limited settings, there is a critical gap in available solutions that:

1. Function effectively without reliable internet connectivity
2. Operate on a variety of devices, including lower-end smartphones and tablets
3. Provide contextually relevant clinical guidance based on available resources
4. Support healthcare providers with varying levels of training and expertise
5. Efficiently manage and synchronize data when connectivity is available

This project addresses these challenges by developing an offline-first clinical decision support system that combines advanced technology with practical design considerations for real-world deployment in resource-constrained healthcare environments [3].

1.3 Project Objectives

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

1. Develop a Progressive Web Application (PWA) with comprehensive offline functionality [1]
2. Implement an intelligent local-first data architecture with bidirectional synchronization [4]
3. Integrate an AI-powered clinical decision support system using pre-trained models that can run locally [5]
4. Design a responsive and intuitive user interface optimized for high-stress, resource-constrained environments [3]
5. Incorporate WHO-aligned clinical guidelines and protocols for common conditions in resource-limited settings [2]
6. Evaluate the system's performance, usability, and clinical utility through simulations and expert feedback [6]

1.4 Significance and Expected Impact

This project has the potential to significantly impact healthcare delivery in resource-limited settings by:

- Improving the quality and consistency of clinical decision-making through evidence-based recommendations adapted to local contexts [7]
- Expanding access to up-to-date medical knowledge and guidelines, even in areas with limited internet connectivity [8]
- Enhancing the efficiency of healthcare providers in high-demand environments through streamlined workflows and decision support [6]
- Supporting less experienced providers with AI-assisted clinical recommendations, potentially increasing the effectiveness of task-shifting initiatives [2]

- Creating a model for future health information systems designed for challenging environments, advancing the field of global health informatics [3]

The interdisciplinary nature of this work—spanning data science, healthcare informatics, artificial intelligence, and human-computer interaction—makes it an ideal Masters project that will build diverse skills while creating a solution with real-world applications.

Chapter 2

Literature Review

2.1 Clinical Decision Support Systems

Clinical decision support systems (CDSS) have been widely studied in high-resource settings, with demonstrated benefits for quality of care, patient safety, and adherence to best practices [6]. Key studies have shown:

- Improved diagnostic accuracy when providers use computerized decision support
- Increased adherence to clinical guidelines and protocols
- Reduction in medication errors and adverse events
- Enhanced efficiency in clinical workflows

However, the majority of research focuses on systems designed for settings with reliable connectivity, advanced infrastructure, and specialized technical support [5].

2.1.1 Comparative Analysis of Existing Clinical Decision Support Systems

A critical examination of existing CDSS reveals significant limitations when applied to resource-constrained settings:

System Type	Key Features	Limitations in Resource-Limited Settings
Cloud-based CDSS	• Comprehensive clinical databases • Advanced analytics capabilities	• Requires continuous internet • Fails when offline • High bandwidth needs [6]
Hospital EMR-integrated CDSS	• Workflow integration • Access to patient history • Decision support at point of care	• Requires hospital infrastructure • High cost • Complex implementation • IT support needs [6]
Mobile health apps	• Portable • User-friendly interfaces • Accessible on smartphones	• Limited offline capabilities • Superficial decision support • Poor synchronization • Battery constraints [9]
AI-powered diagnostics	• Pattern recognition • Natural language processing • Automated analysis	• High computational requirements • Training data bias toward high-resource settings • Connectivity dependent [5]

Table 2.1: Comparison of Existing Clinical Decision Support Systems

Notable examples highlight these limitations:

- **UpToDate and DynaMed**: Industry-leading clinical reference tools that require constant internet connectivity, making them unusable in areas with intermittent connections [6].

- **Epic's Cognitive Computing Platform**: While powerful, it is tightly integrated with Epic's electronic health record system, requiring infrastructure that is prohibitively expensive for resource-limited settings [6].
- **WHO's IMCI Digital**: Attempts to provide decision support for child health in developing countries but offers limited offline functionality and no synchronization mechanisms [2].
- **Ada Health and Babylon**: AI-powered diagnostic apps that require substantial bandwidth for API calls and lack meaningful offline capabilities [5].

These comparative examples demonstrate a critical gap in current CDSS offerings: systems either provide sophisticated clinical decision support but require robust infrastructure, or they function in resource-limited settings but offer only basic functionality. No current solution adequately addresses both dimensions [3].

2.2 Healthcare Technology in Resource-Limited Settings

Research on digital health technologies in resource-limited settings has identified several critical factors for successful implementation [3]:

- Functionality without consistent internet connectivity
- User interfaces designed for high-stress, time-constrained environments
- Consideration of varying levels of digital literacy among users
- Adaptability to local infrastructure, resource constraints, and clinical contexts
- Sustainable deployment models that don't require intensive technical support

Studies have shown that appropriately designed digital health solutions can improve healthcare delivery in challenging environments [7], but many implementations fail due to insufficient attention to these contextual factors.

2.2.1 Implementation Challenges in Resource-Limited Settings

Field studies of health information system deployments in resource-limited settings have documented recurring implementation challenges [3, 10]:

- **Connectivity issues**: Systems designed for constant connectivity fail unpredictably, leading to abandonment by users after frequent frustrations [10].
- **Device limitations**: Many deployments assume higher-end devices than are actually available, resulting in poor performance and usability issues [3].
- **Contextual mismatch**: Clinical recommendations that assume access to medications, diagnostics, or specialists that aren't available locally can undermine provider trust in the system [2].
- **Training and support gaps**: Complex systems requiring extensive training or ongoing technical support often fail after initial implementation [9].
- **Data synchronization challenges**: Systems that don't effectively manage offline data often result in fragmented or lost clinical information [4].

These implementation challenges highlight the need for purpose-built solutions that anticipate and address the specific constraints of resource-limited healthcare settings.

2.3 Offline-First Application Architecture

Recent advances in web technologies have enabled the development of sophisticated offline-first applications [1]:

- Progressive Web Applications (PWAs) that combine the best features of web and mobile applications
- Local-first data architectures that prioritize client-side storage and processing
- Intelligent synchronization strategies that optimize for intermittent connectivity
- Edge computing approaches that bring computational capabilities closer to the point of care

These technologies create new possibilities for healthcare applications that can function reliably in environments with limited connectivity while still benefiting from cloud resources when available [4].

2.3.1 Advances in Offline-First Web Technologies

Recent developments in offline-first web technologies demonstrate promising approaches for resource-constrained settings [1, 4]:

- **Service Workers**: Enable sophisticated caching strategies and background synchronization, allowing web applications to function completely offline [1].
- **IndexedDB and Local Storage**: Provide robust client-side storage capabilities for structured data, enabling complex applications to function without server connectivity [4].
- **Conflict-free Replicated Data Types (CRDTs)**: Mathematical structures that enable conflict resolution for concurrent data modifications, critical for systems with intermittent synchronization [11].
- **Workbox and PWA Frameworks**: Simplify the development of production-grade offline applications by abstracting complex caching and synchronization logic [1].

These technologies have been successfully applied in various industries but remain underutilized in healthcare applications, particularly for resource-limited settings [4].

2.4 AI-Assisted Clinical Decision Making

Artificial intelligence, particularly through recent advances in large language models (LLMs) and generative AI, has shown promising results for clinical decision support [5]:

- Ability to analyze patient symptoms and suggest potential diagnoses
- Generation of contextually relevant treatment recommendations
- Natural language processing of clinical notes and patient descriptions
- Adaptation to local guidelines and available resources

However, challenges remain in deploying these technologies in resource-limited settings [8], including:

- Computational requirements for sophisticated AI models
- Need for offline operation when connectivity is unavailable
- Ensuring recommendations are appropriate for available resources
- Maintaining privacy and security of sensitive health data

2.4.1 Current Approaches to AI for Resource-Limited Healthcare

Recent innovations demonstrate several approaches to implementing AI for clinical decision support in resource-constrained environments [5, 12]:

- **Model distillation and compression**: Techniques to reduce the size and computational requirements of AI models while preserving accuracy, enabling deployment on lower-end devices [12].

- **Edge AI frameworks**: Tools like TensorFlow Lite and ONNX Runtime that optimize model performance on resource-constrained devices [5].
- **Hybrid AI architectures**: Systems that combine lightweight on-device models for essential offline functionality with more sophisticated cloud-based models when connectivity is available [5].
- **Pre-computed response caching**: Strategies to store common AI responses locally, reducing the need for real-time computation [4].

These approaches demonstrate that AI-assisted clinical decision support is technically feasible in resource-limited settings, though significant integration challenges remain [8].

2.5 Research Gap

The literature review reveals a significant gap in clinical decision support systems specifically designed for resource-limited settings that:

- Function effectively offline while intelligently using online resources when available [1]
- Incorporate AI-assisted decision support optimized for limited computational resources [5]
- Adapt recommendations based on locally available resources and capabilities [2]
- Present information in ways optimized for high-stress clinical environments [3]

The critical research gap is the absence of integrated systems that successfully combine offline-first architecture, resource-appropriate AI, context-aware clinical guidance, and interfaces designed for challenging environments. While individual technologies show promise, no existing solution successfully integrates these elements into a cohesive system suitable for real-world deployment in resource-limited settings [8, 3].

This project aims to address this gap by integrating advances in offline-first architectures, AI-assisted clinical decision support, and user interface design optimized for challenging healthcare environments.

Chapter 3

Methodology

3.1 System Architecture

The proposed system will implement a local-first architecture with the following components:

Component	**Description**
Frontend Framework	Next.js for the progressive web application
Local Database	IndexedDB (via Dexie.js) for client-side data storage
Synchronization Layer	Custom bidirectional sync with conflict resolution
AI Integration	Google's Generative AI (Gemini) with offline fallbacks
Clinical Knowledge Base	Structured WHO guidelines and protocols

Table 3.1: System Architecture Components

3.1.1 Progressive Web Application

The system will be implemented as a Progressive Web Application (PWA) using Next.js, which provides [1]:

- Cross-platform compatibility (Android, iOS, desktop browsers)
- Offline functionality through service workers
- Installation on devices without app store requirements
- Automatic updates when connectivity is available

3.1.2 Data Storage and Management

The system will use a local-first data approach with [4]:

- IndexedDB (via Dexie.js) for primary client-side storage
- Structured data models for patients, consultations, and clinical reference material
- Compression and optimization for efficient storage on mobile devices
- Encryption of sensitive patient data for security

3.1.3 Synchronization Strategy

The system will implement an intelligent synchronization strategy [4]:

- Prioritize critical clinical data for synchronization
- Queue modifications while offline for later synchronization
- Implement version control to handle concurrent modifications
- Provide transparent sync status and conflict resolution

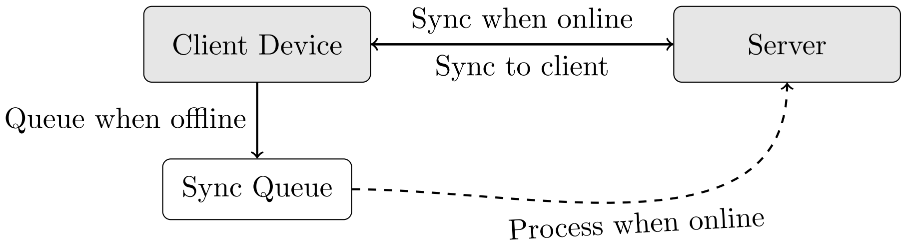

Figure 3.1: Data Synchronization Flow

3.2 AI-Assisted Clinical Decision Support

The AI component will provide the following capabilities [5]:

- Differential diagnosis suggestions based on patient symptoms and demographics
- Treatment recommendations aligned with WHO guidelines
- Adaptation to resource constraints (medication availability, diagnostic capacity)
- Natural language processing for clinical notes and symptom descriptions
- Fallback to rule-based recommendations when AI is unavailable

3.2.1 AI Implementation Approach

The system will use a hybrid approach for AI-assisted decision support [5]:

- Online mode: Connect to Google's Generative AI (Gemini) for comprehensive analysis
- Offline mode: Use lightweight local models or rule-based systems as fallback
- Cache common queries and responses for improved offline performance
- Queue complex queries for processing when connectivity returns

3.2.2 Clinical Knowledge Integration

The system will incorporate structured clinical knowledge [2]:

- WHO guidelines and protocols for common conditions in resource-limited settings
- Medication formularies adapted to typically available medications
- Decision trees for triage and clinical management
- Reference materials optimized for offline access

3.3 User Interface Design

The interface will be optimized for the following considerations [3]:

- High-stress, time-constrained environments
- Variable lighting conditions (indoor/outdoor use)
- Touch interfaces with potential for stylus input
- Minimal training requirements
- Voice input capabilities for hands-free operation in clinical settings

3.4 Web-Based vs. Local Application Architecture Decision

The choice between web-based and local application architecture is crucial for ATLAS's success in resource-limited settings. This section analyzes both approaches and justifies the selected hybrid architecture.

Factor	Pure Web-Based	Pure Local	Hybrid PWA (Selected)
Connectivity Requirements	Always online	None	Intermittent acceptable
Performance	Network dependent	Fast	Fast offline, sync when online
Data Persistence	Server dependent	Always local	Local with cloud backup
Updates	Real-time	Manual	Automatic when online
Device Storage	Minimal	High	Moderate
Scalability	High	Limited	High
Security	Centralized	Device-only	Layered

Table 3.2: Architecture Comparison for Resource-Limited Settings

3.4.1 Architecture Comparison

3.4.2 Critical Decision Factors for Resource-Limited Settings

Connectivity Constraints: Research demonstrates that internet connectivity in resource-limited settings is often intermittent, unreliable, or expensive [3]. Pure web-based applications fail completely without connectivity, making them unsuitable for critical healthcare applications where continuous availability is essential.

Device Limitations: Healthcare providers in low-resource settings often use entry-level smartphones or tablets with limited storage and processing power [10]. Pure local applications require significant storage and regular manual updates, which is impractical in these environments.

Clinical Workflow Integration: Studies of mobile CDSS implementations show that systems requiring constant connectivity cause workflow disruptions and are often abandoned by users after experiencing frequent failures [13].

Resource Optimization: Field deployments in resource-constrained environments require solutions that balance functionality with practical limitations including bandwidth costs, device capabilities, and maintenance requirements [9].

3.4.3 Justification for Progressive Web App Architecture

The hybrid PWA approach addresses the unique challenges of resource-limited healthcare settings through several key advantages:

Offline-First Design: ATLAS functions completely offline for core clinical decision support, ensuring continuous availability during connectivity outages while maintaining full functionality for critical healthcare tasks [1].

Intelligent Synchronization: When connectivity becomes available, the system implements a prioritized approach:

- Prioritizes critical patient data for upload
- Downloads updated clinical guidelines and protocols
- Syncs AI model improvements and cached responses
- Resolves data conflicts using conflict-free replicated data types (CRDTs)
- Optimizes bandwidth usage through compression and differential updates

Resource Optimization: PWAs require significantly less device storage than native applications while providing equivalent functionality, making them suitable for lower-end devices commonly used in resource-limited settings [1].

Deployment Advantages: PWAs can be deployed without app store approval, enabling rapid updates and easier distribution in regions with limited access to official app stores or where users may have restrictions on app installations [3].

3.4.4 Technical Implementation Strategy

Service Workers: Implementation of sophisticated caching strategies ensures offline availability of critical features, clinical guidelines, and patient data while enabling background synchronization when connectivity is restored.

IndexedDB Integration: Local storage of patient data, clinical guidelines, AI response cache, and application state using IndexedDB provides robust offline functionality with efficient data retrieval.

Background Sync: Automated queuing of data modifications while offline ensures no data loss and seamless synchronization when connectivity returns, critical for maintaining continuity of patient care.

Conflict Resolution: Implementation of operational transformation algorithms handles concurrent data modifications across multiple devices, ensuring data integrity in collaborative healthcare environments.

> This architectural approach balances the need for reliable offline operation with the benefits of cloud connectivity, making it ideal for the challenging conditions in resource-limited healthcare settings where both reliability and resource efficiency are paramount [10].

3.4.5 Key Interface Components

The user interface will include:

- Patient management dashboard with offline search capabilities
- Structured clinical assessment workflows

- Interactive differential diagnosis visualization
- Context-aware treatment recommendation display
- Simplified data entry optimized for mobile devices
- Multi-modal input options (touch, voice, structured forms)

3.5 Evaluation Methods

The system will be evaluated through a comprehensive assessment approach that combines technical performance testing, usability evaluation, and clinical validation [6].

3.5.1 Performance Metrics

Key performance metrics will include:

Table 3.3: Comprehensive Evaluation Metrics and Targets

Metric Category	Specific Measurements	Target Thresholds
System Performance	• Response time • App size and memory • Battery consumption • Storage requirements	• <2s response time • <100MB app size • <10% battery impact • <500MB storage

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Table 3.3 – Continued from previous page

Metric Category	Specific Measurements	Target Thresholds
Offline Functionality	• Feature availability • Data persistence • Recovery time	• 100% core features • Zero data loss • <30s recovery
Synchronization	• Bandwidth usage • Conflict resolution • Sync completion time	• <5MB per daily sync • >95% correct resolution • <5min on 2G networks
Clinical Recommendation	• Diagnostic accuracy • Treatment appropriateness • Guideline adherence	• >80% accuracy • >90% appropriateness • >95% guideline adherence

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Metric Category	Specific Measurements	Target Thresholds
Usability	• System Usability Scale • Task completion rates • Error rates • Workflow efficiency	• SUS score >70 • >90% completion • <5% error rate • 30% faster than paper

3.5.2 Evaluation Process

The evaluation will follow a staged approach:

1. **Technical performance testing** in simulated connectivity environments:
   - Laboratory testing of offline functionality under various network conditions
   - Measurement of system responsiveness on target devices (entry-level Android tablets and smartphones)
   - Assessment of data synchronization efficiency with simulated intermittent connectivity
   - Stress testing with various database sizes and concurrent operations
2. **Usability testing with healthcare professionals** using clinical scenarios:
   - Structured task-based evaluation with clinicians experienced in resource-limited settings
   - Cognitive walkthrough assessments of key workflows
   - System Usability Scale (SUS) evaluation

    - Qualitative feedback on interface design, workflow integration, and perceived utility

3. **Expert review of clinical recommendations and decision support**:
    - Comparison of AI-generated recommendations with WHO guidelines
    - Assessment of recommendation appropriateness for resource-limited settings
    - Evaluation of diagnostic accuracy using standardized clinical scenarios
    - Review of context-aware adaptation to different resource levels
4. **Iterative refinement based on evaluation feedback**:
    - Prioritization of issues based on severity and impact
    - Implementation of improvements to address identified limitations
    - Re-evaluation of critical metrics after modifications
5. **Final assessment against project objectives**:
    - Comprehensive report documenting achieved performance against target metrics
    - Identification of remaining limitations and future development needs
    - Recommendations for real-world deployment and scaling

This rigorous evaluation approach will provide quantitative evidence of the system's performance, usability, and clinical utility, enabling objective assessment of its potential impact in resource-limited settings.

3.6 Ethical and Data Governance Considerations

The development and evaluation of the ATLAS system will adhere to strict ethical and data governance principles to ensure privacy, security, and appropriate use of health information.

3.6.1 Data Privacy and Security Framework

The system will implement a comprehensive data protection approach:

- **Local encryption**: All sensitive patient data stored on devices will be encrypted using industry-standard algorithms (AES-256)
- **Secure synchronization**: Data transmission during synchronization will use end-to-end encryption with TLS 1.3
- **Privacy by design**: Implementation of data minimization principles, collecting and storing only essential clinical information
- **Access controls**: Role-based access controls to restrict data access based on user role and permissions
- **Audit logging**: Comprehensive audit trails of all data access and modifications for accountability

3.6.2 Regulatory Compliance

The system design will incorporate compliance with relevant healthcare data regulations:

- **HIPAA alignment**: While primarily targeting global contexts, the system will implement safeguards aligned with HIPAA principles
- **GDPR considerations**: Implementation of data subject rights (access, correction, deletion) and minimization principles
- **WHO guidelines**: Adherence to WHO guidelines for digital health interventions in low-resource settings

3.6.3 Ethical AI Implementation

The AI components will be developed with specific ethical considerations:

- **Transparency**: Clear indication to users when recommendations are AI-generated vs. directly from clinical guidelines
- **Bias mitigation**: Evaluation and mitigation of potential biases in AI recommendations, particularly for populations underrepresented in training data
- **Human oversight**: Design that keeps healthcare providers in control of clinical decisions, with AI serving in an advisory capacity
- **Appropriate uncertainty communication**: Clear presentation of confidence levels and limitations in AI-generated recommendations

3.6.4 Evaluation Ethics

For the evaluation phase, the following ethical safeguards will be implemented:

- **De-identified test data**: Use of synthetic or de-identified patient data for all system testing
- **Informed consent**: Comprehensive informed consent process for healthcare providers participating in usability evaluations
- **Ethical review**: Submission of evaluation protocols for review by Northeastern University's Institutional Review Board
- **Equity considerations**: Inclusion of diverse stakeholders in the evaluation process to ensure the system meets the needs of various users and contexts

This ethical framework ensures that the ATLAS system development and evaluation will adhere to the highest standards of data protection, privacy, and responsible AI use in healthcare contexts.

Chapter 4

Implementation Plan

4.1 Technical Implementation

4.1.1 Frontend Development

The frontend will be developed using:

- Next.js for the Progressive Web Application framework [1]
- React for component-based UI development
- Tailwind CSS for responsive styling
- Service workers for offline functionality
- Web Speech API for voice input capabilities

4.1.2 Backend Services

The backend will consist of:

- Node.js API server for data synchronization

- PostgreSQL database for central data storage
- Integration with Google's Generative AI API
- Authentication and authorization services
- Analytics and monitoring capabilities

4.1.3 Data Management

The data management approach will include [4]:

- Structured data models for patients, consultations, and clinical reference
- IndexedDB for client-side storage via Dexie.js
- CRDT-based conflict resolution for synchronization
- Compression and encryption for sensitive data
- Optimized sync protocols for limited bandwidth

4.2 Clinical Content Development

4.2.1 Clinical Guidelines Integration

The system will incorporate [2]:

- WHO guidelines for common conditions in resource-limited settings
- Structured representation of clinical decision pathways
- Adaptation of recommendations based on resource availability
- Context-specific clinical reference materials

4.2.2 AI Training and Integration

AI integration will involve [5]:

- Integration with Google's Generative AI (Gemini)
- Development of prompt engineering strategies for clinical scenarios
- Implementation of fallback mechanisms for offline operation
- Validation of AI recommendations against clinical guidelines

4.3 Timeline and Milestones

Table 4.1: Project Timeline and Deliverables

Phase	Activities and Deliverables
Phase 1 (8 weeks): Research and Planning	• Literature review and requirements gathering
	• System architecture design • Clinical guideline selection and structuring • Development of evaluation protocols **Milestone 1.1** (Week 4): System architecture document **Milestone 1.2** (Week 8): Requirements specification

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Table 4.1 – Continued from previous page

Phase	Activities and Deliverables
Phase 2 (12 weeks): Core System Development	• Offline-first data architecture implementation
	• User interface component development • Clinical knowledge base integration • Basic synchronization functionality **Milestone 2.1** (Week 12): Working prototype with local storage **Milestone 2.2** (Week 16): Basic UI implementation **Milestone 2.3** (Week 20): Clinical knowledge integration
Phase 3 (8 weeks): AI Integration	• Generative AI capabilities integration
	• Offline AI fallback mechanisms • Multimodal input implementation • Synchronization protocol refinement **Milestone 3.1** (Week 24): AI recommendations in online mode **Milestone 3.2** (Week 28): Offline fallback implementation

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Table 4.1 – Continued from previous page

Phase	**Activities and Deliverables**
Phase 4 (8 weeks): Testing and Evaluation	• Technical performance testing
	• Usability testing with clinical scenarios • Expert evaluation of recommendations • Iterative refinement based on feedback **Milestone 4.1** (Week 32): Performance testing report **Milestone 4.2** (Week 36): Usability evaluation results
Phase 5 (4 weeks): Documentation	• System documentation
	• Academic manuscript preparation • Demonstration materials development • Final project presentation **Milestone 5.1** (Week 38): System documentation **Milestone 5.2** (Week 40): Final project presentation

4.4 Required Resources

The following resources will be needed for this project:

- Development hardware (laptop/desktop computer)
- Mobile devices for testing (various Android/iOS devices)
- Cloud hosting environment for backend services
- Google Generative AI API access
- Access to clinical guidelines and protocols [2]
- Collaboration with healthcare providers for evaluation

Chapter 5

Expected Outcomes and Innovation

5.1 Expected Deliverables

This project is expected to produce:

1. A fully functional progressive web application for clinical decision support [1]
2. An innovative offline-first data architecture adaptable to other healthcare applications [4]
3. Evaluation data on the effectiveness of AI-assisted clinical decision support in resource-limited settings [5]
4. At least one academic publication in a relevant peer-reviewed journal
5. Open-source contributions to the healthcare informatics community

5.2 Innovation and Contribution

This project introduces several innovative aspects that differentiate it from existing approaches to clinical decision support:

1. **Adaptive AI with resource awareness:** Unlike current AI systems that provide generalized recommendations, ATLAS will implement contextual awareness of locally available resources. The system will dynamically adjust treatment recommendations based on available medications, diagnostic capabilities, and referral options, avoiding the common pitfall of recommending optimal but unavailable interventions [7].

2. **Intelligent offline synchronization:** Current healthcare applications typically use simplistic synchronization approaches that either fail completely offline or create duplicative records. ATLAS will implement sophisticated CRDT-based synchronization with clinical priority awareness, ensuring that critical patient data is synchronized first when limited bandwidth becomes available [4, 11].

3. **Multi-modal input optimized for clinical environments:** While existing systems primarily rely on touch input, ATLAS will integrate voice recognition optimized for clinical terminology and structured data capture specifically designed for fast-paced clinical workflows. This addresses the unique challenges of data entry in high-stress, time-constrained environments [3].

4. **Context-aware knowledge retrieval:** Rather than presenting generic clinical guidelines, ATLAS will dynamically surface relevant guidance based on patient presentation, available resources, and provider expertise level. This represents a significant advance over current systems that either provide comprehensive but overwhelming information or oversimplified guidance [2].

5. **Visual differential diagnosis support:** ATLAS will implement interactive visualizations that help providers understand diagnostic possibilities and treatment tradeoffs, a significant improvement over text-heavy approaches in current systems. These visualizations will be specifically optimized for low-end devices with variable screen qualities [6].

Key Innovation: Integration of Technologies for Resource-Limited Settings

While individual components (offline PWAs, local databases, AI) exist separately, ATLAS uniquely integrates these technologies into a cohesive system specifically designed for challenging healthcare environments where standard solutions fail.

This integration addresses the fundamental gap between sophisticated systems that require robust infrastructure and simplified mobile apps that lack meaningful clinical decision support capabilities.

Figure 5.1: Core innovation of the ATLAS system

The key innovation of this project is the integration of advanced technologies (AI, offline-first architecture, responsive UI) specifically designed for challenging healthcare environments where standard solutions fail [8].

5.3 Potential Impact

The potential impact of this project includes:

- **Improved quality of care** in resource-limited settings through evidence-based decision support that respects local constraints [7]
- **Enhanced clinical decision-making** for healthcare providers with limited specialized training, potentially reducing diagnostic errors and improving treatment appropriateness [2]

- **More efficient use of scarce healthcare resources** through optimized clinical workflows and resource-aware recommendations [6]
- **A model for future health information systems** designed for challenging environments, advancing the field of global health informatics with potential applications beyond clinical decision support [3]
- **Increased healthcare provider satisfaction and retention** in resource-limited settings by providing supportive tools that reduce cognitive burden and decision fatigue [14]

Chapter 6

Conclusion

This project addresses a critical need in global health informatics by creating a purpose-built clinical decision support system for resource-limited settings. By combining advanced technologies with practical design considerations, it has the potential to meaningfully impact healthcare delivery in underserved regions while advancing the fields of health informatics, artificial intelligence, and human-computer interaction.

The interdisciplinary nature of this work—spanning data science, healthcare informatics, artificial intelligence, and human-computer interaction—makes it an ideal Masters project that will build diverse skills while creating a solution with real-world applications.

> This project not only presents interesting technical challenges but also aligns with global health priorities to improve healthcare access and quality in resource-limited settings. The resulting system could serve as a model for future health information systems designed for challenging environments [15].

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