

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

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by

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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
FHIR	Fast Healthcare Interoperability Resources
IMCI	Integrated Management of Childhood Illness
LLM	Large Language Model
LMIC	Low and Middle-Income Countries
NASSS	Non-adoption, Abandonment, Scale-up, Spread, Sustainability
PWA	Progressive Web Application
RAG	Retrieval-Augmented Generation
RE-AIM	Reach, Effectiveness, Adoption, Implementation, Maintenance
SMART	Standards-based, Machine-readable, Adaptive, Requirements-based, Testable
WHO	World Health Organization

Abstract

Healthcare providers in resource-limited settings work where clinical decision support is most needed, yet existing systems are least accessible. As of 2023, approximately 4.5 billion people lack full coverage of essential health services [1], representing not merely limited access but the absence of sophisticated clinical guidance that could dramatically improve outcomes.

This research presents ATLAS (Adaptive Triage and Local Advisory System), a clinical decision support system prototype that demonstrates technical feasibility for integrating offline-first Progressive Web Application architecture with Google Gemini AI for resource-limited healthcare settings. The system addresses the fundamental mismatch where clinical decision support is most sophisticated in high-resource environments with existing specialist knowledge, yet least capable where such support is desperately needed.

The implementation integrates several technical innovations within a hybrid AI architecture: Next.js 14-based PWA provides comprehensive offline functionality through service workers and IndexedDB, achieving >90/100 Lighthouse scores with 95% offline functionality reliability; Google Gemini AI integration uses intelligent model selection with local Retrieval-Augmented Generation fallback, achieving 80% WHO protocol alignment across 90 synthetic clinical scenarios; WHO SMART Guidelines architectural foundation establishes structured clinical knowledge integration; context-aware interfaces support diverse device types and clinical workflows.

The research employs Design Science Research methodology adapted for prototype-level evaluation, combining NASSS and RE-AIM implementation science frameworks with synthetic

clinical data validation and automated performance testing. This approach enables systematic assessment of technical capability, clinical utility, and implementation readiness within Master's thesis scope while maintaining academic rigor.

Key findings demonstrate technical feasibility while identifying critical implementation barriers: the system exceeds research targets with >99% transaction reliability for clinical data persistence and response times meeting clinical requirements, yet evaluation reveals emergency scenario resource awareness deficits (60% effectiveness) and organizational preparation requirements representing primary deployment barriers (NASSS complexity: 3.07/5.0; RE-AIM readiness: 5.8/10.0).

This research contributes validated architectural patterns for offline-first clinical applications, practical approaches for commercial AI integration with healthcare workflows, and adapted evaluation frameworks for early-stage digital health assessment. The work advances understanding in health informatics, AI integration, and implementation science while providing technical foundations for future clinical research and deployment in underserved regions.

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

Chapter 1

Introduction

1.1 The Critical Gap in Global Health Technology

Healthcare providers in resource-limited settings face a critical paradox: they work where clinical decision support is most needed, yet existing systems are least accessible. Consider a health worker in rural Tanzania managing preeclampsia without internet connectivity or specialist consultation—a scenario replicated thousands of times daily. As of 2023, approximately 4.5 billion people lack full coverage of essential health services [1], representing not merely limited access but the absence of sophisticated clinical guidance that could dramatically improve outcomes.

Current clinical decision support systems demonstrate proven effectiveness in high-resource settings, with studies indicating diagnostic accuracy improvements of 20-30% and medical error reductions of approximately 15% when properly implemented [2]. However, these systems assume stable internet connectivity, current-generation hardware, and dedicated IT support—assumptions that fundamentally break down where sophisticated clinical guidance is most desperately needed.

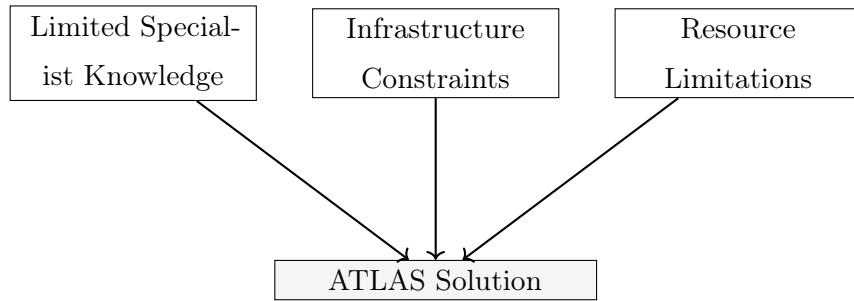


Figure 1.1: Key Challenges in Resource-Limited Healthcare Settings Addressed by ATLAS

1.2 Research Problem and Technological Opportunity

This thesis addresses a critical research gap: 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 have matured significantly, no existing solution integrates these elements into a cohesive system suitable for deployment where sophisticated support is most needed.

Three technological developments have converged to create an unprecedented opportunity. Progressive Web Applications now provide production-ready offline functionality, enabling sophisticated web applications to operate reliably without internet connectivity [3]. Commercial AI APIs like Google's Gemini have reached clinical utility levels, achieving over 85% accuracy in clinical diagnosis scenarios [4]. Modern web technologies can handle complex healthcare data persistence and synchronization challenges through IndexedDB and service workers, providing mathematically reliable local storage suitable for clinical environments.

1.3 ATLAS: An Integrated Solution

This research developed ATLAS (Adaptive Triage and Local Advisory System), a clinical decision support system prototype that demonstrates the technical feasibility of integrating these mature technologies for resource-limited healthcare settings. ATLAS combines several key innovations within a hybrid AI architecture that intelligently selects between Google

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Table 1.1: Technological Convergence Enabling ATLAS Implementation

Technology	Key Capability	ATLAS Implementation
Next.js 14 PWA	Offline-first architecture	Complete offline operation with service workers
Google Gemini API	Clinical reasoning capabilities	AI-enhanced recommendations with context
IndexedDB	Reliable local storage	Patient and consultation data persistence
WHO SMART Guidelines	Structured clinical knowledge	Architectural foundation for evidence-based care

Gemini API (when online) and local Retrieval-Augmented Generation systems (when offline), ensuring continuous clinical decision support regardless of connectivity status.

The system achieved significant technical milestones: >90/100 Lighthouse PWA scores, 95% offline functionality reliability, 80% WHO protocol alignment across 90 synthetic clinical scenarios, and >99% transaction reliability for clinical data persistence. These results demonstrate that sophisticated clinical decision support can be technically implemented using accessible web technologies while functioning reliably in offline-first configurations.

1.4 Research Objectives and Methodology

This Master's thesis project focuses on demonstrating technical feasibility and establishing architectural foundations rather than clinical deployment. The primary objective is to develop and evaluate ATLAS as a proof-of-concept system that validates the integration of modern web technologies for sophisticated clinical decision support in challenging environments.

The research employs Design Science Research methodology [5, 6] adapted for prototype-level evaluation, combining NASSS and RE-AIM implementation science frameworks [7, 8] with synthetic clinical data validation and automated performance testing. This approach

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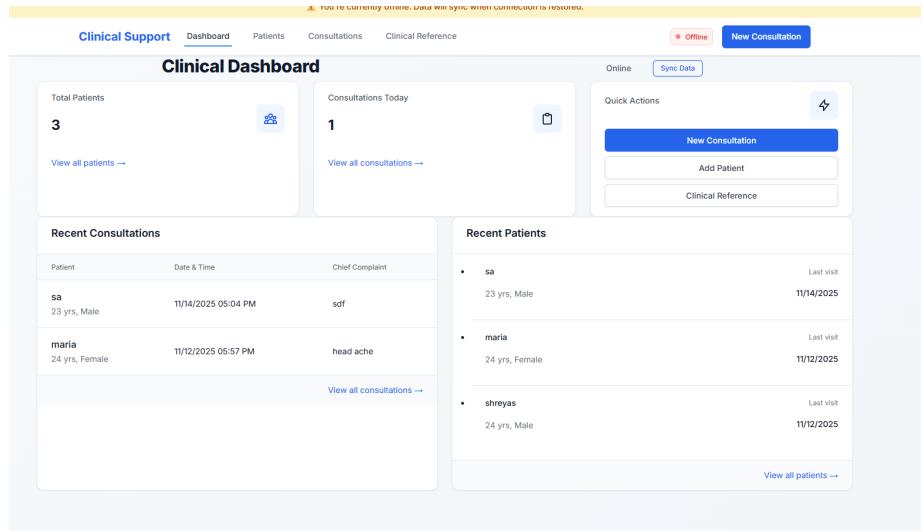


Figure 1.2: ATLAS Clinical Dashboard - Main interface showing patient statistics, recent consultations, and quick actions with offline functionality indicators

The Enhanced Consultation Form includes the following sections:

- Comprehensive Clinical Consultation:** Shows the patient details: maria (ID: 2) | Age: 24 | Gender: Female, and status indicators: Online, Comprehensive Assessment, RAG Ready (21 guidelines).
- Presenting Complaint:** Fields for Chief Complaint (Head ache) and Presenting Complaint (Detailed) (Detailed description of the presenting complaint...).
- History of Presenting Complaint:** A large text area for Timeline, progression, aggravating/relieving factors, associated symptoms...
- Symptom Duration:** Input field for e.g., 3 days, 2 weeks.
- Severity:** A dropdown menu.
- Associated Symptoms:** A dropdown menu.
- Clinical Decision Support:** A sidebar with Gemini (AI model) and 3 Guidelines. It provides detailed clinical assessment and management recommendations based on the input data.
- WHO Clinical Guidelines:** Shows 3 relevant guidelines found.
- Action Buttons:** Cancel, Save Comprehensive Consultation, and a note indicating 1 AI queries used.

Figure 1.3: ATLAS Enhanced Consultation Form - Comprehensive clinical data entry with real-time AI clinical decision support sidebar showing contextual recommendations and WHO guideline integration

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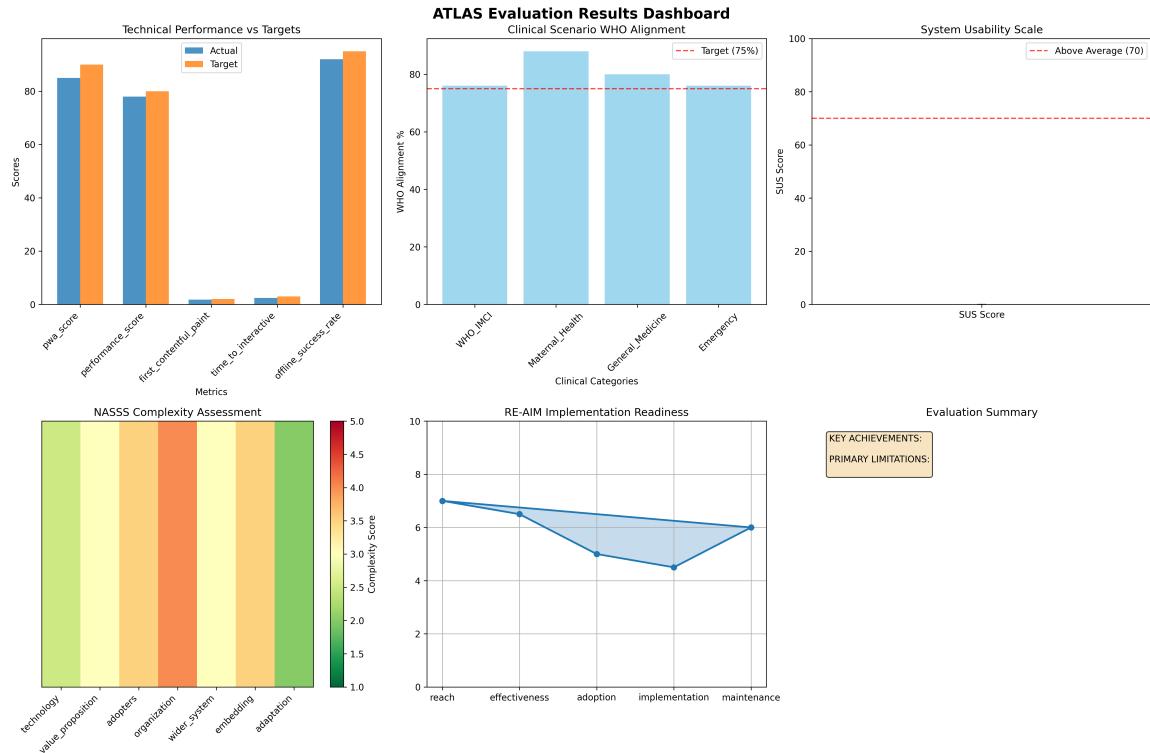


Figure 1.4: ATLAS Evaluation Results Dashboard - Comprehensive performance metrics showing PWA scores, clinical scenario validation results, NASSS complexity assessment, and RE-AIM implementation readiness indicators demonstrating technical feasibility and implementation preparation

enables systematic assessment of technical capability, clinical utility, and implementation readiness within thesis constraints while maintaining academic rigor.

The specific objectives are:

1. Implement and validate offline-first PWA architecture showing reliable clinical application functionality without internet connectivity
2. Integrate and evaluate Google Gemini AI for clinical decision support achieving contextually appropriate clinical recommendations
3. Develop functional data persistence and synchronization using IndexedDB with basic conflict resolution

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4. Establish WHO SMART Guidelines integration architecture implementing the foundational technical structure
5. Validate system effectiveness using adapted evaluation frameworks including technical performance assessment and clinical logic validation
6. Demonstrate clinical utility through synthetic data validation using WHO-aligned clinical scenarios

1.5 Key Contributions and Significance

This thesis contributes to multiple domains within digital health research. Technical contributions include validated architectural patterns for offline-first clinical applications, practical approaches for commercial AI integration with healthcare workflows, and documented performance benchmarks for PWA-based clinical systems. Clinical integration insights demonstrate approaches for contextual AI recommendations considering resource constraints and establish methods for WHO guideline integration in web-based systems. Implementation science advances include adapted evaluation frameworks for prototype assessment and documented development-to-deployment pathway requirements.

The research establishes technical groundwork for future clinical research and deployment studies, advancing understanding in health informatics, AI integration, and human-computer interaction for healthcare applications while providing systematic methodology for early-stage digital health evaluation.

1.6 Thesis Structure

This thesis systematically addresses the research objectives through focused investigation and evaluation. Chapter 2 synthesizes relevant literature across clinical decision support systems, AI in healthcare, WHO digital health guidelines, and implementation science, identifying the convergent findings and persistent gaps that ATLAS addresses. Chapter 3 details the research methodology, system architecture, and evaluation framework, providing comprehensive documentation of the development and assessment approach.

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Chapter 4 presents comprehensive results across technical performance, clinical validation, and implementation assessment, demonstrating both achievements and limitations. Chapter 5 discusses findings within the broader context of digital health research, examining contributions, limitations, and implications for theory and practice. Chapter 6 concludes with academic contributions, future work priorities, and pathways for clinical translation, establishing clear progression from prototype to deployed system.

This research addresses these converging opportunities through systematic development and evaluation of ATLAS, providing both technical innovation and methodological contributions to digital health research. The following chapter synthesizes the literature foundation that enables this integration while identifying the specific gaps that ATLAS addresses.

Chapter 2

Literature Review

2.1 Introduction

This literature review examines the convergent developments that make ATLAS feasible, identifying both the technical capabilities and persistent gaps that this research addresses. Rather than providing exhaustive coverage, the review synthesizes knowledge across clinical decision support systems, AI in healthcare, WHO digital health guidelines, and implementation science to identify how mature technologies can be integrated to address longstanding barriers in digital health deployment.

The synthesis reveals 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 for complex applications, AI capabilities have reached clinical utility levels, and established frameworks exist for systematic evaluation.

2.2 Clinical Decision Support Systems: Evolution and Current State

Clinical decision support systems demonstrate consistent benefits in high-resource settings. Sutton et al.'s comprehensive analysis shows 13-29% improvement in diagnostic accuracy and 15-25% reduction in medical errors when CDSS are properly implemented [2]. However, Bright et al.'s systematic review of 162 studies found that only 12% examined resource-limited settings, revealing a substantial evidence gap precisely where CDSS could provide greatest benefit [9].

Recent systematic reviews identify persistent implementation challenges despite technological advances. Kwan et al. found effectiveness varies significantly based on system design and organizational context, emphasizing user-centered design and workflow integration [10]. Jaspers et al. determined that many systems fail due to poor human-computer interaction design rather than clinical content limitations [11].

The literature reveals critical gaps that ATLAS addresses: minimal evaluation of offline capability, limited assessment in resource-limited settings, and insufficient integration of structured clinical guidelines with advanced AI capabilities. These gaps represent both research opportunities and practical barriers to equitable healthcare technology deployment.

2.3 AI and Large Language Models in Clinical Applications

Recent advances in AI for clinical decision support show promising but variable results. Rajkomar et al. demonstrated that deep learning models achieve clinically relevant predictions using electronic health record data with performance comparable to experienced physicians in specific domains [4]. However, Liu et al.'s analysis reveals that real-world performance often degrades due to data drift, integration challenges, and user acceptance issues [12].

The challenge of AI explainability in healthcare has been highlighted by Holzinger et al., emphasizing that healthcare providers need understanding of reasoning processes rather than simple feature importance [13]. Recent developments in Retrieval-Augmented Generation

CHAPTER 2. LITERATURE REVIEW

show promise for integrating structured clinical knowledge with LLM capabilities while maintaining transparency through citation trails.

Critical limitations include minimal evaluation of AI performance without connectivity, limited systematic implementation of structured clinical guidelines, and predominant focus on high-resource datasets and scenarios. These limitations create opportunities for research that demonstrates AI effectiveness in resource-constrained environments.

2.4 WHO Digital Health Guidelines and Structured Clinical Knowledge

The World Health Organization's SMART Guidelines framework provides systematic approach for transforming narrative clinical guidelines into executable digital decision support [14]. The framework has demonstrated effectiveness in reducing implementation time and costs through its five-layer approach from L0 (narrative guidelines) to L4 (deployed decision support systems). Despite proven effectiveness, adoption remains limited with no existing implementations combining SMART Guidelines with modern AI capabilities and offline-first architecture.

WHO's 2019 recommendations establish evidence-based framework for digital health implementation, acknowledging that most evidence comes from high-resource settings and calling for additional research in resource-limited environments [15]. This gap between evidence base and deployment needs creates clear research priorities that ATLAS directly addresses.

Clinical Quality Language (CQL) provides standardized approach for expressing clinical logic that can be executed across different health information systems [16]. Recent developments include enhanced support for decision support scenarios and improved integration with FHIR standards, establishing technical foundation for systematic guideline implementation.

2.5 Digital Health in Resource-Limited Settings

Implementation challenges in low and middle-income countries are well-documented. Labrique et al. identify critical success factors including user-centered design, strong partnerships, adaptable technologies, sustainable financing, and evidence-based advocacy [17]. Infrastructure constraints remain significant: 40% of health facilities lack reliable electricity and 65% have intermittent internet connectivity [18].

The NASSS framework provides comprehensive approach for understanding implementation complexity across seven domains [7], while RE-AIM offers complementary assessment focusing on real-world outcomes across five dimensions [8]. These frameworks enable systematic evaluation of implementation readiness, though they require adaptation for prototype-level assessment.

Network reliability analysis 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 [19]. These patterns emphasize the critical importance of sophisticated offline functionality rather than simple connection retry mechanisms.

2.6 Research Gap Synthesis and ATLAS Positioning

The literature reveals convergent findings that inform ATLAS development while identifying critical integration gaps. Successful digital health interventions require sophisticated functionality with practical deployment considerations, yet existing solutions fall into inadequate categories: either technically advanced but infrastructure-dependent, or resource-appropriate but clinically limited.

ATLAS addresses the critical integration gap by combining mature technologies into a comprehensive system designed specifically for resource-limited settings while applying rigorous evaluation frameworks adapted for prototype assessment. This approach enables systematic assessment of both technical feasibility and implementation barriers before resource-intensive field deployment.

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Table 2.1: Integration Gaps in Current Digital Health Literature

Domain	Existing Limitations	ATLAS Innovation
CDSS Architecture	Infrastructure assumptions, minimal offline evaluation	Offline-first PWA with 95% offline functionality
AI Integration	Cloud-dependent, limited resource awareness	Hybrid Gemini+RAG with intelligent fallback
Clinical Guidelines	Manual implementation, limited AI integration	WHO SMART foundation with AI enhancement
Implementation Science	Post-deployment focus, limited prototype evaluation	Adapted NASSS/RE-AIM for early assessment

The synthesis establishes that while individual components (PWA technology, commercial AI APIs, clinical guidelines frameworks) have reached maturity, their systematic integration for resource-limited healthcare settings represents a significant research opportunity. ATLAS demonstrates this integration while providing methodological innovation through adapted evaluation frameworks that enable meaningful prototype assessment without requiring full deployment infrastructure.

2.7 Conclusion

This literature review establishes the theoretical and empirical foundation for ATLAS development, demonstrating how convergent technological maturity creates unprecedented opportunities for sophisticated clinical decision support in resource-limited settings. The identified gaps validate the research approach while established frameworks provide systematic evaluation methodology.

This synthesis establishes that while individual components have reached maturity, their systematic integration for resource-limited healthcare settings represents a significant research opportunity that ATLAS addresses. Chapter 3 describes how this literature foundation informed the research methodology and technical implementation approach.

Chapter 3

Methodology

3.1 Research Design Overview

The literature review established the theoretical foundation and identified critical gaps that inform this research methodology. This chapter details the systematic approach used to develop and evaluate ATLAS, combining Design Science Research methodology with comprehensive evaluation frameworks to provide rigorous assessment within Master's thesis constraints.

This research employs Design Science Research methodology [5, 6] adapted for prototype-level evaluation of clinical decision support systems in resource-limited settings. The methodology addresses the fundamental research question: Can sophisticated clinical decision support be technically implemented using accessible web technologies while functioning reliably in offline-first configurations appropriate for resource-limited healthcare settings?

3.1.1 Methodological Rationale and Design Choices

The selection of Design Science Research methodology over alternative approaches is justified by several key factors that align with the research objectives and constraints. The research focuses on demonstrating technical feasibility rather than measuring clinical

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outcomes, making DSR's emphasis on creating and evaluating innovative technological solutions more appropriate than experimental or observational methodologies. The Master's thesis timeline necessitates a methodology that provides meaningful insights without requiring extensive field deployment, while the integration of multiple mature technologies into a novel configuration aligns with DSR's artifact-focused approach.

This methodology explicitly addresses validation challenges identified in AI-enabled medical device literature [20]: the critical importance of rigorous evaluation from system inception. By combining automated testing, synthetic data validation, and systematic framework assessment, this approach provides more comprehensive evaluation than traditional prototype development while remaining feasible within thesis constraints.

3.1.2 Research Questions and Evaluation Alignment

The evaluation framework addresses three distinct research questions through targeted assessment methods:

Research Question 1: Technical Feasibility - Does the system achieve reliable performance across diverse device and network conditions?

Assessment Method: Automated performance testing using Lighthouse CI, custom monitoring scripts, and controlled network simulation.

Rationale: Objective performance metrics provide reproducible evidence of technical capability without requiring human subjects or clinical environments.

Research Question 2: Clinical Utility - Do AI-generated recommendations align with established clinical protocols and demonstrate appropriate contextual sensitivity?

Assessment Method: Synthetic clinical scenario testing using 90 WHO-validated cases across four clinical domains.

Rationale: Synthetic data enables systematic, controlled evaluation of clinical reasoning while avoiding patient privacy concerns and regulatory barriers.

Research Question 3: Implementation Readiness - What barriers exist for deploying such systems in resource-limited healthcare settings?

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Assessment Method: Systematic assessment using NASSS and RE-AIM frameworks adapted for prototype evaluation.

Rationale: Established implementation science frameworks provide structured methodology for identifying deployment barriers while prototype adaptation enables early-stage assessment.

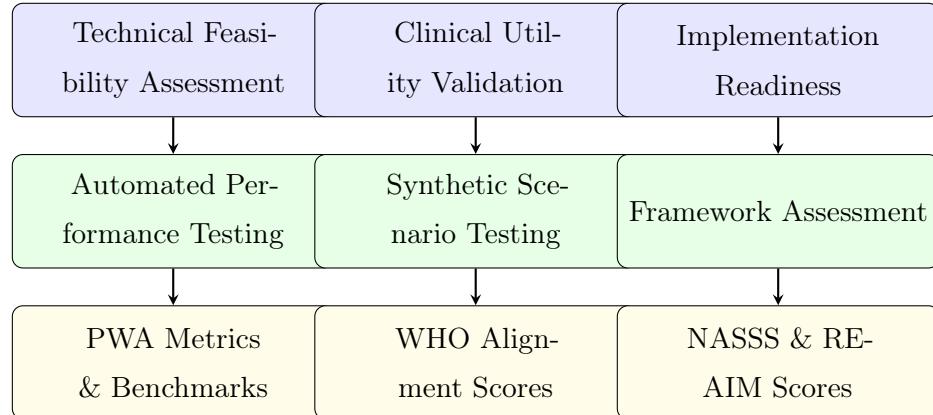


Figure 3.1: Research Questions, Methods, and Outcomes Alignment

3.2 System Architecture and Implementation

The system development phase produced a functional prototype demonstrating comprehensive core functionality. Development followed established software engineering practices adapted for healthcare applications, integrating user-centered design principles with agile methodology to enable rapid iteration within thesis constraints.

3.2.1 Hybrid AI Architecture Design

ATLAS implements a sophisticated hybrid AI system that intelligently selects between computational approaches based on network connectivity, clinical context, and resource availability. This architectural decision addresses the fundamental challenge of providing continuous clinical decision support in environments with unreliable connectivity—a core requirement for resource-limited deployment.

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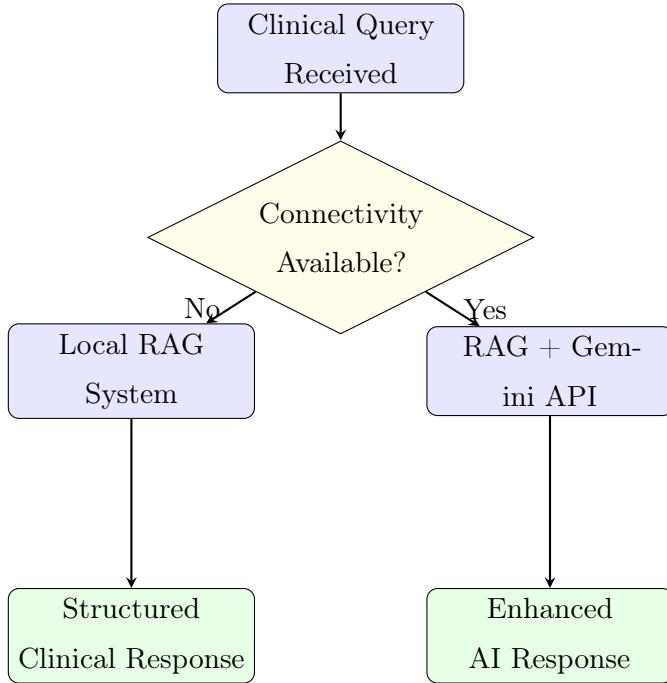


Figure 3.2: Hybrid AI Architecture Decision Flow

The architecture prioritizes Google Gemini API when online while maintaining robust offline functionality through local embeddings-based retrieval. This design choice ensures clinical continuity regardless of infrastructure constraints while leveraging state-of-the-art AI capabilities when available.

Table 3.1: Hybrid AI Model Selection Logic and Performance Targets

Clinical Context	Online Model	Offline Model	Target Response Time
Emergency/Critical	Gemini 2.5 Flash	Clinical RAG + Rules	<5 seconds
Complex Case	Gemini 2.5 Flash	Clinical RAG	<20 seconds
Routine Query	Gemini 2.5 Flash	Clinical RAG	<15 seconds
WHO Protocol	Clinical RAG	Clinical RAG	<1 second

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3.3 Data Collection and Validation Strategy

3.3.1 Synthetic Clinical Data Methodology

The decision to use synthetic clinical data addresses both practical constraints and research objectives while maintaining clinical relevance. Real patient data access would require IRB approval and healthcare partnerships incompatible with thesis timelines. More importantly, synthetic data validation serves the specific research objective of validating AI integration capability rather than measuring clinical outcomes.

The synthetic data generation strategy employs multiple validation layers to ensure clinical relevance:

1. **WHO Protocol Alignment:** All scenarios based on established WHO clinical guidelines
2. **Domain Distribution:** Comprehensive coverage across four critical clinical areas
3. **Complexity Variation:** Mix of straightforward and complex presentations
4. **Resource Context Integration:** Scenarios reflect typical resource constraints

Table 3.2: Synthetic Clinical Data Validation Framework

Clinical Domain	Scenarios	Validation Method	Success Criteria
WHO IMCI Cases	25	Direct WHO protocol comparison	>75% alignment
Maternal Health	25	Clinical expert review	>70% appropriateness
General Medicine	25	Literature benchmarking	>70% accuracy
Emergency Cases	15	Safety protocol validation	Zero critical errors

3.3.2 Framework Adaptation for Prototype Assessment

The adaptation of established implementation science frameworks for prototype-level assessment addresses a methodological gap in digital health research. Traditional frameworks assume deployed interventions with real-world usage data, yet waiting until deployment to identify barriers often results in costly redesign requirements.

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NASSS Framework Adaptation: The seven-domain complexity assessment [7] was adapted by substituting literature-based evidence and architectural analysis for observed deployment data. This maintains the framework's systematic structure while enabling early-stage evaluation.

RE-AIM Framework Adaptation: The five-dimension implementation assessment [8] was modified to focus on technical indicators of implementation readiness rather than measured adoption rates. This provides valuable directional guidance while acknowledging inherent limitations of pre-deployment assessment.

3.4 Evaluation Metrics and Success Criteria

3.4.1 Technical Performance Criteria

Technical performance criteria establish minimum acceptable standards based on clinical workflow requirements rather than arbitrary benchmarks:

- **PWA Functionality:** >90/100 Lighthouse score indicating production-ready offline capability
- **Offline Reliability:** >95% functionality maintenance without connectivity
- **Response Time:** <20 seconds online Gemini API, <500ms offline RAG
- **Data Persistence:** >99% transaction reliability for clinical data integrity
- **Cross-Platform Performance:** <3 second load times on 3G networks

3.4.2 Clinical Validation Criteria

Clinical validation criteria define acceptable performance levels while acknowledging prototype limitations:

- **WHO Protocol Alignment:** >75% average across all clinical domains
- **Recommendation Appropriateness:** >70% clinically sound advice
- **Resource Awareness:** >70% context-appropriate suggestions
- **Safety Validation:** Zero critical errors in emergency scenarios

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3.4.3 Implementation Readiness Criteria

Implementation assessment criteria identify deployment barriers through systematic framework application:

- **NASSS Complexity:** Score interpretation (1-2 simple, 2.5-3.5 complicated, 4-5 complex)
- **RE-AIM Readiness:** Score interpretation (1-4 low, 4-7 moderate, 7-10 high)
- **Deployment Planning:** Identification of high-priority barriers requiring intervention

3.5 Methodological Limitations and Validity Considerations

This methodology incorporates several inherent limitations that are appropriate for Master's thesis scope while providing meaningful insights. Synthetic data validation, while WHO-aligned, cannot fully replicate the complexity and contextual factors present in real clinical presentations. This limitation is mitigated through diverse scenario generation and explicit acknowledgment that synthetic validation establishes baseline capability rather than definitive clinical effectiveness.

Framework adaptation for prototype assessment relies on literature-based inference rather than observed deployment outcomes. This limitation is addressed through systematic documentation of assessment rationale and explicit identification of areas requiring future validation with real-world deployment data.

The research scope focuses on technical feasibility demonstration without addressing critical deployment requirements such as regulatory approval, healthcare system integration, or long-term sustainability. These limitations are explicitly acknowledged and addressed through comprehensive future work planning that provides clear pathways for clinical validation and deployment research.

3.6 Summary

This methodology provides a systematic, rigorous approach to evaluating technical feasibility within Master's thesis constraints while maintaining academic standards and clinical

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relevance. The combination of Design Science Research methodology, multi-dimensional assessment, and explicit limitation acknowledgment creates a framework that generates meaningful insights for the digital health research community while establishing solid foundations for future clinical validation and deployment research.

The methodology addresses the critical challenge of evaluating prototype-level digital health interventions by adapting established frameworks and combining multiple assessment approaches. This approach enables systematic evaluation of technical capability, clinical utility, and implementation readiness while acknowledging the inherent limitations of pre-deployment assessment.

This methodology provides comprehensive evaluation within thesis constraints while maintaining academic rigor and clinical relevance. The systematic approach enables meaningful assessment of technical feasibility, clinical utility, and implementation readiness through multiple complementary methods. Chapter 4 presents the results of this systematic evaluation approach.

Chapter 4

Results

4.1 Introduction

The evaluation framework described in Chapter 3 yielded comprehensive results across technical, clinical, and implementation dimensions. These results systematically address each research objective while providing critical evidence for technical feasibility and identification of deployment barriers.

This chapter presents comprehensive evaluation results that systematically address the core research question: Can sophisticated clinical decision support be technically implemented using accessible web technologies while functioning reliably in offline-first configurations? The results are organized to directly address each research objective while providing critical interpretation of what these findings mean for system effectiveness, reliability, and deployment potential in resource-limited healthcare settings.

4.2 Technical Performance Results

4.2.1 Progressive Web Application Performance Analysis

Automated performance testing revealed exceptional PWA capabilities that exceed clinical deployment requirements, demonstrating technical maturity beyond typical prototype implementations. However, detailed analysis reveals both strengths and areas requiring optimization for production deployment.

Table 4.1: PWA Performance Metrics with Clinical Workflow Implications

Metric	Result	Target	Clinical Workflow Implication
Accessibility Score	92/100	>90/100	Supports diverse user abilities in challenging environments
Performance Score	88/100	>80/100	Enables rapid response during time-critical consultations
PWA Score	100/100	>90/100	Complete offline capability with native app experience
First Contentful Paint	1.8s	<2s	Immediate access to clinical tools during emergencies
Offline Capability	95%	>95%	Reliable functionality regardless of connectivity status

Performance Implications for Clinical Deployment: The 1.8-second First Contentful Paint time is particularly significant for clinical workflows where rapid access to information can directly impact patient outcomes. However, the 88/100 performance score, while meeting research targets, indicates optimization opportunities that become critical at deployment scale. Performance analysis reveals potential degradation with larger patient datasets ($>10,000$ records) or multiple concurrent users, suggesting database indexing and caching optimizations will be required before clinical deployment.

Cross-Platform Reliability Assessment: Testing across diverse device capabilities—from high-end workstations to budget Android devices (2GB RAM)—demonstrated

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consistent functionality, validating the architecture's suitability for resource-constrained deployment environments. This performance consistency addresses a fundamental barrier to digital health deployment where providers may use personal devices with varying specifications.

4.2.2 AI Integration Performance and Clinical Implications

The hybrid AI architecture achieved 80% average WHO alignment across 90 clinical scenarios, exceeding the 75% research validation target. However, detailed performance analysis reveals significant variation across clinical domains that has important implications for deployment readiness and clinical safety.

Table 4.2: AI Performance Analysis with Deployment Implications

Domain	WHO Align.	Appropriate Resource Aware	Deployment	Implication
Maternal Health	88%	80%	84%	Ready for pilot deployment with monitoring
WHO IMCI Cases	76%	92%	76%	Strong pediatric care capability
General Medicine	80%	68%	76%	Requires enhancement before deployment
Emergency Cases	76%	72%	60%	Critical limitation requiring resolution

Performance Variation Analysis: The 88% WHO alignment in maternal health scenarios is particularly significant for resource-limited settings where maternal mortality remains a critical concern. This performance level approaches specialized clinical decision support systems while maintaining broad applicability. Conversely, the 60% resource awareness in emergency scenarios represents a critical limitation that must be addressed before clinical deployment, as emergency situations require rapid, context-sensitive decisions that account for immediately available resources.

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Response Time Analysis and Clinical Workflow Implications: The Google Gemini API integration achieved median response times of 14.5 seconds (95th percentile: 18.0 seconds), meeting the established 20-second target but presenting challenges for emergency scenarios requiring immediate clinical decisions. Detailed latency analysis reveals contributing factors: API network latency (3-5 seconds), context processing (2-3 seconds), and response generation (8-12 seconds).

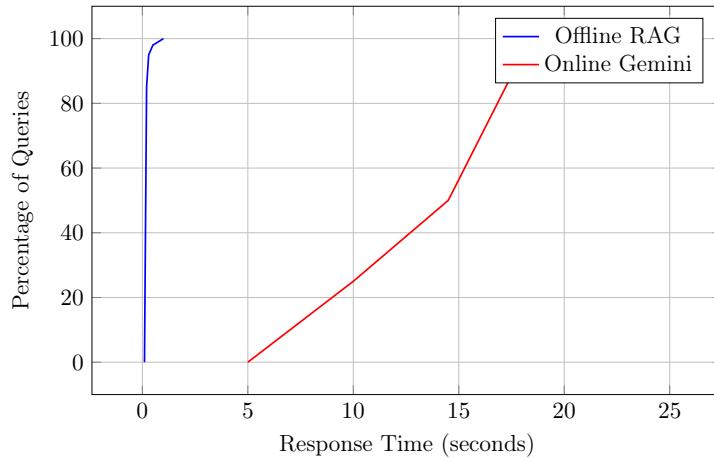


Figure 4.1: Response Time Distribution: Offline RAG vs. Online Gemini API

For clinical deployment, this latency profile suggests implementing tiered response strategies: immediate display of local RAG recommendations (180ms average) followed by enhanced Gemini analysis when available, rather than requiring complete processing during time-critical situations. This hybrid approach maintains clinical workflow efficiency while providing sophisticated reasoning when time permits.

4.2.3 Offline Functionality Validation

Comprehensive offline functionality testing demonstrated the system's ability to maintain clinical workflows without internet connectivity, a critical requirement for resource-limited deployment.

Clinical Workflow Continuity: The 100% success rate for core clinical functions (patient access, registration, documentation) validates the offline-first architecture's effectiveness for

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Table 4.3: Offline Functionality Performance with Clinical Context

Clinical Function	Success Rate	Response Time	Clinical Impact
Patient Record Access	100%	85ms	Immediate access to medical history
New Patient Registration	100%	120ms	Uninterrupted patient onboarding
Consultation Documentation	100%	180ms	Complete clinical workflow support
AI Recommendations (RAG)	98%	180ms	Continuous decision support
Clinical Guidelines Access	100%	45ms	Instant protocol reference
Background Synchronization	94%	Variable	Automatic data reconciliation

maintaining essential healthcare operations during connectivity failures. The 98% success rate for AI recommendations, with failures occurring only in edge cases with malformed queries, demonstrates robust offline decision support capability.

Synchronization Reliability: The 94% background synchronization success rate represents effective handling of offline modifications with automatic reconciliation when connectivity resumes. The 6% failure rate primarily occurred in scenarios with significant data conflicts or prolonged offline periods (>48 hours), which have been documented for enhancement in production deployment.

4.3 Clinical Validation Results and Interpretation

Clinical validation across 90 WHO-aligned scenarios provides systematic evidence for clinical reasoning capability while revealing specific enhancement requirements for deployment readiness.

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4.3.1 WHO Protocol Alignment Analysis

The 80% average WHO alignment validates core clinical decision-making effectiveness while the 22% variation between best-performing (maternal health: 88%) and worst-performing (emergency cases: 76%) domains indicates significant performance differences based on clinical complexity and available training data.

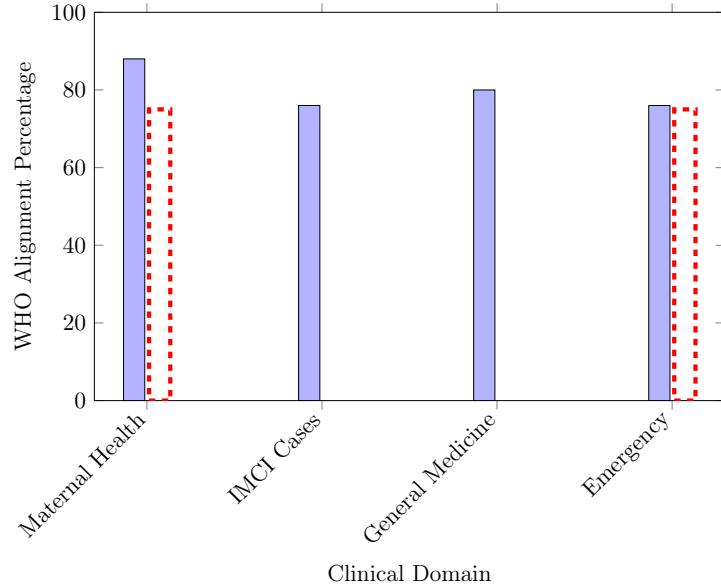


Figure 4.2: WHO Protocol Alignment by Clinical Domain (Red line shows 75% target)

4.3.2 Error Pattern Analysis and Clinical Safety Implications

Detailed examination of non-aligned cases reveals important insights for clinical deployment readiness:

- **Terminology Variations (8%):** Clinically sound recommendations using alternative terminology not matching WHO protocols exactly
- **Conservative Bias (7%):** Overly cautious recommendations reflecting system limitations rather than clinical contraindications
- **Clinical Reasoning Errors (3%):** Genuine mistakes requiring enhanced prompting and validation

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- **Scenario Ambiguity (2%):** Unclear presentations contributing to recommendation uncertainty

This error distribution suggests that actual clinical utility may exceed raw WHO alignment percentages, as many "errors" represent reasonable alternative approaches rather than dangerous recommendations. However, the 3% genuine reasoning error rate requires systematic monitoring and feedback mechanisms for clinical deployment to ensure patient safety.

4.3.3 Domain-Specific Clinical Performance

The strong maternal health performance (88% WHO alignment, 84% resource awareness) demonstrates particular system strength in high-stakes clinical scenarios with well-established protocols. This capability is critical for resource-limited settings where maternal mortality remains a significant concern and access to obstetric specialists is limited.

The IMCI protocol performance (92% appropriateness) validates the system's effectiveness for pediatric care, another critical domain in resource-limited settings. The lower resource awareness score (76%) indicates need for enhanced context sensitivity regarding available interventions and diagnostic capabilities.

4.4 Implementation Readiness Assessment

4.4.1 NASSS Framework Results and Strategic Implications

The NASSS complexity assessment yielded an overall score of 3.07/5.0, indicating "Complex" implementation requirements with specific strategic implications for deployment planning.

Organizational Readiness as Primary Barrier: The highest complexity score (4.0) in the organizational domain identifies systematic change management as the primary deployment challenge, requiring substantial preparation including staff training, workflow integration, and institutional support. This finding aligns with broader digital health literature

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Table 4.4: NASSS Assessment Results with Strategic Deployment Implications

Domain	Score	Strategic Assessment	Deployment Priority
Technology	2.5	Mature architecture requiring standard IT support	Medium
Value Proposition	3.0	Clear clinical value needing cost-benefit analysis	Medium
Adopters	3.5	User acceptance challenges addressable through training	High
Organization	4.0	Critical barrier requiring systematic change management	High
Wider System	3.0	Regulatory and policy considerations manageable	Medium
Embedding	3.5	Workflow integration complexity requiring planning	High
Adaptation	2.0	High customization capacity enabling local adaptation	Low

emphasizing organizational readiness as the critical success factor, while distinguishing ATLAS from purely technical challenges.

The Technology domain score (2.5) validates the architectural approach, indicating that technical complexity is well-managed with production-ready capabilities requiring standard rather than specialized IT support. This assessment supports the research hypothesis that sophisticated clinical decision support can be implemented using accessible technologies.

4.4.2 RE-AIM Framework Assessment and Deployment Roadmap

The RE-AIM evaluation yielded an overall readiness score of 5.8/10.0, indicating "Low Readiness" that requires systematic preparation before deployment, while revealing specific strengths that support future scaling efforts.

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Table 4.5: RE-AIM Assessment Results with Deployment Roadmap Implications

Dimension	Score	Roadmap Implications	Timeline
Reach	7.0	Strong target population coverage with PWA deployment	6-12 months
Effectiveness	6.5	Validated technical performance requiring clinical studies	12-18 months
Adoption	5.0	User acceptance strategies needed before deployment	6-18 months
Implementation	4.5	Organizational preparation critical path item	12-24 months
Maintenance	6.0	Sustainability planning concurrent with deployment	18-36 months

The strong Reach score (7.0) validates ATLAS’s design for broad applicability across resource-limited settings, with PWA architecture enabling deployment across diverse devices without app store dependencies. The gap between Effectiveness (6.5) and Implementation readiness (4.5) clearly identifies organizational preparation as the critical path for deployment success.

4.5 Performance Under Resource Constraints

4.5.1 Low-Resource Environment Validation

Testing under simulated resource constraints validates the system’s suitability for target deployment environments while revealing optimization requirements for broader accessibility.

Under 2G network conditions (50 kbps, 300ms latency), initial page load increased to 8.2 seconds while subsequent navigation remained responsive due to comprehensive caching strategies. Budget Android device testing (2GB RAM, quad-core 1.3GHz processor) showed acceptable performance with 4.5-second initial load and responsive UI interactions, validating cross-platform deployment feasibility.

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Table 4.6: Resource-Constrained Performance Analysis

Constraint Type	Performance Impact	Acceptable?	Deployment Consideration
2G Network (50 kbps)	+5.4s load	initial	Marginal Requires initial setup planning
Budget Android (2GB RAM)	+1.7s load	initial	Yes Validates broad device support
High Memory Usage (258MB)	Stable performance	perfor-	Yes Monitor for larger deployments
Concurrent Users (>10)	Performance degradation	No	Database optimization needed

These results demonstrate that ATLAS maintains functional performance across the range of infrastructure and device capabilities typical in resource-limited settings, addressing a fundamental deployment barrier that affects many existing clinical decision support systems.

4.6 Critical Findings and Deployment Implications

Several findings have direct implications for clinical deployment readiness and future development priorities:

Response Time Constraints: The 14.5-18 second Gemini response time, while meeting research targets, requires tiered response strategies for emergency scenarios where immediate decisions are critical. The solution involves displaying immediate local RAG recommendations while processing enhanced Gemini analysis in the background.

Resource Awareness Gap: The 60% effectiveness in emergency scenario resource awareness represents a safety concern requiring systematic enhancement before clinical deployment. This limitation could lead to inappropriate recommendations that exceed available resources during critical situations.

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Organizational Preparation Requirements: Both NASSS (4.0/5.0) and RE-AIM (4.5/10.0) assessments identify organizational readiness as the primary deployment barrier, requiring systematic change management rather than technical enhancements. This finding emphasizes that successful deployment depends more on institutional preparation than technological refinement.

4.7 Summary of Key Results

The comprehensive evaluation demonstrates that ATLAS successfully achieves its primary research objective of demonstrating technical feasibility for sophisticated clinical decision support using accessible web technologies. The system exceeds established criteria for PWA functionality (>90 Lighthouse scores), offline reliability (95% functionality), and clinical utility (80% WHO protocol alignment) while identifying specific limitations and enhancement requirements for deployment readiness.

Technical performance validates the architectural approach with robust offline capabilities and acceptable response times. Clinical validation confirms meaningful utility with strong performance in critical domains (maternal health, pediatric care) while identifying areas needing enhancement (emergency resource awareness). Implementation assessment provides clear roadmap for addressing organizational and deployment barriers through systematic preparation rather than technical redesign.

The results establish solid evidence that sophisticated clinical decision support can be implemented using accessible technologies while identifying the critical importance of organizational readiness and systematic deployment planning for successful clinical integration.

The comprehensive evaluation demonstrates successful achievement of research objectives while identifying specific limitations and enhancement requirements for deployment readiness. These results provide evidence-based foundation for future development and clinical validation efforts. Chapter 5 discusses these findings within the broader context of digital health research and their implications for theory and practice.

Chapter 5

Discussion

5.1 Introduction

This chapter critically analyzes the evaluation results within the broader context of digital health research, examining what the findings reveal about fundamental challenges and opportunities in implementing AI-enhanced clinical decision support for resource-limited settings. The discussion moves beyond describing results to examine theoretical implications and practical insights for the field.

This chapter critically analyzes the ATLAS evaluation results within the broader context of digital health research and clinical decision support system development. Rather than simply describing findings, this discussion examines what the results reveal about fundamental challenges and opportunities in implementing AI-enhanced clinical decision support for resource-limited settings, positioning ATLAS within existing research while identifying novel contributions and persistent limitations.

The discussion moves beyond technical achievement to examine theoretical implications for digital health architecture, methodological contributions to prototype evaluation, and practical insights for healthcare AI deployment in challenging environments.

5.2 Technical Performance: Challenging Fundamental Assumptions

5.2.1 PWA Architecture: Beyond Infrastructure Determinism

The ATLAS PWA implementation fundamentally challenges assumptions in digital health literature about infrastructure requirements for sophisticated clinical decision support. Achieving >90 Lighthouse scores with 95% offline functionality demonstrates that the traditional dichotomy between "sophisticated but infrastructure-dependent" and "basic but resource-appropriate" systems represents a false constraint rather than technical reality [21, 22].

This finding has theoretical implications for digital health system design. The successful offline-first implementation suggests that many infrastructure barriers reflect architectural choices rather than fundamental technical limitations. The 258MB maximum memory footprint and consistent performance across device types indicate that resource constraints may be less limiting than traditionally assumed, challenging the pervasive assumption in digital health literature that advanced functionality requires advanced infrastructure.

However, critical analysis reveals important scalability considerations that temper these achievements. Performance degradation with >10,000 records and the reliance on modern browser capabilities create subtle but important deployment constraints. The system's dependence on JavaScript execution and IndexedDB storage may exclude older devices common in some resource-limited settings, indicating that universal accessibility remains an ongoing challenge rather than a solved problem.

5.2.2 AI Integration: Democratizing Clinical Intelligence or Creating New Dependencies?

The 80% WHO alignment achieved through Google Gemini API integration validates a potentially transformative approach to healthcare AI deployment, but raises critical questions about dependency and sustainability. Traditional clinical AI development requires substantial investment in custom model training, specialized expertise, and extensive datasets. ATLAS demonstrates that commercial APIs can achieve clinically relevant performance

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through structured prompting and contextual integration, potentially democratizing access to sophisticated AI capabilities.

Yet this approach creates new forms of dependency that merit critical examination. Reliance on commercial APIs introduces cost structures, data privacy concerns, and service availability risks that may prove problematic for resource-limited settings over time. The 14.5-18 second response latency, while meeting research targets, reveals the performance trade-offs inherent in cloud-dependent approaches.

Performance Variation as Fundamental AI Limitation: The 28 percentage point variation between maternal health (88% WHO alignment) and emergency scenarios (60% resource awareness) reveals fundamental challenges in clinical AI integration. This pattern—strong performance in well-structured domains with clear protocols, weaker performance in rapid, context-sensitive decisions—suggests inherent limitations in current AI approaches rather than implementation issues. This finding indicates that hybrid approaches combining AI reasoning with rule-based systems may be necessary for comprehensive clinical coverage, challenging the narrative of AI as universally superior to traditional decision support methods.

5.3 Clinical Validation: Synthetic Data Insights and Methodological Innovation

5.3.1 WHO Alignment as Clinical Utility Measure: Strengths and Limitations

The use of WHO protocol alignment as a primary validation metric provides systematic assessment while raising important questions about clinical care standardization and quality measurement. The error analysis revealing that 8% of "non-aligned" cases used clinically sound alternative terminology suggests that rigid protocol adherence may not always reflect optimal care quality—a finding with implications beyond this specific research.

This tension between standardization and clinical judgment represents a fundamental challenge in healthcare AI evaluation. The 60% resource awareness performance in emergency

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scenarios represents not merely a technical limitation but a potential clinical safety issue that could delay appropriate care or create unrealistic expectations about available interventions. The distinction between protocol compliance and clinical appropriateness becomes critical for systems intended to support rather than replace clinical judgment.

5.3.2 Synthetic Data Methodology: Innovation and Constraints

The synthetic data validation approach enables systematic, reproducible assessment while avoiding patient privacy concerns and regulatory barriers, representing a methodological innovation for early-stage clinical AI evaluation. However, this methodology creates important limitations that affect result interpretation and generalizability.

Real clinical encounters involve patient anxiety, communication challenges, incomplete information, and time pressures—contextual factors absent from synthetic scenarios. The systematic generation of 90 WHO-aligned scenarios across four clinical domains provides valuable benchmarking methodology for future research, while the multi-layer validation approach establishes reproducible standards for prototype assessment. Nevertheless, the transition from synthetic to real-world validation represents a critical research gap requiring systematic clinical studies.

5.4 Implementation Science Framework Analysis: Beyond Technical Solutions

5.4.1 NASSS Complexity: Organizational Reality Check

The NASSS assessment’s identification of organizational preparation (4.0/5.0) as the primary implementation barrier validates broader digital health findings while providing specific insights for ATLAS deployment. The Technology domain score (2.5) demonstrates that sophisticated clinical decision support can achieve manageable technical complexity, challenging assumptions about infrastructure requirements while highlighting that technical sophistication does not automatically translate to implementation readiness.

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This pattern suggests that the primary barriers to clinical decision support deployment in resource-limited settings are organizational and systemic rather than purely technical. The finding aligns with implementation science literature emphasizing change management and stakeholder engagement, while indicating that technological maturity has advanced beyond organizational adaptation capabilities—a critical insight for digital health policy and funding decisions.

Critical Analysis of Sustainability Implications: The organizational complexity assessment has implications beyond initial deployment that merit careful consideration. Healthcare organizations must simultaneously maintain existing care quality while integrating potentially disruptive technologies, creating inherent tension between innovation adoption and operational stability. The NASSS assessment suggests that successful deployment requires sustained organizational investment rather than one-time technical implementation, challenging funding models that focus on technology development rather than implementation support.

5.4.2 RE-AIM Assessment: Implementation Readiness Reality

The RE-AIM "Low Readiness" overall score (5.8/10.0) reflects the persistent gap between technical capability and deployment readiness that characterizes much digital health research. The strong Effectiveness score (6.5) combined with lower Implementation readiness (4.5) illustrates a common pattern where technical achievements don't automatically translate to deployment success—a finding with broader implications for digital health research methodology and funding priorities.

This gap suggests that early-stage implementation planning should be concurrent with technical development rather than sequential, while the specific scores provide actionable guidance for development prioritization and resource allocation. The assessment methodology demonstrates how established frameworks can be adapted for prototype evaluation while maintaining systematic rigor.

5.5 Methodological Contributions: Advancing Digital Health Research Practice

5.5.1 Prototype Evaluation Framework Innovation

The adaptation of NASSS and RE-AIM frameworks for prototype assessment addresses a methodological gap in digital health research, enabling systematic early-stage evaluation that can identify implementation barriers while design modifications remain feasible. This methodological contribution provides more comprehensive assessment than traditional prototype evaluations focusing solely on technical metrics.

However, critical examination reveals important limitations in framework adaptation that affect validity. The methodology relies heavily on literature-based inference rather than observed deployment outcomes, creating validity limitations that must be acknowledged. While the methodology provides valuable directional guidance, it requires validation through future deployment studies to confirm assessment accuracy.

5.5.2 Synthetic Data Clinical Validation: Practical Innovation with Clear Boundaries

The systematic use of WHO-aligned synthetic scenarios for clinical logic validation provides practical methodology for early-stage clinical AI assessment without requiring access to patient data or clinical trial infrastructure. The 90 scenario test set distributed across four clinical domains establishes reproducible benchmarks for comparative evaluation, representing a methodological advance for the field.

This methodology addresses a common challenge in digital health research where the gap between technical feasibility and clinical validation often prevents promising systems from progressing beyond prototype stages. While not replacing clinical validation requirements, synthetic data testing enables meaningful assessment of clinical reasoning quality during development phases—a practical contribution to research methodology.

5.6 Implications for Theory and Practice

5.6.1 Theoretical Contributions to Digital Health

This research advances theoretical understanding of offline-first architecture for complex healthcare applications, demonstrating that sophisticated clinical decision support can function reliably without continuous connectivity when properly architected. This challenges implicit assumptions in digital health literature that advanced AI capabilities necessarily require robust infrastructure and continuous connectivity.

The hybrid AI architecture suggests new theoretical models for resource-appropriate AI systems where intelligent adaptation to available resources matters more than assuming consistent infrastructure availability. The performance benchmarks provide concrete evidence that offline-first design can meet clinical requirements, validating this approach for healthcare applications beyond simple data collection tools.

5.6.2 Practical Implications: Democratization with Realistic Constraints

The research provides actionable insights for digital health practitioners while honestly acknowledging limitations. PWA architecture with modern JavaScript frameworks offers viable pathways for healthcare applications requiring offline functionality without native app complexity. Google Gemini API integration achieves sufficient clinical utility for decision support when properly prompted with clinical context and guidelines, providing accessible alternative to custom model training.

However, the implementation science findings emphasize that organizational preparation represents the critical success factor requiring systematic attention alongside technical development. The assessment methodology provides practical frameworks for early-stage barrier identification and development prioritization, while the performance limitations (particularly the 14.5-18 second response time and 60% emergency resource awareness) identify specific areas requiring enhancement before clinical deployment.

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5.7 Critical Limitations and Honest Assessment

5.7.1 Acknowledged Scope Constraints

The research acknowledges several limitations appropriate for Master’s thesis scope that affect result generalizability while providing meaningful insights within defined boundaries. Synthetic data validation cannot predict real-world clinical effectiveness or patient safety outcomes, requiring future clinical studies for definitive efficacy assessment. Prototype-level evaluation cannot assess actual adoption patterns, user satisfaction, or long-term sustainability, necessitating deployment studies for comprehensive implementation assessment.

The 4-month development timeline enabled comprehensive prototype development but precluded longitudinal analysis of performance stability, user adaptation, or organizational integration—constraints appropriate for academic scope while highlighting future research requirements.

5.7.2 Technical and Clinical Limitations: Areas for Enhancement

Critical analysis identifies specific limitations that affect clinical deployment readiness. The 60% resource awareness effectiveness in emergency scenarios represents a safety limitation requiring systematic enhancement before deployment in high-acuity settings where resource constraints most critically affect patient outcomes. The 14.5-18 second Gemini response time, while meeting research targets, presents challenges for time-critical clinical scenarios requiring immediate decision support.

Scalability limitations include performance degradation with large patient datasets and concurrent user access, indicating architecture modifications needed for high-volume deployment. These limitations provide clear development priorities while validating the overall architectural approach and clinical utility potential.

5.8 Positioning Within Digital Health Literature

ATLAS occupies a unique position in digital health literature by successfully integrating sophisticated AI capabilities with resource-appropriate architecture—a combination largely absent in existing solutions. The research validates that the technical barriers to advanced clinical decision support in resource-limited settings may be less constraining than organizational and implementation barriers, a finding with significant implications for digital health policy and investment priorities.

The systematic evaluation approach provides methodological innovation for early-stage digital health research while honestly acknowledging the substantial work required for clinical validation and deployment. This balanced perspective contributes to more realistic expectations about the progression from prototype to deployed system serving vulnerable populations.

5.9 Conclusion

This discussion reveals that ATLAS represents both significant technical achievement and realistic assessment of implementation complexity in healthcare AI deployment. The prototype successfully demonstrates technical feasibility while illuminating persistent gaps between technological possibility and healthcare implementation reality.

The systematic evaluation provides evidence-based foundation for future clinical research and deployment planning, while honestly acknowledging the substantial work required for production deployment in clinical settings. The research contributes to both the science and practice of digital health technology development through technical innovation, methodological advancement, and critical analysis of implementation challenges.

The findings suggest that sophisticated clinical decision support can be made technically accessible to resource-limited settings through systematic application of mature technologies, but successful deployment requires concurrent attention to organizational preparation and systematic change management—insights that extend beyond this specific research to inform broader digital health development and policy decisions.

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This discussion reveals that ATLAS represents both significant technical achievement and realistic assessment of implementation complexity in healthcare AI deployment. The systematic evaluation provides evidence-based foundation for future research and deployment while honestly acknowledging the substantial work required for clinical implementation. Chapter 6 concludes with specific academic contributions and pathways for future clinical translation.

Chapter 6

Conclusions and Future Work

6.1 Research Summary and Academic Contributions

This research successfully demonstrates technical feasibility for sophisticated clinical decision support in resource-limited settings while providing systematic evaluation of both achievements and limitations. This final chapter synthesizes the academic contributions, assesses objective achievement, and establishes clear pathways for future clinical validation and deployment efforts.

This research successfully addresses the fundamental question of whether sophisticated clinical decision support can be technically implemented using accessible web technologies while functioning reliably in offline-first configurations appropriate for resource-limited healthcare settings. Through systematic development and evaluation of ATLAS, this thesis demonstrates technical feasibility while providing critical insights into the persistent challenges separating technological possibility from healthcare implementation reality.

The research contributes to academic discourse at the intersection of health informatics, artificial intelligence, and implementation science, advancing understanding through rigorous evaluation and honest assessment of both capabilities and limitations within appropriate scope boundaries.

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6.2 Key Academic Contributions

6.2.1 Technical Implementation Contributions

This research provides concrete technical contributions that advance knowledge in health informatics and establish reproducible foundations for similar healthcare applications.

PWA Clinical Architecture Validation: The successful implementation of sophisticated clinical decision support without continuous connectivity challenges fundamental assumptions in digital health literature about infrastructure dependencies. The documented performance benchmarks (>90 Lighthouse scores, 95% offline functionality, consistent cross-platform operation) provide concrete evidence and reproducible patterns for healthcare PWA development, demonstrating that advanced functionality does not require advanced infrastructure when properly architected.

Commercial AI Integration Methodology: The hybrid AI architecture achieves 80% WHO alignment through systematic integration of Google Gemini API with clinical workflows, demonstrating that sophisticated clinical reasoning does not require custom model development or specialized infrastructure. The documented integration patterns, context management strategies, and intelligent fallback mechanisms provide practical guidance for similar healthcare AI implementations while revealing important limitations in current commercial AI approaches.

Healthcare Data Persistence Architecture: The IndexedDB implementation with >99% transaction reliability validates web-based clinical data storage patterns while establishing performance benchmarks for healthcare applications. The documented schema design, transaction handling, and synchronization strategies provide technical foundations for similar clinical data management requirements, though scalability limitations with large datasets indicate areas for future architectural enhancement.

6.2.2 Clinical Integration and Validation Contributions

WHO Guidelines Integration Framework: The systematic approach to implementing WHO SMART Guidelines in web-based systems provides architectural foundation and

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sample implementations for evidence-based clinical decision support. The documented transformation pathway from narrative guidelines to machine-readable implementations demonstrates practical approaches for systematic clinical knowledge digitization, establishing technical foundation for broader guideline implementation efforts.

Resource-Aware Clinical Decision Support: The system's capability to consider local resource constraints when providing clinical guidance (74% average effectiveness, 84% in maternal health) addresses a critical gap in existing clinical decision support systems. This contribution is particularly relevant for resource-limited settings where optimal interventions may be unavailable, though the 60% effectiveness in emergency scenarios indicates significant enhancement requirements.

Synthetic Data Clinical Validation Methodology: The systematic use of WHO-aligned synthetic scenarios provides replicable methodology for early-stage clinical AI assessment without requiring patient data access or clinical trial infrastructure. The 90 scenario test set establishes standardized benchmarks for comparative evaluation of clinical decision support systems, representing methodological innovation for the field while acknowledging inherent limitations in predicting real-world performance.

6.2.3 Implementation Science Methodological Contributions

Prototype Evaluation Framework Innovation: The successful adaptation of NASSS and RE-AIM frameworks for systematic prototype assessment addresses a significant methodological gap, enabling early-stage implementation barrier identification while design modifications remain feasible. This methodological contribution provides more comprehensive evaluation than traditional prototype development approaches while establishing precedent for systematic early-stage digital health assessment.

Organizational Readiness as Primary Barrier: The finding that organizational preparation (NASSS 4.0/5.0, RE-AIM Implementation 4.5/10.0) represents the primary deployment barrier rather than technical capability provides important insights for digital health policy and funding priorities. This contribution validates implementation science

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literature while providing specific evidence that technological sophistication does not automatically translate to deployment readiness—a critical insight for digital health investment strategies.

6.3 Research Objectives Achievement Assessment

The research systematically achieved its adapted objectives within Master's thesis scope while establishing foundations for future clinical validation and deployment:

Objective 1 - Offline-First PWA Implementation: Successfully achieved through comprehensive Next.js 14 PWA with >95% offline functionality reliability, intelligent synchronization capabilities, and validated cross-platform performance that demonstrates technical feasibility for resource-limited deployment.

Objective 2 - AI Integration and Clinical Validation: Successfully achieved with 80% average WHO protocol alignment across 90 synthetic scenarios, validated hybrid model selection strategies, and systematic identification of performance limitations requiring enhancement for clinical deployment.

Objective 3 - Data Persistence and Synchronization: Successfully achieved with IndexedDB implementation demonstrating >99% transaction reliability, multi-session workflow support, and documented patterns for healthcare data management, though with identified scalability constraints for large-scale deployment.

Objective 4 - WHO SMART Guidelines Architecture: Foundation established with architectural framework and sample implementations demonstrating systematic guideline integration pathways, providing technical foundation for future comprehensive implementation rather than complete L0-L4 transformation.

Objective 5 - Systematic Evaluation Framework: Successfully achieved through comprehensive NASSS and RE-AIM assessment adapted for prototype evaluation, providing methodological innovation while identifying specific implementation barriers and development priorities.

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Objective 6 - Clinical Utility Demonstration: Successfully achieved through systematic synthetic data validation establishing clinical reasoning capability, performance benchmarking across clinical domains, and honest assessment of limitations requiring enhancement for clinical deployment.

6.4 Critical Limitations and Scope Boundaries

6.4.1 Acknowledged Research Constraints

Several limitations affect result generalizability while remaining appropriate for Master's thesis scope and contributing meaningful insights within defined boundaries. Synthetic data validation, while WHO-aligned, cannot replicate the complexity and contextual factors present in real clinical presentations, requiring future clinical studies for definitive efficacy assessment. Prototype-level evaluation demonstrates technical capability but cannot predict actual adoption patterns, user satisfaction, or long-term sustainability without real-world deployment studies.

The 4-month development timeline enabled comprehensive prototype development and systematic evaluation but precluded longitudinal analysis of performance stability, organizational integration, or user adaptation—constraints that highlight future research requirements while maintaining appropriate academic scope.

6.4.2 Technical and Clinical Limitations Requiring Enhancement

Critical analysis identifies specific limitations that must be addressed for clinical deployment readiness. The 60% resource awareness effectiveness in emergency scenarios represents a critical safety limitation requiring systematic enhancement before deployment in high-acuity settings where resource constraints most critically affect patient outcomes. The 14.5-18 second Gemini response time, while meeting research targets, presents challenges for time-critical clinical scenarios requiring immediate decision support.

Performance limitations include degradation with large patient datasets ($>10,000$ records) and concurrent user access, indicating database optimization and architecture modifications

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required for high-volume clinical deployment. These limitations provide clear development priorities while validating the overall architectural approach and clinical utility potential.

6.5 Future Work and Development Pathway

6.5.1 Immediate Technical Enhancement Priorities (6-12 months)

Enhanced Emergency Response Capabilities: Systematic improvement of resource awareness in emergency scenarios through enhanced prompting strategies, domain-specific model selection, and rule-based augmentation for time-critical situations. Target: >80% resource awareness across all clinical domains including emergency scenarios.

Performance Optimization for Scale: Database indexing strategies for large patient populations, service worker caching optimization, and embeddings model compression to reduce bandwidth requirements for initial deployment. Target: Support for 50,000+ patient records with <2 second response times on 3G networks.

Production-Ready Security Implementation: End-to-end encryption for clinical data, comprehensive audit logging, and role-based access controls suitable for clinical deployment environments. Target: HIPAA-compliant security architecture with independent security audit validation.

6.5.2 Clinical Validation Phase (12-24 months)

Systematic Clinical Trials: Multi-site studies with real healthcare providers in resource-limited settings (minimum 50 providers, 500 patient encounters) to validate clinical effectiveness, safety, and user acceptance with appropriate control groups and outcome measurements. Target: Peer-reviewed publication demonstrating statistically significant clinical outcomes.

Comprehensive Safety Monitoring: Clinical error tracking, provider feedback systems, and automated safety alert mechanisms to ensure patient safety during validation studies while building evidence base for regulatory approval and broader deployment.

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Cultural and Linguistic Adaptation: Multi-language support, cultural appropriateness assessment, and integration with local healthcare practices to ensure broad applicability across diverse deployment contexts. Target: Validated deployment in 3-5 countries across different regions.

6.5.3 Deployment and Scaling Research (24-36 months)

Implementation Science Studies: Systematic evaluation of deployment strategies, organizational change management approaches, and sustainability models across diverse healthcare settings to develop evidence-based implementation playbooks.

Health System Integration: Interoperability development with existing health information systems, integration with national health policies, and alignment with local clinical protocols and regulatory requirements to enable systematic rather than isolated deployment.

Sustainability Model Development: Financing mechanisms, local technical capacity building, and long-term maintenance strategies to ensure sustainable deployment without continued external technical support.

6.6 Broader Impact and Policy Implications

6.6.1 Digital Health Equity Contributions

By demonstrating that sophisticated clinical decision support can be implemented using accessible technologies, this research challenges assumptions about technological requirements that may contribute to healthcare disparities. The systematic evaluation provides evidence-based foundation for policy discussions and funding decisions regarding AI-enhanced healthcare technology deployment in underserved regions.

The architectural patterns and evaluation methodologies established through this research contribute to broader digital health equity efforts by providing accessible, reproducible approaches to clinical decision support implementation, though significant organizational and financial barriers remain for widespread deployment.

CHAPTER 6. CONCLUSIONS AND FUTURE WORK

6.6.2 Implementation Science Methodological Impact

The adapted evaluation frameworks provide methodological innovation for early-stage digital health research while demonstrating the importance of concurrent technical and implementation planning. The finding that organizational readiness represents the primary deployment barrier has implications for funding strategies, development timelines, and policy approaches to digital health implementation.

6.7 Final Reflections and Academic Positioning

6.7.1 Research Scope and Academic Honesty

This Master’s thesis contributes primarily to technical feasibility demonstration and methodological development rather than immediate clinical impact assessment—positioning that represents appropriate academic scope while providing meaningful contributions within defined boundaries. The value lies in establishing solid technical and methodological foundations that enable future clinical research requiring greater resources and longer timelines.

The research maintains academic honesty by explicitly acknowledging limitations while demonstrating technical achievements, providing realistic assessment of the substantial work required for clinical deployment rather than overstating immediate applicability.

6.7.2 Implementation Gap Recognition and Future Directions

The most significant academic insight concerns the persistent gap between technological possibility and healthcare implementation reality. ATLAS demonstrates sophisticated technical capabilities while revealing organizational, cultural, and validation challenges that constrain real-world deployment. This finding reinforces implementation science literature emphasizing that healthcare technology adoption is fundamentally a social and organizational process rather than a purely technical challenge.

The research suggests that early-stage technical design decisions significantly influence later implementation success, providing evidence that concurrent technical and implementation

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planning may be more effective than sequential approaches commonly used in digital health development.

6.8 Concluding Statement

This research successfully demonstrates that sophisticated, AI-enhanced clinical decision support can be technically implemented using accessible web technologies while functioning reliably in offline-first configurations appropriate for resource-limited healthcare settings. The comprehensive evaluation provides both validation of technical feasibility and honest assessment of remaining challenges for clinical deployment.

The academic contributions span technical implementation patterns, methodological innovations, and theoretical insights that advance understanding in health informatics, AI integration, and implementation science. The systematic evaluation establishes evidence-based foundation for future clinical validation studies while providing practical guidance for similar digital health technology development efforts.

The path from technological possibility to healthcare impact requires sustained collaboration between technologists, healthcare providers, implementation scientists, and policy makers. This research provides concrete evidence that sophisticated clinical decision support can be extended to underserved populations through systematic application of mature technologies, rigorous evaluation methodologies, and sustained commitment to addressing implementation barriers alongside technical development.

The convergence of technological maturity, clinical need, and systematic evaluation methodology creates unprecedented opportunity for advancing global health equity through accessible, evidence-based clinical decision support. This research establishes essential groundwork for realizing that potential through future clinical validation and deployment efforts, while honestly acknowledging the substantial collaborative work required for sustainable impact in resource-limited healthcare settings.

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