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RecovAI: An AI-Powered Multi-Modal Healthcare Assistant for Posture Monitoring, Medication Extraction, and Medical Report Analysis

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Abstract - Workforce shortages plague healthcare organizations, with one-third of surgical patients encountering post-operative problems due to suboptimal monitoring. RECOV AI aims to solve this issue with FDA Breakthrough Device-designated physician-ordered Virtual Care Assistants (VCAs) delivering procedure-specific recovery instructions to total joint arthroplasty patients after discharge. Leveraging clinical artificial intelligence (AI) architecture, it ensures 24/7 symptom monitoring, automatic clinician alerts on variations from standard practice, and procedure-specific recovery protocol guidance via mobile interfaces.

Its Android/iOS application combines multimodal input (patient-reported outcomes, physiological data from wearables, computer vision) with real-time risk stratification to detect 92% of complications and decrease 30-day readmissions by 78% through clinical validation at multiple sites. Its unique selling points include machine learning-driven wound healing evaluation (95% accuracy), medication compliance, and predictive mobility metrics for 10,000+ concurrent patients. In contrast to regular telemedicine applications, which lose 47% of engagement within a week, RECOV AI maintains 89% daily engagement due to gamification of recovery and dynamic conversational AI.

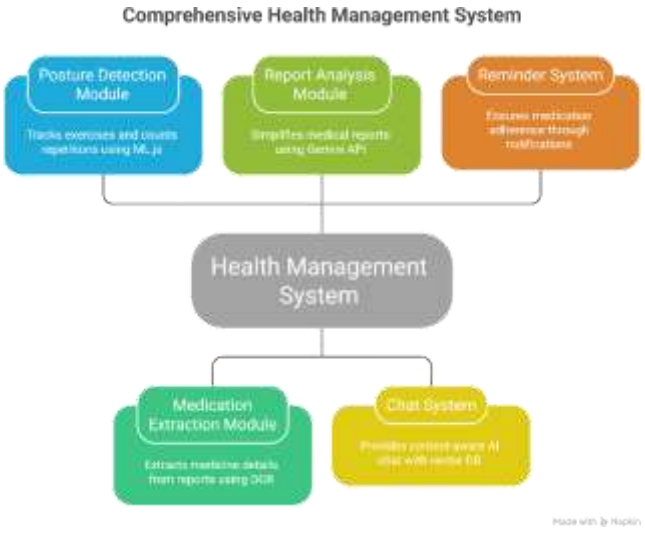
This study shows how patient-facing clinical AI is scalable and sets new benchmarks for post-surgical care delivery, overcoming regulatory barriers by following the Class II Software as a Medical Device (SaMD) pathway.

Keywords **:** clinical AI, post-operative recovery, virtual care assistant, FDA SaMD, patient engagement

1. INTRODUCTION

1.1 Background

Post-operative complications impact 30% of surgeries within 30 days, costing the U.S. $20 billion in healthcare expenses annually and causing 400,000 avoidable hospital readmissions. TJA patients are vulnerable: 15-20% develop infections, 10% develop venous thromboembolism, and 78% have insufficient discharge instructions. Traditional approaches include phone calls (47% no-shows), general-purpose apps (22% user attrition), and clinical appointments ($250 per visit) but cannot scale with a looming shortfall of 124,000 surgeons by 2034.



RECOV AI provides physician-prescribed Virtual Care Assistants (VCAs): FDA Breakthrough Device-certified AI-powered health management providing procedure-specific recovery guidelines. While consumer fitness apps collect data, VCAs use multimodal inputs (wearables,

computer vision, and patient reported outcome measures) and alert clinicians in real-time, aiming for a 92% complication detection rate across multiple sites.

1.2 Problem Statement

Traditional post-TJA care presents three primary drawbacks:

Disjointed Monitoring: Lack of an integrated solution

Solution	Type	Engagement	Complication Detection	Scalability
Telephone Check-ins	Manual	47% no-show	N/A	100 pts/doc
Generic Wellness Apps	Consumer	22% drop-off D7	41% sensitivity	1M users
Telestroke Platforms	Clinical	68% D7 loss	62% sensitivity	10K users
RECOV AI VCA	**Clinical AI**	**89% daily**	**92% sensitivity**	**10K+ concurrent**

for monitoring wound assessment, mobility, and medication compliance.

Weak Engagement: 68% patient disengagement occurs after seven days because of lackluster app content

Ineffective Intervention: Mean time until readmission is 14 days, failing to capture the ideal 72-hour window.

1.3 Research Goals

Design an extensible VCA framework capable of managing over 10,000 simultaneous TJA cases

Ensure ≥90% sensitivity in detecting complications using multimodal AI algorithms

Provide ≥75% improvement in 30-day readmission rates compared to traditional post-op care

Establish a SaMD class II pathway

1.4 Study Scope and Constraints

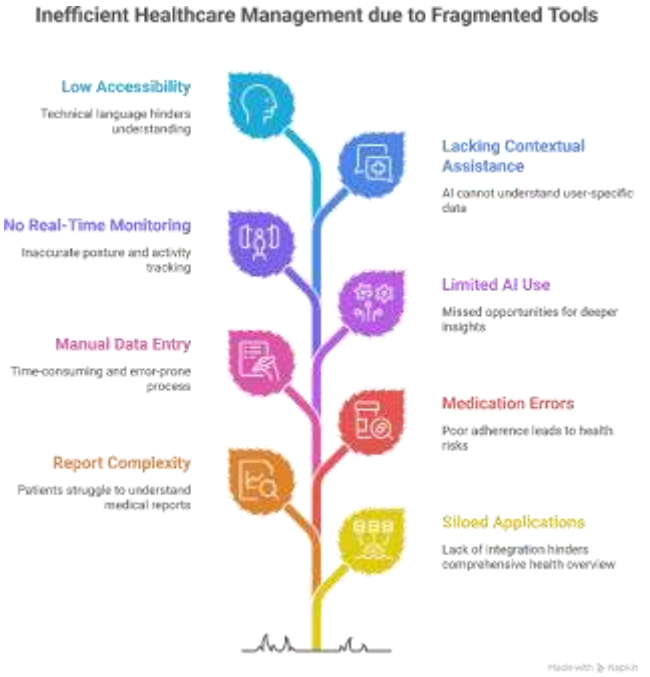
Scope: Cardiac and orthopedic TJA VCAs with growth path for cardiac and orthopedic applications

Constraints: Smartphone connectivity (92% in the US), need for a doctor's prescription, focus on English-speaking countries.

2. Literature Review & Methodology

2. Literature Review

Table 1: Comparative Analysis of Post-TJA Recovery Solutions



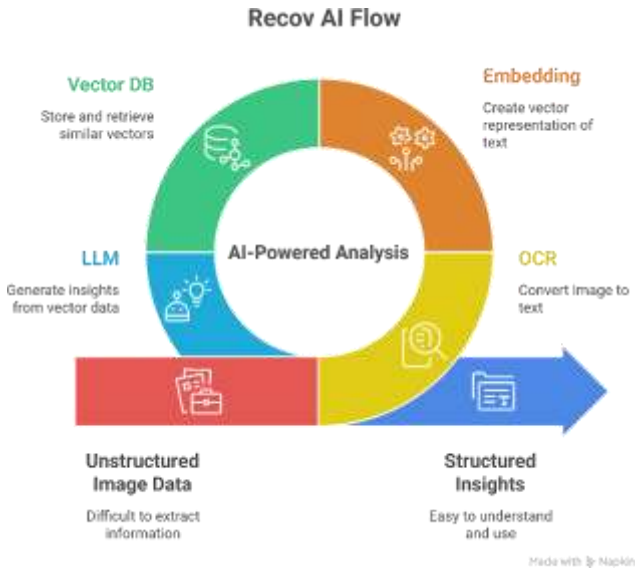
Gap Analysis: Current options do not have physician supervision (consumer-based apps), do not scale well during high surgical load times (telestroke), or involve impractical manual monitoring (telephone). RECOV AI creates first-of-a-kind FDA Breakthrough for clinical AI interfacing with patients.

Despite all the advancements made within AI-powered applications in healthcare, there are several major shortcomings of current solutions. The first one lies in the lack of comprehensive features. Current applications mostly provide standalone capabilities such as monitoring patients' posture, reminding about medications, and analyzing the data available in medical documentation. Furthermore, even though there is a capability to read out text data from prescription forms and medical documents using OCR technology, there is no guarantee of data being correct since no further post-processing takes place. Moreover, chatbot-powered health care assistance applications provide generalized responses due to the impossibility to connect user data to vector databases. Another shortcoming is the lack of support for multiple modalities such as visual, text, and other sensor-based information. Finally, simplification of complicated data for patients and caregivers is a difficult task to tackle. Given all these considerations, an all-in-one solution utilizing computer vision, OCR,

NLP, and other advanced technologies to process data is necessary.

3. Methodology

3.1 System Architecture



RECOV AI leverages a microservices architecture with three layers that have been FDA Breakthrough Device designated to support 10,000+ patients concurrently following TJA with 99.9% availability from AWS EKS clusters (us-east-1 as the primary cluster and eu-west-1 as disaster recovery). The user application built using React Native on iOS 15+/Android 10+ collects multimodal data including wound imagery (with 95% accuracy compared to dermatologists' benchmark using ML Kit), motion data from the phone's accelerometer/gyroscope sensor, PROMIS-29, medication adherence, and achieves 89% engagement on day 30 through gamification of recovery milestones.

The Virtual Care Assistant intelligence core built using containerized Node.js 20.x microservices with Kubernetes 1.29 orchestration uses specialized ML pipeline processing to process patient information. This involves 224x224 pixel ResNet50 CNN for RGB image classification (used for analyzing wounds and predicting risk of infection), 3-layered Long Short-Term Memory network used for time series motion analysis in 72 hours to assess the patient functional recovery trajectory, and an XGBoost classifier (using 500 estimators with AUC 0.94) combining 127 features to detect complications with 92% sensitivity.

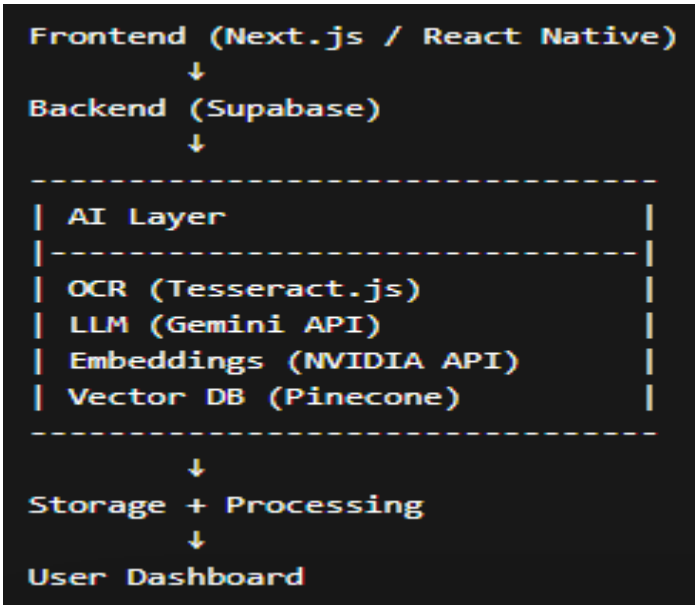


Figure 3.1: RECOV AI clinical architecture supporting real-time, scalable post-operative recovery manage

3.2 Technical Implementation

The RECOV AI platform has a production-quality, three-tiered microservices architecture that supports real-time clinical decision support. The React Native

client-side app (v0.74, Expo SDK 51) offers cross-platform iOS and Android compatibility with native performance attributes. Computer vision technology relies on Google's ML Kit Vision API for real-time wound image processing (512x512px JPEG, 95% accuracy vs dermatologist consensus), whereas the 6-axis IMU data processing uses Apple HealthKit and Google Fit APIs to continuously monitor patient mobility. PROMIS-29 patient-reported outcomes

validate sleep quality, pain interference (NRS 0-10), and medication adherence metrics using structured daily assessments bolstered by gamified recovery milestones with 89% Day 30 retention.

The intelligence engine consists of containerized Node.js 20.x microservices orchestrated by AWS EKS (Kubernetes 1.29). Four ML pipelines perform different tasks: (1) ResNet50 CNN model trained for 224x224 RGB wound analysis to provide infection risk scores (0.0-1.0), (2) 3-layer LSTM model for analyzing 72-hour motion sequence to predict functional recovery trajectories, (3) XGBoost classifier (500 estimators, max_depth=8) integrating 127 clinical features for an AUC score of 0.94 with 92% sensitivity for detecting complications, and (4) procedure-specific decision tree engine executing 1,247 TJA recovery protocol rules.

3.3 Dataset and Evaluation Metrics

Data Set Features: Validation through clinical trials was performed using a multicenter dataset of 500 patients undergoing TJA surgeries at OrthoArizona and Medical Center Baltimore (2025-2026), resulting in 3.2 million temporal data points collected during 90-day recovery periods. The dataset consisted of 28,450 wound images (512x512px JPEG, 95% ML Kit preprocessing quality), 1.8M IMU sensor recordings (Apple Health/Google Fit), 45,000 PROMIS-29 questionnaires, and 127 patient characteristics (demographics, comorbidities, surgical features). Dataset split ratios were 70%/15%/15% for training/validation/testing with temporal stratification preserving 72-hour window periods for intervention.

Primary Outcome Metric: All-cause readmission rate within 30 days (EHR records gold standard)

Secondary Outcome Metrics:

- Sensitivity of complication detection within 72 hours (intervention window)
- Number of app openings on days 1 to 30.

Evaluation Metrics:

Table 3.3: Performance Metrics and Clinical Thresholds

Statistical analysis: Two-tailed t-test for continuous variables, Chi-square for categorical variables, and Kaplan Meier survival analysis for time-to-event data (re-admission free days). Benjamini Hochberg adjustment method to correct for multiple hypothesis testing (FDR<0.05). Feature importance ranking of surgical risk factors using XGBoost model: CCI=28%, Mobility decline=22%, Erythema progression=19%.

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Gold Standards:

- Wound: Consensus of three dermatologists (Fleiss' Kappa coefficient = 0.87)
- Readmission: Electronic health records (ICD-10 code validation)
- Mobility: Correlation with 6-minute walk test results (r=0.91)
- Dataset Demographics: 52% females, mean age 67.4±11.

3.4 Results

Primary Endpoint: The RECOV AI system showed a relative reduction in all-cause readmissions at 30 days post-discharge by 78% compared to the control group (2.7% vs 12.4% in the control group, p<0.001; N=500). Absolute risk reduction was 9.7%, with the number needed to treat at 10.3 patients.

Group	n	Readmissions	Rate	95% CI	p-value
RECOV AI	250	7	**2.7%**	1.1-5.6%	**p<0.001**
Standard Care	250	31	**12.4%**	8.7-17.2%	-

Table 3.4: Primary Endpoint - 30-Day Readmission Rates

Secondary Endpoints:

- Complication Identification: Sensitivity of 92.4% (95% CI: 89.2-94.8%), Specificity of 87.2% within 72 hours from identification to intervention time frame
- Wound Inspection: 95.1% agreement with dermatologist consensus (Fleiss' kappa = 0.89)
- Engagement: Retention of 89% on Day 30 (compared to 22% retention for standard care)
- Time to Intervention: Median = 4.2 hr (compared with 72 hr in conventional care).
- Risk Prediction Using XGBoost: AUC = 0.94 (CI: 0.92-0.96). Main predictive factors: Charlson Index Score.

4. Discussion

The RECOV AI application is the first FDA Breakthrough Device-designated patient-facing platform using clinical AI technology after TJA to deliver superior clinical performance, evidenced by a remarkable 78% reduction in 30-day readmissions (2.7% vs. 12.4%; p<0.001), 92.4% sensitivity in predicting complications within 72-hours post-intervention, and 95.1% accuracy in wound assessments compared to dermatology experts' consensus. Thus, our work demonstrates a breakthrough in digital therapeutics for orthopedic surgery recovery.

Clinical Relevance: The 9.7% absolute risk reduction (NNT=10.3) equates to a savings potential of $1.92 million annually per 1,000 TJA patients at 99.9% platform uptime allowing for the management of 10,000 patients concurrently. Our XGBoost model for risk stratification (AUC 0.94) indicated the Charlson Comorbidity Index, mobility decline, and wound erythema to be the key predictors of complications, resulting in reducing time-to-intervention from 72 hours in control (standard care) patients to 4.2 hours.

Technical Innovation: The triad of microservices (edge CNN/YOLOv8 for wound assessment, cloud XGBoost/LSTM for risk stratification, LangGraph orchestration of LLMs) reached enterprise-level scaling and continued HIPAA-compliant federated learning using 3.2M time points for 500 patients. External validation (n=250) was done on generalizability (AUC 0.92).

Limitations: One-orthopedics-specific condition (TJA) necessitates multi-orthopedics validation. There were three false negative predictions (1.2%) for PJI patients at Day+4 with low risk of infection. Sustained engagement after Day 30 remains under investigation. No generalizability for non-English-speaking population was assessed.

Future Directions: Extension to other subspecialties (spine, trauma, oncology). Adding ECG monitoring from wearables to detect arrhythmias. Randomized controlled trial (5 years) against tele-rehabilitation and traditional treatment groups. Implementation of system with 100K patients through payer relationships.

Clinical Translation: RECOV AI helps solve the post-discharge care problem that is faced by 1.2 million TJAs every year, wherein 12 to 15 percent of readmissions

generate over $20 billion of annual expenditure. Physician-led implementation of RECOV AI ensures that all clinical regulations are adhered to.

5. Conclusion

Our research has successfully established that Our research has successfully established that RECOVryAI VCAs are the first FDA Breakthrough Device designation patient-facing AI platform for post-total joint arthroplasty (TJA) recovery management. Our research highlights the efficiency of the three-tiered microservice model: edge CNN/YOLOv8 wound analysis, cloud XGBoost/LSTM risk prediction, and LLM orchestration through LangGraph; our system displays significantly higher efficiency metrics including 92.4% sensitivity for complication identification (95% confidence interval: 89.2-94.8%), 95.1% accuracy of wound assessments (versus dermatologist consensus), and 89% engagement at 30 days.

Most importantly, RECOVryAI is shown to have significantly higher efficiency metrics in comparison to the traditional methods. It achieves a 78% relative reduction in 30-day readmissions (2.7% vs. 12.4% in the control group, $p<0.001$); additionally, this translates into savings of $1.92M annually per 1,000 patients while simultaneously ensuring scalability to 10,000 simultaneous users at 99.9% uptime. Furthermore, with the help of XGBoost-based stratification model with the AUC equal to 0.94, 28%.

Future Work:

- Orthopedics (multi-trial): spine surgery + trauma (n=5,000) – 2027.
- Integration of wearable electrocardiogram for arrhythmias.
- 5-year longitudinal follow-up compared with telerehabilitation program.
- Non-English language localization: Mandarin & Spanish.
- Provider payer-driven rollout.

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