

FITSHIELD: A MULTI-MODAL AI FITNESS COMPANION FOR PERSONALIZED WELLNESS AND BEHAVIORAL MOTIVATION

**HYBRID ML-DRIVEN DYNAMIC AND LOCALIZED ADAPTIVE PROFILING WITH EXPLAINABLE
INTELLIGENCE**

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Project Proposal Report

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DECLARATION

I declare that this is my own work, and this proposal does not knowingly incorporate any material previously submitted for a degree or diploma at any other university or higher education institution, nor does it contain any material that has been previously published or written by another person apart from where proper acknowledgment is given in the text.

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ABSTRACT

Non-Communicable Diseases (NCDs) are the leading cause of death in Sri Lanka, driven by unhealthy lifestyles and a lack of personalized, culturally relevant health guidance. While AI-powered wellness applications exist, they often fail because they rely on static user profiles and opaque "black box" recommendations that do not adapt to an individual's changing behavior or local context, leading to disengagement and low trust.

This research proposes the development of a Hybrid ML-Driven Dynamic and Localized Adaptive Profiling with Explainable Intelligence component for an AI-powered fitness and nutrition web system. This component addresses the critical need for personalization by creating a unified, living digital profile for each user. It will continuously ingest and process diverse data streams, including demographic information, lifestyle habits, dietary preferences (focused on Sri Lankan foods), and behavioral feedback such as workout completion rates.

The core innovation lies in its hybrid approach, combining classical machine learning (e.g. clustering for user segmentation), deep learning (e.g. for pattern recognition in activity data), and rule-based logic to dynamically update user profiles in real-time. Crucially, it will integrate Explainable AI (XAI) techniques to provide transparent, interpretable reasoning behind its personalized fitness, nutrition, and wellness recommendations. By leveraging Python, Scikit-learn, and TensorFlow, this component will ensure that all recommendations are not only dynamically adapted to the user's evolving lifestyle but also culturally grounded in Sri Lankan datasets. This fosters user trust, improves the accuracy of personalization, and promotes long-term engagement, forming the intelligent core of the broader NCD prevention system.

Keywords

Adaptive Profiling, Explainable AI (XAI), Hybrid Machine Learning, Personalization, User Modeling, NCD Prevention, Sri Lanka

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LIST OF ABBREVIATIONS

NCD - Non-Communicable Disease

AI - Artificial Intelligence

ML - Machine Learning

DL - Deep Learning

XAI - Explainable Artificial Intelligence

BMI - Body Mass Index

API - Application Programming Interface

SLIIT - Sri Lanka Institute of Information Technology

MRI - Medical Research Institute

SHAP - SHapley Additive exPlanations

LIME - Local Interpretable Model-agnostic Explanations

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1. INTRODUCTION

1.1 Background and Context

The rising burden of Non-Communicable Diseases (NCDs) in Sri Lanka, responsible for 83% of annual deaths, is a complex challenge rooted in lifestyle factors such as physical inactivity, unhealthy diets, and rapid urbanization. While digital health interventions offer a scalable solution, their effectiveness is often limited by a fundamental flaw: a lack of deep, adaptive personalization. Most existing platforms treat users as static entities, providing generic recommendations that quickly become irrelevant as user circumstances change.

In the Sri Lankan context, this problem is compounded by a cultural mismatch. Global apps fail to account for local dietary staples like rice and curry, leading to low user adoption. Furthermore, the "black box" nature of many AI models erodes user trust.

This research proposes a Hybrid ML-Driven Dynamic and Localized Adaptive Profiling with Explainable Intelligence component to serve as the central intelligence for FITSHIELD.

1.2 Literature Review

The foundation of effective personalization is a robust user model. Research by Srivastava et al. demonstrated Random Forest classifiers for lifestyle data, but lacked continuous updates. Kelders et al. emphasized that personalization and goal-setting drive adherence.

Explainable AI (XAI) in Healthcare: Techniques such as SHAP and LIME allow interpretation of complex model predictions, increasing user trust and adherence.

Localization: Failure of generic systems in non-Western contexts is well-documented (Aranda-Jan et al.). This component grounds profiling logic in Sri Lankan datasets from the MRI and MoH STEPS surveys.

1.3 Research Gap

Identified gaps: (1) Existing systems rely on static profiles that fail to adapt to real-time changes; (2) AI platforms operate as opaque black boxes; (3) Lack of unified data streams combining demographic, behavioral, dietary, and activity telemetry; (4) No profiling engine calibrated on Sri Lankan health datasets; (5) Underexplored combination of hybrid ML (K-Means + LSTM) with XAI.

2. OBJECTIVE

2.1 Main Objective

To design and implement a Hybrid ML-Driven Dynamic and Localized Adaptive Profiling component with Explainable Intelligence that continuously learns from user interactions and Sri Lankan health datasets to create and maintain an evolving user profile, providing transparent and culturally relevant recommendations.

2.2 Specific Objectives

- * Design a unified data schema ingesting heterogeneous user telemetry.
- * Develop a hybrid ML pipeline combining K-Means clustering and RNN/LSTM sequence models.
- * Integrate SHAP / LIME explainability.
- * Ground profiling in Sri Lankan context using MRI and STEPS data.
- * Expose dynamic profiles via secure REST APIs.
- * Evaluate accuracy and user trust impact via controlled testing.

3. METHODOLOGY

Design Science Research (DSR) methodology across five phases:

- * Phase 1: Requirements Analysis and Data Integration (user onboarding, telemetry logs, MRI/STEPS datasets).
- * Phase 2: Hybrid ML Model Development (K-Means clustering for archetypes, LSTM networks for longitudinal adherence patterns, hybrid rule engine for updates).
- * Phase 3: Explainable AI (XAI) Integration with SHAP to generate natural-language explanations.

3. Methodology (Cont.) & Ethics

* Phase 4: API Development & System Integration (standalone Python/Flask microservice with /profile/update and /recommendation/explain endpoints).

* Phase 5: Evaluation and Validation (clustering coherence, LSTM MSE, SUS usability testing with A/B trust evaluation).

Ethical Considerations

Compliance with SLIIT ethical guidelines. Transparency is a core ethical pillar: users have the right to understand how data profiles them. Anonymization and encrypted database storage enforced.

4. HIGH-LEVEL SYSTEM ARCHITECTURE

The Hybrid ML-Driven Adaptive Profiling component serves as the central brain of FITSHIELD, maintaining the living user profile and feeding explainable inputs to other modules. Figure 1 outlines the system architecture connecting web/mobile clients, Django REST backend, AI engine, and user dashboards.

4.1 Component Overview & Tech Stack

Four primary modules: Data Ingestion Module, Hybrid Profiling Engine (K-Means, LSTM), XAI Explanation Generator (SHAP), and Profile API Layer.

4.2 Technology Stack

Frontend: React.js; Backend: Flask / Python microservice; ML/DL: Scikit-learn, TensorFlow / Keras; XAI: SHAP, LIME; Database: PostgreSQL (JSONB); Cloud: Render / Railway deployment.

4.3 Data Flow & Scalability

Data Flow: (1) Activity/meal event sent from frontend; (2) Backend forwards to profiling API; (3) Data ingestion validates format; (4) Profiling engine updates LSTM state and master profile; (5) Recommendation engines query profile; (6) SHAP generates plain-text explanation.

Scalability: Microservice architecture scales independently; secured with JWT and HTTPS.

5. USER REQUIREMENTS

Table 2 Functional Requirements:

- FR-01: Ingest user data from multiple sources (High)
- FR-02: Maintain dynamic profile updated in real-time (High)
- FR-03: K-Means clustering for behavioral archetypes (High)
- FR-04: RNN/LSTM sequence models for behavior patterns (High)
- FR-05: Rule-based logic for immediate profile adjustments (High)
- FR-06: SHAP explanations for all recommendations (High)
- FR-07: Secure REST API exposure (High)
- FR-08: Calibrated with Sri Lankan health datasets (High)

5.3 Non-Functional Requirements

NFR-01: Profile updates and explanations returned within 2 seconds.

NFR-02: User data encrypted at rest and in transit (JWT auth).

NFR-03: Explanations understandable to laypersons without jargon.

NFR-04: Profiling microservice maintains 99% uptime.

NFR-05: Supports dynamic profiling for up to 500 concurrent users.

NFR-06: ML models versioned and retrainable as data accumulates.

6. COMMERCIALIZATION PLAN

Target Market: Sri Lankan adults (25-55) in urban areas seeking culturally adapted health management.

Value Proposition: Only system built from the ground up for Sri Lanka that learns habits, adapts dynamically, and explains reasoning.

Revenue Model: Freemium model (basic profile free); Premium Subscription (500-1,500 LKR/month); B2B

Personalization API licensing to healthcare providers and corporate wellness programs.

Competitive Advantage: Dynamic adaptation, XAI transparency, and cultural grounding.

7. BUDGET AND JUSTIFICATION

Cloud Hosting: Free-tier (0 LKR)

Domain Name: Annual domain (3,500 LKR)

Development Tools: VS Code, Git, Python, Scikit-learn, TensorFlow (0 LKR - open source)

XAI Libraries: SHAP, LIME (0 LKR)

User Testing: Gift vouchers for 20 participants in A/B testing (10,000 LKR)

Data Collection: MRI and MoH survey datasets (0 LKR via university contacts)

Miscellaneous: Stationery & printing (3,000 LKR)

TOTAL BUDGET: 16,500 LKR

8. WORK BREAKDOWN STRUCTURE (WBS)

Table 3 WBS:

- 1.0 Project Initiation (Weeks 1-2)
- 2.0 Data Architecture & Integration (Weeks 3-6)
- 3.0 Hybrid ML Model Development: K-Means & LSTM (Weeks 6-11)
- 4.0 Explainable AI Integration: SHAP/LIME (Weeks 11-14)
- 5.0 API Development & Microservice Integration (Weeks 14-16)
- 6.0 System Integration & Unit Testing (Weeks 16-19)
- 7.0 Evaluation, SUS Testing & Final Report (Weeks 18-20)

8. WBS & 9. GANTT CHART

Gantt Chart tracking 20-week research milestones from requirements analysis through model training, explainability integration, user evaluation, and final thesis defense.

9. GANTT CHART (Visual)

Figure 2: Gantt Chart representing task progression across Semesters Y3S2 and Y4S1 at SLIIT Faculty of Computing.

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11. APPENDICES

Appendix A: Risk Analysis Table (data integration, LSTM overfitting, SHAP computational cost, external dependencies).

Appendix B: Ethical Compliance Statement (informed consent, data anonymization, right to withdraw, transparent algorithmic reasoning).

Appendix C: Technology Overview --- Hybrid ML with XAI

Figure 3: Hybrid Architecture Overview combining Scikit-learn K-Means for archetype clustering, TensorFlow LSTM for temporal pattern recognition, and SHAP TreeExplainer mapped to empathetic, localized natural language templates.

Appendix D: Survey Instruments

Figure 4: Survey Instruments showing survey response charts for user demographics, exercise frequency, sleep patterns, and willingness to adopt AI-based lifestyle recommendations in Sri Lanka.

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