

FITSHIELD: PERSONALIZED FITNESS AND NUTRITION MOBILE APPLICATION

SMART SUPPLEMENTARY ADVISORY RECOMMENDATION

R26-IT-099

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

The widespread use of dietary supplements without proper guidance has become a growing public health concern. Many individuals rely on informal sources such as social media and peer recommendations without considering medical conditions, existing medications, or individual physiological differences. This can lead to serious risks, including drug-supplement interactions, nutrient toxicity, and ineffective health outcomes.

This research proposes an intelligent, user-centered supplement advisory system that provides personalized recommendations while ensuring safety and informed decision-making. The system integrates a Random Forest-based recommendation model with a rule-based interaction detection mechanism to identify and prevent harmful supplement-drug combinations. Additionally, it includes a personalized scheduling module and a comparative decision support feature that enables users to evaluate supplement options based on cost and quality.

The system will be developed using modern web and machine learning technologies, including React.js, Django, PostgreSQL, and Scikit-learn. The expected outcomes include achieving a recommendation accuracy (F1-score) above 0.75, interaction detection precision above 0.90, and system usability exceeding a SUS score of 70. The proposed solution aims to deliver a safe, reliable, and personalized platform that improves supplement usage practices and supports better health outcomes.

Keywords

Supplement Recommendation, Drug-Supplement Interaction, Personalized Health, Machine Learning, Decision Support System

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TABLE OF CONTENTS

Project Proposal Report	1
DECLARATION	2
ABSTRACT	3
ACKNOWLEDGEMENT	4
TABLE OF CONTENTS	5
LIST OF TABLES	6
LIST OF FIGURES	7
LIST OF ABBREVIATIONS	7
LIST OF APPENDICES	7
1. INTRODUCTION	8
1.1 Background and Context	8
1.2 Literature Review	9
1.3 Research Gap	11
2. OBJECTIVES	12
2.1 Main Objective	12
2.2 Specific Objectives	12
3. METHODOLOGY	14
3.1 Component Overview	14
3.2 Research Approach	15
3.3 Data Collection	15
3.4 Technical Methods and Algorithms	16
3.5 Tools and Technologies	17
3.6 Validation Strategy and Performance Metrics	20
3.7 Ethical Considerations	20
4. HIGH-LEVEL SYSTEM ARCHITECTURE	21
4.1 Overview of Proposed Solution	21
4.2 Individual Component Architecture	23
4.3 Component Description	24
4.4 Scalability and Security Considerations	25
5. USER REQUIREMENTS	26
5.1 Stakeholder Identification	26
5.2 Functional Requirements	26
5.3 Non-Functional Requirements	27

TABLE OF CONTENTS & LIST OF TABLES

6. COMMERCIALIZATION PLAN	29
6.1 Target Market and Customer Persona	29
6.2 Value Proposition	29
6.3 Revenue Model and Pricing Strategy	29
6.4 Competitive Advantage	30
6.5 Intellectual Property Considerations	31
7. BUDGET AND JUSTIFICATION	32
8. WORK BREAKDOWN STRUCTURE (WBS)	33
9. GANTT CHART	36
10. REFERENCES LIST	37
APPENDICES	38
Appendix A - Survey Instruments	38
Appendix B - System Architecture Diagram	39
Appendix C - Risk Analysis	40
Appendix D - Ethical Considerations	40

LIST OF TABLES

Table 1: Literature Review	10
Table 2: Research gap Justification	11
Table 3: Specific Objectives Table	13
Table 4: Tools and Technologies Table	20
Table 5: Individual Component Architecture	24
Table 6: Component Description Table	25
Table 7: Stakeholder Identification	27
Table 8: Functional Requirements	28
Table 9: Non-Functional Requirements	29
Table 10: Revenue Model and Pricing Strategy	31
Table 11: Budget And Justification Table	33
Table 12: Work Breakdown Structure (WBS) Table	35
Table 13: Risk Analysis Table	41

LIST OF FIGURES & ABBREVIATIONS

LIST OF FIGURES

Figure 1: High-Level System Architecture	23
Figure 2: Component Diagram	24
Figure 3: Work Breakdown Structure (WBS)	36
Figure 4: Gantt Chart	37
Figure 5: Survey Instruments	39
Figure 6: System Architecture Diagram	40

LIST OF ABBREVIATIONS

AI - Artificial Intelligence
API - Application Programming Interface
AES - Advanced Encryption Standard
BMI - Body Mass Index
DSR - Design Science Research
ML - Machine Learning
RF - Random Forest
SHAP - SHapley Additive exPlanations
SUS - System Usability Scale
TLS - Transport Layer Security
WCAG - Web Content Accessibility Guidelines

LIST OF APPENDICES

Appendix A - Survey Instruments
Appendix B - System Architecture Diagram
Appendix C - Risk Analysis
Appendix D - Ethical Considerations

1. INTRODUCTION

1.1 Background and Context

The global dietary supplement industry has experienced substantial growth in recent years, reaching an estimated market value of USD 177 billion in 2023 and projected to exceed USD 300 billion by 2030 [1]. This rapid expansion is largely driven by increasing health consciousness, the rise of fitness culture, and a growing emphasis on preventive healthcare. Consequently, dietary supplements including vitamins, minerals, protein powders, herbal extracts, and omega fatty acids have become a routine component of daily health practices for millions of individuals worldwide.

Despite this widespread adoption, supplement consumption remains largely unguided and inadequately regulated at the individual level. A significant proportion of users make decisions without consulting healthcare professionals, instead relying on informal sources such as social media, peer influence, gym communities, and product marketing claims. Bailey et al. reported that over 68% of supplement users in the United States had never sought professional medical advice regarding their supplement use [2]. This trend reflects a broader global pattern in which individuals prioritize convenience and accessibility of information over clinically validated guidance.

Such uninformed consumption introduces critical risks that elevate dietary supplement usage from a personal wellness choice to a public health concern. One of the most significant risks is the potential for drug-supplement interactions. Certain supplements can alter pharmacokinetic and pharmacodynamic processes, leading to reduced drug efficacy or harmful side effects. For instance, St. John's Wort has been shown to induce cytochrome P450 enzymes, thereby reducing the effectiveness of medications such as antiretrovirals and oral contraceptives [3]. Similarly, systematic reviews have identified over 150 clinically relevant drug supplement interactions, highlighting the scale and complexity of this issue.

In addition to interaction risks, inappropriate supplement use such as excessive dosages or unsuitable combinations, can lead to adverse physiological effects, including nutrient toxicity, hepatotoxicity, renal stress, and hormonal imbalances [5]. Beyond safety concerns, uninformed supplement selection often results in suboptimal health outcomes, as the effectiveness of supplementation depends on precise alignment with individual health needs, dietary deficiencies, and lifestyle factors.

While digital health platforms have emerged to support personal wellness management, their capabilities in supplement guidance remain limited. Applications such as MyFitnessPal, HealthifyMe, Cronometer, and FitnessAI primarily focus on calorie tracking, diet monitoring, and fitness recommendations, offering little to no personalized, safety-aware supplement advisory. Where supplement recommendations exist, they are typically generic and fail to incorporate critical user-specific variables such as medical history, medication use, or potential interaction risks.

1.2 Literature Review

Research related to intelligent health recommendation systems spans several key areas, including personalized recommendation models, drug-supplement interaction detection, comparative decision support, adherence optimization, and explainable artificial intelligence.

In the domain of personalized health recommendation systems, recent studies highlight the effectiveness of machine learning techniques in generating accurate and user-specific recommendations. A systematic review by Chen et al. (2022) analyzing 47 studies found that ensemble models, particularly Random Forest and Gradient Boosting, consistently outperform single-model approaches in terms of prediction accuracy and generalizability [7]. These models leverage multiple user attributes such as demographic information, behavioral patterns, and health indicators to produce more precise recommendations. Furthermore, Topol (2023) emphasizes that AI-driven systems incorporating individual variability, including medical history and lifestyle factors, significantly improve user engagement and adherence compared to generic approaches [8]. Hybrid recommendation architectures have also been shown to mitigate cold-start problems by combining collaborative and content-based filtering techniques [9]. However, most existing systems are limited to diet and fitness applications, with minimal focus on personalized dietary supplement recommendations.

Drug supplement interaction detection has been extensively studied within clinical pharmacology due to the increasing use of complementary and alternative medicine. Tsai et al. (2021) identified over 150 clinically significant drug-supplement interactions, highlighting the widespread nature of potential risks [4]. Recent advancements incorporate computational approaches, including rule-based systems and natural language processing techniques applied to biomedical literature, achieving precision rates exceeding 90% in identifying known interactions [11]. These systems typically utilize structured pharmacological databases combined with unstructured clinical data to enhance detection coverage. Despite their high accuracy, such solutions are primarily confined to clinical environments and are not widely accessible to general consumers through digital health platforms.

Comparative decision support and price transparency have also been recognized as critical factors influencing user decision-making. Research indicates that providing users with comparative information, such as price, product quality, and ratings, significantly improves purchasing decisions and promotes cost-effective behavior [12], [13]. Studies in e-commerce and health platforms demonstrate that multi-criteria decision support systems enhance user satisfaction by presenting multiple evaluation factors simultaneously. However, most existing health recommendation systems do not integrate such comparative features, particularly in the context of dietary supplements.

Supplement adherence and usage scheduling remain key challenges in health management systems. Studies report adherence rates ranging from 40% to 60% [14]. Research by Vrijens et al. (2012) shows that personalized scheduling aligned with individual routines significantly improves adherence [15]. Additionally, nutrient bioavailability is influenced by intake timing, suggesting that improper scheduling can reduce supplement effectiveness [16].

1.2 Literature Review (Cont.)

Transparent and interpretable recommendation systems increase user confidence and engagement [17]. Lundberg and Lee (2017) introduced the SHAP framework, which provides feature-level explanations for machine learning outputs [18]. Recent studies demonstrate that explainable AI can improve user trust by up to 34% [19], highlighting its importance in health-related applications. Nevertheless, many existing systems still function as black-box models without providing sufficient interpretability.

Table 1: Literature Review Summary

Author(s)	Institution / Source	Contribution	Key Limitation
Chen et al. (2022)	International Review	Ensemble ML (Random Forest, GBM)...	Focus mainly on diet & fitness, ...
Topol (2023)	International	Personalization using medical hi...	Does not address supplement-spec...
Tsai et al. (2021)	Clinical Pharmacology	Rule-based systems achieving >90...	Confined to hospital/clinical de...
Nielsen (2021)	Consumer Research	Price-quality comparison improve...	Not applied in health or supplem...
Bales & Ritchie (2020)	Nutrition Research	Importance of supplement timing ...	No implementation in intelligent...

1.3 Research Gap

As illustrated in Table 2, recent studies have made significant advancements in individual domains such as personalized recommendation systems, drug-supplement interaction detection, comparative decision support, adherence optimization, and explainable artificial intelligence. However, these contributions remain fragmented and are typically implemented in isolation. Existing systems either focus on general health recommendations, clinical decision support, or consumer purchasing behavior, without addressing the full complexity of dietary supplement usage.

A critical limitation identified across the literature is the absence of a unified, consumer-oriented platform that integrates these capabilities into a single intelligent system. In particular, current solutions fail to combine personalized health profiling, real-time safety screening for drug-supplement interactions, cost-aware decision support, and adaptive scheduling mechanisms.

Table 2: Research Gap Justification

Research Area	Recent Findings	Limitations	Identified Gap
Personalized Health Systems	Advanced ML models provide accur...	Focus mainly on diet/fitness, li...	Lack of supplement systems consi...
Drug-Supplement Detection	Rule-based and NLP approaches re...	Limited to clinical hospital set...	Absence of real-time consumer-ac...
Comparative Decision Support	Price and quality comparisons im...	Not integrated in health recomme...	Lack of cost-aware supplement de...
Supplement Adherence & Scheduling	Personalized scheduling improves...	No adaptive scheduling in curren...	Lack of intelligent timing-based...
Explainable AI in Health	SHAP models improve user trust a...	Many systems still function as b...	Lack of explainable outputs in s...
System Integration	Technologies operate in isolated...	Fragmented tools require manual ...	No unified platform integrating ...

2. OBJECTIVES

2.1 Main Objective

The main objective of this research is to design and implement a comprehensive dietary supplement advisory system that enhances the safety, effectiveness, and personalization of supplement usage. The system focuses on delivering user-specific recommendations, improving decision-making through relevant information, and promoting responsible supplement consumption by addressing existing limitations in current digital health solutions.

2.2 Specific Objectives

The following specific objectives are measurable, aligned with the four identified research gaps (G1-G4), and directly map to the methodology phases and system design components:

Table 3: Specific Objectives Table (Part 1: SO1 - SO3)

SO	Gap	Specific Objectives	Measurable Success Criteria
SO1	G1	To analyze user-specific health ...	Identification of key influencin...
SO2	G2	To develop a framework for detec...	Interaction detection module ach...
SO3	G3	To incorporate comparative decis...	Users identify cost-effective su...

2. OBJECTIVES (Cont.)

Table 3: Specific Objectives Table (Part 2: SO4 - SO6)

SO	Gap	Specific Objectives	Measurable Success Criteria
SO4	G4	To design personalized supplemen...	Improvement in user adherence ra...
SO5	G5	To integrate explainable recomme...	Increase in user trust and compr...
SO6	G6	To combine all features into a u...	System successfully integrates a...

3. METHODOLOGY

This study is guided by the Design Science Research (DSR) approach, which offers an organized framework for the iterative design, development, and assessment of the suggested AI product. The following steps are taken by the methodology:

3.1 Component Overview

The proposed AI-driven dietary supplement advisory system is composed of several interrelated components, each designed to address the specific research gaps identified in the literature review:

- * 1. User Profile Management: Collects and maintains individual user data, including medical history, current medications, dietary patterns, lifestyle factors, and supplement usage history. Serves as the foundation for personalized recommendations and risk assessments.
- * 2. Supplement Recommendation Engine: Generates personalized supplement suggestions based on the user profile. Integrates multi-criteria decision factors such as nutrient requirements, health objectives, and potential deficiencies. Designed to deliver context-aware recommendations aligned with individual needs.

3. METHODOLOGY (Cont.)

- * 3. Drug-Supplement Interaction Detector: Screens recommended supplements against user medications to identify potential adverse interactions using clinical databases.
- * 4. Comparative Decision Support Module: Provides transparent comparisons of available supplements, including pricing, brand quality, and alternative options.
- * 5. Personalized Scheduling and Adherence Module: Generates tailored intake schedules, aligning supplement consumption with meals, routines, and nutrient bioavailability.
- * 6. Explainable AI and User Interface: Integrates explainable AI techniques (e.g. SHAP) to provide interpretable reasoning behind recommendations.

3.2 Research Approach

The research follows the DSR cycle: (1) Problem identification and motivation (Section 1.2-1.3), (2) Definition of objectives (Section 2), (3) Design and development (Phases 2-4), (4) Demonstration (prototype system), and (5) Evaluation (model validation and usability testing).

3.3 Data Collection (Primary Methods)

- * Surveys / Questionnaires: Collect responses from users about which supplements they take, dosage frequency, and side effects.
- * Interviews: Conduct structured discussions with nutritionists, athletes, and pharmacists to establish clinical safety baselines.
- * Focus Groups & Logs: Ingest continuous user intake logs and side effect reports to validate longitudinal compliance.

3.4 Technical Methods and Algorithms

Secondary Data Collection Methods

- * Medical / Health Records: Anonymized records documenting adverse effects from supplement use.
- * Pharmacological Databases: DrugBank, NMCD, and clinical interaction datasets for rule encoding.

Random Forest Classification (Recommendation Engine)

The Random Forest algorithm is selected as the primary recommendation engine based on prior research demonstrating its effectiveness in health recommendation and safety screening tasks. Studies show that ensemble tree models consistently achieve higher precision and recall on multi-feature health profile datasets than single-model classifiers or collaborative filtering alone.

Random Forest handles mixed numeric and categorical variables well, provides robustness against class imbalance, and produces feature importance rankings that feed into SHAP explainability pipelines.

Rule-Based Interaction Detection Engine

A production rule system encodes established drug-supplement interaction knowledge derived from sources such as DrugBank and NMCD. Each rule captures: (1) condition-supplement pair, (2) interaction type (pharmacokinetic, pharmacodynamic, or absorption), (3) severity classification, and (4) recommended action (filter, warn, or flag for consultation).

Content-Based Similarity Filtering (Recommendation Refinement)

Cosine similarity is computed between user nutritional need vectors and supplement characteristic vectors, allowing re-ranking of recommendations beyond initial classification to solve cold-start issues.

3.4 Technical Methods (Cont.)

Decision Logic Engine (Scheduling & Results Timeline)

This module generates personalized supplement schedules and predicts expected outcomes across two operational layers:

1. Scheduling Logic: Supplement timing recommendations are generated using a structured decision logic module based on published bioavailability research. Examples include:

- * Fat-soluble vitamins (A, D, E, K) post-meal with dietary lipids for optimal intestinal absorption.
- * Iron supplements between meals, away from calcium-rich foods and caffeine to avoid chelation.
- * Probiotics pre- or post-meal depending on specific strain acid tolerance.

2. Results Timeline Logic: For each supplement, the system estimates a realistic timeline for expected health effects based on:

- * Supplement Type: e.g. Vitamin D (weeks to months for serum 25(OH)D correction), protein powder (days to weeks for muscle protein synthesis), omega-3 (weeks to months for triglyceride modulation).
- * Dosage & Formulation: Bioavailability and daily intake relative to tolerable upper intake levels (UL).
- * User Baseline Health Status: Initial deficiency severity and metabolic profile.
- * Health Goal: Specific measurable targets (e.g. "enhanced athletic recovery" vs. "bone density support").

3.5 Tools and Technologies

Table 4: Tools and Technologies Table (Frontend & Backend)

Layer / Purpose	Candidate Platforms	Comparison	Best Solution	Justification
Frontend Development	React, Angular, Vue	React is highly suitable for com...	React.js	React supports dynamic forms, re...
Backend Development	Flask, Django, FastAPI	Flask requires manual auth setup...	Django	Django is the best choice becaus...

3.5 Tools and Technologies (Cont.)

Table 4: Tools and Technologies Table (Database, ML, Styling)

Layer / Purpose	Candidate Platforms	Comparison	Best Solution	Justification
Database Management	PostgreSQL, MongoDB	PostgreSQL is ideal for structur...	PostgreSQL	PostgreSQL manages structured us...
Machine Learning	Scikit-learn, TensorFlow	Scikit-learn excels at tabular c...	Scikit-learn	Efficient, practical, and integr...
Styling / UI Design	Tailwind CSS, Bootstrap	Tailwind provides utility-first ...	Tailwind CSS	Supports rapid development of cl...

3.6 Validation Strategy

Tools and Technologies (Deployment & Operations)

- * Data Visualization: Chart.js selected for interactive dose-response curves and adherence dashboards.
- * Version Control: GitHub for team branch management, CI/CD actions, and release documentation.
- * Hosting & Deployment: Render / Cloud environment supporting managed PostgreSQL and Python runtime.

3.6 Validation Strategy and Performance Metrics

Model validation will be conducted at multiple levels to ensure accuracy, reliability, and usability. At the model level, the recommendation engine will be evaluated using 5-fold cross-validation on the Random Forest classifier, targeting a minimum F1-score of 0.75.

The interaction detection module will be validated against a curated benchmark dataset of documented drug-supplement interactions from DrugBank and clinical literature, targeting precision ≥ 0.90 and recall ≥ 0.85 .

At the system level, overall usability will be assessed using the System Usability Scale (SUS) with 20 participants, targeting a score ≥ 70 and end-to-end latency < 3 seconds.

3.7 Ethical Considerations

Ethical considerations are a critical aspect of this research to ensure the protection of participant rights and data privacy. Informed consent will be obtained from all user testing participants prior to data collection, in accordance with SLIIT Research Ethics Committee requirements.

All personal health data will be anonymized before model training and securely stored in AES-256 encrypted databases, with access restricted to authorized system components only.

The system will clearly present its outputs as decision-support guidance rather than medical prescriptions, and all recommendations will include a visible disclaimer encouraging users to consult qualified healthcare professionals before initiating any supplement regimen.

Furthermore, the research complies with Sri Lankan data protection regulations and institutional ethical guidelines. Participants retain the right to withdraw from the study at any time without penalty or consequence.

4. HIGH-LEVEL SYSTEM ARCHITECTURE

4.1 Overview of Proposed Solution

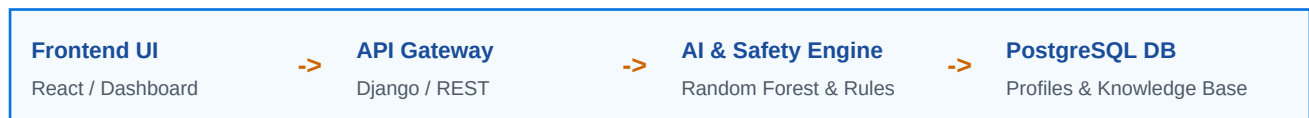
The proposed system is a four-module AI-powered fitness and nutrition web platform designed for personalized health management in Sri Lanka (Project R26-IT-099). Each module addresses a distinct functional domain and communicates with others via REST APIs through a shared backend and cloud-based architecture. The four modules and their relationships are:

- * IT22621542 - Adaptive Habit Evolution Engine (AHEE): Continuously monitors user behavior such as workout completion, consistency, and engagement patterns to adjust routines dynamically.
- * IT22248176 - AI-Based Exercise Posture Recognition and Injury Prevention System: Captures real-time video input via mobile device camera to evaluate biomechanical alignment.
- * IT22169044 - Smart Supplement Advisory Recommendation System: Analyzes user health profiles including age, BMI, dietary patterns, and medical conditions to recommend suitable dietary supplements with DrugBank interaction checks.
- * IT22065476 - Health-Aware Dietary Recommendation and Food-Drug Interaction Detection System: Generates personalized meal plans while detecting contraindications against medication.

System Architecture Diagram

Figure 1 illustrates the high-level system architecture connecting user onboarding, database clusters, ML inference engines, and output components:

Figure 1: High-Level System Architecture



4.2 Individual Component Architecture

Table 5: Individual Component Architecture

Component	Description
User Input Module	Collects and validates health pr...
Recommendation Engine	Random Forest and similarity-bas...
Interaction Detection Module	Rule-based logic evaluates poten...
Price Comparison Module	Retrieves and displays pricing a...
Schedule Generator	Applies decision logic to create...
Web Dashboard	React.js frontend visualizes rec...

4.3 Component Description Table

Table 6: Component Description Table

Component	Role	Technology
Health Profile Onboarding	Collects and validates user age,...	React.js form, Django REST API
Random Forest Engine	Generates ranked list of safe, s...	Scikit-learn Random Forest, Pyth...
Rule-Based Interaction Module	Cross-references candidate supplements against medication list	Python rule engine, DrugBank dat...
Content-Based Similarity Filter	Refines recommendation ranking b...	Scikit-learn, NumPy
Price Comparison Module	Retrieves and displays brand-level pricing, ratings, and availability	REST API integration, React.js t...
Decision Logic Scheduling	Generates daily supplement sched...	Python decision logic, React cal...
SHAP Explainer	Provides feature-level attributi...	SHAP TreeExplainer, React UI
Web Dashboard	Unified React interface renderin...	React.js, Chart.js

4.4 Scalability and Security Considerations

The proposed system is designed to ensure scalability and security in handling sensitive health-related data and increasing user demand:

Scalability

- * **Modular Microservice Structure:** The backend services are developed using a modular architecture that supports horizontal scaling to accommodate growing concurrent users.
- * **Efficient Database Indexing:** High-frequency queries on user profiles and interaction rules are optimized using B-tree indexing in PostgreSQL.
- * **Stateless API Design:** REST API endpoints operate statelessly, allowing round-robin load distribution across containerized instances.

Security & Data Protection

- * **JWT Authentication:** Secure token-based access control is enforced across all API endpoints to prevent unauthorized data tampering.
- * **AES-256 Encryption:** All sensitive personal health data, medication histories, and allergy lists are encrypted both at rest and in transit (TLS 1.3).
- * **Audit Logging:** Safety-critical screening events and model outputs are immutably logged for clinical traceability.

5. USER REQUIREMENTS

5.1 Stakeholder Identification

Primary users include health-conscious adults, fitness practitioners, and individuals with chronic conditions requiring clinical screening. Secondary stakeholders include nutritionists, trainers, and system administrators.

Table 7: Stakeholder Identification

Stakeholder	Role	Key Needs
Primary User (End User)	Adults seeking personalized supp...	Personalized recommendations, sa...
Secondary User (Healthcare)	Nutritionists, dietitians, and trainers	Client health summaries, recomme...
System Administrator	Maintains supplement DB and rule bases	Data management tools, rule upda...

Table 8: Functional Requirements (Part 1: FR-01 - FR-05)

ID	Requirement	Priority	Stakeholder
FR-01	Collect user health profile data including age, BMI, medical history, and goals.	High	End User
FR-02	Analyze profile and generate ranked list of suitable supplement recommendations.	High	End User
FR-03	Screen candidate supplements against medications using rule-based engine.	High	End User
FR-04	Generate personalized daily usage schedule based on meal times and bioavailability.	High	End User
FR-05	Estimate expected time window for noticeable results based on scientific evidence.	High	End User

5.3 Non-Functional Requirements

Table 9: Non-Functional Requirements (NFR-01 - NFR-06)

ID	Category	Requirement Statement	Acceptance Criterion
NFR-01	Performance	Generate recommendations, safety...	Response time < 3 seconds for 95...
NFR-02	Accuracy	Recommendation model and interac...	F1 >= 0.75 across 5-fold CV; int...
NFR-03	Usability	System shall achieve intuitive u...	System Usability Scale (SUS) sco...
NFR-04	Security	All personal health data must be...	AES-256 encryption at rest, TLS ...
NFR-05	Reliability	System shall maintain continuous...	99% uptime monitored over 30-day...
NFR-06	Scalability	System architecture shall scale ...	Load tested up to 1,000 concurre...

5.3 Non-Functional Requirements (Cont.)

Table 9: Non-Functional Requirements (NFR-07 - NFR-09)

ID	Category	Requirement Statement	Acceptance Criterion
NFR-07	Maintainability	Supplement database and interact...	Admin console update cycle < 30 minutes.
NFR-08	Accessibility	Web interface complies with mode...	Validated WCAG 2.1 Level AA compliance.
NFR-09	Auditability	System logs each recommendation ...	100% of generated recommendation...

6. COMMERCIALIZATION PLAN

6.1 Target Market and Customer Persona

The primary target market comprises health-conscious adults aged 20 to 55 who actively use dietary supplements for fitness, wellness management, or chronic condition support. Secondary markets include corporate wellness programs, gyms, and clinical wellness centers.

6.2 Value Proposition

The proposed system delivers value across five key pillars: (1) Clinical Safety screening against drug interactions; (2) Personalized ML-driven recommendations; (3) Price transparency and product quality comparisons; (4) Bioavailability scheduling; and (5) Explainable AI outputs.

Table 10: Revenue Model and Pricing Strategy

Tier / Model	Features	Pricing Approach	Purpose
Free Plan	Basic supplement info, general g...	Free	Attract new users and drive plat...
Premium Subscription	Personalized recommendations, in...	Monthly / Annual	Primary recurring B2C revenue st...
Upgraded Tier	Advanced clinical reports, prior...	Higher tier subscription	High-value power users and athle...

6.4 Competitive Advantage

Institutional / Enterprise Plan

Bulk user access, corporate wellness analytics, and custom clinic integration provided via tiered enterprise licensing agreements.

Key Competitive Advantages

- * Clinical Safety First: Unlike generic fitness apps, FITSHIELD screens every supplement candidate against prescription medications and chronic conditions.
- * Explainable Transparency: Users receive clear feature-level SHAP explanations instead of opaque black-box lists.
- * Multi-Criteria Price Comparison: Helps users find affordable alternatives without compromising quality.
- * Bioavailability Optimization: Intake timings are scientifically matched to meals and nutrient synergy.

6.5 Intellectual Property Considerations

SLIIT may protect the system architecture, curated interaction rule sets, and unique recommendation algorithms as intellectual property.

Data ownership, validation procedures, and knowledge sharing agreements will be outlined in collaboration agreements with nutritionists and medical specialists.

Core assets slated for IP protection include:

- * Curated Sri Lankan and global drug-supplement interaction rule bases.
- * Multi-criteria price-to-potency scoring algorithms.
- * Bioavailability scheduling decision logic matrices.

7. BUDGET AND JUSTIFICATION

Table 11: Budget and Justification Table

Item	Category	Estimated Cost (LKR)	Justification
Frontend & Backend Hosting	Cloud Hosting	26,767	Deploy prototype web application...
Managed PostgreSQL Database	Database Hosting	22,943	Securely store user profiles, su...
Domain Name (.com)	Domain / Branding	3,594	Custom domain for public access ...
SSL Certificate	Security	0	Managed TLS 1.3 provided free by...
Development Tools	Software Tools	0	Open-source stack (VS Code, Pyth...
Public / Open Datasets	Data	0	Publicly available DrugBank and ...
UI/UX Design Tools	Design	0 - 5,000	Templates and visualization assets.
Testing & Demo Expenses	Operations	5,000	User testing participant support...
Contingency (10%)	Risk Reserve	5,330	Buffer for unforeseen hosting or...
Estimated Total Budget	Total	58,000 - 64,000	Total estimated cost for full FY...

8. WORK BREAKDOWN STRUCTURE (WBS)

Table 12: Work Breakdown Structure (WBS) Table (Phase 1.0 - 6.0)

WBS ID	Task	Sub-Tasks	Duration	Deliverable
1.0	Project Initiation & Literature ...	1.1 Literature review; 1.2 Platf...	Weeks 1-3	Research gap report & SRS docume...
2.0	Data Collection & Preprocessing.	2.1 Supplement data clean; 2.2 D...	Weeks 4-6	Cleaned dataset & rule base v1...
3.0	Recommendation Engine Developme...	3.1 Random Forest design; 3.2 Co...	Weeks 7-9	Trained model (F1 >= 0.75)
4.0	Interaction Detection Module	4.1 Rule base encoding; 4.2 Cros...	Weeks 10-12	Validated screener (Precision >=...
5.0	Price Comparison & Scheduling..	5.1 Pricing API integration; 5.2...	Weeks 13-14	Pricing module & schedule genera...
6.0	Frontend Dashboard Development	6.1 Onboarding form; 6.2 Recomme...	Weeks 15-16	Complete React frontend

8. WORK BREAKDOWN STRUCTURE (Cont.)

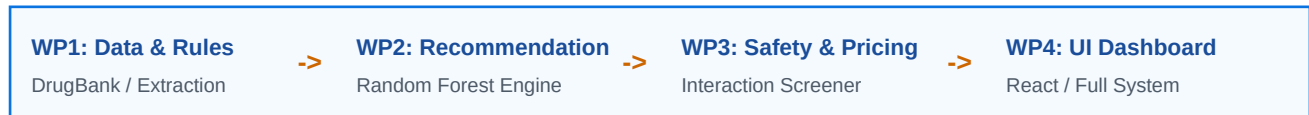
Table 12: Work Breakdown Structure (WBS) Table (Phase 7.0 - 9.0)

WBS ID	Task	Sub-Tasks	Duration	Deliverable
7.0	Backend Integration	7.1 Django REST endpoints; 7.2 J...	Week 17	Fully integrated platform backen...
8.0	Evaluation and User Testing	8.1 User study with 20 participa...	Weeks 18-19	Evaluation report & SUS results...
9.0	Documentation & Final Report	9.1 Technical documentation; 9.2...	Week 20	Final thesis report & slide deck

Figure 3: Work Breakdown Structure Diagram

Visual decomposition of research work packages into modular engineering tracks:

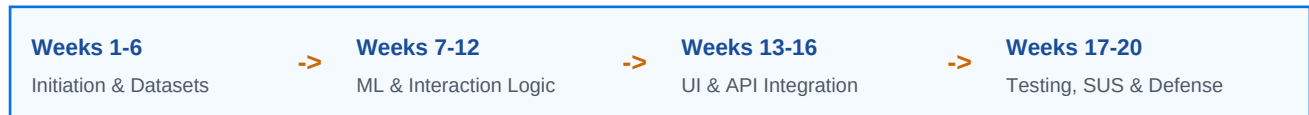
Figure 3: WBS Structural Flowchart



9. GANTT CHART

Timeline mapping across the 20-week academic development lifecycle at SLIIT Faculty of Computing:

Figure 4: Academic Lifecycle Gantt Chart



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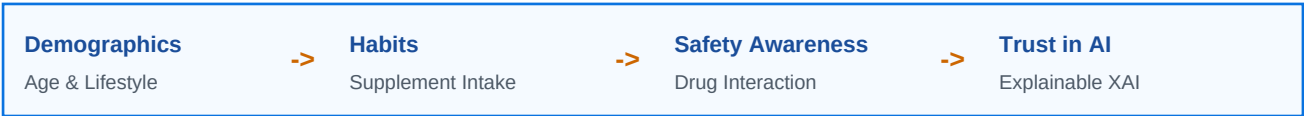
APPENDICES

Appendix A - Survey Instruments

To gather structured input on supplement usage patterns, health profile information, and system usability, user survey instruments were created. Participants in the study provided feedback through structured online question forms.

Survey metrics evaluated: (1) Age distribution and supplement usage frequency; (2) Daily rest and exercise habits; (3) Awareness of food-drug interaction contraindications; (4) Comfort with AI-based health decision support recommendations.

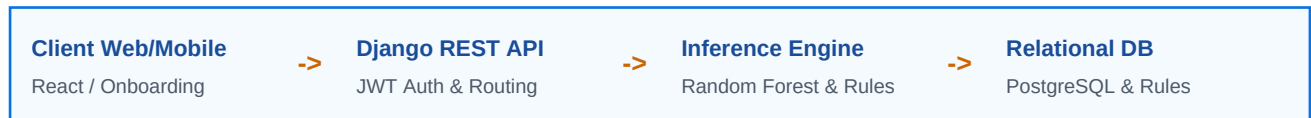
Figure 5: Survey Instrument Breakdown



Appendix B - System Architecture Diagram

Comprehensive multi-tier technical architecture diagram illustrating client presentation, REST gateway, ML inference layer, DrugBank rule verification, and persistent database entities:

Figure 6: Detailed Technical Architecture



Appendix C & D: Risk Analysis & Ethics

Table 13: Risk Analysis Table

Risk	Likelihood	Impact	Mitigation Strategy
Insufficient interaction dataset...	Medium	High	Augment public datasets with cur...
ML model underfitting or overfit...	Medium	High	k-fold cross-validation, hyperpa...
Drug-supplement rule base incomple...	Medium	Very High	Iterative expansion validated ag...
Data privacy breach of user heal...	Low	Very High	AES-256 at-rest encryption, TLS ...
External API unavailability	Low	Medium	Cached fallback data; abstract i...
Project scope creep	Medium	Medium	Strict WBS adherence; weekly sup...

Appendix D - Ethical Considerations (Cont.)

- * Informed consent was obtained from all user testing participants before any data collection commenced.
- * All personal health information is anonymized prior to model training and stored in AES-256 encrypted databases.
- * The system clearly communicates that all recommendations are decision-support guidance, not medical prescriptions, with visible professional consultation disclaimers on all output screens.
- * The research complies with SLIIT Ethics Review Committee guidelines and applicable Sri Lankan data protection regulations.
- * Participants may withdraw from user testing at any time without penalty.
- * Health measurements will not be stored with directly identifiable personal information.

Report End * Sri Lanka Institute of Information Technology (SLIIT) * Department of Information Technology *
Academic Year 2026