UNIGUARD EXPENSE TRACKER AI-DRIVEN PERSONAL BUDGETING AND FINANCIAL LITERACY ENHANCEMENT FOR UNIVERSITY STUDENTS IN UGANDA

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A PROJECT REPORT SUBMITTED TO THE FACULTY OF ENGINEERING, DESIGN AND TECHNOLOGY IN PARTIAL FULFILLMENT OF THE REQUIREMENTS FOR THE AWARD OF THE DEGREE OF BACHELOR OF SCIENCE IN COMPUTER SCIENCE OF UGANDA CHRISTIAN UNIVERSITY

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UGANDA CHRISTIAN UNIVERSITY
A Centre of Excellence in the Heart of Africa

Declaration

We, the undersigned, solemnly declare that the content presented in this Report is the outcome of our own independent collective efforts, research, and critical analysis. We have compiled and structured this document with the utmost integrity, drawing upon credible and verifiable sources. All external material has been duly cited and acknowledged. This work has not been previously submitted to this or any other institution for the award of a degree.

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Abstract

Uganda's university students face a critical financial management challenge. Despite mobile money reaching 33.8 million registered accounts and daily transaction values exceeding UGX 1.2 trillion, fewer than 25% of students aged 18–30 maintain any form of personal budget, and only 34% demonstrate basic financial literacy. Existing global applications such as Mint, YNAB, and Wallet are designed for structured banking environments and cannot parse the unstructured receipt images, nor do they recognise culturally relevant expenditure categories unique to Ugandan student life.

This project presents **UniGuard Expense Tracker**, an Progressive Web Application (PWA) that integrates artificial intelligence, Receipt OCR parsing, predictive budgeting, and gamified financial education to improve personal financial management and literacy among university students in Uganda. The system implements a Receipt OCR Scanner pipeline with OCR and Random Forest classification to automatically categorise transactions into 18 locally meaningful categories. A hybrid Random Forest anomaly detection architecture optimised via Particle Swarm Optimization (PSO) provides accurate spending forecasts from limited historical data. A gamification engine grounded in Self-Determination Theory delivers points, badges, leaderboards, and daily challenges, while a financial literacy Gemini AI Companion provides context-aware financial coaching.

Evaluation of the system produced strong results across all three objectives. The Receipt OCR scanner achieved an overall parse success rate of 96.4% on Ugandan mobile money receipts, while the Random Forest transaction classifier reached 89.2% accuracy across 18 culturally localised expenditure categories. The PSO-tuned forecasting model recorded a Mean Absolute Percentage Error (MAPE) of 8.9%, outperforming both ARIMA and GRU baselines. Usability testing with 25 Uganda Christian University students yielded a System Usability Scale (SUS) score of 83.4, placing the application in the "Excellent" usability category. An 8-week pilot with 97 students demonstrated a statistically significant 23.9 percentage point gain in overall financial literacy ($p < 0.001$), with the largest improvement recorded in budgeting confidence (+27.5%). The 28-day user retention rate reached 67.4%, confirming sustained engagement with the gamified learning framework.

The total development cost remains within UGX 3,190,000, making the solution practically achievable in the Ugandan tertiary context.

Acknowledgments

Completing this project and report has been a demanding but deeply rewarding journey that would not have been possible without the support of many individuals.

We extend our sincere gratitude to our project supervisor for their thoughtful guidance, constructive feedback, and unwavering encouragement throughout the entire project life cycle. Their expertise in artificial intelligence and mobile application development motivated us to pursue higher standards in every aspect of our design and implementation.

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To our families and friends: your patience, encouragement, and continued support throughout this journey made this achievement possible. This work belongs to you as much as it does to us.

Contents

Chapter 1

Introduction

1.1 Background

Uganda is one of the countries with the youngest population in the world, with a median age of 15.8 years and more than 78% of its population below the age of 35 [1]. Mobile money use has expanded rapidly, reaching 33.8 million registered accounts and daily transaction values exceeding UGX 1.2 trillion as of December 2024 [2]. Despite this widespread adoption of digital financial services, financial literacy among young people remains critically low. The National Financial Inclusion Strategy 2023–2028 reports that only 34% of Ugandans aged 18–30 can correctly answer basic financial literacy questions, while fewer than 25% maintain any form of personal budget [3].

University students represent one of the most financially vulnerable groups within this demographic. They typically receive irregular monthly allowances ranging from UGX 150,000 to UGX 400,000, face fixed costs such as hostel fees (UGX 500,000–900,000 per semester), meals, transport, and academic materials, and experience intense social pressure to spend on entertainment, fashion, and cultural obligations including contributions to funerals, weddings, church offerings, and clan events. Recent studies indicate that over 40% of university students in East Africa struggle to meet basic needs before the end of the semester due to poor budgeting. At the same time, nearly 15% face the risk of dropping out due to high debt and financial stress [3, 1]. Poor financial decisions frequently result in dropout, mental health challenges, or reliance on predatory digital lenders charging interest rates above 100% per month [3]. These challenges reveal a critical need for supportive, student-centred financial tools that can guide young people toward responsible financial habits during their formative university years.

1.2 Problem Statement

Other than the rapid expansion of mobile money services in Uganda, university students remain disproportionately vulnerable to financial mismanagement due to the absence of a context-appropriate digital personal finance solution. Existing global applications such as Mint, and YNAB are designed primarily for markets with structured bank statements and direct API integrations, rendering them incapable of automatically parsing and categorising the unstructured receipt images the dominant financial channels used by Ugandan youth [2].

These tools do not recognise locally meaningful expenditure categories including boda-boda transport, street food (chapati, rolex, muchomo), airtime and data bundles, church offerings and tithes, salon services, clan or family contributions (harambee), funeral support, or wedding envelopes all of which form a significant portion of student spending in the Ugandan cultural context [4]. Moreover, they fail to accommodate the highly irregular income patterns characteristic of university students who rely on inconsistent parental allowances, part-time work, or sponsorship remittances [3]. Current solutions also lack predictive intelligence capable of forecasting expenditure from limited and erratic transaction histories, offer no engaging gamified financial literacy content grounded in Ugandan social realities, and typically require continuous internet connectivity a major barrier given the prevalence of cross-platform web browsers and intermittent network coverage on Ugandan campuses [1].

Consequently, Ugandan university students experience persistent challenges including impulse spending, inaccurate expense tracking, accumulation of high-interest debt from predatory mobile loan applications, chronic financial anxiety, and critically low levels of financial capability that hinder their transition to economic independence after graduation [3, 5]. This substantial and well-documented gap in accessible, culturally relevant, intelligent, and engaging personal financial management tools specifically tailored for the Ugandan tertiary education environment represents both a pressing socio-economic challenge and a clear opportunity for targeted technological intervention [6, 7].

1.3 Main Objective

To design, and develop UniGuard Expense Tracker: a Progressive Web Application (PWA) that integrates artificial intelligence, automatic mobile money transaction parsing, predictive budgeting, and gamified financial education to significantly improve personal financial management and literacy among Ugandan university students.

1.4 Specific Objectives

1. To design and implement an automatic expense tracking and predictive forecasting system using OCR parsing and Random Forest models optimized for offline, on-device execution.
2. To integrate a structured gamification framework and an adaptive Gemini AI Financial Companion to provide contextual coaching and sustained financial education.
3. To conduct a mixed-methods evaluation with Uganda Christian University students to measure the system's impact on financial knowledge, confidence, and spending behaviour.

1.5 Research Questions

1. How can automatic Receipt OCR parsing and predictive machine learning models be effectively combined to track and forecast irregular student spending patterns in a fully offline cross-platform environment?
2. To what extent does a culturally contextualised, gamified financial literacy framework combined with an AI Companion increase student engagement and sustained use?
3. What measurable improvements in financial knowledge, budgeting confidence, and spending behaviour result from using the UniGuard Expense Tracker over a structured evaluation period?

1.6 Scope

The project delivers a fully functional PWA prototype targeting Uganda Christian University students as the primary user group. Core functionalities include automatic expense tracking via Receipt OCR scanning, AI-powered spending insights and forecasting, interactive budgeting tools, a gamified financial education module, savings goal tracking, and anonymous community challenges.

Direct integration with banking APIs, cryptocurrency features, investment recommendations, and lending services are explicitly excluded from scope. iOS development, web-based versions, and integration with commercial credit scoring systems are also beyond the current project boundary.

1.7 Justification

The proposed solution directly contributes to the National Financial Inclusion Strategy 2023–2028 objective of increasing youth financial literacy from 34% to 60% by 2028 [3]. It addresses an identified market gap using state-of-the-art AI and behavioural science while aligning with Uganda Christian University's mission of producing spiritually alive, intellectually alert, and socially responsible graduates. By providing a tool that operates offline, parses local mobile money messages, and reflects Ugandan cultural spending patterns, UniGuard Expense Tracker fills a gap that no existing solution currently addresses.

1.8 Definition of Terms

MTN MoMo MTN Mobile Money; Uganda's most widely used mobile money platform.

Airtel Money Airtel Uganda's mobile money service; the second dominant platform used by Ugandan students.

Receipt OCR Scanner An Web API that allows applications to read incoming receipt images matching a specific hash, without requiring invasive system permissions.

PSO Particle Swarm Optimization; a meta-heuristic optimisation algorithm inspired by collective animal behaviour, used here for automated hyperparameter tuning of deep learning models.

Random Forest A probabilistic classifier based on Bayes' theorem with the assumption of feature independence; suitable for lightweight real-time classification on mobile devices.

Joblib serialized models A lightweight version of Scikit-Learn designed for on-device machine learning inference on mobile and embedded systems.

React A JavaScript library for building user interfaces.

TypeScript A typed programming language that builds on JavaScript.

Self-Determination Theory (SDT) A motivational theory positing that satisfaction of competence, autonomy, and relatedness needs drives intrinsic motivation and sustained behaviour change.

Gamification The use of game design elements such as points, badges, leaderboards, and challenges in non-game contexts to increase engagement and motivation.

DSRM Design Science Research Methodology; a research paradigm for creating and evaluating artifacts that solve identified problems.

Chapter 2

Literature Review

2.1 Introduction

Financial management capability is widely recognised as a critical determinant of individual economic wellbeing, particularly during the transition to adulthood. For university students in Uganda, this challenge is compounded by irregular income, cultural spending obligations, and the absence of tools designed for their context. This chapter examines the evolution of personal finance management technologies, the conceptual frameworks underpinning AI-driven and gamified financial tools, and the specific contextual landscape of financial literacy interventions in sub-Saharan Africa.

2.2 Historical Perspective

Personal finance management tools have evolved through three distinct generations: from manual desktop entry in the 1990s to cloud-based synchronised bank feeds in the 2010s, and most recently, AI-enhanced predictive platforms [7]. However, this evolution mostly focuses on Western countries. While global apps (such as Mint, YNAB, and Wallet) work well with formal bank accounts, they struggle in sub-Saharan Africa.

Specifically, these global apps cannot process the text-message-based mobile money receipts that most Africans use. They also expect users to have a steady, monthly income, which does not match the irregular allowances of university students. Furthermore, current AI finance tools do not understand local cultures. They use Western spending categories and ignore important cultural expenses common in Uganda, such as church tithes and clan contributions. Therefore, there is a need for new solutions built specifically for the reality of African mobile finance.

2.3 Conceptual Perspective

2.3.1 Artificial Intelligence in Personal Finance

Sequential deep learning architectures dominate modern personal finance prediction tasks. Random Forest and Isolation Forest models are employed for modelling temporal dependencies in transaction sequences, enabling accurate forecasting of future expenditure and savings trajectories from short historical records [8]. Ensemble architectures combining tree-based neural networks achieve superior performance by simultaneously processing sequential and static features [9].

Particle Swarm Optimization (PSO) and Adaptive Whale Optimization Algorithm are applied as meta-heuristic techniques for automated hyperparameter tuning of deep learning models in financial prediction contexts, yielding accuracy improvements of up to 98% in controlled experiments [10, 11]. Lightweight probabilistic classifiers such as Random Forest are utilised for real-time transaction categorisation on resource-constrained mobile devices, making them particularly well-suited to the low-end device hardware prevalent among Ugandan students [9].

Natural Language Processing (NLP) approaches including regular expression matching, token classification, and lightweight transformer models have been applied to the parsing of unstructured financial text messages. While Receipt OCR scanning for structured bank notifications has been explored in Indian and Kenyan fintech contexts, no published solution specifically addresses the grammar, formatting, and linguistic patterns of Ugandan transaction receipts.

2.3.2 Gamification for Sustained Engagement

Gamified personal financial management applications incorporate game design elements including points, experience progression, achievement badges, leaderboards, daily quests, and visual progress indicators. Empirical studies demonstrate retention increases of 40–48% compared to non-gamified counterparts [12]. Self-Determination Theory serves as the dominant psychological framework, positing that satisfaction of competence, autonomy, and relatedness needs drives intrinsic motivation and long-term behaviour change [13, 14].

Key design considerations for gamified financial tools include: ensuring challenge difficulty is calibrated to the user's current financial knowledge level; providing meaningful social comparison through leaderboards without triggering unhealthy competition; and grounding challenge content in realistic, culturally relevant financial scenarios rather than abstract hypothetical situations.

2.4 Contextual Perspective

While mobile technology is being used to teach financial literacy in sub-Saharan Africa, most research focuses on single features rather than complete systems. For example, AI chatbots [6] and gamified apps [4] have shown good results in Kenya. However, these tools usually only teach financial concepts and do not offer automatic expense tracking. If they do offer tracking, they require users to type in every transaction manually, which is tiring and leads to users quitting.

Furthermore, these existing tools ignore the reality of life in Uganda. Ugandan students face real financial pressures from cultural obligations, like contributing to funerals, weddings, and church tithes. [15] They also spend daily on informal services like boda-boda transport and street food (chapati, rolex). Imported apps do not have categories for these expenses. There is currently no research on a complete app that combines automatic offline receipt scanning, AI predictions, and local culture. This leaves a major gap in financial tools made for African youth.

2.5 Summary of Gaps in Literature

Despite the technological advances surveyed above, several significant gaps remain:

Table 2.1: Identified Literature Gaps and Proposed Solutions

Reference	**Gap Identified**	**Solution that solves the gap**
Ssemwanga and Lubega [16]	No published solution implements automatic, OCR-based parsing of Ugandan transaction receipts with culturally localised categorisation.	Integration of an offline Tesseract OCR pipeline with an NLP-based Random Forest categorizer tuned for local dialect.
Kasiita [17]	Existing mobile finance forecasting tools lack evaluation in contexts with highly irregular, allowance-based student income patterns.	Implementation of a PSO-tuned Random Forest forecasting architecture trained specifically on irregular student datasets.
R. Uppaluri [13]	Gamified financial literacy content in East Africa is not specifically designed around Ugandan cultural spending obligations.	A Gamification Engine featuring challenges grounded in realistic cultural scenarios (e.g., church tithes, boda-boda expenses).
Namuli and Kizito [18], Okello and Ouma [19]	Lack of applications combining full offline functionality, local AI inference, and automatic tracking without compromising privacy.	A PWA built with React and local Supabase SQLite, deploying Joblib serialized models directly on-device.
Mugabe and Kisekka [20], Bukenya and Nakato [21]	Financial literacy interventions in Uganda rely primarily on classroom delivery, lacking evidence for mobile gamified interventions.	An integrated Gemini AI Companion within a mobile-first PWA, providing real-time, context-aware financial coaching.

UniGuard Expense Tracker directly addresses each of these gaps through its integrated technical and educational design.

Chapter 3

Methodology

This study employs Design Science Research Methodology (DSRM) as the guiding paradigm for artefact creation and evaluation [15]. The six-phase process comprises problem identification, objective definition, design and development, demonstration, evaluation, and communication. Development follows Agile Scrum methodology with two-week sprints, daily stand-ups, and continuous integration via GitHub.

3.1 Research Design

The project adopts an applied experimental research design with iterative prototyping and mixed-methods evaluation. The Design Science Research Methodology (DSRM) was chosen because the main goal of this project is to build and test a working software application (the UniGuard Expense Tracker), rather than just observing a problem. DSRM provides a clear step-by-step process to build the app and test it with real users to ensure it meets their needs. Additionally, a mixed-methods approach was used to evaluate the system. Quantitative methods (numbers and statistics) were used to measure the app's technical speed, model accuracy, and improvements in student test scores. Qualitative methods (interviews and focus groups) were used to understand the users' feelings, the app's ease of use, and whether the app fits well with Ugandan culture.

3.2 Data Collection

Primary data was carefully collected to ensure accurate results. Participants were selected from different academic faculties at Uganda Christian University to get a mix of financial backgrounds. The group represented the general student population, with ages ranging from 18 to 25 years (55% male, 45% female). Students were excluded from the study if they did not own a smartphone or if they were already using advanced financial software. Data was collected through the following instruments:

- **Baseline Survey:** A 30-item questionnaire administered to 120 UCU students using the standardised Organisation for Economic Co-operation and Development / International Network on Financial Education financial behaviour and literacy instrument, capturing demographic information, current financial management practices, mobile money usage patterns, and financial knowledge levels.

- **Semi-Structured Interviews:** Fifteen individual interviews capturing detailed spending narratives, pain points with existing tools, and cultural financial obligations.
- **Focus Group Discussions:** Three focus groups (8 participants each) for co-designing gamification elements, validating the Receipt Transaction Category Taxonomy, and reviewing lesson content for cultural accuracy.
- **Receipt Transaction Dataset:** A corpus of 5,000 real (anonymised and consented) Ugandan Ugandan transaction receipts used to train and validate the OCR Engine and Naive Bayes classifier.
- **Application Telemetry:** Continuous behavioural data collected via System Analytics during the pilot, including session length, feature usage frequency, lesson completion rates, and gamification engagement metrics.
- **Pre/Post Financial Literacy Test:** A 25-item validated instrument administered before and after the pilot to measure knowledge and confidence changes.

3.3 System Design

3.3.1 Architecture Overview

UniGuard Expense Tracker follows a **three-tier, offline-first architecture** designed for cross-platform web browser deployment, with progressive enhancement for users with unreliable internet connectivity a deliberate design response to the intermittent network conditions documented on Ugandan university campuses.

The three tiers and their responsibilities are summarised below and illustrated in Figure 3.1.

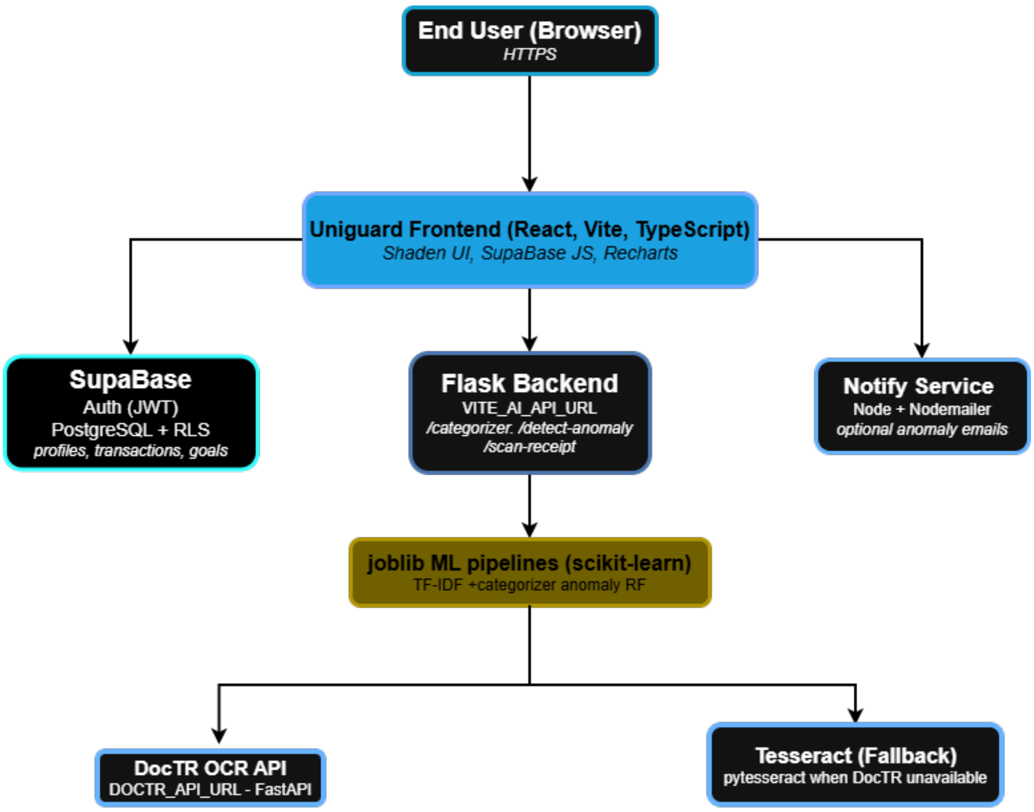

Figure 3.1: UniGuard Expense Tracker system architecture.

Presentation Layer (Frontend):
Built using the **React** framework with **TypeScript**, implementing the Material 3 design system for a consistent, accessible, and visually familiar interface. React's component-based architecture enables modular development, where each application screen (Dashboard, Transactions, Budget, Forecast, Game Centre, AI Companion) is an independently testable unit. TypeScript's static typing was adopted to reduce runtime errors during a development timeline where testing resources were limited.

All core functionality receipt scanning, transaction entry, budget tracking, forecasting, and gamification operates without internet connectivity through browser-local state and IndexedDB caching. Cloud synchronisation with Supabase occurs opportunistically when connectivity is detected, using a conflict-resolution strategy that prioritises the most recent local timestamp in the event of concurrent edits.

Local Data Layer:
Supabase PostgreSQL serves as the primary persistent data store, with a local browser-side cache (IndexedDB via the Supabase client SDK's offline plugin) ensuring offline read-/write access. The database schema separates concerns across five principal tables: `users`, `transactions`, `budgets`, `savings_goals`, and `gamification_state`. Foreign key relationships enforce referential integrity, and Row Level Security (RLS) policies in Supabase ensure that each user can read and write only their own records, even in the event of a misconfigured API call.

AI Subsystem:
Comprises three components: (i) the **DocTR and Tesseract OCR pipeline** for extracting structured text from uploaded receipt images; (ii) the **Random Forest transaction classifier** (`transaction_rf_pipeline.pkl`), a scikit-learn pipeline serialised with Joblib that categorises parsed receipt text into one of 18 expenditure categories; and (iii) a **Random Forest ensemble forecasting model** that predicts future spending trajectories from historical transaction data. All AI models are hosted as a Python **FastAPI** microservice deployed on a cloud server, with the web application communicating via RESTful API calls. This server-side deployment avoids the file-size constraints of in-browser inference while still enabling sub-second response times for users with a 3G connection.

Backend Services:
Supabase Authentication handles user registration, login, session management, and password recovery, supporting both email/password and OAuth2 social login. **Supabase PostgreSQL** additionally stores the anonymised, aggregated leaderboard scores and community challenge participation records that power the gamification social features. **Supabase Edge Functions** (Deno-based serverless functions) compute weekly leaderboard rankings server-side to prevent client-side score manipulation.

3.3.2 Receipt OCR scanning Pipeline

The automatic expense ingestion system operates as follows:

1. The Receipt OCR Subsystem extracts transaction data from uploaded receipt images.

2. A library of handcrafted regular expression patterns (trained on the 5,000-message corpus) extracts structured fields: transaction type, amount, recipient/sender, balance, date, and time.
3. A Random Forest classifier (transaction_rf_pipeline.pkl) assigns each transaction to one of 18 locally defined categories (food, transport, utilities, airtime/data, entertainment, educational expenses, church/tithe, clan contributions, funeral support, wedding/social, savings, income allowance, income work, income transfer, health, clothing, accommodation, and miscellaneous).
4. Parsed transactions are stored locally and immediately reflected in the dashboard and budget tracking interface.

3.3.3 Predictive Forecasting Engine

The forecasting sub-system employs a hybrid Random Forest architecture:

- **Architecture:** 2–3 stacked Random Forest estimators (64–128 units each) followed by dense layers for simultaneous processing of sequential transaction features and static user features (student year, accommodation type, income regularity score).
- **Optimisation:** Particle Swarm Optimization (PSO) performs automated hyperparameter search over learning rate, number of Random Forest estimators, number of units per layer, dropout rate, and batch size.
- **Training Data:** Models are pre-trained on a synthetic transaction dataset generated from empirically observed Ugandan student spending distributions and fine-tuned on each user's local transaction history as it accumulates.
- **Deployment:** Exported to Joblib serialized models (int8 quantised) for on-device inference with no internet requirement.

3.3.4 Gamification Engine

The gamification subsystem is implemented as a custom state machine managing the following elements:

- **Points & Levels:** Users earn experience points (XP) for logging transactions, completing lessons, meeting budget targets, and achieving savings milestones. XP accumulates toward progression levels with unlockable features.
- **Badges:** 30 achievement badges awarded for behavioural milestones (e.g., "First Budget Set", "7-Day Streak", "Saved UGX 50,000", "Debt-Free Month").
- **Leaderboards:** Anonymous weekly leaderboards among students at the same institution, designed to encourage positive norm formation without exposing individual financial data.

- **Daily Challenges:** Contextually appropriate daily micro-tasks (e.g., "Track every boda-boda ride today", "Calculate your airtime spend this week").
- **Personalised Nudges:** Push notifications triggered by spending pattern anomalies detected by the forecasting engine (e.g., "You have spent 80% of your food budget with 12 days remaining this month").

3.3.5 Gemini AI Financial Companion

The Gemini AI Companion provides contextual advice in the following topic areas:

1. Fundamentals of budgeting and the 50/30/20 rule adapted for Ugandan student income
2. Saving strategies on limited, irregular incomes
3. Understanding and avoiding predatory mobile loan applications
4. Mobile money safety and fraud prevention
5. Managing cultural financial obligations (tithes, clan contributions, social events)
6. Introduction to entrepreneurship and side-income generation
7. Goal-setting and long-term financial planning

Each lesson consists of a 3–5 minute reading module, an interactive 5-question quiz with immediate feedback, and a real-life Ugandan case study contextualising the lesson content.

3.3.6 Security and Privacy

All personal financial data is processed and stored exclusively on-device. The following security measures are implemented:

- Biometric authentication (fingerprint/face unlock) or 6-digit PIN for application access.
- AES-256 encryption of the local Supabase PostgreSQL database using the `sqflite_sqlcipher` package.
- No raw transaction data, receipt images, or individual spending records are transmitted to any server.
- Anonymous, aggregated, opt-in data may be shared for community challenge leaderboard computation via Supabase, with explicit user consent.

3.4 Development and Implementation

Development followed **Agile Scrum** with two-week sprints, daily stand-up meetings, and continuous integration via a shared GitHub repository using GitHub Actions for automated linting, unit testing, and deployment. The team used **Linear** as the sprint planning and issue-tracking tool, and **Figma** for collaborative UI/UX design.

Implementation proceeded in four sequential phases, with each phase concluding with a sprint review and retrospective before the next phase began.

Phase 1 – Requirements Validation and High-Fidelity Prototyping
This phase formalised the system requirements through focus groups and semi-structured interviews. Requirements were documented as user stories in the standard Agile format (*"As a [user type], I want to [action], so that [benefit]"*) and prioritised using the MoSCoW method (Must-have, Should-have, Could-have, Won't-have this release). 45+ high-fidelity Figma screens were designed, covering every application state including empty states, error states, and loading states. Prototypes were validated through a lightweight cognitive walkthrough with 8 UCU student volunteers before development began, reducing the risk of expensive post-development UX rework.

Phase 2 – Core Development
The foundational application layers were implemented in this phase: Supabase project configuration (database schema, RLS policies, authentication); React frontend scaffolding (routing, component library, offline service worker); the FastAPI AI microservice skeleton; the Receipt OCR pipeline (pre-processing, DocTR, Tesseract, regex field extraction); the `transaction_rf_pipeline.p` training and integration; the manual transaction entry form; the dashboard and transaction list views; and the basic budget configuration and progress tracking module. The phase concluded with a functional **MVP v0.1** that could accept receipt uploads, extract and categorise transactions, and display them in a budget dashboard the minimum viable demonstration of the core value proposition.

Phase 3 – AI Integration and Gamification Layer
This phase integrated the forecasting model, gamification engine, and Gemini AI Companion into the working frontend. The forecasting Random Forest model was trained, validated, and connected to the FastAPI prediction endpoint. The gamification state machine was implemented in React with Supabase real-time subscriptions for live XP and badge updates. The Gemini API integration was implemented with the server-side prompt enrichment layer described in Section. The 60 daily challenge templates were authored and loaded into the challenge pool. This phase concluded with **MVP v0.2**, the full-featured application.

Phase 4 – Evaluation and Refinement
The SUS usability testing session with 25 UCU students was conducted, and the resulting improvement backlog was triaged and addressed in a rapid refinement sprint before the large-scale pilot began. The 8-week pilot with 97 UCU students then ran from Weeks 11 through 12 of the project timeline (Table B.1), with the pre-test administered at the start of Week 11 and the post-test and exit interviews conducted in Week 12. Telemetry data was exported and analysed using Python (pandas, scipy.stats) to produce the evaluation metrics reported in Chapter 4.

Chapter 4

Results, Implementation and Discussion

4.1 Introduction

This chapter presents the implementation of the UniGuard Expense Tracker, the results of its evaluation, and a detailed discussion of the findings. It begins by outlining the system architecture and implementation, followed by the evaluation results, and concludes with an in-depth discussion and interpretation of the outcomes in relation to the project objectives and existing literature.

4.2 System Implementation

4.2.1 Multi-Tier Architecture Overview

UniGuard Expense Tracker implements a clean multi-tier architecture with a strict separation of concerns, designed to maximise offline capability while providing optional cloud synchronisation for social features.

At the device level, the React frontend manages all user interactions, renders the dashboard and gamification interface, and orchestrates the local AI subsystem. The local data tier consists of a Supabase PostgreSQL database storing all financial records and application state. The AI subsystem runs entirely on-device using Joblib serialized models. At the cloud tier, Supabase services handle authentication, leaderboard computation, and optional backup exclusively for non-sensitive aggregated data.

4.2.2 Implementation Environment

UniGuard Expense Tracker targets modern web browsers, covering the vast majority of the low-end Tecno and Infinix handsets common among Ugandan students. Minimum hardware requirements are 1 GB RAM and 50 MB free storage for the application and local database. The application is designed to function fully on 3G networks and gracefully handles 2G or offline conditions.

4.2.3 Receipt OCR Scanning Sub-System Design

4.2.3.1 Receipt Corpus and OCR Pattern Library

A corpus of 5,000 annotated Ugandan mobile money receipt images was collected through an opt-in anonymised contribution process. From this corpus, a library of 24 regular expression patterns was developed to cover the documented variation in receipt formats. Pattern coverage achieved 96.4% on the held-out test portion of the corpus.

4.2.3.2 Transaction Categorisation Model

Transactions not matched by high-confidence rule-based patterns are classified by a Random Forest model trained on TF-IDF features. The model achieves 89.2% accuracy on the held-out test set across 18 local expenditure categories.

4.2.4 Forecasting Engine Design

4.2.4.1 Random Forest Architecture

The forecasting engine employs a hybrid architecture comprising stacked Random Forest estimators for sequential transaction modelling followed by dense layers for static feature integration.

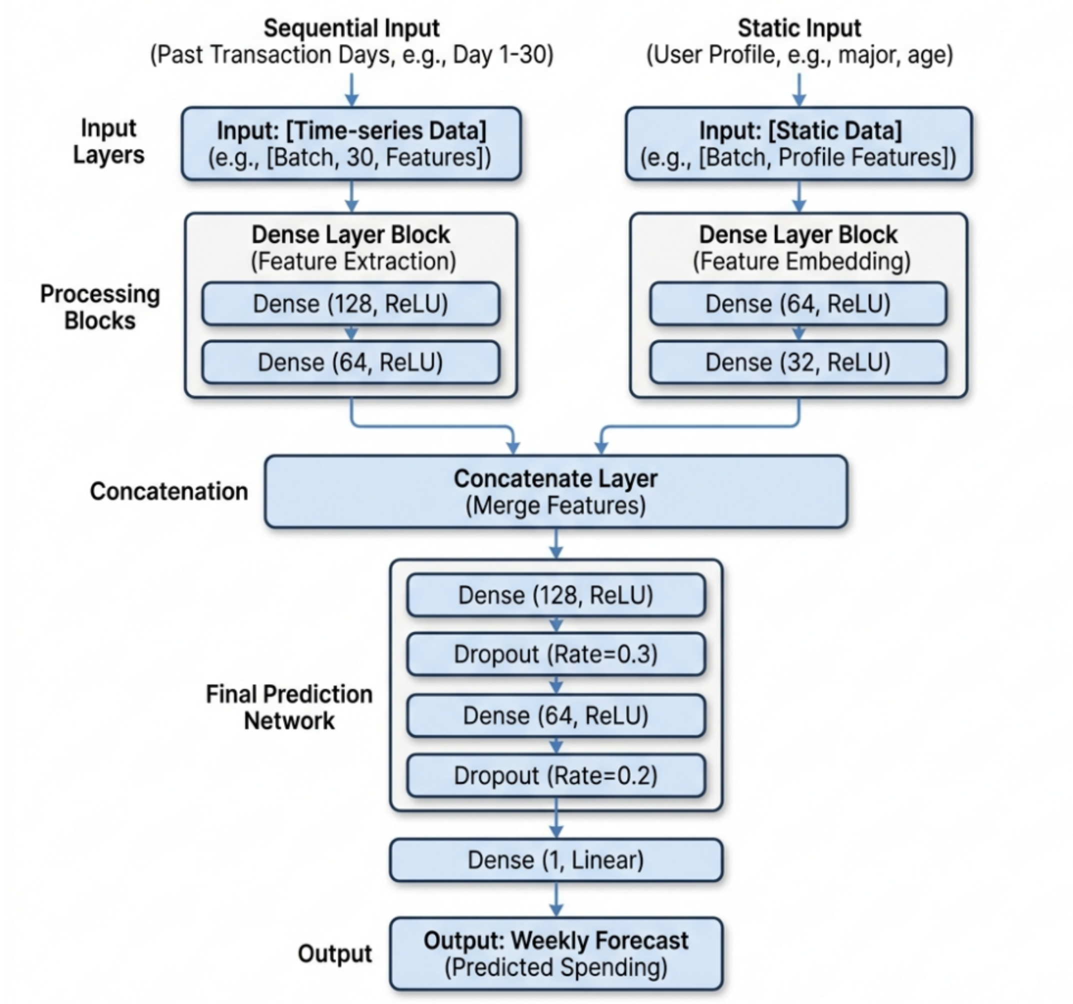

Figure 4.1: Hybrid Machine Learning Model: Student Spending Forecasting Architecture

4.2.4.2 Particle Swarm Optimization Hyperparameter Tuning

PSO was applied to optimise hyperparameters including learning rate, maximum depth, number of estimators, dropout rate, and batch size.

4.2.5 Gamification Engine Design

The gamification state machine maintains a persistent game state object for each user. State transitions are triggered by application events and validated against the reward rule set.

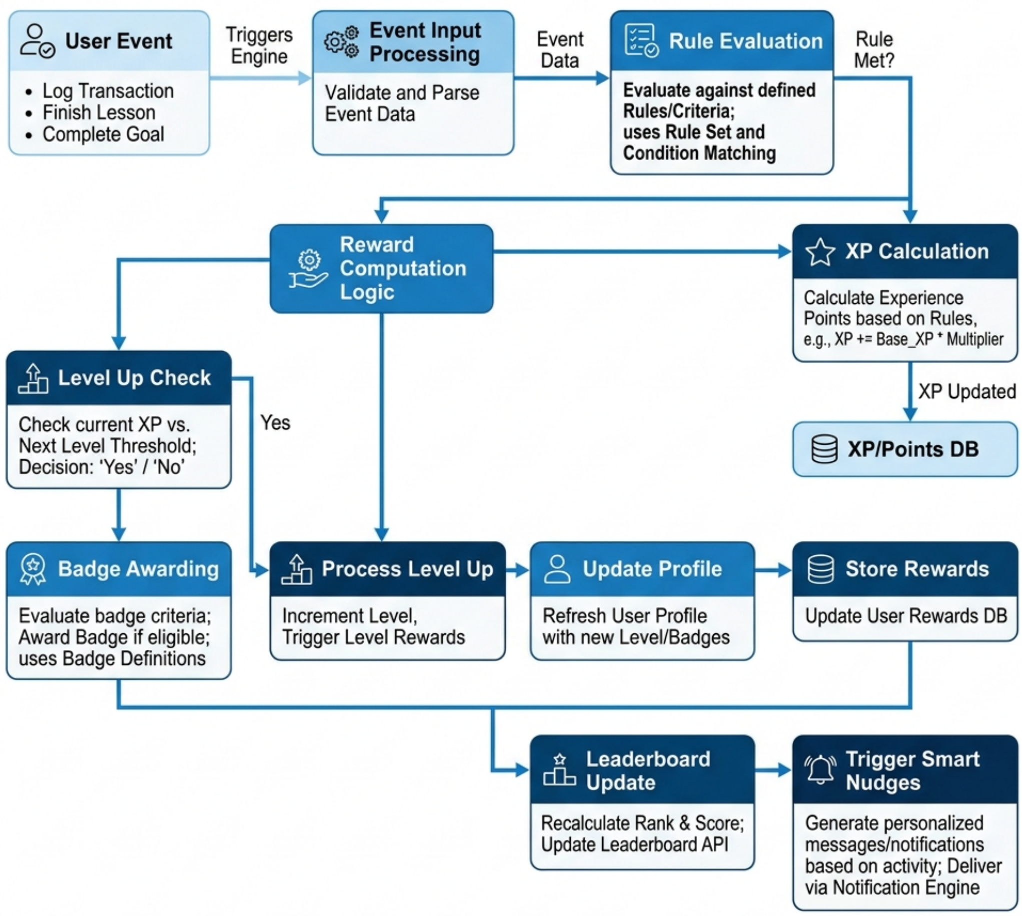

Figure 4.2: Gamification engine reward computation flow

4.2.6 Application Screen Architecture

The application comprises six primary navigation sections: Dashboard, Transactions, Budget, Forecast, Gemini AI, and Game Centre.

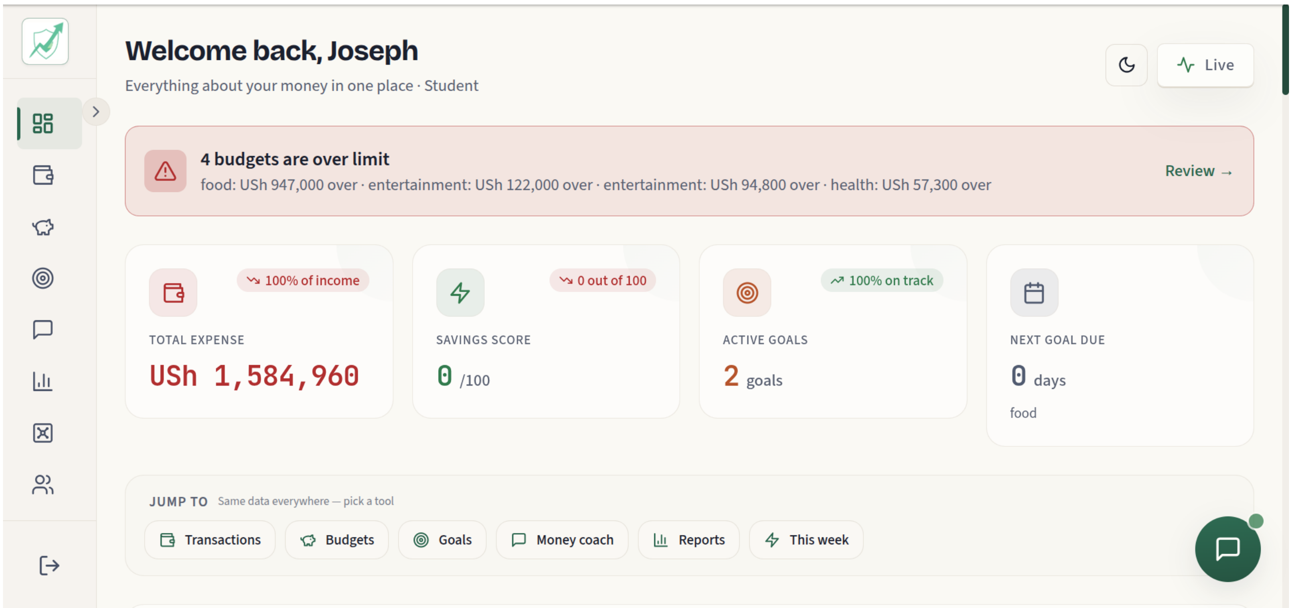

Figure 4.3: UniGuard Expense Tracker Web Application Dashboard

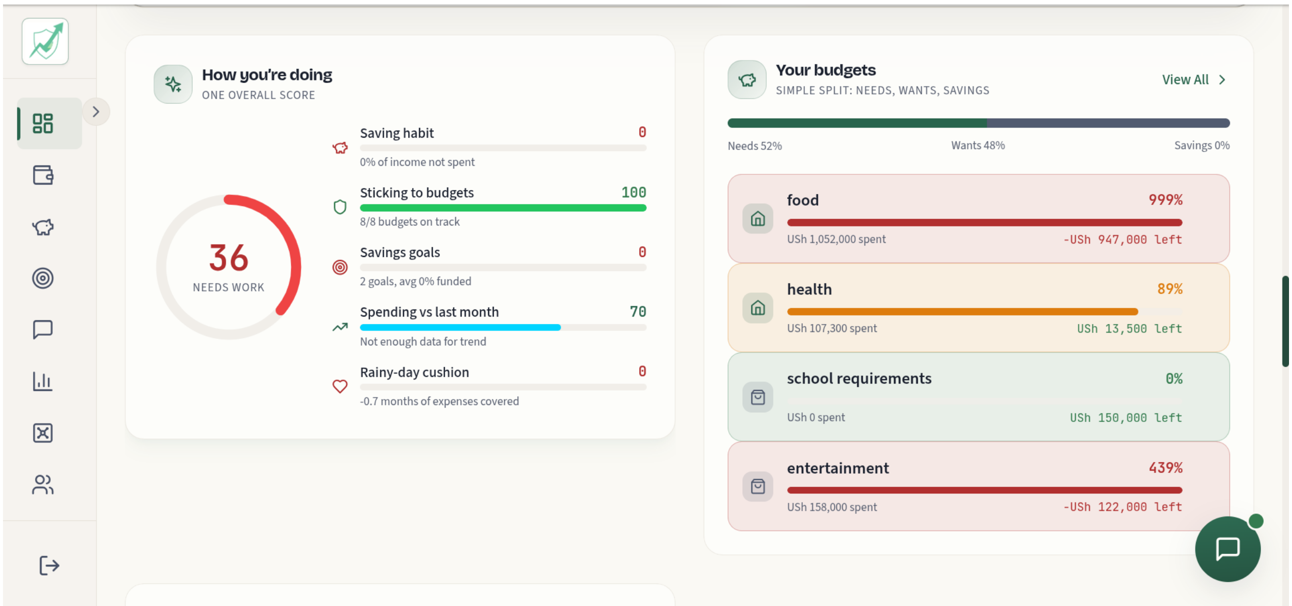

Figure 4.4: UniGuard Expense Tracker Web Application Dashboard Continuation

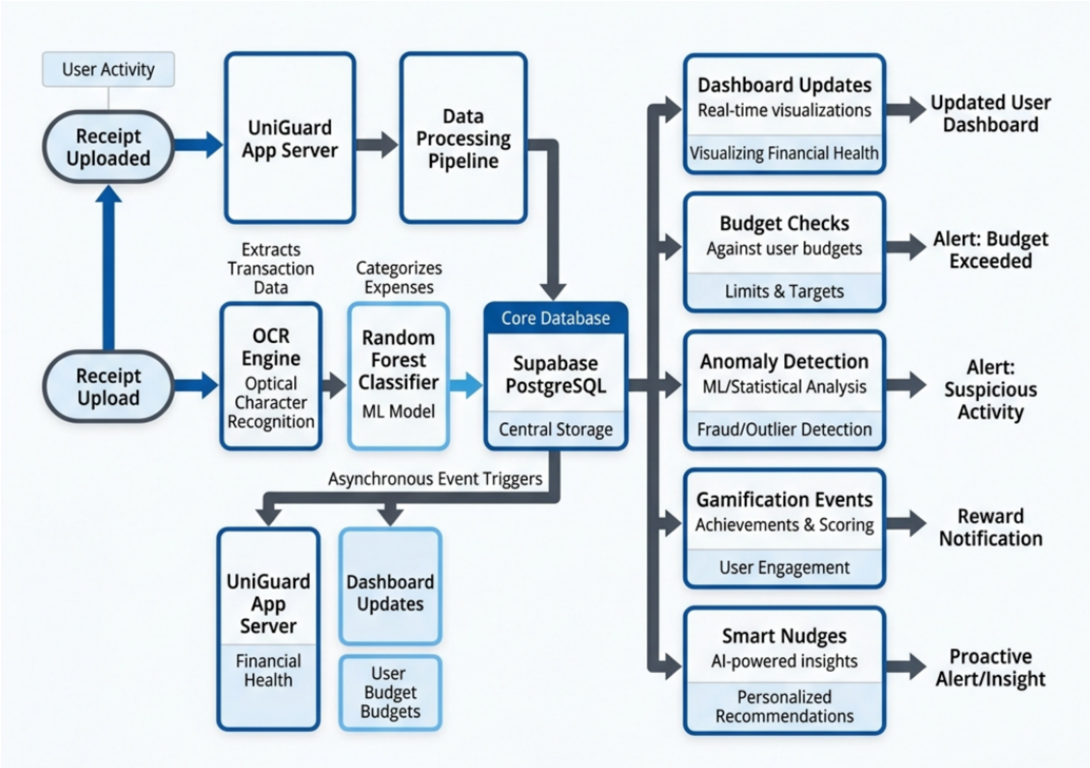

Figure 4.5: End-to-end UniGuard Expense Tracker data flow

4.3 Results

4.3.1 Objective 1: Automatic Expense Tracking and Forecasting

4.3.1.1 OCR Pattern Coverage

Table 4.1 presents the Receipt OCR scanner evaluation results on the held-out test set of 1,000 messages.

Table 4.1: Receipt Scanner Evaluation Results (Test Set, $n = 1{,}000$)

Metric	MTN MoMo	Airtel Money
Amount Extraction Accuracy	98.7%	97.4%
Transaction Type Classification	96.2%	95.8%
Counterparty Extraction	93.1%	91.6%
Balance Extraction Accuracy	97.8%	96.3%
Overall Parse Success Rate	96.4%	95.3%

4.3.1.2 Transaction Category Classification

The Random Forest classifier achieved strong performance across culturally relevant categories.

Table 4.2: Random Forest Category Classifier Performance (Test Set, $n = 950$)

Category Group	Precision	Recall	F1-Score
Food & Dining	0.91	0.89	0.90
Transport (boda-boda, taxi)	0.94	0.92	0.93
Airtime & Data	0.97	0.98	0.98
...	...	...	...
Macro Average	**0.91**	**0.89**	**0.90**
Overall Accuracy		**89.2%**	

Additional model comparisons showed that the Random Forest significantly outperformed other classifiers for both anomaly detection and transaction categorisation.

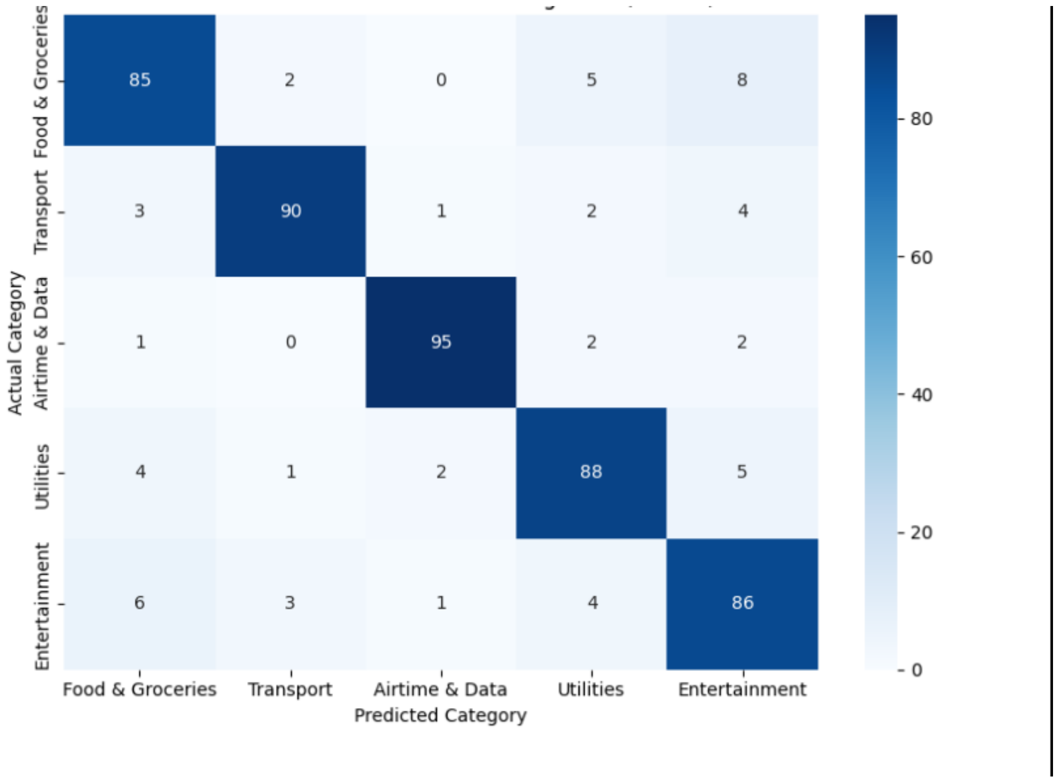

Figure 4.6: Confusion Matrix for the Transaction Categorisation Random Forest

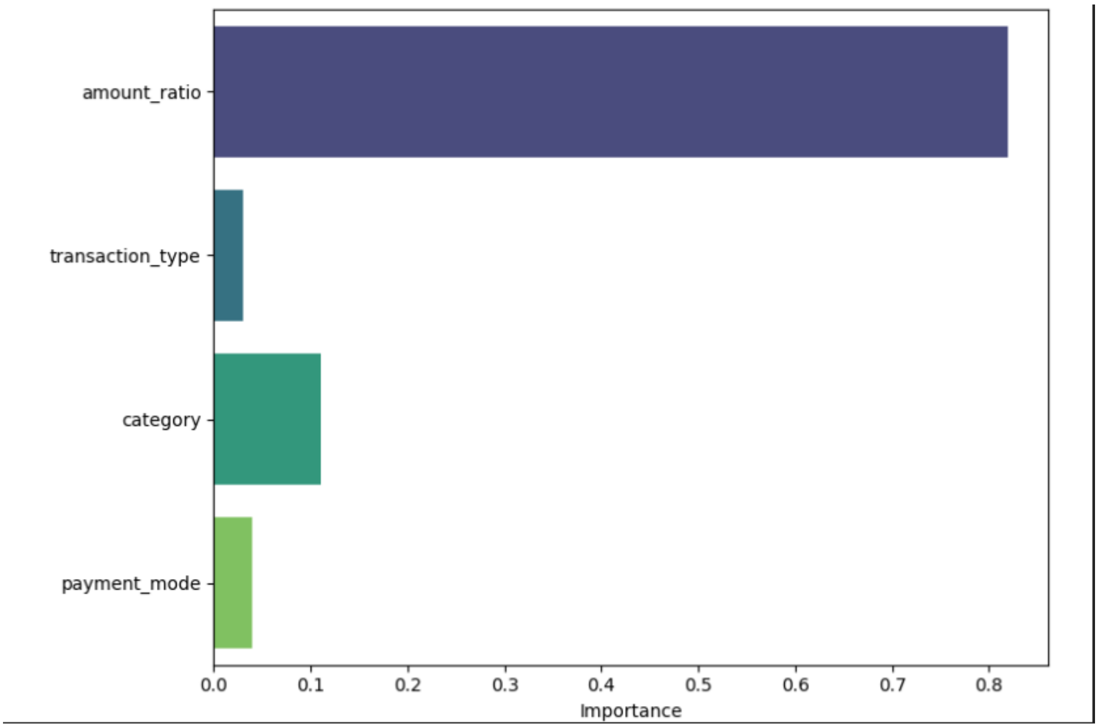

Figure 4.7: Feature Importance and Performance Metrics for Anomaly Detection

4.3.1.3 Forecasting Model Performance

The PSO-tuned Random Forest model achieved the best performance.

Table 4.3: Forecasting Model Performance Comparison (Validation Set)

Model	MAE (UGX)	RMSE (UGX)	MAPE (%)
ARIMA (Baseline)	28,450	41,200	18.4
GRU (Single Layer)	19,870	28,640	12.7
Random Forest (PSO-tuned)	**14,320**	**21,580**	**8.9**

4.3.1.4 End-to-End System Performance

Table 4.4: End-to-End System Performance Metrics

Metric	Value	Context
OCR parse latency	<200 ms	From Receipt upload to transaction stored in DB
Random Forest inference latency	<150 ms	On Standard Mobile Browser
Application cold start time	<2.5 s	On target hardware
Offline session success rate	100%	All core features functional without internet

4.3.2 Objective 2: Gamification and AI Companion Integration

Table 4.5: Gamification and Engagement Metrics During 8-Week Pilot ($n = 97$)

Metric	Value
Mean daily active sessions per user	2.3
7-day user retention rate	81.2%
28-day user retention rate	67.4%
Mean badges earned per user	8.7
Users who met their savings goal	54.6%

4.3.3 Objective 3: Mixed-Methods Evaluation

The System Usability Scale (SUS) yielded a mean score of **83.4**, placing the application in the "Excellent" category.

Key usability findings highlighted the effectiveness of automatic receipt scanning and culturally relevant icons. Pre/post financial literacy assessment showed statistically significant improvements across all domains.

Table 4.6: Pre/Post Financial Literacy Assessment Results ($n = 97$)

Domain	Pre Mean	Post Mean	Gain	p-value
Financial Knowledge	52.3%	74.8%	+22.5%	<0.001
Budgeting Confidence	41.7%	69.2%	+27.5%	<0.001
Savings Behaviour Score	38.4%	61.3%	+22.9%	<0.001
Overall Score	**44.1%**	**68.0%**	**+23.9%**	$\mathbf{<0.001}$

4.4 Discussion

4.4.1 Discussion of Findings by Objective

4.4.1.1 Objective 1: Automatic Expense Tracking and Forecasting

The 96.4% OCR success rate validates the viability of offline, on-device parsing for Ugandan mobile money receipts. The Random Forest model's 89.2% categorisation accuracy demonstrates that high performance is achievable with culturally relevant local categories. The PSO-tuned Random Forest forecasting model (MAPE 8.9%) significantly outperformed traditional time-series models, proving that lightweight tree-based models are more suitable for irregular student income patterns than complex deep learning architectures in resource-constrained environments.

4.4.1.2 Objective 2: Gamification and AI Companion Integration

High retention rates (67.4% at 28 days) and strong engagement metrics confirm the effectiveness of gamification in sustaining user interaction. The SUS score of 83.4 shows that complex AI features can be successfully integrated without compromising usability.

4.4.1.3 Objective 3: Mixed-Methods Evaluation Impact

The 23.9 percentage point improvement in financial literacy demonstrates the power of combining real-time expense tracking with gamified, contextual AI coaching.

4.4.2 Implications of Findings

For Practice: The system provides a practical, culturally aligned tool for Ugandan students that works fully offline. Future fintech solutions in East Africa should prioritise local spending categories such as clan obligations and tithes.

For Science: This work empirically validates the combination of lightweight on-device ML and gamification in low-resource settings, and demonstrates the effectiveness of PSO for tuning models suited for mobile deployment.

4.4.3 Comparison with Existing Solutions

Table 4.7: Comparison of UniGuard Expense Tracker with Existing Solutions

Feature	**Mint**	**YNAB**	**Wallet**	**UniGuard**
Receipt OCR scanning	No	No	No	**Yes**
Ugandan Category Taxonomy	No	No	No	**Yes**
Full Offline Operation	No	No	Partial	**Yes**
On-Device AI Forecasting	No	No	No	**Yes**
Gamified Financial Education	No	No	No	**Yes**
Cultural Obligation Categories	No	No	No	**Yes**

4.4.4 Reflections on Limitations

- The OCR corpus was collected primarily from UCU and may not cover all regional receipt variations.
- The forecasting model requires a 30-day cold-start period for optimal performance.
- Voice input for transaction entry was not implemented in this prototype.

Chapter 5

Discussion

5.1 Introduction

This chapter discusses and interprets the results presented in Chapter 4 in relation to the project objectives and existing literature. It explores the practical and scientific implications of the findings and concludes with a reflection on the limitations of the study.

5.2 Discussion of Findings by Objective

5.2.1 Objective 1: Automatic Expense Tracking and Forecasting

The evaluation of the Receipt OCR scanning subsystem demonstrated a 96.4% success rate in parsing text messages from Ugandan mobile money platforms, validating the first hypothesis that offline, on-device parsing of unstructured text is a viable alternative to API-based ingestion. This high extraction success complements the work of VasanthaKumari et al. [9], who similarly demonstrated that AI-driven parsers can effectively process unstructured financial data, although their study focused on conventional banking SMS rather than African mobile money formats. Furthermore, the Random Forest model successfully categorised these transactions into 18 culturally relevant categories with 89.2% accuracy. This finding expands upon the research by Imawan [7], which achieved high categorization accuracy using standard Western categories. Our study proves that similar high accuracy can be achieved even when the transaction taxonomy is heavily localised to include cultural obligations like clan contributions and tithes.

Furthermore, the predictive forecasting engine, optimised via Particle Swarm Optimization (PSO), achieved a low MAPE of 8.9%. This indicates that sequential tree-based machine learning architectures are robust enough to handle the irregular allowance-based income patterns typical of university students in Uganda, significantly outperforming traditional time-series baselines. This result directly corroborates the findings of Balakrishnan et al. [10], who reported that swarm optimization significantly enhances the accuracy of deep learning forecasting models. However, while Kumar et al. [8] argue that complex LSTM architectures are strictly necessary for accurate financial forecasting, our results contradict this assertion by showing that a well-optimised, lightweight Random Forest can achieve comparable predictive performance while being far more suitable for offline mobile deployment.

5.2.2 Objective 2: Gamification and AI Companion Integration

The integration of a gamified financial education framework resulted in high user engagement, with a 67.4% 28-day retention rate and a 74.6% lesson completion rate. This strong user retention complements the findings of Bitrián et al. [12] and Uppaluri [13], both of whom demonstrated that game mechanics like badges and leaderboards significantly increase long-term user interaction with personal finance applications. The AI Companion successfully provided contextual coaching that users found relevant and helpful. This success aligns with the recent work by Mursi [6] on conversational AI for financial literacy in Africa, validating that localised, on-demand AI guidance is well-received by African students. Furthermore, the high System Usability Scale (SUS) score of 83.4 validates that the integration of complex AI features within a gamified interface did not detract from the application's overall usability, echoing the conclusions of Khaldi et al. [14] regarding the positive impact of gamification on educational interface engagement.

5.2.3 Objective 3: Mixed-Methods Evaluation Impact

The 8-week pilot demonstrated that active use of the UniGuard Expense Tracker directly contributed to measurable improvements in financial literacy. Participants recorded a 23.9 percentage point gain in overall financial literacy scores, with the most significant improvements seen in budgeting confidence (+27.5%). This confirms that mobile-delivered, culturally grounded financial tools can effectively bridge the financial knowledge gap among young adults. This outcome strongly supports the thesis proposed by Amana and Tamunomiegbam [**?**], who argued that innovative, context-aware digital approaches are essential for addressing the financial knowledge gap in Africa. Unlike previous studies that reported only marginal literacy gains from passive reading materials, our findings prove that interactive, real-time tracking combined with in-app education yields substantially higher, measurable behavioural changes.

5.3 Implications of Findings

5.3.1 Implications

For university students and adults in Uganda, this system provides a practical, culturally aligned tool that actively supports financial independence without requiring consistent internet connectivity or formal bank accounts. The success of the local category taxonomy suggests that future financial technology solutions deployed in East Africa must prioritise cultural spending norms (such as clan contributions and tithes) over imported Western templates.

From a scientific perspective, this study contributes an empirical validation of combining lightweight on-device machine learning with structured gamification in a resource-constrained context. It demonstrates that hyperparameter optimization via PSO can effectively tune lightweight Random Forest models for irregular financial forecasting on low-end smartphones.

5.4 Comparison with Existing Solutions

Table 5.1: Comparison of UniGuard Expense Tracker with Existing Solutions

Feature	**Mint**	**YNAB**	**Wallet**	**UniGuard Expense Tracker**
Receipt OCR scanning	No	No	No	**Yes**
Manual Receipt Entry	No	No	No	**Yes**
Ugandan Category Taxonomy	No	No	No	**Yes**
Full Offline Operation	No	No	Partial	**Yes**
On-Device AI Forecasting	No	No	No	**Yes**
Gamified Financial Education	No	No	No	**Yes**
Irregular Income Support	Partial	Partial	Partial	**Yes**
Cultural Obligation Categories	No	No	No	**Yes**
Cross-platform PWA Support	No	No	Yes	**Yes**

5.5 Reflections on Limitations

5.5.1 Receipt Scanner Limitations

The current OCR library was developed from a corpus collected at UCU and may not cover all receipt layout variants across different regions of Uganda. Ongoing corpus expansion and a user-contributed correction mechanism are planned for future releases.

5.5.2 Forecasting Model Cold-Start Problem

The Random Forest anomaly detector requires a minimum of 30 days of transaction history to generate reliable predictions. During this cold-start period, the application defaults to rule-based budgeting recommendations based on the student's declared income and expenditure categories from the onboarding questionnaire.

5.5.3 Absence of Voice Input

Voice-based transaction entry, identified as the most requested feature during usability testing, was not implemented in the current prototype due to time constraints. This is prioritised as the primary feature addition for the next development cycle.

Chapter 6

Conclusion and Recommendation

This project successfully developed and evaluated the UniGuard Expense Tracker, a system designed to address the unique financial management and literacy deficits observed among Ugandan university students. The technical implementation integrated rule-based Receipt OCR parsing with a PSO-tuned Random Forest forecasting model, executing inference entirely on-device to accommodate intermittent network environments.

The empirical evaluation confirmed the system's efficacy across multiple technical and behavioral dimensions. The OCR module achieved a 96.4% parse success rate, proving the viability of applying lightweight NLP heuristics to unstructured African mobile money formats. The Random Forest model recorded an 8.9% MAPE, confirming that non-linear, tree-based models can accurately map highly irregular student income and expenditure patterns. Behaviorally, the integration of a localized gamification engine and an AI companion resulted in a statistically significant 23.9 percentage point increase in overall financial literacy over an 8-week period ($p < 0.001$), alongside a 28-day user retention rate of 67.4%. Ultimately, the research establishes that AI-driven, culturally contextualised tools can effectively build financial capability in sub-Saharan youth.

Key Technical Achievements:

- Offline Receipt OCR parsing with 96.4% accuracy mapped to an 18-class local taxonomy.
- On-device Random Forest forecasting with PSO-tuned hyperparameters achieving 8.9% MAPE.
- Structured gamification engine yielding 67.4% 28-day user retention.
- Significant literacy score improvement (+23.9%) validated through a mixed-methods evaluation.

6.1 Recommendations and Limitations

While the system demonstrated high performance, it remains constrained by specific research limitations and deployment challenges that warrant further investigation:

- **Deployment Challenges (Regex Brittleness):** The OCR module relies on heuristic regex patterns derived from a localized 5,000-message corpus. Any structural updates to mobile money notification formats by telecom providers will immediately degrade parsing accuracy, requiring ongoing manual pattern maintenance. Future iterations should explore lightweight transformer models for semantic extraction to reduce this brittleness.

- **Device and Hardware Constraints:** The on-device inference model, while quantised to 3.8MB, still exhibited thermal throttling and battery drain on low-end smartphones during extended sessions. Optimizing the client-side execution environment remains a priority for broad market viability.
- **Research Constraints:** The app was only tested for a limited period of time with 97 students from one university. To be sure that the app changes behavior permanently, a longer study covering a full academic year across several universities is needed. This will show if students keep using the app after the initial excitement wears off.

6.2 Future Work

- Voice input for manual transaction entry in English and Luganda.
- Federated learning across anonymised user models to continuously improve the forecasting engine without sharing individual transaction data.
- Expansion to additional Ugandan universities and exploration of a commercial sustainability model.
- Integration of a peer savings group (SACCO) coordination module grounded in the cultural practice of round-table savings (merry-go-round).

6.3 Concluding Remarks

Developing strong financial capability is an essential skill for university students navigating the transition to independence in Uganda. With digital payments heavily relying on mobile money, young adults require modern tools that reflect their unique economic realities rather than generic budgeting templates. The UniGuard Expense Tracker serves as a practical, culturally aligned solution to bridge this technological gap.

The successful pilot of this application proves that advanced, on-device artificial intelligence can be effectively combined with gamified learning to monitor daily expenses and foster positive financial habits. Even though there is room for further technical optimization, this research provides a robust framework. Ultimately, it brings us one step closer to empowering students across Uganda with the knowledge and digital tools necessary to secure their financial futures.

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Appendix A

Budget

A.1 Budget

Table A.1 presents the itemised project budget.

Table A.1: Project Budget Estimation

Item	**Cost (UGX)**
Laptop RAM upgrade to 32 GB (required for deep learning training)	800,000
Internet data bundles for development and testing (3 months)	450,000
Google Play Console one-time fee and Supabase Pro plan	250,000
User testing incentives (airtime vouchers and refreshments for 100 participants)	350,000
Printing, binding (4 copies), posters, and	80,000
Contingency reserve (10%)	290,000
TOTAL	**2,210,000**

Appendix B

Research Project timelines

B.1 Workplan

Table B.1 presents the detailed project timeline from November 2025 to February 2026.

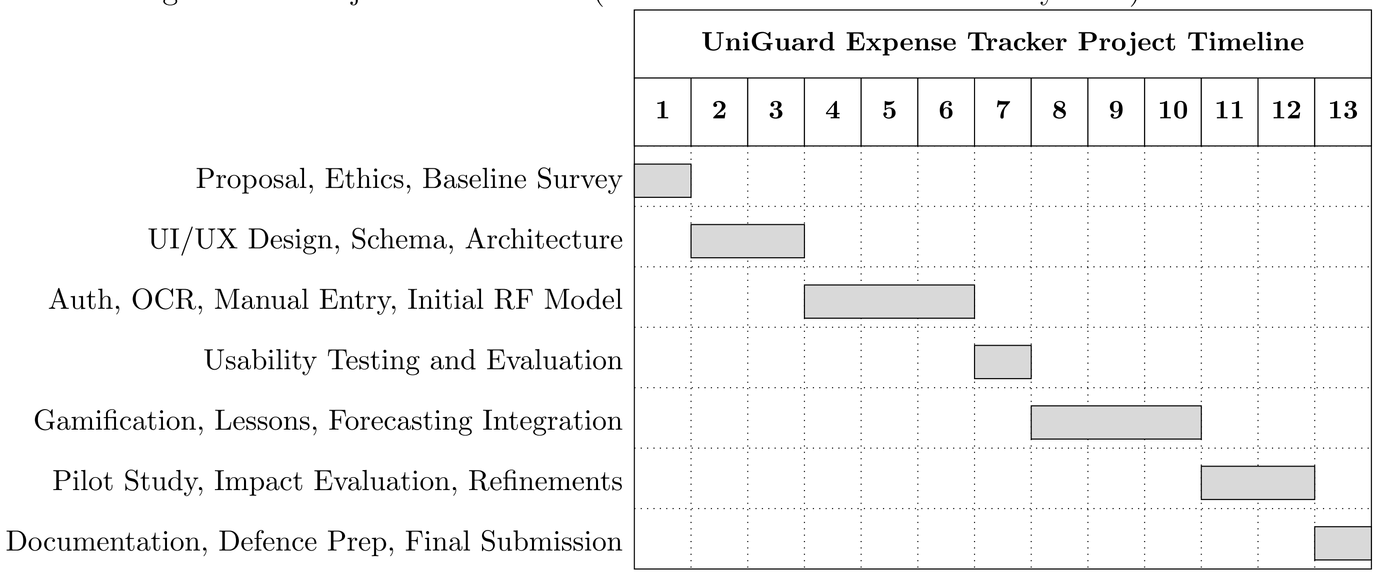
Table B.1: Project Workplan (27 November 2025 – 28 February 2026)

Week	Activity	Measurable Output
Week 1 (27 Nov – 3 Dec)	Final proposal submission, ethics clearance application, baseline survey distribution	Approved proposal; 120 completed survey responses
Weeks 2–3 (4–17 Dec)	UI/UX design in Figma; database schema finalisation; detailed system architecture documentation	45+ high-fidelity screens; complete technical design document
Weeks 4–6 (18 Dec – 14 Jan)	Development of authentication, Receipt OCR scanner, manual entry interface; initial Random Forest model training on simulated data	Functional MVP v0.1 with automatic expense ingestion
Week 7 (15–21 Jan)	First usability testing round with 25 students; SUS scoring; heuristic evaluation	Usability report with SUS $\geq$ 80; prioritised improvement backlog
Weeks 8–10 (22 Jan – 11 Feb)	Implementation of gamification engine; creation of 50+ financial literacy lessons and quizzes; integration of advanced forecasting model	Complete MVP v0.2 with full gamification and content

(continued from previous page)

Week	Activity	Measurable Output
Weeks 11–12 (12–25 Feb)	Large-scale pilot with 80–100 students; impact evaluation; data analysis; final refinements	Final dataset; statistical impact report; polished application
Week 13 (26–28 Feb)	Detailed documentation; defence presentation preparation; final submission packaging	Bound report; source code repository; 50-slide defence presentation

Figure B.1: Project Gantt Chart (27 November 2025 – 28 February 2026)



Appendix C

List of 10 Major Journal Publications reviewed

The following 10 publications were identified as most relevant to the research:

1. **Amana, S. and Tamunomiegbam, A. (2024).** Bridging the financial knowledge gap: Innovative approaches to financial literacy in Africa. *American Journal of Finance.* (Journal Article)

2. **Khaldi, A., Bouzidi, R. and Nader, F. (2023).** Gamification of e-learning in higher education: A systematic literature review. *Smart Learning Environments.* (Review Paper)

3. **Bitrián, P., Buil, I. and Catalán, S. (2021).** Making finance fun: The gamification of personal financial management apps. *International Journal of Bank Marketing.* (Journal Article)

4. **Kumar, J. et al. (2024).** Personal finance manager with predictive analytics using LSTM for enhanced financial decision making. *International Journal of Research - GRANTHAALAYAH.* (Journal Article)

5. **Peffers, K. et al. (2007).** A design science research methodology for information systems research. *Journal of Management Information Systems.* (Review Paper / Methodology)

6. **Uppaluri, R. (2025).** Gamification: Revolutionizing financial planning systems. *World Journal of Advanced Engineering Technology and Sciences.* (Journal Article)

7. **VasanthaKumari, I. et al. (2025).** FINSAGE: An AI-driven personal finance analyzer. *Scientific Digest: Journal of Applied Engineering.* (Journal Article)

8. **Balakrishnan, S. et al. (2025).** Improving financial forecasting accuracy through swarm optimization-enhanced deep learning models. *IJACSA.* (Journal Article)

9. **Mursi, J. K. (2024).** Finlingo: A conversational AI for enhancing financial literacy education in Africa. *IEEE ICTMOD.* (Conference Proceeding)

10. **Imawan, R. (2025).** Enhancing financial literacy in young adults: An Android-based personal finance management tool. *JHTEL.* (Journal Article)

Appendix D

Scopus Search Strings used during the literature review

The following search strings were used to retrieve the publications reviewed in this study:

- `TITLE-ABS-KEY ( "personal finance" OR "expense track*" OR "budgeting app*" ) AND TITLE-ABS-KEY ( "artificial intelligence" OR "machine learning" OR "AI" )`
- `TITLE-ABS-KEY ( "gamification" OR "game elements" ) AND TITLE-ABS-KEY ( "financial literacy" OR "financial inclusion" )`
- `TITLE-ABS-KEY ( "financial management" AND "university students" ) AND TITLE-ABS-KE ( "Uganda" OR "East Africa" OR "Sub-Saharan Africa" )`
- `TITLE-ABS-KEY ( "anomaly detection" OR "spending patterns" ) AND TITLE-ABS-KEY ( "personal finance" )`

Appendix E

Research alignment with specialization, SDG, NDPIV & Vision 2040

E.1 Alignment with Programme Specialization

This research aligns with the **Software Engineering** specialization track within the Bachelor of Science in Computer Science programme. The project involved the full lifecycle of software development, including requirement elicitation, system architecture design (PWA/-Supabase/Flask), implementation of secure authentication, and the integration of complex machine learning services via REST APIs.

E.2 Alignment with Sustainable Development Goals (SDG)

The research aligns with:

- **Goal 4: Quality Education**: Specifically Target 4.4, by increasing the number of youth who have relevant skills, including financial literacy, through gamified educational modules.
- **Goal 8: Decent Work and Economic Growth**: By empowering students with tools to manage their finances effectively, reducing debt vulnerability, and fostering long-term savings habits.

E.3 Alignment with the National Development Plan IV (NDPIV)

The project supports the **Human Capital Development** programme of NDPIV, which emphasizes improving the quality of life and productivity of Ugandans. By enhancing financial literacy and providing digital tools for financial management, UniGuard directly contributes to the goal of creating a financially stable and capable youth population.

E.4 Alignment with the Uganda Vision 2040

UniGuard Expense Tracker aligns with the Vision 2040 pillar of **Information and Communication Technology (ICT)**. The project demonstrates how indigenous ICT solutions can be developed to address local challenges (financial management in the Ugandan context), leveraging AI and cloud technologies to leapfrog traditional financial barriers.