FIN-AI: An Intelligent, Secure, and Predictive Mobile Platform for Family Personalized Financial Management

Kaaran Raahul S
Department of Computer Science
Adelphi University
kaaranraahulsenthi@mail.adelphi.edu

Srija Julakanti
Department of Computer Science
Adelphi University
srijajulakanti@mail.adelphi.edu

Surinder Kaur
Department of Computer Science
Adelphi University
surinderkaur@mail.adelphi.edu

***Abstract*—Managing personal finances has become increasingly complex due to the use of multiple bank accounts, credit cards, subscriptions, and digital payment platforms, while existing Personal Finance Management (PFM) tools largely rely on static tracking and retrospective analytics with limited personalization, predictive insight, and security awareness. FIN-AI addresses these limitations by introducing an intelligent, secure, and predictive mobile financial management platform that integrates time-series forecasting, machine learning–based credit card recommendations, reward optimization, anomaly detection, and AI-driven conversational assistance within a unified architecture. Built using React Native, Node.js, MongoDB, Firebase Authentication, the Plaid API, and Splunk monitoring, FIN-AI enables secure financial data aggregation, predictive analytics, and real-time system observability. An Ollama-based large language model provides privacy-preserving natural-language financial guidance through local deployment. Preliminary evaluations demonstrate stable frontend–backend integration, accurate transaction handling, functional machine learning services, and effective security monitoring, positioning FIN-AI as an affordable, adaptive, and comprehensive solution to the limitations of existing personal finance tools.**

***Index Terms*—Personal Finance Management, Machine Learning, Fraud Detection, Large Language Model, Authentication and Security, Database.**

I. Introduction

The rapid digitization of financial services has significantly increased the complexity of personal and family financial management. Modern users routinely manage multiple bank accounts, credit cards, subscriptions, loans, and digital wallets across disparate platforms. This fragmentation creates challenges in maintaining financial awareness, optimizing spending behavior, tracking recurring obligations, and identifying anomalous or fraudulent activity. As a result, individuals often experience missed payments, inefficient credit card usage, overlooked reward opportunities, and increased exposure to financial risk.

Existing Personal Finance Management (PFM) applications such as Mint, YNAB, PocketGuard, Monarch Money, and Copilot provide basic transaction aggregation, spending visualization, and category-based summaries. While these tools offer convenience, they largely rely on static rule-based categorization and retrospective analytics, focusing on historical spending rather than proactive guidance. Prior studies indicate that most commercial PFM systems lack predictive intelligence, adaptive learning mechanisms, and personalized decision support capable of optimizing budgets, credit card rewards, or future expenditures [1], [2]. Furthermore, these platforms often impose rigid data-ingestion methods that require continuous bank linking, discouraging adoption among privacy-conscious users.

Recent research emphasizes the growing demand for intelligent financial systems that provide forward-looking insights, personalized recommendations, and real-time security monitoring [3], [4]. However, current solutions frequently lack integrated anomaly detection, system-level observability, and transparent security mechanisms. In addition, premium subscription costs ranging from \$15 to \$40 per month limit accessibility for students and lower-income users, further widening the gap between financial tools and those who could benefit most from them [6]. These limitations highlight the need for an affordable, intelligent, and security-aware financial management platform.

FIN-AI is designed to address these challenges by introducing a unified, mobile-first personal finance ecosystem that integrates predictive analytics, machine learning–driven recommendations, conversational AI assistance, and real-time security monitoring. The system combines time-series forecasting, reward optimization, and hybrid machine learning models to provide personalized credit card recommendations, budget planning, and spending predictions. Secure financial data aggregation is enabled through the Plaid API, while Firebase Authentication and MongoDB support access control and encrypted data storage. An Ollama-based large language model (LLM) enables natural-language interaction for budgeting and financial guidance, and Splunk provides comprehensive monitoring, anomaly detection, and traffic-flow analysis across the application.

This paper presents the complete design and implementation of FIN-AI, including its multi-layer system architecture, data flow and preprocessing strategies, machine learning pipeline, and security monitoring infrastructure. The paper further reports preliminary results from prototype evaluation, demonstrating stable system integration, functional ML microservices, and effective observability. By combining affordability, adaptive intelligence, and security-focused design, FIN-AI advances the state of modern personal finance management systems and addresses key limitations of existing tools.

A. Author Contributions

The contributions of the authors to the FIN-AI system are summarized as follows:

Kaaran Raahul S led the design and implementation of the machine learning pipeline for credit card prediction and reward optimization. He contributed to backend and frontend development, implemented Plaid API integration for secure financial data aggregation, and coordinated end-to-end system functionality.

Srija Julakanti contributed to the integration of the Ollama-based large language model (LLM) for budget recommendation and conversational financial assistance. She worked extensively on frontend and backend development, MongoDB data modeling, and led the migration of Plaid integration from a WebView-based approach to the native SDK.

Surinder Kaur focused on system security and observability by integrating the Splunk monitoring platform. She designed and implemented security monitoring features, including audit logging, anomaly detection, and the traffic-flow dashboard used to analyze user activity and system behavior.

II. Literature Review

This section reviews prior work relevant to FIN-AI, focusing on personal finance management systems, machine learning–based recommender and predictive models, fraud detection techniques, large language models in financial applications, and security and data management practices. The discussion aligns with the key index terms of this paper: Personal Finance Management, Machine Learning, Fraud Detection, Large Language Models, Authentication and Security, and Database Systems.

A. Personal Finance Management Systems

Personal Finance Management (PFM) tools such as Mint, YNAB, PocketGuard, Monarch Money, and Copilot are widely adopted for tracking expenses, categorizing transactions, and visualizing spending behavior. These platforms primarily rely on static rule-based categorization and descriptive analytics, providing retrospective summaries of financial activity. While effective for basic awareness, they offer limited predictive intelligence and rarely adapt to evolving user behavior. Johnson [1] highlights that most commercial PFM systems lack learning mechanisms capable of generating proactive recommendations or optimizing financial decisions over time.

Another recurring limitation is restricted data-entry flexibility. Many systems require continuous bank-account linking, which discourages privacy-conscious users. Although some tools support manual entry or receipt scanning, transparency and accuracy remain limited. As financial ecosystems grow more complex, prior studies emphasize the need for PFM platforms that support multi-source data ingestion, real-time analytics, and predictive modeling to improve financial decision-making [6]. FIN-AI addresses these gaps by combining flexible data ingestion with predictive forecasting and personalized optimization.

B. Machine Learning in Recommender and Predictive Systems

Machine learning techniques have been widely applied to recommender systems to capture latent user preferences and behavioral patterns. Matrix factorization remains a foundational approach for collaborative filtering, enabling personalization beyond explicit categories or rules. Logistic regression continues to be favored for its interpretability in decision-support systems, particularly in binary or ranking-based predictions, while ensemble methods such as Random Forests improve robustness by modeling nonlinear relationships [5].

Recent financial applications increasingly combine multiple models to balance accuracy, interpretability, and adaptability. Time-series forecasting methods further enhance predictive capabilities by modeling temporal spending patterns, enabling forecasts of future expenses, recurring payments, and budget constraints. FIN-AI adopts a hybrid machine learning approach that integrates these techniques to provide personalized credit card recommendations, reward maximization strategies, and spending forecasts tailored to individual users.

C. Fraud Detection and Anomaly Identification

Fraud detection in financial systems has traditionally relied on rule-based heuristics and static thresholds. While simple to implement, these approaches struggle to adapt to evolving fraud patterns and often generate high false-positive rates. Machine learning based anomaly detection methods, including Isolation Forests and statistical deviation models, offer improved adaptability and accuracy [4].

Beyond model-level detection, system-level observability has emerged as a critical component of modern financial platforms. Splunk-based monitoring enables real-time log analysis, event correlation, and anomaly detection across application workflows. Prior work demonstrates that combining behavioral analytics with centralized monitoring infrastructure improves fraud detection and operational security [7]. FIN-AI integrates Splunk to monitor transaction activity, authentication events, and traffic flow, enabling early detection of anomalous behavior without excessive data exposure.

D. Large Language Models in Financial Applications

Conversational agents have been introduced in financial applications to assist users with budgeting and spending queries. Early systems relied heavily on rule-based templates and predefined responses, limiting their adaptability and contextual understanding. Recent advancements in large language models (LLMs) enable more natural and context-aware interactions, improving user engagement and interpretability.

However, the use of LLMs in finance raises concerns related to privacy, explainability, and data governance. Research emphasizes that financial LLMs should operate on processed or summarized data rather than raw transactional records to preserve user privacy and regulatory compliance. FIN-AI follows this principle by integrating an Ollama-based LLM that provides budget recommendations and financial insights using internal analytics outputs, ensuring conversational intelligence without direct exposure of sensitive data.

E. Authentication, Security, and Data Management

Secure authentication and data management are foundational requirements for financial applications. Firebase Authentication provides scalable identity management, multi-device support, and secure token-based access control. For data persistence, NoSQL databases such as MongoDB are commonly used due to their flexibility in handling heterogeneous financial records and evolving schemas.

Research on financial data systems emphasizes the importance of encryption, access control, audit logging, and minimal data retention to ensure regulatory compliance and user trust [3]. FIN-AI incorporates these best practices through encrypted storage, role-based access, structured audit logging, and Splunk-based observability, aligning system security with modern financial software standards.

Overall, prior work reveals that existing solutions often address isolated aspects of financial management, such as tracking, recommendation, or security, but rarely integrate all components into a cohesive and affordable platform. FIN-AI advances the state of the art by unifying predictive analytics, machine learning–driven recommendations, conversational AI, and real-time security monitoring within a single mobile-first system.

III. Methodology / System Design

A. System Development Approach

The development of FIN-AI followed an applied system development and evaluation approach, focusing on building a functional personal finance management application that integrates secure financial data aggregation, analytics, machine learning, and conversational assistance. The primary goal of the system was to help users and families better understand their financial behavior, track expenses, manage budgets, and optimize credit card usage through data-driven insights.

Rather than focusing on a single algorithmic contribution, this project emphasized the integration of multiple technologies into a cohesive system. The development process was iterative and incremental. Core features such as authentication, transaction ingestion, analytics, and budgeting were implemented first, followed by advanced features such as machine learning recommendations and AI-assisted budget creation. Each feature was tested individually before being integrated into the full application.

B. System Architecture Overview

FIN-AI is designed as a mobile-first application supported by a backend service layer and external APIs. The system consists of four primary components: a mobile frontend, a backend server, third-party services for authentication and banking data, and analytical and machine learning modules. Communication between components occurs through secure REST APIs. The mobile application serves as the primary interface for users and is responsible for presenting financial information, visualizations, and interactive tools. The backend server handles business logic, data processing, security enforcement, and communication with external services such as Firebase and Plaid. Analytical and machine learning components operate as backend services that process transaction data and generate insights for budgeting, recommendations, and anomaly detection.

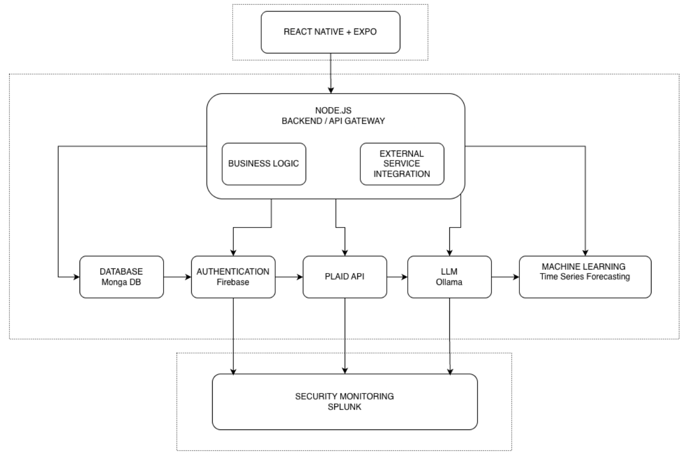

Fig. 1. System Architecture

C. Frontend Design and Mobile Application Implementation

The FIN-AI mobile application was developed using Expo with React Native to support cross-platform deployment on both Android and iOS devices from a single codebase. This framework was chosen to simplify development and testing while ensuring consistent user experience across platforms. The frontend is structured using reusable components, with separate screens for the home dashboard, forecast view, transaction history, budgeting, and AI chat assistant. Navigation and screen transitions are managed centrally, allowing financial data and user state to persist smoothly across the application. For interface design and visual consistency, FIN-AI uses lucide-react-native to implement icons and UI elements. This library provides lightweight, scalable icons that integrate well with React Native and support accessible design practices. The user interface emphasizes clarity and readability, particularly for financial information such as balances, spending summaries, and budgets. All values displayed on the frontend are retrieved through authenticated backend APIs, and no sensitive financial logic or calculations are performed on the client side.

D. Backend Implementation and Database Design

The backend of FIN-AI is implemented using Node.js with the Express framework, which provides an efficient and scalable environment for handling concurrent API requests.

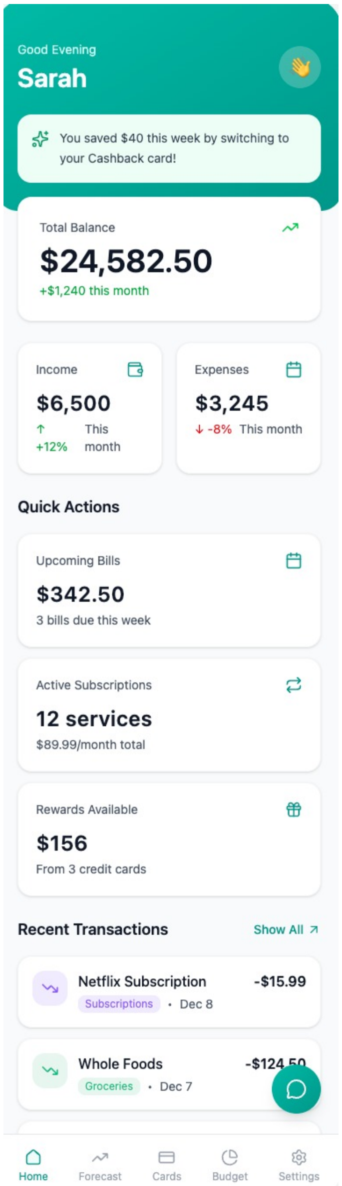

Fig. 2. Dashboard

Express middleware is used to manage authentication validation, request routing, and error handling. The backend coordinates all core application logic, including transaction ingestion, recurring payment detection, budget calculations, and communication with external services such as Firebase and Plaid.

FIN-AI uses MongoDB as its primary database due to its flexible document-oriented schema, which is well suited for storing financial transactions, user profiles, budgets, and household account relationships. Data is organized into separate collections to improve maintainability and query performance. Sensitive information is encrypted at rest, and the backend supports full account deletion workflows, ensuring that all user data is permanently removed when requested.

E. External API Integrations and Secure Banking Connectivity

FIN-AI integrates with the Plaid API to enable secure connections to user bank accounts and credit cards. Plaid provides tokenized, read-only access to financial data, allowing FIN-AI to retrieve transaction histories and account balances without storing banking credentials. The Plaid integration supports both individual and family-linked accounts, enabling consolidated financial views while maintaining secure access controls.

Although Plaid supplies detailed transaction data, it does not explicitly identify recurring subscriptions or upcoming bills. FIN-AI addresses this limitation by analyzing transaction frequency, merchant consistency, and payment patterns to infer recurring expenses such as rent, subscriptions, and credit card payments. These derived insights are then used to populate features such as upcoming bills, active subscriptions, and spending forecasts while preserving user privacy and data security.

F. User Authentication and Account Security

User authentication and account management in FIN-AI are implemented using Firebase Authentication. Firebase was selected because it provides secure, scalable, and industry-standard authentication mechanisms suitable for financial applications. During user registration, passwords are encrypted and securely stored by Firebase using hashing and salting techniques. FIN-AI does not store or directly manage user passwords.

Login activity is continuously monitored to detect potential unauthorized access. Each login attempt is recorded, including whether the attempt was successful or failed. If a user enters an incorrect password five consecutive times, the system temporarily blocks the account. At this point, the user is informed that their account has been locked for security reasons and is instructed to contact a helpdesk support number for assistance. This approach was implemented to reduce the risk of brute-force attacks while still allowing legitimate users to regain access through manual verification.

Authentication tokens issued by Firebase are used to authorize all subsequent requests to the backend. Only authenticated users with valid tokens can access financial data, budgets, or analytics.

G. Bank Account Integration Using Plaid API

FIN-AI integrates bank accounts and credit cards using the Plaid API. Plaid acts as a secure intermediary between the application and financial institutions. Users link their bank accounts through Plaid's interface, and FIN-AI receives access tokens that allow read-only access to transaction and balance data. No banking credentials are stored within the FIN-AI system.

Plaid provides detailed transaction-level data, including transaction amount, date, merchant name, and category. However, Plaid does not explicitly identify recurring payments such as subscriptions, rent, or credit card bills. To address this limitation, FIN-AI performs additional analysis on the transaction data to infer recurring financial obligations.

H. Transaction Analysis and Recurring Payment Detection

After transaction data is retrieved from Plaid, it undergoes preprocessing and analysis on the backend. Transactions are grouped by merchant name and category, and historical patterns are analyzed to identify recurring payments. Payments that occur at regular intervals with similar amounts are classified as recurring transactions. This logic is used to identify subscriptions, rent payments, and recurring credit card bills.

Using this inferred data, FIN-AI calculates upcoming bills, including the bill type, expected amount, and estimated due date. This information is displayed on the home screen so users can quickly understand their upcoming financial obligations. The system also calculates the number of active subscriptions, the next subscription payment date, and the total amount expected to be paid for subscriptions in the current cycle.

I. Home Screen Financial Summary

The home screen of FIN-AI is designed to provide a concise yet comprehensive overview of the user's financial status. It displays the total account balance aggregated across linked accounts, upcoming bills with due dates, active subscriptions, rewards and cashback information, and recent transactions.

Rewards information is calculated by analyzing transaction categories and matching them against known reward structures for linked credit cards. Recent transactions are sorted chronologically and displayed to allow users to quickly review recent spending activity.

All values shown on the home screen are computed dynamically based on processed transaction data rather than raw Plaid responses.

J. Forecast and Spending Analysis

The forecast screen provides users with insights into their spending behavior over time. Spending is grouped into categories such as groceries, transportation, bills, subscriptions, and shopping. Users can view spending for different time ranges, including the current month, the previous week, the last 90 days, or a custom date range.

Category-level spending is calculated by aggregating transaction amounts within the selected time window. Visual representations help users identify spending trends and areas where expenses may be increasing unexpectedly.

K. Transaction History and Search Functionality

FIN-AI includes a detailed transaction history screen that allows users to view and explore their financial activity. Users can filter transactions by time period, including monthly views, recent weeks, or custom date ranges. A search function allows filtering based on transaction name, category, description, or amount. This feature was implemented to give users full visibility into their financial data and to support detailed review and auditing of expenses.

L. Budget Creation and Household Budget Management

The application allows users to create detailed budgets at both individual and household levels. Users can assign spending limits to predefined categories or create custom categories based on personal financial needs. Budget utilization is calculated by comparing actual spending against allocated limits in real time.

For household accounts, FIN-AI aggregates spending across multiple members. The system tracks spending by each member and compares it against the shared household budget. Visual indicators show whether spending remains within budget or exceeds planned limits, helping families manage shared finances collaboratively.

M. Machine Learning-Based Credit Card Recommendations

FIN-AI incorporates a machine learning–based recommendation system to help users optimize credit card usage by considering both historical and temporal spending patterns. In addition to analyzing transaction histories, spending categories, and credit card reward structures, the system applies time-series forecasting techniques to model recurring user behavior and seasonal trends. This temporal modeling enables FIN-AI to anticipate future spending patterns rather than relying solely on past averages, allowing the system to recommend the most suitable credit card for upcoming transactions.

The recommendation logic combines interpretable models such as logistic regression with more flexible ensemble methods, including random forests, to capture nonlinear relationships between user spending behavior and reward optimization. Time-series forecasts of category-level spending are incorporated as features into the prediction pipeline, improving the model's ability to identify which card is likely to yield the highest rewards over an upcoming period. All models are trained using publicly available datasets to avoid direct exposure to sensitive user financial data, ensuring privacy and ethical data usage. The system presents its recommendations through an explainable interface, clearly communicating how predicted spending trends and reward structures contribute to maximizing user savings.

N. AI Chat Assistant and Automated Budget Creation

FIN-AI includes an AI-powered chat assistant that enables users to interact with the system using natural language. The assistant is designed to support common financial tasks such as viewing spending summaries, checking upcoming bills, understanding budget usage, and receiving guidance for financial planning. Rather than acting as a generic chatbot, the assistant is tightly integrated with FIN-AI's internal analytics and budgeting modules, allowing responses to be grounded in the user's actual financial data. When a user requests budget creation through the chat interface, the system retrieves processed historical spending data from the backend. This data is analyzed to determine typical spending patterns across categories such as groceries, transportation, subscriptions, and bills. Based on these patterns, the system automatically generates category-level budget recommendations that reflect

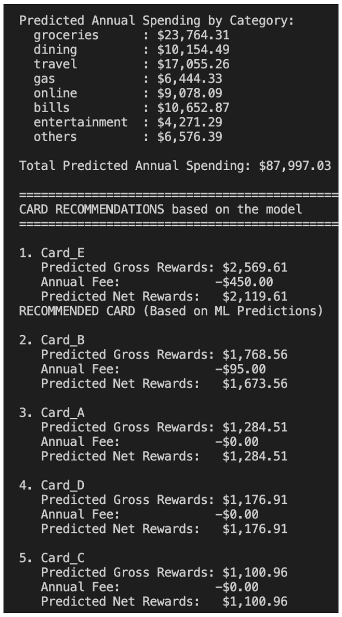

Fig. 3. Model Suggestion

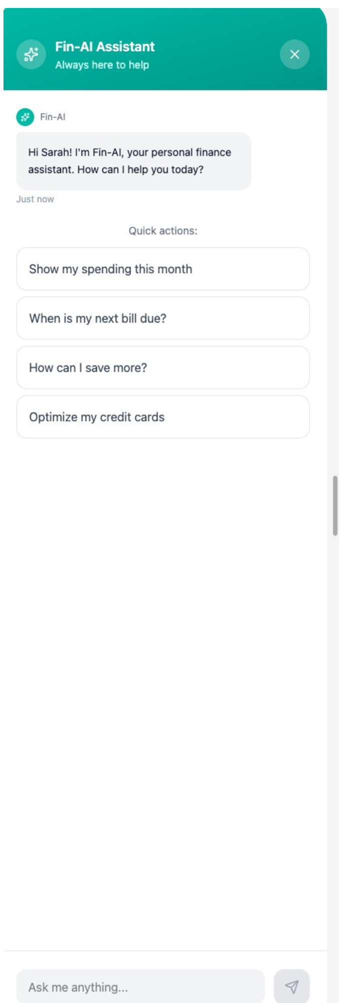

Fig. 4. AI ChatBot - LLM(Ollama Model)

the user's past behavior. Users retain full control over these recommendations and may accept them as suggested, adjust category limits, or create entirely new budget categories as needed. This approach reduces the manual effort required to set up budgets and provides additional support for users who may not be familiar with structured budgeting practices.

The conversational assistant is implemented using Ollama, a locally hosted large language model platform. Ollama was selected specifically because it operates as a self-hosted service rather than a third-party cloud-based API. The model runs on the application's own server infrastructure and communicates directly with the FIN-AI backend. This design eliminates dependency on external paid AI APIs and allows the chat feature to be offered in the free version of the application without imposing additional costs on users. In contrast to many existing financial applications that restrict AI-based assistance to paid tiers, FIN-AI's architecture enables broader accessibility while maintaining cost efficiency.

From a privacy and security perspective, the use of Ollama provides significant advantages. All user queries and model responses are processed and stored locally on the application's own servers rather than being transmitted to external AI providers. As a result, no financial data is shared with third-party AI services. The conversational assistant operates exclusively on processed and aggregated internal data, ensuring that raw banking information retrieved through Plaid is never exposed to the language model. This architecture significantly reduces privacy risks and aligns with the system's overall emphasis on user trust and data control.

By hosting the AI model internally and avoiding external API calls, FIN-AI achieves a balance between intelligent user interaction, cost efficiency, and strong privacy guarantees. This implementation choice supports long-term scalability and ensures that advanced AI-driven assistance can remain available to users without compromising security or increasing operational costs.

O. Security Monitoring and Traffic Flow Analysis Using Splunk

As shown in Fig. 5, the FIN-AI system integrates Splunk to provide real-time visibility into backend traffic and security events.

FIN-AI integrates the Splunk platform as a centralized security monitoring and observability layer to provide real-time visibility into backend operations, authentication behavior, and application traffic. The backend services generate structured audit logs capturing critical events such as user authentication attempts, Plaid API interactions, request routing, error responses, and system exceptions. These logs are securely transmitted to Splunk using the HTTP Event Collector (HEC), ensuring reliable and scalable log ingestion without impacting application performance.

Within Splunk, the collected logs are indexed and visualized through a dedicated Backend Security Dashboard. This dashboard enables continuous monitoring of authentication

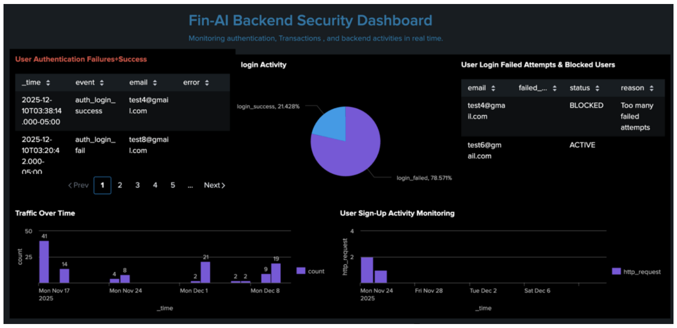

Fig. 5. Splunk Traffic Flow Dashboard

patterns, including successful and failed login attempts, abnormal access frequency, and unauthorized access indicators. In addition, backend traffic flow is analyzed to track request volumes, endpoint usage, latency distributions, and error trends across the system. By correlating traffic metrics with user and service identifiers, FIN-AI can identify unusual activity such as sudden traffic spikes, repeated access failures, or anomalous third-party service interactions. The Traffic Flow feature plays a critical role in behavioral analysis by providing a holistic view of user navigation paths and backend request sequences across the application. This feature allows administrators to trace how users move through the system, detect deviations from expected interaction patterns, and assess potential misuse or automated behavior. Combined with Splunk's alerting mechanisms, the system supports early detection of suspicious activity, proactive incident response, and informed security decision-making. Overall, the integration of Splunk enhances FIN-AI's security posture, operational reliability, and transparency, while maintaining compliance with privacy and data minimization principles.

P. User Data Control and Privacy

User trust and data privacy are central to the design of FIN-AI. Users are given the ability to delete their account and all associated data at any time. When an account is deleted, user profiles, transactions, budgets, and analytics are permanently removed from the system.

All data transmission is encrypted, and sensitive data is encrypted at rest. These measures ensure that users feel confident linking their financial accounts and using the application for long-term financial management.

IV. Preliminary Results

At the time of writing, approximately 80% of the FIN-AI system has been implemented and validated through functional and integration-level testing. The mobile frontend developed using React Native with Expo has been successfully integrated with the backend services, enabling smooth navigation across dashboards, transaction views, subscription summaries, and AI-assisted budgeting features. User interactions trigger consistent API responses, confirming reliable communication between the client and server layers.

The Plaid API integration has been validated using sandbox and dummy financial accounts, allowing FIN-AI to securely retrieve account balances, categorized transactions, merchant details, and historical spending records. The data ingestion and preprocessing pipeline correctly normalizes and standardizes incoming data from multiple sources, including bank-linked accounts and manual inputs. Budget summaries, category-level spending visualizations, and upcoming payment forecasts are rendered accurately in the user interface, demonstrating the correctness of feature extraction and aggregation logic.

The machine learning microservice has been successfully deployed and integrated with the backend. The preprocessing pipeline for time-series forecasting and credit card recommendation has been verified, and the models are able to ingest cleaned datasets and generate prediction outputs. While full-scale model training and optimization are ongoing, initial inference tests confirm that the recommendation pipeline is operational and ready for deployment with trained models.

From a security and observability perspective, Splunk has been successfully integrated using structured backend logs transmitted via the HTTP Event Collector. Real-time dashboards display authentication events, backend traffic patterns, API error rates, and user activity flows across the application. The Traffic Flow feature provides visibility into request sequences and usage behavior, confirming the system's ability to support early anomaly detection and operational monitoring. These results demonstrate that FIN-AI achieves stable system integration, functional observability, and readiness for advanced analytics and optimization.

V. Future Work

Future development of FIN-AI will focus on expanding intelligent capabilities, strengthening security analytics, and preparing the system for production deployment. A primary area of focus is the completion and optimization of the machine learning models, including full training and evaluation of the time-series forecasting and credit card recommendation pipeline using expanded datasets. Future iterations will explore lightweight optimization techniques and hybrid learning strategies to further improve reward maximization and spending prediction accuracy.

The conversational AI component will be extended to support deeper reasoning and contextual understanding through multi-turn dialogue and enhanced prompt orchestration. Additional safeguards will be introduced to ensure explainability, privacy preservation, and controlled access to financial insights when interacting with the Ollama-based LLM. This will enable more personalized and proactive budget recommendations while maintaining strict data governance.

On the security side, FIN-AI will incorporate advanced Splunk Machine Learning Toolkit features to enable automated anomaly detection, behavioral baselining, and predictive alerting. The Traffic Flow dashboard will be enhanced to support long-term trend analysis, cross-user behavioral comparisons, and early detection of coordinated or automated misuse. System-wide optimizations, including backend performance tuning, improved caching strategies, and refined UI accessibility, will also be pursued to ensure scalability, reliability, and an improved user experience as FIN-AI transitions toward real-world deployment.

VI. Conclusion

FIN-AI presents an intelligent, secure, and predictive personal finance management platform that integrates machine learning driven recommendations, Splunk-based security monitoring, conversational AI, and modern mobile application development practices. By addressing key limitations of traditional PFM systems, FIN-AI unifies personalized credit card recommendations, reward optimization, time-series–based spending forecasts, and anomaly detection within a single, cohesive mobile ecosystem. The system emphasizes affordability, transparency, and privacy-conscious design, making advanced financial insights accessible to a broader user base.

Ongoing and future development efforts will focus on further optimizing the machine learning models, enhancing fraud and behavioral anomaly detection through advanced Splunk analytics, and refining the user experience for scalability and reliability. As FIN-AI progresses toward production readiness, it demonstrates the potential of integrating predictive intelligence and real-time security monitoring to improve financial decision-making and overall user financial well-being.

References

[1] B. Johnson, "Advances in recommender systems for personal finance applications," *IEEE Transactions on Knowledge and Data Engineering*, vol. 33, no. 4, pp. 1121–1134, 2021.

[2] Y. Koren, R. Bell, and C. Volinsky, "Matrix factorization techniques for recommender systems," *Computer*, vol. 42, no. 8, pp. 30–37, 2009.

[3] E. Rahm and H. H. Do, "Data cleaning: Problems and current approaches," *IEEE Data Engineering Bulletin*, vol. 23, no. 4, pp. 3–13, 2000.

[4] S. Lee and H. Kim, "Machine learning approaches for financial fraud detection: A survey," *Proceedings of the International Conference on Data Science*, pp. 45–56, 2021.

[5] L. Breiman, "Random forests," *Machine Learning*, vol. 45, no. 1, pp. 5–32, 2001.

[6] M. Fowler, *Patterns of Enterprise Application Architecture*. Addison-Wesley, 2002.

[7] Splunk Inc., "Intelligent fraud detection with Splunk Machine Learning Toolkit," White Paper, 2023.

[8] Plaid Inc., "Secure financial data aggregation and open banking," Technical Documentation, 2023.

[9] M. S. Rahman, S. I. Khan, M. S. Mia, and M. R. Hossain, "Harnessing machine learning and AI for predictive financial modeling: A new era in business management and risk optimization," Research Article, 2024.

[10] Ollama Project, "Local large language models for AI-assisted applications," Technical Documentation, 2024.