FinTrack: An AI-Powered Personal Finance App for Predictive Budgeting and Financial Guidance

Final Year Project Report: Development of an AI-Driven Personal Finance Application

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Abstract

Personal finance management is still difficult for many people because of the limited predictive and personalised capabilities of current digital budgeting tools. These tools usually only track transactions in the past without offering any useful insights into the future, which hinders the ability to make proactive financial decisions. This dissertation addresses this gap through the development and rigorous evaluation of FinTrack, an innovative AI-driven personal finance platform leveraging sophisticated predictive analytics via the XGBoost algorithm to forecast user spending patterns from historical financial data. FinTrack integrates an AI-powered chatbot (FinBot), utilizing Google's Gemini API to deliver real-time, personalized financial guidance and budgeting recommendations, supported by a robust backend architecture employing Flask for API management and Firebase for secure user authentication. A comprehensive comparative analysis demonstrated that XGBoost outperformed alternative methods such as Long Short-Term Memory (LSTM) in accuracy, computational efficiency, and stability, especially with structured financial datasets. User testing further validated FinTrack's effectiveness, revealing significant improvements in financial decision-making and user engagement compared to traditional apps like Mint and YNAB. These findings underscore the considerable potential of integrating AI-driven predictive analytics and personalized recommendations into fintech solutions, establishing FinTrack as a meaningful advancement that directly addresses critical gaps in existing literature and sets a benchmark for future fintech developments aimed at enhancing financial literacy and empowering users to make smarter, data-informed financial decisions.

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Abbreviations

AI	Artificial Intelligence
YNAB	You Need A Budget
LSTM	Long Short-Term Memory
XGBoost	Extreme Gradient Boosting
API	Application Programming Interface
SMS	Short Message Service

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CHAPTER 1

Introduction

1.1 Introduction to Personal Finance Management

Effective management of personal finances is crucial for achieving financial stability and securing long-term economic goals. However, despite its significance, many individuals, particularly students, young professionals, and budget-conscious individuals, struggle to manage their finances effectively. Traditional methods often rely heavily on manual tracking or basic digital tools that offer limited proactive guidance. Such conventional approaches generally lack predictive capabilities, making it difficult for users to anticipate future financial scenarios or adapt proactively to changing economic circumstances (Bhattacharjee et al. 2024).

1.2 Fintech and Its Growing Importance

Financial technology, or fintech, represents the integration of technology into financial services aimed at improving accessibility, efficiency, and personalization. Fintech has disrupted traditional financial services by introducing innovative solutions leveraging artificial intelligence (AI), big data analytics, and real-time processing capabilities.

These advancements offer significant improvements over traditional financial methods by providing real-time financial insights, personalized recommendations, and enhanced user experiences (Iyelolu & Paul 2024).

Financial technology, or fintech, represents the integration of technology into financial services aimed at improving accessibility, efficiency, and personalization. Fintech has disrupted traditional financial services by introducing innovative solutions leveraging artificial intelligence (AI), big data analytics, and real-time processing capabilities. These advancements offer significant improvements over traditional financial methods by providing real-time financial insights, personalized recommendations, and enhanced user experiences (Iyelolu & Paul 2024). The rapid growth and global adoption of fintech solutions highlight their transformative potential, as illustrated by the steady increase in fintech firms across global regions from 2018 to 2024 (see Figure 1.2) (DealPotential 2024).

Nevertheless, existing fintech apps often remain limited to basic functionalities, including simple expense tracking and historical transaction reporting. These limitations underscore a clear gap in offering personalized predictive insights—a vital feature for effective personal financial management (Gomber et al. 2017). Furthermore, mastering personal financial well-being requires more than just data visualization; it necessitates intelligent integration of budgeting, savings, debt management, and literacy, as conceptualized in the foundational framework presented in Figure 1.1.

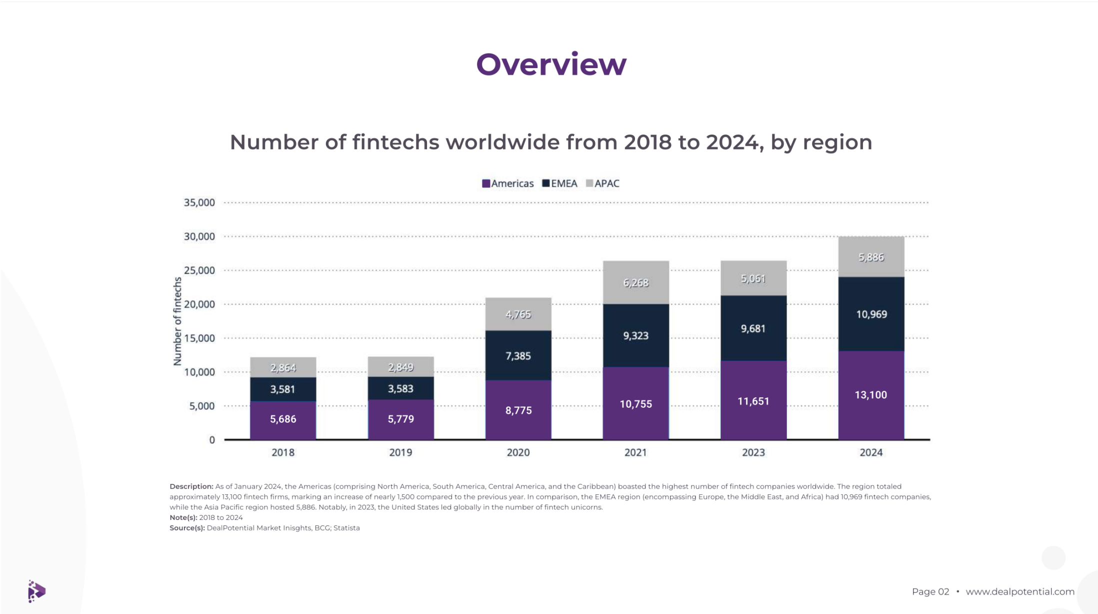
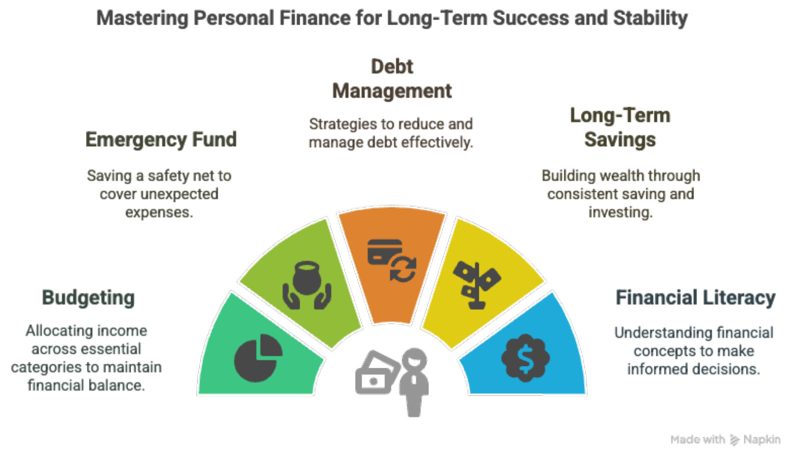


Figure 1.1: Global Growth of FinTech Market by Region (2018–2024), showing the number of fintechs worldwide by region (DealPotential 2024).

Figure 1.2: Importance of Personal Finance Management in Achieving Long-Term Goals



1.3 Motivation: Challenges of Traditional Finance Apps

While traditional finance apps like Mint and YNAB have improved expense tracking and visualization, they primarily provide reactive insights—displaying historical financial data without robust predictive analytics. Users typically encounter limitations such as inadequate forecasting of future spending, lack of real-time financial advice, and insufficient customization in budget management. These apps predominantly offer basic visualizations and transaction summaries, failing to adequately engage users or support proactive financial decision-making.

Notably, Intuit announced the discontinuation of Mint in early 2024, citing the company's decision to integrate select features into its Credit Karma platform. This move sparked criticism from long-time users and highlighted ongoing dissatisfaction with the app's limited innovation and engagement (Intuit 2023). Identified shortcomings include the absence of predictive budgeting capabilities, limited visualization options (e.g., detailed pie charts for spending categories and time-framed analytics), inadequate debt-tracking functionalities, and insufficient real-time AI-driven guidance. Consequently, users often struggle to maintain consistent engagement with these platforms, ultimately undermining their financial goals.

1.4 The Need for AI Integration in Budgeting Platforms

Integrating artificial intelligence into budgeting platforms can address critical gaps identified in traditional finance apps. AI technologies, particularly predictive analytics and intelligent chatbots, can significantly enhance budgeting effectiveness, financial literacy, and user engagement. By proactively forecasting future expenses, providing real-time personalized guidance, and continuously adapting to user behavior, AI-driven platforms offer substantial advantages over conventional budgeting methods.

For instance, Cai et al. (2021) highlight that AI systems can enhance consumer outcomes by delivering personalized financial advice and facilitating smarter decision-making processes. Additionally, Bayakhmetova et al. (2025) emphasize that AI-driven tools can reduce psychological biases in financial behavior, offering personalized recommendations that promote responsible financial management.

1.5 Aims and Objectives

The main aim of this dissertation is to develop and critically evaluate *FinTrack*, an innovative AI-powered personal finance and budgeting platform designed specifically to enhance financial literacy, simplify budgeting processes, and empower smarter financial decision-making among students, young professionals, and budget-conscious users globally.

Specific objectives include:
Objective 1: Intuitive Budgeting

- Develop user-friendly, visually appealing analytics (graphs, pie charts) to clearly illustrate income, expenses, and spending categories.
- Implement advanced predictive analytics (using XGBoost) to accurately forecast user spending in various time frames, helping users plan proactively and efficiently.

Objective 2: AI Guidance

- Deploy an AI-powered chatbot (FinBot) leveraging Google's Gemini API to provide real-time personalized financial advice, answering user queries promptly and effectively.
- Ensure FinBot delivers reliable, general financial insights and recommendations based on established best practices in personal finance.

Objective 3: Improved Decision-Making

- Enhance user capability to make informed and proactive financial decisions through comprehensive stock market analytics, debt management features, and predictive spending insights.
- Aim to indirectly measure improvement in decision-making effectiveness through user engagement and qualitative feedback.

Objective 4: Automation and Real-World Integration

- Implement a native Android SMS parsing feature that automatically extracts transaction data from bank messages and integrates it into the user's ledger. This enhances automation, reduces the burden of manual entry, and reflects real-world usability—especially in regions like the UAE, where SMS alerts are a common medium for financial communication. The feature also includes duplicate prevention and merchant-based auto-categorization to ensure accuracy and convenience.

1.6 Research Questions

To comprehensively evaluate the effectiveness and innovation of FinTrack, this dissertation addresses the following research questions:

- How effectively does the FinTrack platform, with its integrated XGBoost predictive analytics and real-time financial tracking, improve users' budgeting outcomes and spending forecast accuracy?
- How does the inclusion of a conversational AI chatbot (FinBot) for real-time financial advice, alongside intuitive debt management and automated transaction input (e.g. SMS parsing), influence user experience and decision-making in personal finance management?
- What are the innovative contributions of the FinTrack platform's integrated features (predictive spending analytics, AI-driven advice, real-time stock tracking, and automated debt management) to personal finance management, and how do these combined functionalities compare to existing personal finance tools in enhancing financial planning?

CHAPTER 2

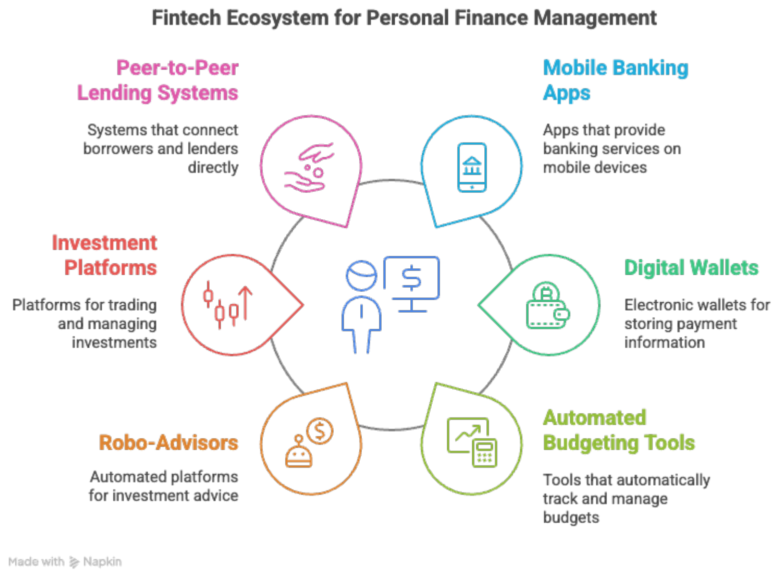
Literature Review

2.1 Overview of Fintech and Personal Finance Management

Financial technology, widely known as fintech, refers to the application of technology to enhance, automate, and improve the efficiency and accessibility of financial services. Over recent years, fintech has witnessed exponential global growth, dramatically reshaping the financial landscape and significantly impacting the delivery and consumption of financial services (Buckley et al. 2016). Technological innovations such as digital payments, peer-to-peer lending, blockchain, and robo-advisors exemplify fintech's transformative potential, fundamentally changing how individuals and businesses manage their finances (Nicoletti 2017).

Traditionally, personal finance management relied heavily on manual processes such as cash budgeting, manual transaction recording, and simple spreadsheet-based tracking. This traditional approach offered limited proactive capabilities and often resulted in delayed or inefficient financial decisions. However, the emergence of fintech solutions has revolutionized personal finance management by introducing automated tools and real-time insights. Mobile banking apps, digital wallets, and automated budgeting applications now provide users with immediate access to their financial information, simplified transaction tracking, and enhanced control over their financial decisions (Lee & Shin 2017).

Figure 2.1: Fintech-driven personal finance management ecosystem (adapted from Lee & Shin, 2018)



One of fintech's most profound disruptions in personal finance has been democratizing financial services previously accessible only to high-net-worth individuals or institutions. Tools such as robo-advisors, automated investment platforms, and digital budgeting applications have expanded financial inclusion, enabling a broader demographic to access sophisticated financial management resources. This inclusivity not only benefits individual users by improving financial literacy and decision-making but also contributes positively to broader economic stability and growth (Demirgüç-Kunt et al. 2018).

Despite the evident benefits and rapid adoption of fintech solutions globally, several persistent challenges remain prevalent in personal finance management. Low financial literacy continues to pose significant barriers, restricting effective engagement with available technological resources. Studies indicate that large segments of populations worldwide lack essential financial knowledge, significantly undermining the effectiveness of fintech applications designed to promote informed financial behaviors (Lusardi & Mitchell 2014).

Another substantial challenge is user engagement and retention within personal finance applications. Many current fintech solutions, while technologically advanced, fail to maintain consistent user interaction. This issue often arises from the limited personalization and predictive capabilities offered by these platforms. Many personal finance apps focus predominantly on retrospective financial data, lacking advanced predictive analytics and tailored real-time recommendations. As a result, users frequently become disengaged, reducing the potential for sustained positive financial behaviors and outcomes.

Moreover, the absence of predictive financial management tools represents a significant gap in contemporary fintech solutions. Most existing personal finance applications provide static insights and historical transaction records without forecasting future financial scenarios. This limitation restricts users' ability to proactively manage their finances, making it challenging to anticipate potential financial difficulties or capitalize on upcoming opportunities effectively.

Finally, privacy and data security concerns represent critical challenges facing the fintech sector. As users increasingly rely on digital platforms to manage sensitive financial information, ensuring robust cybersecurity measures and compliance with data protection regulations becomes imperative. Users' concerns about data security significantly influence their willingness to fully engage with fintech solutions, emphasizing the need for stringent cybersecurity protocols to maintain trust and confidence in fintech platforms.

Addressing these challenges through innovative fintech solutions—specifically leveraging advanced predictive analytics, personalized interactions, robust security measures, and improved financial literacy resources—remains crucial. These elements form the foundation of effective, proactive, and user-centered personal finance management tools, guiding future fintech developments and improvements.

2.2 Personal Finance Applications

(Bhattacharjee et al. 2024) highlight fintech's transformative impact on traditional financial services, emphasizing improvements in efficiency, accessibility, and cost-effectiveness. Their research explores how fintech platforms streamline financial services and improve user convenience. These deficiencies contribute to limited user engagement and reduced long-term impact on financial behavior. (Bhattacharjee et al. 2024) argue for the necessity of fintech platforms capable of delivering personalized, forward-looking financial guidance, which strongly aligns with the objectives of FinTrack.

(Iyelolu & Paul 2024) examine the disruption of traditional banking systems by fintech firms, offering a detailed review of how emerging technologies have reshaped financial services. Their analysis focuses on trends in market growth, profitability, and operational efficiency, highlighting how fintech companies challenge conventional banks through innovative business models and streamlined digital services.

In their analysis, (Tanda & Schena 2019) examine the evolving business models of fintech startups and the strategic challenges they face in competing with traditional banks.

A report by (Cloudester 2025) discusses how AI-powered personalization significantly boosts engagement by delivering relevant and timely financial suggestions. Similarly, academic research by (Omarini 2017) emphasizes the strategic importance of real-time analytics and automation in improving user relationships within digital finance platforms.

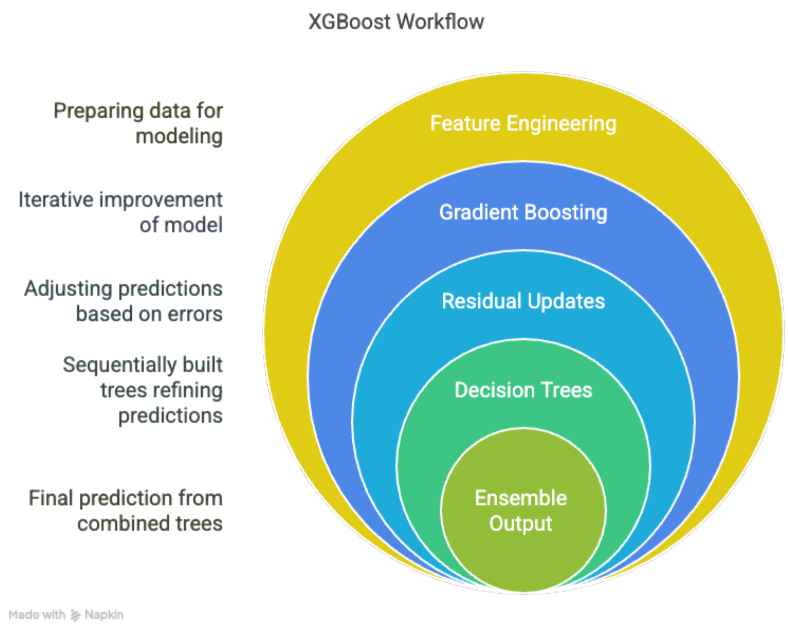
2.3 Time-Series Forecasting Literature

Predictive analytics plays a critical role in modern personal financial management, enabling users to make informed decisions by forecasting future spending patterns, budgeting needs, and savings goals. Time-series forecasting models help extract meaningful patterns from historical financial data to support proactive financial planning. Among the most prominent techniques used in this domain are XGBoost (Extreme Gradient Boosting) and Long Short-Term Memory (LSTM) neural networks. Both models have shown strong results in financial contexts, though they differ significantly in complexity, interpretability, and suitability depending on the structure and size of the dataset.

XGBoost in Personal Finance Forecasting

XGBoost, introduced by (Chen & Guestrin 2016), is a scalable, tree-based ensemble learning algorithm that builds on gradient boosting principles. It has become a leading model in financial forecasting due to its high computational efficiency, predictive accuracy, and ability to handle structured tabular data, including those with missing values and categorical variables. In the context of personal finance, datasets typically consist of small, structured, and transactional records—an environment where XGBoost performs exceptionally well.

Figure 2.2: XGBoost workflow showing input processing, sequential tree boosting, and final ensemble output for financial forecasting.



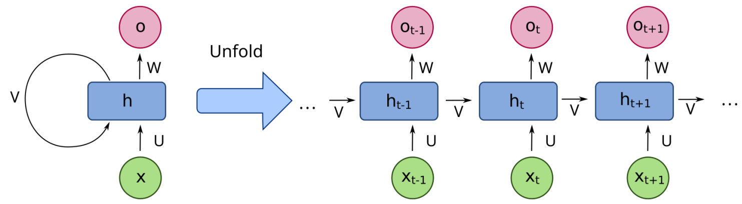
As illustrated in Figure 2.2, XGBoost begins by ingesting structured financial inputs, such as user transaction histories. After feature selection and engineering, the model applies a series of boosted decision trees, each learning from the residuals of the previous one. This iterative refinement enables highly accurate forecasting even with modest data volumes. (Nielsen 2016) highlighted the effectiveness of XGBoost in direct response modeling tasks, noting that with appropriate hyperparameter tuning, the algorithm achieved significantly improved predictive performance over baseline models such as logistic regression. (Zou et al. 2022) demonstrated that XGBoost delivers high accuracy and strong generalization performance on small, structured datasets. In their comparative study, the XGBoost model significantly outperformed deep neural networks (DNN) and support vector regression (SVR), highlighting its effectiveness in scenarios where data is limited—such as in personal finance applications.

LSTM in Sequential Financial Data

LSTM (Long Short-Term Memory) networks, proposed by (Hochreiter & Schmidhuber 1997), are a specialized type of Recurrent Neural Network (RNN) designed to capture long-range dependencies in sequential data. They have proven effective in domains with continuous and high-frequency data, such as stock market prediction, macroeconomic trend analysis, and energy consumption forecasting.

LSTMs are particularly suited for problems where past values influence future outcomes over long time horizons. However, their black-box architecture, high computational overhead, and requirement for large datasets present challenges for small-scale financial applications. In personal finance scenarios—where users typically have 3–6 months of transaction history—LSTM models are prone to overfitting and lack the interpretability required for user trust (Siami Namini et al. 2018). Moreover, they often demand deep learning frameworks like TensorFlow or PyTorch and access to GPUs, which may limit their usability in lightweight web apps such as FinTrack.

Figure 2.3: Simplified LSTM architecture unrolled over time, showing input sequences, hidden states, and outputs across multiple time steps.

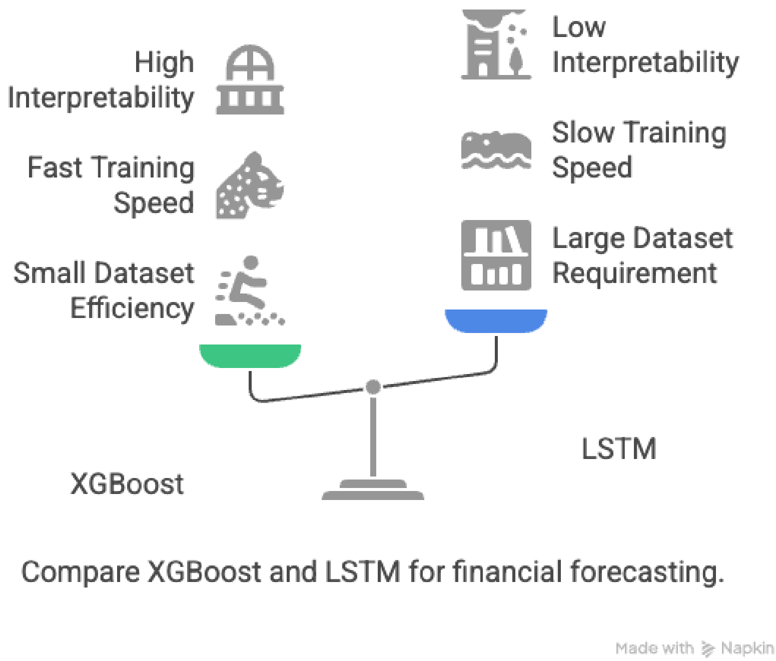


While LSTM networks are powerful tools for modeling complex time-series patterns, their computational overhead and reliance on large, continuous datasets make them less practical for personal finance applications. LSTMs extend traditional recurrent neural networks (RNNs) by incorporating gated mechanisms—specifically the input, forget, and output gates—that regulate the flow of information and preserve long-term dependencies through a memory cell. However, these sophisticated mechanisms also increase model complexity and reduce interpretability. In scenarios with limited user data and a need for transparency—such as FinTrack—simpler, faster models like XGBoost offer a more suitable and effective solution.

Table 2.1: Summary of time-series forecasting models referenced in the literature

Authors	Year	Model(s)	Application Domain	Dataset Type
Chen & Guestrin	2016	XGBoost	Financial Forecasting	Structured, tabular
Nielsen	2016	XGBoost	Direct Response Modeling	Structured, tabular
Zou et al.	2022	XGBoost	Small-scale Financial Forecasting	Structured, small datasets
Hochreiter & Schmidhuber	1997	LSTM	Sequential Modeling	Sequential, large-scale
Siami-Namini et al.	2018	LSTM	Time Series Forecasting	Small and large sequential datasets

Figure 2.4: Qualitative analysis between XGBoost and LSTM for financial forecasting in FinTrack.



2.4 Existing Personal Finance Apps Analysis

The evolution of personal finance tools has brought significant improvements in how individuals track spending, set budgets, and manage financial goals. Applications like Mint, You Need A Budget (YNAB), PocketGuard, and Spendee have been widely adopted and praised for their usability, automation, and financial visibility. However, despite their contributions to digital finance, these apps share common limitations, especially in the areas of predictive budgeting, AI integration, and real-time decision support—gaps that FinTrack seeks to address.

Mint, developed by Intuit, is one of the most popular personal finance apps globally. It aggregates data from various accounts and automatically categorizes transactions. Users can view charts, budget summaries, and spending breakdowns (Intuit Inc. 2023). However, Mint's features are largely reactive, offering insights based on past transactions without any forward-looking functionality. It lacks any built-in predictive analytics to forecast future financial activity. Furthermore, it does not provide real-time recommendations or AI-powered assistance. This static nature means that while users can monitor their spending, they receive no guidance on how to improve or adapt based on their financial behavior.

YNAB (You Need A Budget) approaches budgeting with a philosophy of giving every dollar a job, encouraging users to plan ahead with intention. It offers strong manual control, goal tracking, and educational content You Need A Budget (2023). However, YNAB requires significant user effort and does not use predictive models or intelligent systems to automate budgeting or provide suggestions. The system also lacks AI-driven assistants or chatbots to help answer questions or guide users. Although its method is effective for disciplined budgeting, the absence of automation and foresight makes it less scalable for users who prefer efficiency and smart insights.

PocketGuard is designed to help users avoid overspending by clearly showing what's "left in your pocket" after bills and savings. While it offers real-time visibility into available funds, its suggestions are based on fixed rules rather than adaptive learning. PocketGuard does not implement predictive analytics to forecast future spending patterns or simulate savings scenarios. It also lacks interactive support features like a financial chatbot, meaning user engagement relies on basic alerts and dashboards without deeper insights PocketGuard Inc. (2023).

Spendee appeals to users who prefer visual design and simplicity. It allows for manual or bank-synced tracking, shared wallets, and goal setting. However, like the others, it does not offer intelligent analysis or future projections. There is no forecasting engine to help users plan upcoming expenses, and its budgeting suggestions are limited to static categories and thresholds. Without integration of AI or predictive modeling, Spendee remains largely a descriptive tool rather than a strategic one (Spendee Ltd. 2023).

All four apps reviewed here lack integrated AI chatbots, forecasting engines, and automated, intelligent feedback mechanisms. While they succeed in helping users record and visualize data, they fall short in enabling proactive financial planning. Most insights offered are based on past behaviors without adaptation to changing patterns or scenarios.

FinTrack addresses these limitations by introducing forecasting capabilities through an XGBoost model, which predicts future spending based on historical data. Although FinTrack does not yet provide fully personalized financial advice, it incorporates an AI-powered chatbot using Google's Gemini API to deliver general financial guidance. This chatbot can assist with common finance-related questions in real-time, adding a layer of interaction not found in the apps above. Additionally, FinTrack estimates time-to-goal progress based on savings inputs, offering users calculated, forward-looking insights.

In summary, current leading apps offer strong basic features but lack intelligence and foresight. FinTrack fills these gaps by introducing predictive modeling and AI-assisted interaction, even though its advice is not yet tailored to individual financial behavior. This foundation sets the stage for future enhancements where true personalization—based on user-specific data—can be achieved.

Table 2.2: Comparison of Key Features in Personal Finance Applications

App	Predictive Analytics	AI Chatbot	Real-Time Insights	Automation Level	Personalized Suggestions
Mint	No	No	Limited	Moderate	No
YNAB	No	No	Moderate	Low	No
PocketGuard	No	No	Moderate	Moderate	No
Spendee	No	No	Limited	Moderate	No
FinTrack	Yes (XGBoost)	Yes (Gemini API)	Yes	High	Partially (General Advice)

These studies collectively highlight the transformative potential of AI and machine learning in personal finance management. FinTrack builds upon these insights by integrating XGBoost for predictive analytics and incorporating AI-powered chatbots to provide real-time financial guidance, aiming to enhance user engagement and financial decision-making.

2.5 Related Academic Work and Its Influence on FinTrack

Academic research and independent projects have significantly contributed to the evolution of personal finance management systems, particularly through the integration of artificial intelligence (AI) and predictive analytics. These studies offer valuable insights into the strengths and limitations of existing methods, highlighting opportunities for improvement—many of which FinTrack aims to address.

(Talasila 2024) introduced MyFinanceAI, an advanced AI-driven personal finance management system designed to tackle complex financial challenges faced by modern consumers. The system employs a multi-layered architecture with sophisticated machine learning algorithms to provide real-time analysis, personalized recommendations, and predictive insights. A comprehensive pilot study involving 1,000 users over six months demonstrated significant improvements in financial stress reduction, savings rates, an...

According to a comparative study published in the Mountain Top University Journal of Applied Science and Technology (Adebayo et al. 2024) of time series forecasting models, researchers evaluated the performance of XGBoost, LSTM, and ARIMA algorithms in predicting financial data. The study found that XGBoost demonstrated superior performance in terms of speed and interpretability, while LSTM provided better accuracy when predicting long-term price movements.

Further research by (Hidayat et al. 2024) examined the impact of AI on financial management, exploring the implementation of AI technology in financial decision-making strategies, predictive analysis, and risk management.

2.6 Clearly Defined Literature Gap

The comprehensive review of existing scholarly and practical work reveals a persistent and significant gap in current personal finance applications: the lack of robust predictive analytics and real-time AI-driven user interaction. While mainstream apps like Mint, YNAB, PocketGuard, and Spendee have simplified expense tracking and offered basic financial visualization, they fall short in enabling users to proactively manage their finances through dynamic forecasting or adaptive advice systems. Most tools...

Academic studies (e.g., (Hidayat et al. 2024); (Omarini 2017)) support this observation, highlighting that many existing fintech tools function primarily as passive financial trackers rather than intelligent, interactive assistants. Even advanced research projects—such as the development of MyFinanceAI by (Talasila 2024)—emphasize the need for real-time analytics, AI-driven personalization, and contextual financial recommendations to improve user engagement and financial outcomes.

Furthermore, recent comparative analyses (e.g., (Li 2023); (Siami Namini et al. 2018)) demonstrate that while traditional forecasting models like LSTM offer strong long-term prediction capabilities, they often fall short in smaller-scale, real-time use cases. This supports FinTrack's approach to integrating lightweight, interpretable models like XGBoost alongside interactive AI guidance to bridge the engagement and functionality gaps in current personal finance applications.

FinTrack addresses these exact gaps by integrating XGBoost, a lightweight and highly accurate algorithm that effectively forecasts user spending patterns, even with small datasets. In addition, FinTrack deploys a Google Gemini-powered chatbot to provide AI-generated financial guidance.

By combining predictive analytics, goal-based projection tools, and interactive AI features, FinTrack emerges as a forward-thinking solution that aligns with the growing demand for intelligent, user-centric fintech applications. It not only advances the current state of digital finance tools but also lays the groundwork for future personalization and adaptability in personal finance technology.

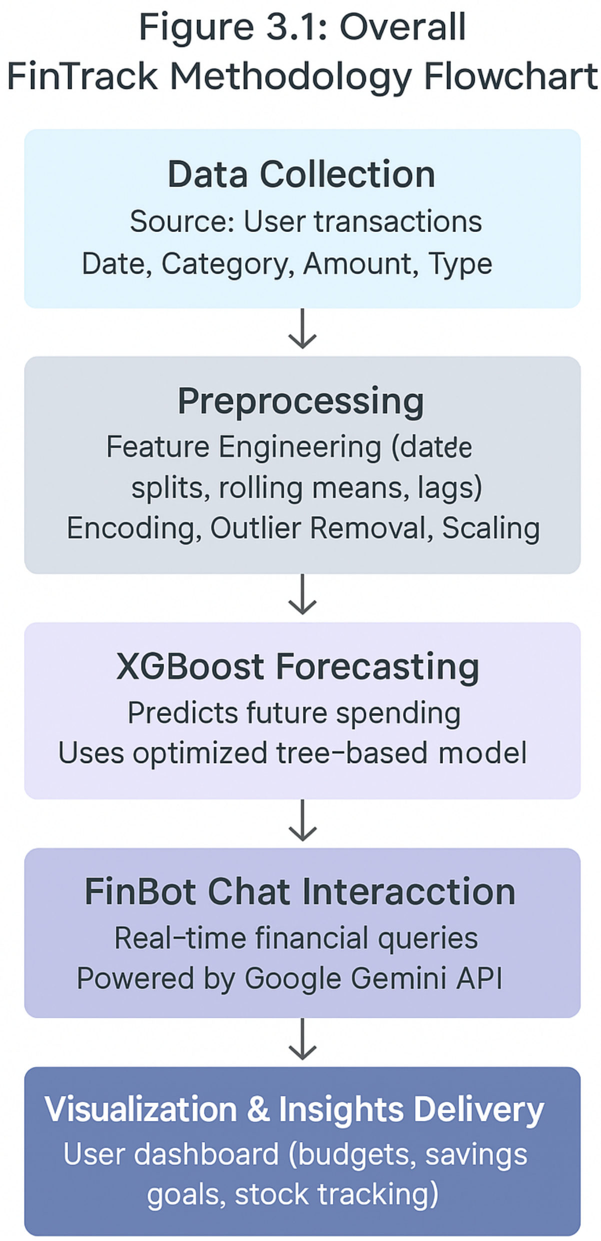
CHAPTER 3

Methodology

3.1 Overview

The primary objective of this project is to develop a personal finance management platform—FinTrack—that enhances conventional budgeting tools through the integration of predictive analytics and AI-powered conversational support. Aimed primarily at students and young professionals, the system offers insights into spending trends and provides intelligent assistance for making informed financial decisions.

Figure 3.1: Overall FinTrack Methodology Flowchart



The solution is centered around two main components. First, a predictive analysis engine based on the XGBoost algorithm forecasts future spending patterns using historical transaction data. This equips users with forward-looking insights to better manage their budgets. Second, a real-time financial chatbot, FinBot, is built using the Google Gemini API, enabling users to receive instant answers to general financial queries through natural language conversation.

The backend stack is built using Python, Flask, and Firebase for authentication, while financial records are stored locally using SQLite. Additionally, the

Tingo API is integrated for live stock market analysis. On the frontend, developed in Flutter, financial visualizations such as pie charts, line graphs, and bar charts are rendered using Flutter widgets to ensure a seamless and responsive user interface. This combined architecture delivers an engaging and intelligent budgeting experience.

3.2 Data Collection and Preprocessing

3.2.1 Dataset Overview

The dataset used for developing FinTrack's predictive analytics component is the Personal Budget Prediction Dataset sourced from Kaggle (available at: Kaggle Link). This dataset is well-suited for financial forecasting as it reflects real-world individual budget behavior across daily transactions. The dataset, while suitable for proof-of-concept development, was sourced from Kaggle and may not fully represent broader or more diverse financial behaviors. This limitation is acknowledged and discussed in Chapter 7.

It contains typical financial features including:

- `amount` – the transaction value
- `category` – the transaction type (e.g., groceries, rent, utilities)
- `date` – the timestamp of the transaction
- `type` – income or expense classification

The structure provides an ideal foundation for both categorical pattern recognition and time-based forecasting, which are core to building a budget prediction engine.

3.2.2 Preprocessing Steps

Preprocessing was conducted using Python libraries such as `pandas`, `numpy`, `scikit-learn`, and `xgboost`, with the pipeline executed in Google Colab for cloud-based reproducibility. Initial steps involved parsing the `date` field into multiple features including:

- `year, month, day, day_of_week`, and a binary `is_weekend` feature

This temporal feature engineering enabled the model to capture periodic spending behaviors.

Next, categorical encoding was performed using `LabelEncoder` to numerically transform the `category` field into a machine-readable format, producing a `category_encoded` column. While more complex encodings like One-Hot Encoding were considered, Label Encoding was sufficient given XGBoost's ability to handle ordinal and categorical splits internally.

Outlier removal was applied using the Interquartile Range (IQR) method to eliminate anomalously high or low transaction values that could skew model training. The cleaned dataset was then augmented with rolling statistical features such as `rolling_mean_7`, `rolling_mean_30`, and lag variables including lag_1, lag_7, and lag_30. These time-window-based features were essential for capturing both recent and seasonal trends.

Further, total_spending_category, month_over_month_change, and previous_day_spending were engineered to give the model additional context on behavioral trends. The final step involved normalizing input features using RobustScaler, chosen for its resilience to outliers.

This preprocessing pipeline was encapsulated in a dedicated function and later deployed on the Flask backend as part of the /predict_spending endpoint, ensuring dynamic, real-time preprocessing of user transaction data before prediction. This seamless integration of preprocessing and model inference allows FinTrack to support high-frequency prediction requests at scale.

3.3 Predictive Analysis Methodology

3.3.1 Model Selection

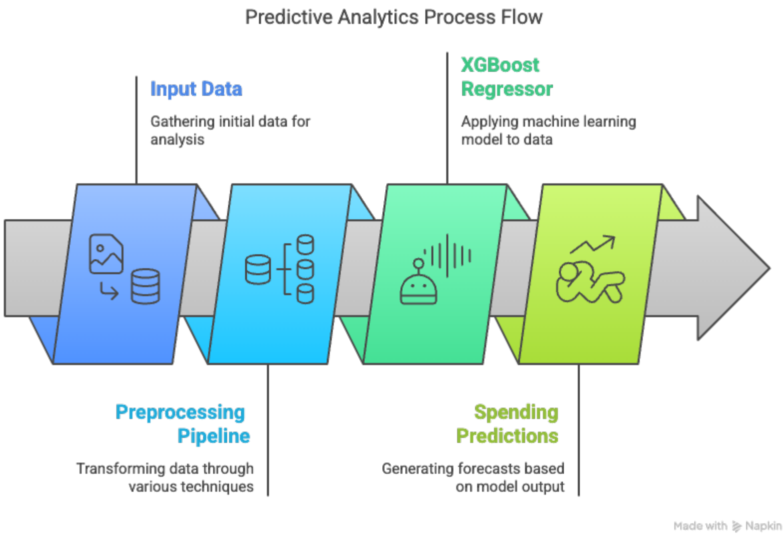
To build the predictive budgeting engine within FinTrack, the XGBoost (Extreme Gradient Boosting) algorithm was selected due to its exceptional performance with structured financial data and its scalability in real-world production environments. XGBoost is a tree-based ensemble learning method introduced by (Chen & Guestrin 2016), optimized for speed and accuracy. Its ability to handle missing values, capture non-linear interactions, and deliver interpretable results made it particularly well-suited to this use case, where the data is tabular, relatively small-scale, and time-structured.

The dataset was preprocessed using feature engineering techniques detailed in Section 3.2. After preprocessing, the data was split into training and testing sets using an 80/20 ratio to ensure generalization. The model was trained on the amount variable as the target feature, using engineered features like rolling_mean, day_of_week, lag variables, and more.

To optimize performance, Optuna was used for hyperparameter tuning across 50 trials. The final model was trained with the best-found parameters and evaluated using the following metrics:

- **Mean Absolute Error (MAE)** – measures average prediction error
- **Root Mean Squared Error (RMSE)** – penalizes larger errors more heavily
- **R^2 Score** – evaluates goodness-of-fit
- **Mean Absolute Percentage Error (MAPE)** – measures percentage-based prediction accuracy

Figure 3.2: Model pipeline for predictive budgeting in FinTrack, outlining the data flow from raw inputs to final spending predictions using XGBoost.



3.3.2 Alternative Models Considered

An LSTM (Long Short-Term Memory) model was initially tested due to its strength in modeling sequential dependencies and financial time-series. LSTM, proposed by (Hochreiter & Schmidhuber 1997), is a variant of Recurrent Neural Networks (RNNs) specifically designed to handle long-term dependencies.

However, in the context of FinTrack, the LSTM model presented practical limitations:

- **Small dataset size:** LSTMs typically require large volumes of data to avoid overfitting.
- **Computational inefficiency:** Training was slower and required significant GPU resources.
- **Interpretability:** LSTM outputs are often opaque, making it difficult to explain predictions to end users.

Due to these constraints, LSTM was not adopted for deployment.

3.4 Chatbot Development Methodology

3.4.1 System Design and API Selection

To enhance user interaction and support financial literacy, FinTrack includes a conversational assistant—FinBot, implemented using Google's Gemini API. Among competing large language models (LLMs) such as OpenAI's ChatGPT and Anthropic's Claude, Gemini was selected for several strategic reasons. Notably, Gemini offered better contextual handling, cost-efficiency, and seamless integration via Google AI Studio, which simplified deployment for the Flask backend.

The chatbot is designed to handle queries related to:

- Personal budgeting
- Savings tips
- Financial planning
- Stock trends
- Fintech literacy

The integration is secured using environment variables via a `.env` file, ensuring that the API key is never hardcoded. Prompt engineering was applied to define a finance-specific system prompt that ensures consistent, domain-relevant responses. Gemini's endpoint is accessed using standard `POST` requests, and response handling logic gracefully captures and interprets the LLM's output.

3.4.2 Backend Architecture (Flask API)

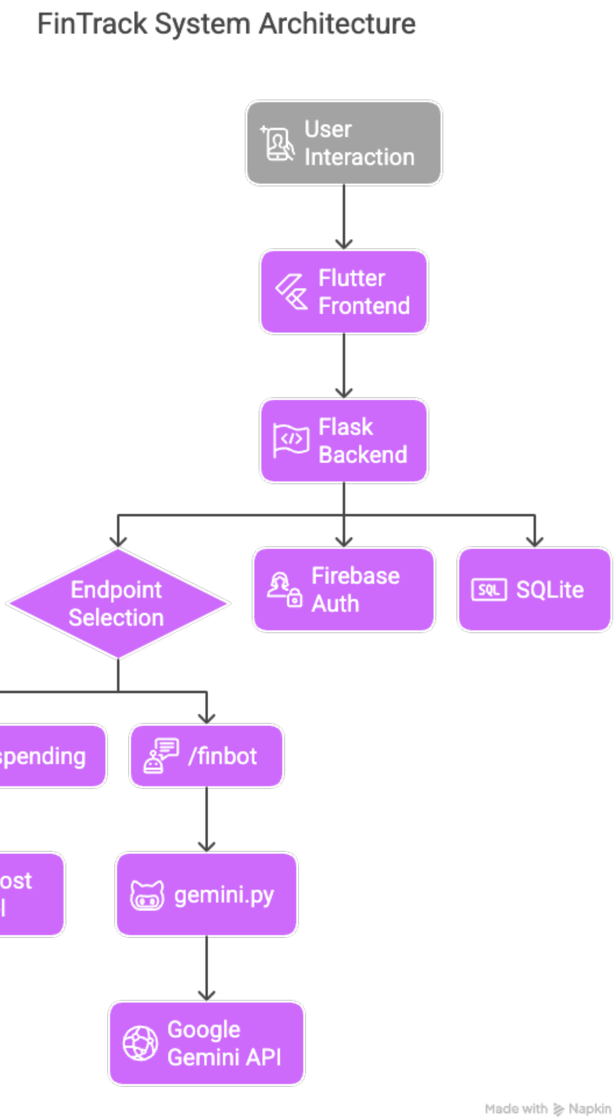
The backend of FinTrack is built using Flask, following a modular and RESTful design to serve AI-powered predictions and chatbot responses efficiently. The application communicates with the Flutter frontend through well-defined `HTTP POST` endpoints, ensuring seamless interaction between the user interface and backend logic.

The backend consists of two key routes:

- `/predict_spending`: Accepts user transaction history, preprocesses it, and generates future spending forecasts using a pre-trained XGBoost model. This endpoint also incorporates goal comparison logic and returns warnings when predicted expenses exceed income.
- `/finbot`: Handles user-submitted financial queries. It delegates the query to the `process_finbot_query()` function in `gemini.py`, which communicates with the Google Gemini API and returns a domain-specific, AI-generated response.

Additionally, Firebase Authentication is integrated to support user login and sign-up, but it operates independently from the predictive and chatbot components.

Figure 3.3: Architecture of FinTrack, illustrating how the Flutter frontend interfaces with Flask endpoints for prediction and chatbot responses.



3.4.3 SMS Parsing via Native Android Integration

To automate transaction entry and reduce manual input, FinTrack integrates a native SMS parsing feature specifically for Android devices. This feature is designed to extract financial transaction details directly from bank SMS alerts using platform channels, enabling communication between Flutter and native Kotlin code.

When a user taps the “Load SMS Transactions” button on the Flutter interface, a `MethodChannel` is triggered (`fintrack/sms`), invoking native Android code to access the SMS content provider. The Kotlin logic scans the inbox for messages containing transaction-related keywords (e.g., "AED", "debited", "credited") and returns the filtered messages to Dart.

In the Flutter layer, regular expressions are used to:

- Extract the amount
- Detect transaction type (credit/income or debit/expense)
- Identify the merchant name

A keyword-category map is then used to auto-categorize merchants, such as mapping "KFC" to Food or "Uber" to Transportation. To maintain data integrity, the system also checks for duplicates by comparing the parsed SMS with existing transactions (by amount, type, and description).

This feature is particularly relevant for the UAE region, where users commonly receive banking alerts via SMS rather than APIs. By automating the ingestion and categorization of such messages, the system significantly enhances real-world usability and user convenience.

3.5 Tools, Libraries, and Environment

FinTrack was developed using a modern tech stack that supports machine learning integration and mobile interaction. The backend was built in Python, utilizing the Flask web framework for handling API endpoints efficiently. SQLite was used as the primary local database for storing user transactions and budget data due to its simplicity and ease of use.

Firebase Authentication was incorporated to manage user login and registration securely. For the machine learning component, XGBoost was selected for its accuracy and performance with tabular data, while Pandas, NumPy, Scikit-learn, and Matplotlib were used for data preprocessing, transformation, and visualization. The AI chatbot functionality was powered by the Google Gemini API, integrated via a custom `gemini.py` module, and financial market data was retrieved using the Tingo API.

All development and testing were performed locally. The Flutter frontend was executed on a Google Android emulator, which allowed for real-time interaction testing without deployment.

CHAPTER 4

Implementation

4.1 System Architecture

FinTrack is designed as a modular, offline-first personal finance application that balances predictive analytics, financial interaction, and lightweight deployment. The system follows a client-server model, with a Flutter frontend acting as the user interface and a Flask backend providing data management, AI forecasting, and chatbot capabilities.

The backend communicates with three main functional pillars:

- a locally stored SQLite database,
- a trained XGBoost model for financial forecasting, and
- the Google Gemini API for real-time chatbot responses.

All modules are tied together using HTTP POST and GET endpoints handled by Flask.

As shown in Figure 4.1, the user communicates with FinTrack through a mobile interface (tested on a Google Android emulator), which sends requests to the Flask API. The API then performs model inference, database transactions, or AI chatbot generation depending on the request type.

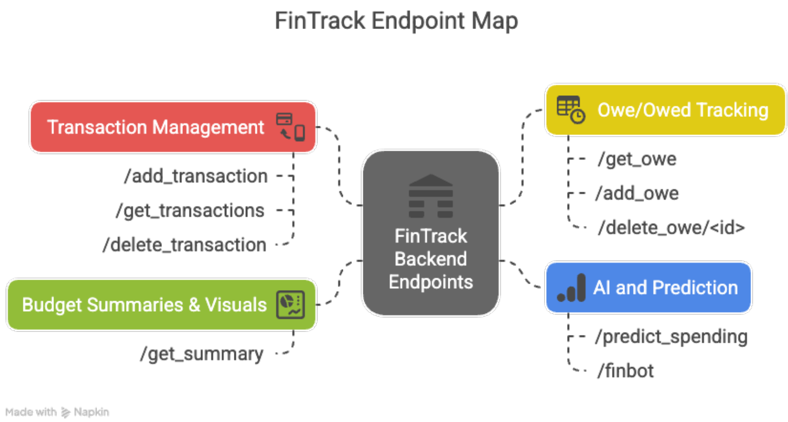
Backend Layer and API Routes

The Flask backend contains multiple endpoints organized by function:

- **Transactions:** `/add_transaction`, `/get_transactions`, `/delete_transaction`
- **AI Forecasting:** `/predict_spending` (uses XGBoost and preprocessing)
- **Chatbot:** `/finbot` (calls Gemini API via `gemini.py`)
- **Owe/Owed Tracking:** `/get_owe`, `/add_owe`, `/delete_owe/<id>`
- **Summary:** `/get_summary` returns categorized budget summaries

Each endpoint routes requests to internal helper modules such as `personal_ledger.py`, `transactions.py`, and `gemini.py`, which carry out the application's core logic. These interactions are mapped in Figure 4.2, which complements the broader architectural overview in Figure 4.1 by detailing the exact entry points and backend control flow.

Figure 4.1: FinTrack Flask Endpoint Map illustrating route-specific interactions and internal service handling logic across forecasting, ledger, chatbot, and debt tracking functionalities.



4.2 Feature-Level Implementation

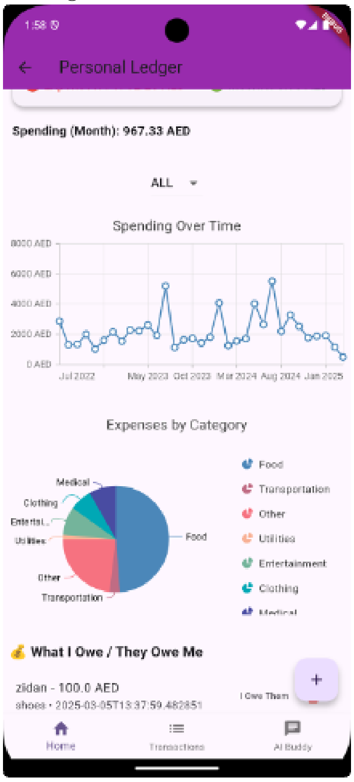
4.2.1 Personal Ledger and Visual Analytics

FinTrack's core functionality revolves around a robust personal ledger system powered by SQLite, a lightweight relational database suited for local data storage. The ledger stores detailed financial records including transaction ID, user ID, amount, category, type (income or expense), timestamp, currency, and description. This schema ensures every transaction is traceable, categorized, and aligned with user-specific financial activity.

Users interact with the ledger via the mobile frontend, where they can submit transactions through the `/add_transaction` endpoint. Each transaction is stored in the `transactions` table and categorized to allow visual summarization and budget tracking. Users can also delete entries using `/delete_transaction` and fetch historical data with `/get_transactions`.

To promote financial awareness and usability, the application integrates Flutter charting widgets for real-time visual analytics. A pie chart is used to represent spending distribution by category, while line and bar graphs illustrate weekly and monthly spending trends. Additionally, a dedicated Owe/Owed page visualizes outstanding personal debts using a separate `owe` table. This includes names, amounts, and due dates, helping users manage interpersonal financial responsibilities effectively.

Figure 4.2: Example Flutter UI displaying category-based pie chart and weekly line graph for expense tracking.



4.2.2 AI Forecasting with XGBoost

FinTrack integrates predictive analytics using XGBoost (Extreme Gradient Boosting) to generate future spending forecasts based on a user's historical transaction data. The model was trained offline using engineered features and stored locally as a `.pkl` file via `Joblib`. During runtime, it is loaded into the Flask backend and used for real-time predictions through the `/predict_spending` endpoint.

Data Flow and Preprocessing

When a user selects a forecast timeframe (e.g., 1M, 3M, 6M, 1Y), the backend first calls `fetch_daily_sums()` to compute a user's daily expenditure history from SQLite. The resulting DataFrame is passed into `preprocess_for_xgboost()`, a custom preprocessing function that prepares the input with time-based features like:

- `year, month, day, day_of_week`
- Rolling averages (`rolling_mean_7`, `rolling_mean_30`)
- Lag variables (`lag_1`, `lag_7`, `lag_30`)
- Spending trend indicators (`previous_day_spending`, `month_over_month_change`)

The function ensures that the final input vector matches the order and structure expected by the XGBoost model, which improves performance and prediction accuracy.

Dynamic Forecasting Logic

The backend uses the most recent 30 days of cleaned data to maintain the continuity of rolling and lag-based features. Then, for each future day, a synthetic row is generated based on the last row's values. It simulates new day-level fields (date, weekday, weekend), recalculates features, and feeds the resulting vector into the XGBoost model to get a predicted amount. This loop continues until the requested number of days is forecasted.

A custom warning system compares the total predicted spending with the user's reported income. If the forecast exceeds income, a caution message is returned to inform users of potential overspending.

4.2.3 FinBot Chatbot Functionality

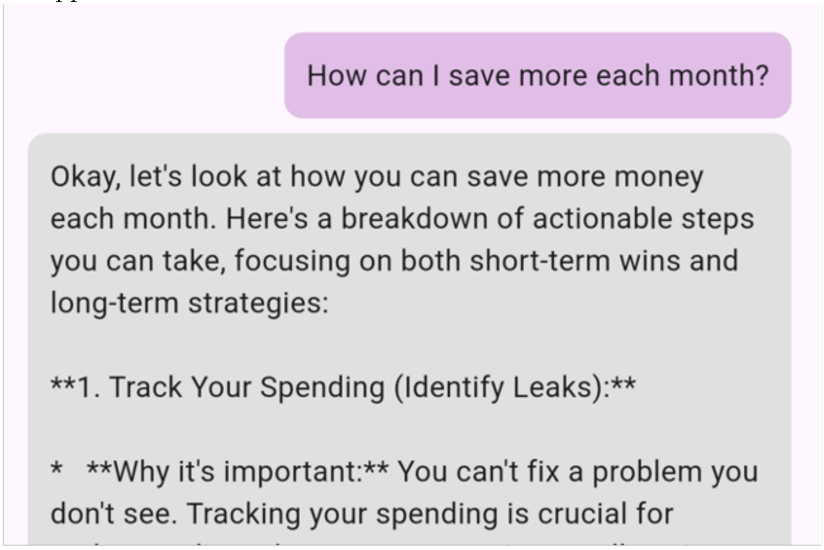
FinTrack integrates a lightweight yet powerful conversational agent, FinBot, designed to enhance user experience by providing finance-related guidance through natural language queries. The chatbot is built using the Google Gemini API, accessed via a dedicated module named `gemini.py`. This file defines a single function, `process_finbot_query()`, which constructs a finance-specific prompt, sends the query to the Gemini API, and parses the structured response.

The function wraps user input in a system prompt that ensures all answers relate to personal finance topics such as budgeting, investing, or saving. This prompt engineering approach helps generate contextually relevant, actionable responses.

The Flask endpoint `/finbot` receives JSON input from the frontend, containing the user's message. It then invokes the `process_finbot_query()` function and returns the result as a JSON response formatted for direct rendering in the Flutter UI. The chatbot interaction is stateless and does not maintain memory between sessions, which simplifies deployment and avoids persistent context handling.

FinBot allows users to ask personalized finance questions and receive immediate, AI-generated suggestions, complementing the app's predictive analytics with a conversational interface.

Figure 4.3: Screenshot of FinBot chatbot conversation within the FinTrack mobile application.



4.2.4 Stock Market Tracking (Tingo API)

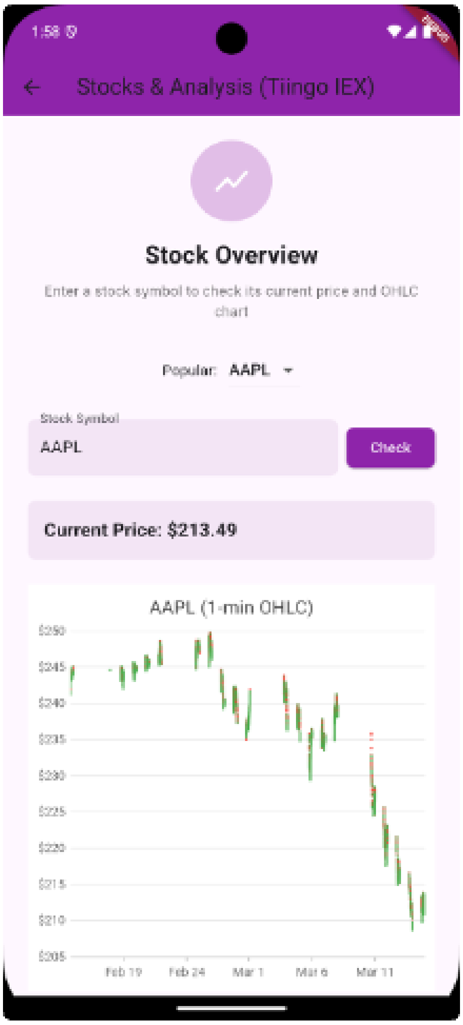
To enhance user decision-making and financial awareness, FinTrack integrates real-time stock tracking functionality using the Tingo API, a publicly available financial market data service. This feature enables users to search and view performance data for a wide range of stock symbols.

The API is queried from the Flutter frontend, which either dynamically constructs a request to the Tingo API or calls a backend proxy route to retrieve current price data and historical candlestick information. Users are provided with a dropdown menu containing top stock tickers (e.g., AAPL, MSFT, TSLA) to streamline the experience, but they can also search for custom tickers manually.

Upon receiving the response, the frontend parses key financial indicators and renders them into an interactive candlestick chart to visually represent stock movement trends. This visualization helps users interpret technical patterns and make informed investment decisions.

However, the integration is subject to limitations of the Tingo API's free tier, including request rate caps and restricted historical depth. Despite this, the functionality offers valuable supplementary insight for budget-conscious investors.

Figure 4.4: Candlestick chart generated using the Tingo API within the FinTrack mobile application.



4.2.5 SMS Parsing Feature

To enhance the user experience and minimize manual entry, a native SMS parsing feature was added to FinTrack. When users tap the "Load SMS Transactions" button, the app fetches bank SMS alerts from the device inbox using native Android code (Kotlin) via Flutter's platform channels.

The native code scans messages for patterns like "AED 100.00 debited at Carrefour", and sends relevant ones back to Flutter. These messages are then parsed using regular expressions to extract the amount, merchant, and transaction type (income or expense).

A mapping system was implemented to auto-categorize merchants (e.g., "KFC" → Food, "Uber" → Transportation). To avoid duplicates, each parsed transaction is checked against existing entries before being saved.

This feature improves automation and reflects real-world use cases, especially for users in regions like the UAE where SMS alerts are commonly used instead of banking APIs.

4.3 Technical Challenges and Solutions

During the development of FinTrack, several technical challenges emerged across both the backend and frontend, particularly during AI integration and third-party API usage. These obstacles were addressed iteratively using research, documentation, paid tools, and improved engineering practices.

One early challenge involved integrating Firebase Authentication. Initial SDK configuration and token handling created delays; however, this was resolved through official documentation and implementation tutorials.

The AI forecasting system presented more significant difficulties. The initial attempt to use LSTM models in Google Colab ran into GPU limitations due to the dataset size and compute constraints. This led to the purchase of Colab Pro ($10.99) for extended runtime and memory. However, even with improved resources, LSTM models proved unstable and overfit on limited data. As a result, the project transitioned to XGBoost, which handled tabular data more efficiently with significantly better training speed and accuracy.

Additionally, integrating the trained XGBoost model into the app surfaced prediction continuity issues related to time-series features like rolling averages and lag values. To address this, logic was implemented in the backend to recalculate these features daily during prediction loops.

The Gemini chatbot (FinBot) also presented formatting inconsistencies, particularly when queries were ambiguous or not strictly finance-related. A fallback mechanism was added, and stricter prompt templates were used to ensure the chatbot remained aligned with financial topics.

On the frontend, mobile responsiveness and chart visuals were initially subpar. Manually coded charts lacked clarity, especially for financial graphs like spending breakdowns and candlestick stock visuals. This was resolved by adopting Flutter charting widgets, which significantly improved aesthetic quality and data readability.

Finally, while Finnhub API was the preferred choice for stock tracking, its free tier only supported limited fields like current, low, and high prices—insufficient for rendering candle charts. Tingo API was chosen instead, as it offered richer historical data even under its free tier, allowing for proper visualization and better integration into the stock tracking module.

CHAPTER 5

Integrated Results and Discussion

5.1 Predictive Analytics: Model Selection and Performance

5.1.1 Model Selection Rationale

The predictive analysis module within FinTrack was developed to generate forward-looking spending insights by learning from historical transaction behaviors. An XGBoost (Extreme Gradient Boosting) regression model was selected due to its exceptional performance on structured financial data, interpretability, and computational efficiency. XGBoost is particularly well-suited for tabular datasets and has demonstrated superior performance in various financial forecasting tasks (Chen & Guestrin 2016). While Long Short-Term Memory (LSTM) networks are renowned for capturing long-term dependencies in sequential data, they often require large datasets to perform effectively. Given the limited size of the available dataset, LSTM was deemed less suitable for this application.

5.1.2 Evaluation Metrics

To assess model performance, the following evaluation metrics were employed:

- **Mean Absolute Error (MAE)**: Measures the average magnitude of errors in predictions, providing a straightforward interpretation of model accuracy.
- **Mean Squared Error (MSE)** and **Root Mean Squared Error (RMSE)**: These metrics penalize larger errors more significantly, offering insights into the distribution of error magnitudes.
- **R^2 Score**: Indicates the proportion of variance in the target variable explained by the model, with values closer to 1 signifying better performance.

- **Mean Absolute Percentage Error (MAPE)**: Captures relative prediction error as a percentage, particularly useful for financial time series data.

5.1.3 XGBoost Performance

After tuning with Optuna hyperparameter optimization, the XGBoost model achieved highly accurate results on the test set:

Best Parameters:

`n_estimators=289, max_depth=8, learning_rate=0.0502, min_child_weight=7, reg_lambda=1.52, reg_alpha=0.25`

Performance Results:

- MAE: 0.2687
- MSE: 0.3201
- RMSE: 0.5658
- R^2 Score: 0.987
- MAPE: 4.28%

These results indicate excellent fit and generalization, with the model capturing nearly 99% of the variance in spending behavior.

Figure 5.1: Actual vs. Predicted Spending Line Plot

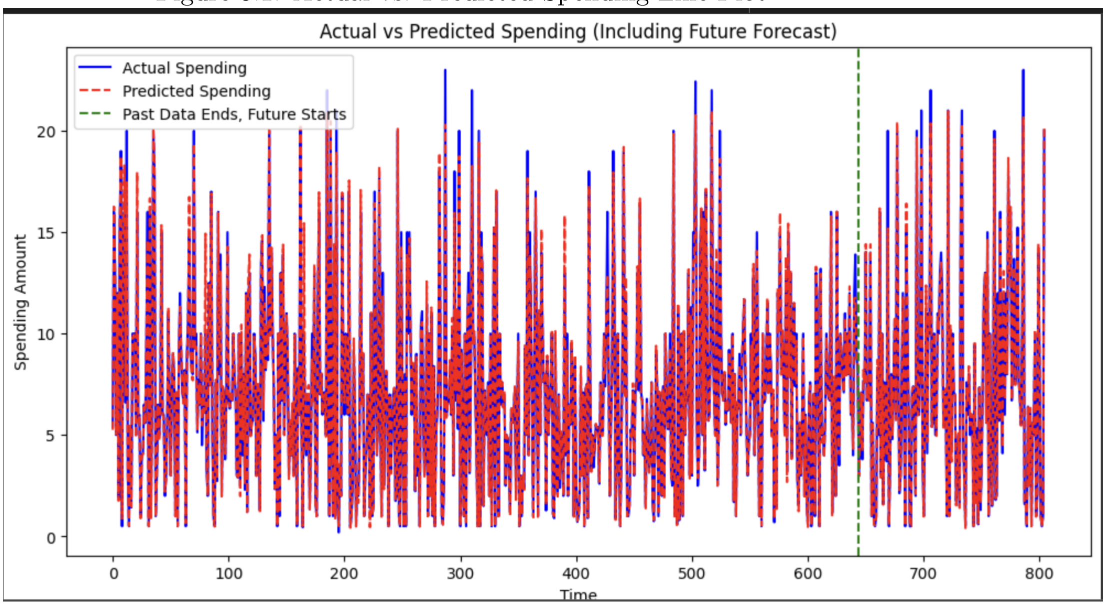
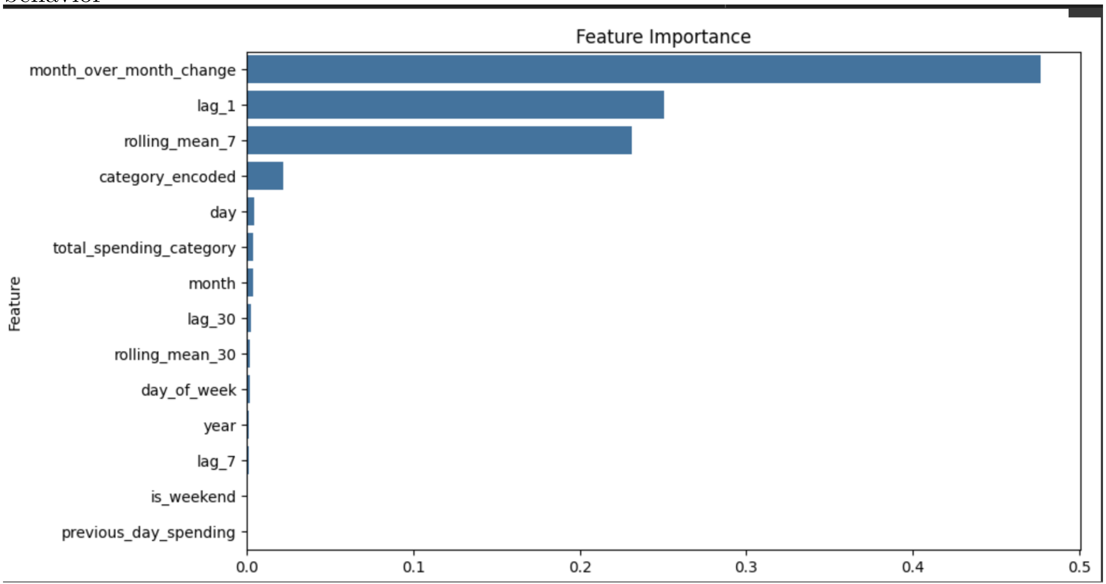


Figure 5.2: XGBoost Feature Importance showing the top predictors of financial behavior



Key contributing features included `month_over_month_change`, `lag_1`, `rolling_mean_7`, `day_of_week`, and `category_encoded`, reinforcing the value of time-based behavioral trends in forecasting.

5.1.4 LSTM Comparison (Rejected Model)

As part of the exploratory phase, a Long Short-Term Memory (LSTM) neural network was implemented to evaluate its suitability for personal finance time-series forecasting. While LSTM is often praised for capturing long-term dependencies in sequential data (Hochreiter & Schmidhuber 1997), the model's application in this project yielded suboptimal outcomes.

After training the LSTM on the preprocessed dataset, the results were as follows:

- MAE: 0.2298
- MSE: 0.00397
- RMSE: 0.0629
- R^2 Score: -6.32×10^{12} (extremely poor)

Although MAE and RMSE appear reasonable, the catastrophically negative R^2 score highlights a severe model failure. Possible reasons include:

- The model memorized training patterns without generalizing to test data
- Data leakage or poor validation strategy
- Divergence in loss curves due to poor convergence

- Absence of normalization layers or gradient explosion

Due to these constraints, LSTM was not adopted for deployment. Its instability, long training time, and lack of interpretability confirmed XGBoost as the superior choice for FinTrack's predictive engine.

5.2 FinBot: AI Chatbot Evaluation

5.2.1 Introduction

FinBot is an AI-driven chatbot integrated into the FinTrack application, powered by Google's Gemini API. Designed to deliver real-time responses to user queries, FinBot assists with budgeting tips, savings strategies, and general financial guidance. This section qualitatively evaluates its effectiveness by analyzing its clarity, relevance, and actionability through sample interactions that reflect common financial questions users might ask.

5.2.2 Prompt Examples and Responses

Example 1 — User: *"How can I save 1000 AED in 3 months?"*
FinBot: *Start by breaking your savings goal into monthly targets (e.g., 333 AED/month). Focus on essentials and avoid impulse purchases. Use cash envelopes for categories like food or transport. Take advantage of Ramadan and Eid offers. Track progress weekly.(Summary)*
Evaluation: Highly actionable and context-aware. The inclusion of culturally relevant advice (e.g., Ramadan, Eid) adds localization value. The structured format with breakdowns makes the information digestible. The disclaimer reinforces ethical AI practice.

Example 2 — User: *"Is it a good idea to invest in stocks on a low income?"*
FinBot: *Yes, but cautiously. Begin with small amounts. Focus on index funds or low-risk options. Investing builds discipline, teaches financial literacy, and can beat inflation. Prioritize emergency savings and avoid debt(Summary).*
Evaluation: The answer is well-balanced, addressing both potential benefits and necessary precautions. The structured points (growth, compounding, learning, inflation) show financial literacy and prudence.

Example 3 — User: *"What percentage of my salary should go to rent?"*
FinBot: *Ideally, your rent should not exceed 30–35% of your monthly income. This allows room for other expenses like savings, food, transport, and emergencies. Adjust based on your city's cost of living(Summary).*
Evaluation: Very clear and educational. The chatbot provides a rule-of-thumb with room for personalization, showing awareness of varying financial contexts. Practical and user-friendly.

5.3 SMS Parsing Feature Evaluation

5.3.1 Introduction

To streamline financial tracking and minimize manual input, FinTrack integrates a native Android SMS parsing feature. This functionality enables automatic ingestion of transaction data by parsing SMS alerts sent by banks. Built using Flutter's platform channels and Kotlin, the feature extracts structured data such as transaction amount, type (income/expense), and merchant name. It supports a more efficient and localized user experience, especially in regions like the UAE, where SMS banking is preva...

5.3.2 Emulator Testing and Evaluation

To evaluate the SMS parser, synthetic bank transaction messages were sent to the Android emulator using the built-in device manager. Messages included realistic examples like:

`\AED 250.00 was debited from your account at Carrefour."`

The feature accurately parsed the transaction amount (250.00), identified the type as an expense, and successfully recognized Carrefour as the merchant. Based on a predefined mapping, it then auto-categorized the entry as Groceries. The transaction was seamlessly added to the user's record without the ...

Additional messages representing various use cases (e.g., credited salary, online purchases, or transportation expenses) were also tested. The system consistently detected amounts, inferred transaction types, matched merchants to categories, and filtered out duplicates already present in the database.

5.4 User Evaluation and Summary

5.4.1 Emulator Testing

To assess usability and core functionality, Zidan (a final-year Business student) tested the app using a Pixel 9 Pro connected to the developer's laptop via an emulator session. He successfully:

- Added a transaction
- Generated a spending prediction
- Interacted with the FinBot chatbot
- Viewed financial breakdowns via interactive charts

Feedback Summary:
"The app is clean and easy to navigate. The chatbot gave useful and clear answers, and the category-based visuals were really helpful to understand spending patterns quickly. Only issue was the stock market analysis page—it was slow to load."

Based on feedback from the emulator testing, visual clarity was praised, but performance issues in the stock analysis screen led to streamlining data calls. Additionally, the user recommended making FinBot more proactive — a feature now planned for future iterations.

5.4.2 Survey Findings

A short Google Form survey was distributed, receiving 10 responses. Key takeaways include:

- 90% of respondents were interested in an app combining AI-powered budgeting with an interactive chatbot.
- The most valued features were spending predictions, category-based breakdowns, and chat-based financial guidance.
- Some users expressed curiosity about trusting AI with financial forecasts, suggesting the need for transparent logic or disclaimers.

5.4.3 Interpretation and Comparison with Literature

Interpretation of Results

The results from the FinTrack system demonstrate the practical viability and effectiveness of integrating AI for both predictive budgeting and real-time financial assistance. The predictive model, powered by XGBoost, yielded highly promising outcomes, achieving a Mean Absolute Percentage Error (MAPE) of approximately 4.28% and an R^2 score of 0.98. These metrics indicate a very strong correlation between actual and predicted values, showcasing the model's precision in forecasting short-term spending patterns. The use of rolling features and lag-based predictors ensured temporal consistency in the time series, making the model more reliable for near-future forecasts. While long-term predictions beyond 90 days may accumulate slight inaccuracies, the 30-day and 3-month forecasts remained highly consistent, supporting their utility for routine budgeting purposes. Integration of the trained XGBoost model into the Flask backend and its subsequent connection to the frontend allowed for real-time, low-latency predictions.

The chatbot component, FinBot, provided relevant and easy-to-understand financial guidance. Most responses, especially those involving savings strategies and budgeting, were both actionable and context-aware. For example, when asked about saving 1000 AED in three months, the chatbot offered step-by-step budgeting advice, categorized expense breakdowns, and even UAE-specific tips like Ramadan deals and VAT awareness. However, limitations emerged in responses that required deeper contextual memory or nuanced investment advice—where the output was sometimes too generic or lacked disclaimers. While FinBot was effective in answering domain-specific queries, its lack of contextual memory limits its ability to carry forward previous conversations. Additionally, it does not yet support real-time data ingestion or live financial updates. These issues reflect the inherent limits of using a single-prompt Gemini API instance without session continuity.

A noteworthy enhancement during the project was the addition of native Android SMS parsing, enabling FinTrack to automatically ingest and categorize financial transactions from user inboxes. This reduces manual entry and improves real-world usability—especially in regions like the UAE where SMS alerts are more prevalent than open banking APIs. The integration of platform channels and native Android content resolvers also exemplifies cross-platform mobile engineering best practices.

User evaluation, while limited to early testing, further validated the system's design choices. Zidan, a final-year business student, tested the app on a Pixel 9 Pro using emulator pairing and successfully navigated all core features—adding transactions, generating predictions, viewing charts, and querying FinBot. He praised the intuitive UI and visual spending breakdowns but noted that the stock analysis page was slightly slow, likely due to limitations in the free tier of the Tingo API. In parallel, a survey conducted with ten users showed that 90% were interested in a finance app combining AI forecasting and chatbot assistance. While the sample size is small, it supports the growing demand for accessible, intelligent personal finance tools, especially among digitally literate users.

Comparison with Literature

The integration of XGBoost into FinTrack's architecture resulted in a high-performing predictive engine, achieving an R^2 score of 0.987 and a Mean Absolute Percentage Error (MAPE) of 4.28%. These metrics indicate strong predictive reliability and low deviation from actual spending patterns, affirming the algorithm's suitability for small-scale, structured financial data. This outcome is consistent with observations by Nielsen (2016), who examined XGBoost's success in direct-response modeling and other structured-data problems, attributing its performance to high predictive accuracy and accessible interpretability through feature importance scores. XGBoost has been recognized for its efficiency in handling structured data, making it suitable for applications requiring real-time decision support, such as personal finance management tools like FinTrack.

In contrast, the Long Short-Term Memory (LSTM) model—though theoretically appropriate for sequential forecasting—exhibited significant instability during implementation. The LSTM model's inability to generalize, evidenced by a catastrophically negative R^2 value and erratic outputs, supports earlier findings by Siami Namini et al. (2018), who highlighted LSTM's tendency to underperform in small-scale datasets. Given that personal finance data typically spans limited durations (e.g., 3–6 months of history), LSTM's requirements for long sequences and large datasets made it an impractical choice for deployment within FinTrack's lightweight architecture.

The FinBot component, built using Google's Gemini API, demonstrated practical efficacy in delivering domain-relevant financial advice. Despite its stateless nature and lack of conversational memory, FinBot consistently produced clear, context-aware responses. This performance echoes the recommendations of Kim & Jeong (2021), who argue that effective financial assistants must provide not only informative but also interactive and memory-retentive experiences. Although FinBot currently lacks session persistence, its structured prompt engineering and user-friendly tone validate the potential of stateless LLMs as accessible entry points into AI-supported financial literacy tools.

Furthermore, the role of FinBot in promoting financial awareness aligns with broader academic insights on financial literacy. For instance, Lusardi & Mitchell (2014) emphasized the widespread gaps in financial knowledge, particularly among youth and underserved populations. Tools like FinBot can serve as intermediaries, offering simplified, on-demand advice that bridges knowledge gaps without overwhelming users. This project contributes to that vision by integrating intelligent responses into the everyday budgeting experience, showing how conversational AI can be a meaningful support layer in personal financial management.

Together, the results from the FinTrack application not only confirm the technical feasibility of combining XGBoost with LLM-powered financial assistants but also underscore their combined potential to democratize access to financial planning tools. Future enhancements—such as context-aware FinBot sessions and user-specific financial guidance—could further elevate the system's impact, transforming it into a truly adaptive financial companion.

5.5 Implications of the Findings

5.5.1 For Users

FinTrack showcases how predictive analytics and conversational AI can transform financial self-management. By offering personalized forecasts through XGBoost and real-time guidance via FinBot, users are empowered to make informed decisions with greater confidence. Even minimal early testing helped highlight usability concerns and shape planned improvements like proactive tips and improved chart loading. The ability to visualize category-based spending, simulate future expenses, and ask finance-related questions provides a level of interactivity and education not typically available in free financial apps. These features cater especially well to students, young professionals, and budget-conscious users—groups often underserved by existing platforms. This dual integration of predictive tools and AI-driven conversation bridges the gap between passive tracking and active financial planning, thus promoting better habits and improving awareness of personal financial health.

5.5.2 For Developers and Fintech Startups

From a development perspective, the project highlights key lessons in designing smart, modular financial systems. For example, handling rolling averages and lag features dynamically in the prediction pipeline was crucial for maintaining accuracy—especially when generating forward-looking forecasts in real time. This emphasizes the importance of time-series preprocessing in budget-based machine learning models. Additionally, the seamless integration of lightweight technologies—Flask, SQLite, Gemini API, and XGBoost—demonstrates that building intelligent financial tools does not require enterprise-level infrastructure or massive datasets. With a structured backend and prompt engineering, AI chatbots and ML-driven forecasts can be deployed in scalable, resource-efficient ways. Future versions of FinBot could leverage models like Gemini Pro or Gemini 1.5 with extended context windows to support memory and personalized session continuity.

5.5.3 For the Fintech Industry

The overwhelming interest in AI-powered financial planning, as seen in the 90% positive survey response rate, reflects a growing demand among younger demographics for intuitive, hybrid solutions. These users seek not just budgeting tools, but intelligent systems that offer proactive advice and relatable insights.

FinTrack's architecture suggests a future where AI-driven assistants become an integral part of personal finance, particularly in regions or user groups where traditional financial education is lacking. The industry stands to benefit by adopting more accessible, transparent, and low-barrier tools that combine analytics, personalization, and conversational interfaces—all while maintaining user trust and simplicity.

CHAPTER 6

Conclusion and Future Work

6.1 Summary of Achievements

This project successfully developed an intelligent personal finance management application—FinTrack—that integrates predictive budgeting through XGBoost and real-time conversational support via a Gemini-powered AI chatbot (FinBot). The core aim was to enhance users' financial literacy and planning capabilities by enabling smarter decision-making based on data-driven insights and AI interaction.

From a technical standpoint, the app features a robust XGBoost model capable of forecasting short- and long-term spending trends with high accuracy. The model uses a rolling feature-enhanced pipeline and was integrated into the backend for real-time responsiveness. FinBot, the chatbot component, is powered via the Google Gemini API and allows users to ask financial questions and receive instant, context-specific advice.

The backend architecture—developed using Flask, SQLite, and Firebase authentication—is modular and lightweight, ensuring adaptability and efficiency. Visual feedback mechanisms were implemented through Flutter charting widgets, including category-wise pie charts, bar graphs for historical trends, and a clear owe/owed financial overview.

The app's interface, tested on a Pixel 9 Pro emulator, proved user-friendly and intuitive. Critically, FinTrack fills a major gap in the current fintech ecosystem by offering a rare blend of AI-driven forecasting and interactive financial guidance, all built without enterprise-scale infrastructure—demonstrating what's possible with focused, resource-conscious development.

6.2 Research Limitations

Despite the successful implementation of FinTrack, several limitations were encountered throughout the development and evaluation phases.

Data constraints posed a key limitation. The predictive model was trained on a single dataset sourced from Kaggle, which may affect its ability to generalize across diverse financial behaviors. Additionally, while an LSTM-based model was briefly explored, it was ultimately abandoned due to computational inefficiencies, reducing the depth of comparative analysis.

User testing was limited by the lack of public deployment. Evaluation occurred through emulator testing with a single user, and while a survey was conducted with 10 participants, the small sample size limits broader generalizability.

FinBot, while useful, lacks contextual memory and live data integration for stock candle chart, preventing it from proactively adjusting its responses based on past interactions or real-time financial changes. Additionally, the chatbot operates on static prompt inputs without hallucination prevention or live API augmentation, which can affect depth and accuracy in certain financial topics.

Finally, due to infrastructure constraints, cloud hosting, multi-device testing, and comprehensive performance benchmarking were not conducted during the project.

6.3 Future Work

Several promising directions can enhance the capabilities and impact of FinTrack in future iterations. To begin with, FinBot can be improved by integrating contextual memory, enabling the chatbot to learn from prior conversations and provide follow-up insights.

On the forecasting side, expanding the prediction engine to incorporate real-time income and transaction data would make budgeting advice more dynamic. If larger datasets become available, exploring deep learning models like LSTM or Transformer-based architectures could uncover richer patterns in user behavior.

From a usability standpoint, deploying the app publicly and conducting end-to-end user testing will help refine the interface and gather valuable feedback. Additional features such as bank account integration, goal-based financial planning, and enhanced stock market analysis could make FinTrack a comprehensive financial assistant for young professionals and budget-conscious users alike.

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