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A Chatbot for personalized financial advisory and Investment Planning in Kenya

By

Sharon Bukaya

096534

Submitted in Partial Fulfilment of the Requirements for the Degree of Master of Science in Computing and Information Systems at Strathmore University

School of Computing & Engineering Sciences, Strathmore University

Nairobi, Kenya

June, 2025.

Declaration and Approval

I declare that this work has not been previously submitted and approved for the award of a degree by this or any other University. To the best of my knowledge and belief, the dissertation contains no material previously published or written by another person except where due reference is made in the dissertation itself.

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Student's Name: Sharon Bukaya

Sign: _____ Date: 27/05/2025

The dissertation of Sharon Bukaya was reviewed and approved for examination by the following:

Professor Ismail Ateya
School of Computing & Engineering Sciences,
Strathmore University.

Dr. Julius Butime,
Dean, School of Computing & Engineering Sciences,
Strathmore University.

Prof. Bernard Shibwabo,
Director of Graduate Studies,
Strathmore University.

Abstract

Financial illiteracy in Kenya remains a significant barrier to economic participation, limiting individuals' access to investment opportunities, insurance products, stock trading, retirement planning, and effective savings strategies. This research addressed the critical gap in affordable, transparent, and customized financial advisory services by developing an AI-powered chatbot tailored specifically for the Kenyan market. The study employed a mixed-methods approach combining exploratory, design-based, and experimental research methodologies to create and evaluate the chatbot system. Data was collected from 1,000 survey respondents representing diverse demographic and economic segments across Kenya, revealing key financial challenges and technology preferences. The chatbot architecture integrated natural language processing using BERT-based models, real-time market data from the Nairobi Securities Exchange and Central Bank of Kenya, and personalized recommendation algorithms. The system achieved 91.76% accuracy in intent recognition and 90.23% in parameter extraction across diverse financial domains. Notable innovations included bilingual support for English and Swahili with code-switching capability, mobile money integration, and culturally adapted financial advice. Performance evaluations demonstrated sub-50ms response times for 95% of queries, making the system accessible even on low-bandwidth connections. The chatbot successfully democratized access to professional-quality financial advisory services, particularly benefiting underserved populations who previously lacked such resources. This research contributes significantly to financial inclusion efforts in Kenya by demonstrating that AI-powered systems can effectively bridge the financial literacy gap when properly contextualized for local markets. The findings have important implications for developing similar solutions in other emerging economies facing comparable financial inclusion challenges.

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List of Abbreviations and Acronyms

AI	Artificial Intelligence
AGOA	African Growth and Opportunity Act
AML	Anti-Money Laundering
ANOVA	Analysis of Variance
API	Application Programming Interface
BERT	Bidirectional Encoder Representations from Transformers
CAPM	Capital Asset Pricing Model
CBK	Central Bank of Kenya
CMA	Capital Markets Authority
CNN	Convolutional Neural Network
COMESA	Common Market for Eastern and Southern Africa
CRB	Credit Reference Bureau
DBR	Design-Based Research
DCF	Discounted Cash Flow
DFS	Digital Financial Services
DQN	Deep Q-Networks
EAC	East African Community
EPS	Earnings Per Share
ESG	Environmental, Social, and Governance
ETF	Exchange-Traded Fund
FSD	Financial Sector Deepening
FX	Foreign Exchange
GPT	Generative Pre-trained Transformer
GUI	Graphical User Interface
HCI	Human-Computer Interaction
HTTP	Hypertext Transfer Protocol
HTTPS	Hypertext Transfer Protocol Secure
ICIFA	Institute of Certified Investment and Financial Analysts
IFRS	International Financial Reporting Standards
IoT	Internet of Things

IPO	Initial Public Offering
IRA	Insurance Regulatory Authority
IRB	Institutional Review Board
JSON	JavaScript Object Notation
JWT	JSON Web Token
KBA	Kenya Bankers Association
KEPSA	Kenya Private Sector Alliance
KES	Kenyan Shilling
KNBS	Kenya National Bureau of Statistics
KRA	Kenya Revenue Authority
KYC	Know Your Customer
LLMs	Large Language Models
LSTM	Long Short-Term Memory
M&A	Mergers and Acquisitions
MFA	Multi-Factor Authentication
MFI	Microfinance Institution
ML	Machine Learning
MSE	Mean Squared Error
MVP	Minimum Viable Product
NER	Named Entity Recognition
NHC	National Housing Corporation
NHIF	National Hospital Insurance Fund
NLP	Natural Language Processing
NPL	Non-Performing Loan
NSE	Nairobi Securities Exchange
NSSF	National Social Security Fund
OAuth	Open Authorization
P/E	Price-to-Earnings Ratio
PDPA	(Kenya's) Data Protection Act
PLS-SEM	Partial Least Squares Structural Equation Modelling
PoS	Part of Speech

RBAC	Role-Based Access Control
REIT	Real Estate Investment Trust
REST	Representational State Transfer
RNN	Recurrent Neural Network
ROA	Return on Assets
ROE	Return on Equity
ROI	Return on Investment
RPA	Robotic Process Automation
SACCO	Savings and Credit Cooperative Organisation
SASRA	SACCO Societies Regulatory Authority
SDK	Software Development Kit
SDH	State Department of Housing
SPSS	Statistical Package for the Social Sciences
SVM	Support Vector Machine
TAM	Technology Acceptance Model
T-Bills	Treasury Bills
TF-IDF	Term Frequency-Inverse Document Frequency
UI	User Interface
USSD	Unstructured Supplementary Service Data
UX	User Experience
XAI	Explainable AI

VT OMNES VNVM SINT

Definition of Terms

AI-Based Chatbot	A service provided by financial professionals to help clients make informed decisions about managing their personal or business finances. This involves analysing financial goals, assets, liabilities, and future objectives to recommend suitable strategies (Investopedia, n.d.).
API Integration	The process of connecting a chatbot to external systems and data sources through Application Programming Interfaces (APIs) enables real-time access to financial data and service delivery (Hana Demma Wube et al., 2022).
BERT (Bidirectional Encoder Representations from Transformers)	A deep learning model for natural language processing that processes words about all other words in a sentence, rather than one by one, thereby improving context understanding in chatbots (Yu et al., 2020).
Capital Asset Pricing Model (CAPM)	A financial model that describes the relationship between systematic risk and expected return for assets, particularly stocks, is used widely for portfolio management and investment evaluation (Madhuranthagan & Shantha, 2021).
Conversational User Interface (CUI)	A digital interface that enables users to interact with a system through conversation, either text or voice-based, forming the foundation of chatbot interaction (Candello & Pinhanez, 2018).
Deep Q-Networks (DQN)	A reinforcement learning technique that integrates Q-learning with neural networks to solve complex problems, thereby enhancing chatbots' decision-making capabilities (Awoga, 2021).
Digital Financial Education	Using digital tools, platforms, and resources to educate individuals on financial topics enhances their financial literacy and ability to make informed financial decisions (Investopedia, n.d.).

Discounted Cash Flow (DCF)	A valuation method used to estimate the value of an investment based on its expected future cash flows, adjusted for the time value of money (Jagannayaki et al., 2024).
Entity Extraction	The process of identifying and categorizing key elements in text into predefined categories such as financial terms, monetary values, dates, and organisations (Sai Sharath & Rekabdar, 2021).
Financial Advisory Services	Professional guidance is provided to individuals and organisations regarding wealth management, investment strategies, and financial planning, tailored to their specific needs and goals (Balaji & Rao, 2019).
Financial Inclusion	The delivery of financial services at affordable costs to disadvantaged and low-income segments of society who traditionally lack access to banking and related services (Fanta & Mutsonziwa, 2021).
Financial Literacy	The possession of knowledge and understanding of financial matters enables individuals to make informed and effective decisions with their financial resources (Goyal & Kumar, 2020).
Human-Computer Interaction (HCI)	The study of how people interact with computers and to what extent computers are developed for successful interaction with humans is crucial for effective chatbot design (Huang & Benyoucef, 2024).
Intent Recognition	The ability of a chatbot to understand the purpose or goal behind a user's input is critical for accurately responding to financial queries and requests (Carlos Alexander Jarquin et al., 2023).
Investment Planning	The process of matching financial goals, risk tolerance, and time horizons with suitable investment vehicles involves analysing various asset classes and strategically allocating resources (Bani Hani, 2020).
Knowledge Base	A centralized repository of information containing financial data, facts, and rules that a chatbot uses to generate accurate responses to user queries (Nguyen et al., 2021).

Large Language Models (LLMs)	Advanced AI systems trained on vast amounts of text data can generate human-like responses to text inputs, enabling chatbots to provide natural and contextually appropriate financial advice (Lakkaraju et al., 2023).
Machine Learning (ML)	A subset of artificial intelligence focuses on building systems that learn from data, identify patterns, and make decisions with minimal human intervention, as seen in chatbots for continuous improvement (Fritz-Morgenthal et al., 2021).
Mobile Banking	Financial services are accessed and delivered via mobile devices, enabling users to conduct financial transactions remotely using mobile applications (Melubo & Musau, 2020).
Natural Language Processing (NLP)	A branch of artificial intelligence that enables computers to understand, interpret, and respond to human language in a valuable way, forming the core technology behind conversational chatbots (Bhupesh Patra & Mahendra Kumar, 2020).
Personalization Techniques	Methods used to tailor content, recommendations, and user interfaces based on individual user data, preferences, and behaviours to enhance relevance and engagement (Wang et al., 2021).
Reinforcement Learning	A type of machine learning where an AI agent learns to make decisions by taking actions in an environment to maximize cumulative reward, used to improve chatbot responses over time (Wang et al., 2021).
Risk Profiling	The process of determining an investor's willingness and ability to take risks in their investment decisions is typically assessed through questionnaires and analysis of their financial situation (Slezakova, 2020).
Robo-Advisors	Automated platforms that provide financial advice or investment management online with minimal human intervention, using algorithms and data to create and manage investment portfolios

	(Abhinav Pal et al., 2021).
Sentiment Analysis	The process of computationally identifying and categorizing opinions expressed in text to determine attitudes toward a particular topic, service, or product (Moses Sugumar & Shalini Chandra, 2021).
User Experience (UX)	The overall experience of a person using a product, particularly in terms of its ease of use and pleasure, is crucial for chatbot adoption and continued engagement (G. Silva & E. Canedo, 2022).
User Profiling	The process of collecting and analysing user data to create detailed representations of individual users, enabling personalized recommendations and experiences based on their specific characteristics and preferences (Bai et al., 2024).

Acknowledgments

I am deeply grateful to the Almighty God for the grace and guidance he has granted me throughout my research and the writing of this dissertation. I would also like to thank Prof. Ismail Ateya Lukandu for his significant experience and ideas in Research Methodology, IT Thesis, Presentation, and Software Modelling. His expertise and advice have been instrumental in helping me navigate the complexities of this work and complete it.

Dedication

This dissertation is therefore dedicated to the fraternity of Strathmore University, to my friends, family, and classmates, whose support has been indispensable in creating an atmosphere conducive to learning, innovation, and development.

Chapter 1: Introduction

1.1 Background to the Study

Financial advice and investment planning encompass providing a comprehensive range of information about various financial products and developing tailored strategies for clients to manage their investments and achieve their financial goals (Slezakova, 2020; Bani Hani, 2020). This process includes assessing an individual's financial objectives, current assets, and liabilities to create a plan for achieving their short-term and long-term goals (Bani Hani, 2020). If there is one thing that financial planning and investment are a good indicator of, it is that managing personal wealth and achieving financial goals is a big issue.

Financial advisers are akin to physicians in the medical field, in that they assist investors in achieving financial well-being (Balaji Rao, 2019). They utilise their knowledge of investments, taxes, and insurance to recommend strategies that achieve the client's short- and long-term objectives, ranging from purchasing a house to saving for college or retirement (Web team, 2013). In financial planning, one assesses the person's desired financial position and the resources available to them, and then takes steps to achieve these goals within a specified period (Bani Hani, 2020).

Traditional financial advice, ranging from door-to-door calls to human intermediaries, is ill-equipped to tackle the complexity and risk management of modern financial products (Abhinav Pal et al., 2021). All these routes are under pressure from technological disruption and shifts in consumer tastes. Cocca (2016) found that robo-advisors and data analytics were changing the way retail investors make investment decisions and manage risk. However, Cocca (2016) also suggested that a hybrid model, combining the old and new forms of advisory, appeared to be the most probable future for wealth management clients. The AI-powered personal finance advisor chatbot promises to address a whole bunch of issues in financial advice and investment planning. This is a significant problem: traditional advisory services are costly, and most people cannot afford them. The chatbot is a solution that makes it more affordable by eliminating much of the manual work. Even better, it is always available, and others, including those living far away or in impoverished nations, can access advice

whenever they need it. The chatbot mitigates the impersonality of traditional methods by utilising AI to assess each person's unique financial circumstances, objectives, and risk appetite, and then recommends investments accordingly.

In the literature on chatbots in personalized financial advice, several vital papers have emphasized the importance of user acceptance, trust, and engagement. Trust on the user's part is a widely reported factor in the uptake of chatbot technology, and users must perceive the technology as safe before interacting with it (Khalid et al., 2021; Zeng et al., 2021). However, knowledge of the technical details of chatbot design, systematic user experience studies, and the emotional dimensions of user engagement is still lacking (Huang & Benyoucef, 2024; Schneider et al., 2023).

These frameworks, such as the Technology Acceptance Model (TAM) and Trust Theory, facilitate an understanding of how users interact with chatbot technology (Newcastle University, n.d.; Analytics Insight, n.d.). However, there is a need for longitudinal studies and comparative analyses between text-based and voice interfaces (Rogers et al., 2023; Chat360, n.d.). Bridging these gaps might also enable chatbots to deliver more effective individualized financial guidance and unlock new possibilities for investment planning. This research aims to map the emerging world of digital financial advice and understand how user needs and preferences are shaped.

It will evaluate the current market for AI-powered financial advice products and examine existing infrastructure that facilitates personalized investment planning. With a chatbot that incorporates user profiling, the study aims to provide personalized financial advice, thereby enhancing the user experience. The research will also evaluate the chatbot's success in delivering personalized recommendations and its overall effectiveness. It will contribute to the growing body of literature on how AI will make financial advising a more consumer-friendly field. Chatbots and AI hold significant potential to enhance individualized student advising; however, empirical research is needed to assess their effectiveness (Thottoli et al., 2024).

Advanced language models, such as BERT, can facilitate the development of

sophisticated financial service chatbots that manage complex client inquiries and uncertainties, as demonstrated by Yu et al. (2020). In Nigeria, for example, Mogaji (2020) reported that banks are increasingly relying on chatbots to enhance the customer experience and increase financial inclusion, primarily through services such as WhatsApp. However, issues related to responsiveness, language support, and privacy persist. These results highlight the potential of chatbots to revolutionize financial services and education, while also underscoring the need to continue developing them to address existing limitations.

1.2 Problem Statement

Financial illiteracy in Kenya remains a pressing issue, affecting individuals' access to and engagement with investment opportunities, insurance, stock trading, retirement planning, and savings. Studies have shown that a lack of financial literacy restricts Kenyans' participation in investment markets, contributes to poor financial planning, and increases vulnerability to financial fraud and mismanagement (Nyang'au & Njoka, 2024; Wachira & Kihiu, 2012). Current government communication strategies for promoting investment opportunities remain limited, as they often fail to reach rural populations or provide sufficient, customized information that can bridge this literacy gap (Owino, 2022; Wasike et al., 2024).

Moreover, the scarcity of affordable, transparent, and customized financial advisory services leaves many Kenyans financially exposed, often leading to unwise budgeting, risky investments, inadequate retirement savings, and heightened susceptibility to fraud (Nyongesa Sande, 2024; Deloitte, 2024). As technological innovations increase access to diverse investment opportunities, financial literacy has become increasingly essential for individuals to make informed financial decisions (Lo & Singh, 2023). A personalized financial advisory and investment planning chatbot could offer an accessible, trustworthy, and cost-effective solution tailored to the Kenyan economic environment. Such a tool could help build a culture of informed financial decision-making, foster greater market participation, and support the country's financial development

goals by equipping citizens with the knowledge needed to navigate increasingly complex financial products safely and securely.

1.3 General Objective

To develop an AI-based chatbot for personalized financial advisory and investment planning, enhancing user decision-making.

1.4 Research objectives

i. To identify factors influencing user needs in digital financial advisory services.
ii. To analyse current trends and demand for AI financial advisory services.
iii. To review existing models for personalized financial advisory and investment planning.
iv. To develop a chatbot integrating user profiling for tailored financial advice.
v. To assess the accuracy of the chatbot in providing personalized recommendations.

1.5 Research Questions

i. What factors influence user needs in digital financial advisory services?
ii. What are the current trends and demand for AI financial advisors?
iii. How effective are existing models for personalized financial advisory?
iv. How can user profiling enhance chatbot-based tailored financial advice?
v. How accurately does the chatbot deliver personalized recommendations?

1.6 Justification

The significance of this work lies in the creation of a personalized and responsive financial advisory chatbot based on AI, tailored to the evolving dynamics of financial markets and user needs. Using Deep Learning and Natural Language Processing, for example, the chatbot can deliver customized investment advice and commentary that adapts to user tastes and market trends. That innovation keeps the user more engaged, providing live updates and tailored advice to make the investment experience as smooth and as efficient as possible. In addition, the chatbot can learn from user experiences and, therefore, will become more accurate in giving advice and making decisions, which will increase users' confidence in personal financial management.

Individual investors and financial advisors will appreciate the improved service and insights the chatbot offers. It will eliminate contradictions in financial advice, shorten response times, and be available 24 hours a day, seven days a week, allowing the service to integrate with people's varied needs and schedules.

While the chatbot will gather data from other financial sources, it will also help people make informed choices, thereby improving their financial literacy and empowerment. The results of this research could inform future improvements to financial advisory services, which will need to respond to an increasing demand for tailored, accessible investment advice in an increasingly complex financial environment.

1.7 Scope and Limitations

The scope of this study encompasses the potential of a personalized chatbot for financial guidance, excluding other areas of wealth management services.

Chapter 2: Literature Review

2.1 Introduction

The present chapter provides the theoretical background for chatbot development, highlighting several key points, including natural language processing (NLP), user profiling, and conversational design, which ensure user engagement and interpretation (Bhupesh Patra & Mahendra Kumar, 2020). Based on a thorough literature search, the author identified existing gaps and weaknesses in financial advisory chatbot models, particularly in aspects such as personalization, security, and adaptability to local contexts (Sugumar Chandra, 2021).

By surveying the relevant architectural styles, design principles, and algorithms, the paper outlines the context in which available frameworks are insufficient and lays the groundwork for innovation (Wei et al., 2021). Second, the chatbot will assess the existing financial advice and investment planning frameworks available in the market, including their strengths and weaknesses, which will be taken into consideration when designing the chatbot for the Kenyan market (Nguyen et al., 2021). The chapter concludes with a worked-out conceptual framework that provides a practical guideline for the efficient conceptual architecture of an intuitive, end-of-course, and usable financial advisor chatbot.

2.2 Theoretical Literature

2.2.1 Financial Advisory Models and Investment Planning

Financial planning models and investment planning are no longer confined to naive rules of thumb; sophisticated analytics and machine learning have been incorporated into the design to enhance the management of choices and risks. The three-statement financial model—comprising an income statement, balance sheet, and cash flow statement—remains the foundation for understanding the performance and financial health of organisations (Štangová Víghová, 2021). This model also provides valuable financial data for financial analysis and decision-making, enabling a comprehensive view of a company's financial condition.

The Capital Asset Pricing Model (CAPM) is the most widely used alternative to the original version. The Fama-French Three-Factor Model is used for portfolio management of investment portfolios, and it has a more realistic account of the cross-sectional variation of the stock returns among countries (Qiu Wang, 2022;

Madhuranthagan Shantha, 2021). In this model, the market risk premium, size premium, and value premium are also considered, and they are highly correlated with additional portfolio returns (Madhuranthagan & Shantha, 2021). Additionally, the role of such auxiliary data in detecting fraud through financial statement analysis is emphasized.

In this case, logistic regression models built on indicators following the fraud triangle can effectively discriminate between fraudulent and non-fraudulent reports (Macedo et al., 2022). These tools, working in conjunction, aid in the design of financial decisions and risk analysis for various applications. With the recent advancements in financial planning and modelling, the integration of machine learning and natural language processing (NLP) methods is gradually gaining increasing focus. For instance, Pagliaro et al. (2021) proposed an innovative machine learning and natural language processing (NLP)-based method that can be generalized to analyse financial advisor notes and, consequently, investor reactions during a market crisis.

This illustrates the continuing importance of big data analytics to financial advice services. Additionally, by applying the Discounted Cash Flow (DCF) method, a commonly used approach for financial valuation and forecasting, one can gain insight into the company's future performance under various scenarios (Jagannayaki et al., 2024). Although the method is subject to its limitations, such as significant discrepancies between the forecasts and observed events (Solodov, 2021), the approach remains in high demand, especially for start-up valuation (Laitinen, 2019).

In addition, merger and acquisition (M&A) models have been enhanced to not only consider the target and acquiring companies but also to account for the value of synergies and increased debt capacity (Hsieh Shen, 2022). These papers collectively demonstrate the ongoing development of financial models and the growing importance of advanced analytics in financial advisory work, aimed at enhancing decision-making, predicting investor behaviour, and providing a more effective solution to financial management across various scenarios.

2.2.2 Artificial Intelligence and Machine Learning in Finance

Artificial intelligence (AI) and machine learning (ML) are evolving the risk management landscape in the financial industry, especially in banking. These technologies enhance credit risk assessment, fraud detection, and regulatory compliance by increasing the power of analysis and facilitating automated decision-making (Milojević Redzepagić, 2021; El Khair Ghoujdam et al., 2024). Additionally, utilising AI and machine learning algorithms enables more informed loan origination and risk assessment through the analysis of large datasets and the identification of intricate patterns, as well as the ability to react to dynamically changing market environments. (Fritz-Morgenthal et al., 2021; Edunjobi Odejide 2024).

However, challenges remain, including model-specific risk, data privacy issues, and demand for expert professionals (El Khair Ghoujdam et al., 2024). To overcome these challenges, there is an urgent need for a well-established risk-informed framework and testing environment to facilitate the responsible, trustworthy, and interpretable use of AI/ML (Fritz-Morgenthal et al., 2021). Fritz-Morgenthal et al. (2021) emphasized that embedding AI into the assignment of credit risk has, as its ultimate consequence, a net positive effect on efficiency and accuracy in banking business workflows, as well as in decision-making and financial management. Edunjobi and Odejide (2024) found similar benefits across financial systems.

2.2.3 User Profiling and Personalization Techniques

User profiling and data collection are essential components of highly effective financial advisory chatbots. Mehmet Kilic et al. (2017) found that cooperative or joint profiling, where clients and advisors work together in the same space on shared displays, has the potential to increase user acceptance of data capture. Their research showed that task awareness, which links the profile information to client goals, increased this acceptance. In principle, chatbots can deliver personalized financial advice at a significantly lower cost than human advisors, and even without a humanizing component, such as anthropomorphism, which can be compensated for through other design elements. These systems can also facilitate the acquisition of new customers and the allocation of capital for banks.

Information interaction challenges raised in the design of conversational systems can be addressed through the analysis of user dialogue data (Candello Pinhanez, 2018). This approach generated 18 design proposals, categorized into Information, Interaction, and Sensorial designs, facilitating the development process. Overall, user data is of great interest for the efficient and intuitive performance of financial advisory chatbots. Studies in user profiling are currently exploring static and dynamic models of user interest representation. Bai et al. (2024) noted that static methods also utilise fixed-length document vectors, which can be too constraining for modelling diverse user intents.

To address this limitation at the expense of reduced profiling power, they proposed dynamic profiling techniques, such as using intent-based document embeddings that contain information relevant to selected queries. Some approaches use reinforcement learning and adversarial training based on the modelling of sequential decision-making of users in mobility patterns (Wang et al., 2021). Others also develop latent user profiles derived from dialogue history, leveraging personalized language models and memory networks to model user-specific properties of language use and language preferences (e.g., Ma et al., 2021). Li and Zhao (2020) employed local and nonlocal methods, utilising shallow and deep learning techniques, including matrix factorization, deep collaborative filtering, and recurrent neural networks, to obtain representations of the users. These advances aim to enhance personalization across a wide range of applications, including those on the World Wide Web, such as chatbots, as well as many other applications.

2.2.4 Financial Inclusion and Digital Financial Services in Kenya

Through digital financial services (DFS), particularly mobile money services like M-Pesa, financial inclusion has spread remarkably in Kenya among previously marginalized segments (Njuguna Wachira, 2023). Wachira and Njuguna (2023) demonstrated that DFS has a positive effect on economic growth and productivity. The use of DFS is influenced by factors such as education, sex, ownership of mobile phones, age, and income (Ngware, 2024). For instance, Melubo and Musau (2020) found that digital banking facilities have been particularly beneficial to

women entrepreneurs, although the issue of low literacy and computer skills remains.

Suggestions for increasing financial inclusion include raising awareness of digital products, mobilizing interest groups, and proposing policy measures to improve basic education and income redistribution (Makau Olando, 2021; Melubo Musau, 2020; Ngware, 2024). The downside to DFS adoption is the issues of gender and educational level; however, chatbots can help make DFS more usable and accessible (Sugumar Chandra, 2021). AI has a stake in achieving digital financial inclusion. As such, it can address risk management and cybersecurity issues, and there remains a strong reason also to investigate the broader consequences (Mhlanga, 2020; Mader et al., 2022).

2.2.5 User Experience (UX) and Human-Computer Interaction (HCI) in Financial Chatbots

Financial chatbot research focuses on the position of financial chatbots in customer service and user interaction, where the level of user satisfaction depends on factors such as humanness, response time, and accuracy (Moses Sugumar Shalini Chandra, 2021; Cynthia Chizoba Ekechi et al., 2024). G. Silva and E. Canedo (2022) established that efficient conversation design, in terms of linguistic, visual, and interactive aspects, enhances the user experience and, more importantly, user engagement. Cynthia Chizoba Ekechi et al. (2024) identified cultural linguistic variation as a significant force in the global expansion of chatbots.

In the context of financial services, chatbots can be employed, for example, to answer customer requests, build customer equity in service, and resolve security issues (Hana Demma Wube et al., 2022). However, it remains a challenge in the process of overcoming regional linguistic disparities and cultural aspects. Shaikh et al. (2023) determined that factors impacting Kenyan users' trust and acceptance of financial chatbots include perceived functionality, ease of use, and security. Raiche et al. (2023) found that trust and acceptance are further influenced by user factors, including self-efficacy, anxiety, learning approaches, and personality traits, which contribute to their development.

Kobets and Kozlovskyi (2022) discovered that personalizing financial advice within chatbots has demonstrated positive impacts on user behaviour and decision-

making, with anthropomorphic designers improving social presence, trust, and the likelihood of compliance with recommendations. Lakkaraju et al. (2023) observed that on the one hand, the naturally generated text based on Large Language Model (LLM) chatbot systems, such as ChatGPT and Bard, is natural; on the other hand, it can produce contradictory and unreliable financial information compared to rule-based chatbots. These findings suggest that while chatbots may influence the decision-making behaviour of individuals regarding their financial decisions, the advice they offer should be treated with caution due to the design and effectiveness of these chatbots.

2.3 Empirical Literature

Table 2. 1 Summary of Empirical Literature Review

AUTHORS	TITLE	APPROACH	FINDINGS	RESEARCH GAPS
Kausik Lakkaraju, Sara E Jones, Sai Krishna Revanth Vuruma, Vishal Pallagani, Biplav Srivastava	LLMs for Financial Advisement: A Fairness and Efficacy Study in Personal Decision Making	Evaluated two LLM-based chatbots (ChatGPT and Bard) and one rule-based chatbot (SafeFinance) on a product discovery task to test for fairness and consistency in responses - Evaluated the LLM-based chatbots on a personal financial planning scenario involving multiple products and tasks, in multiple languages and dialects - Introduced two evaluation metrics - Inter-System Inter-Person Difference (ISIP) to assess bias and Inter-System Answer Difference (ISA) to assess efficacy of the chatbots.	Both ChatGPT and Bard, the LLM-based chatbots, struggled to consistently retrieve information from external sources and provide accurate responses. However, the LLM-based chatbots were not able to show consistent and reliable financial information despite absence of significant bias with respect to user names. The rule-based chatbot, SafeFinance, could give safe and trustworthy answers that could be tracked to their source, and it performed better than the LLM-based chatbots.	Dimension of chatbot response and its variability across time that is very hard to specify the reference test cases-Chatbot could not perform the numeric reasoning test-Lack of good representation of chatbot response, and not adequate incorporation of user context-Lack of good support for languages of target populations, e.g., African American Vernacular English, and Telugu.
Moses Sugumar, Shalini Chandra	Do I Desire Chatbots to be like Humans? Exploring Factors for Adoption of Chatbots for Financial Services	Survey design with a Likert scale instrument - Sampling of chat-bot users and non-users (with a sub-sample of chat-bot financial services users) - Online administration of the survey (with 250 usable responses of 284 total responses) - Partial least squares structural equation modelling (PLS-SEM) for data analysis.	Performance expectancy, habit, likeability, and social presence are major determinants of intention to adopt chatbots for financial applications. Effort expectancy was not an important predictor of chatbot adoption, probably due to the absence of any learning slope for chatbot use. Social influence and hedonic motivation did not have much impact on the intention to adopt chatbots for financial services.	Small sample size and generalizability of results - Potential inclusion of other factors in the model to increase the model's ability - Regional sample bias, as respondents were primarily from East Asia - Cross-sectional study design, which would not be likely to include changes over time - Non-significant results for certain hypothesized factors such as effort expectancy, hedonic motivation, social influence, and anthropomorphism, which may differ in other settings.
Federico Milana, Enrico Costanza, J. Fischer	Chatbots as Advisers: the Effects of Response Variability and Reply Suggestion Buttons	The paper adopted a simulated social trading platform with two goals—social trading and image tagging—to build up a sufficiently realistic interaction scheme in which participants could alternatively switch tasks between these two goals. Subjects received an initial budget of 1000 virtual pounds to invest, that is, from which they could make additional funds by performing the image tagging task. They got a fixed payment and a reward on their capital earnings. - The study used a 2x2 factorial design with the independent variables of response variability (varied/not varied) and reply suggestion buttons (available/not available), resulting in 4 experimental conditions.	Subjects tended to follow the chatbot's investment recommendation more often when the chatbot responded differently and presented response suggestion buttons. Subjects sent fewer messages and fewer actions when the chatbot responded with different answers than when the answers were the same.	Participants listened to the chatbot's investment advice more often when the chatbot gave different answers and buttons for suggestion of reply more often. Members sent fewer posts and fewer actions when the chatbot responded inconsistently versus when the chatbot-responses were consistent.
AVA: A Financial Service Chatbot Based on Deep Bidirectional Transformers	S. Yu, Yuxin Chen, Hussain Zaidi	Featuralization of a chatbot based on deep bidirectional transformer (BERT) representations - Exploration and characterization of various uncertainty measures for the BERT model, such as information entropy and variance over the probability distribution of the BERT dropout sampling - Mixed-integer programming applied to determine the decision thresholds in a controlled way from the aforementioned uncertainty measures - Featuralization of BERT as a language model for automatic spelling correction by directly combining the probabilities of the masked language model and word edit distances.	The chatbot is able to identify 381 intents, to determine to respond "I don't know" and to transfer to human operators inquiry that is still doubtful. The paper reports on and compares methods for measuring uncertainty in BERT, including information entropy and variance of the dropout sampling, and opts to optimize decision thresholds using mixed-integer programming. In the paper, BERT is suggested as a language model for automatic spell correction, and the probabilities from the masked language model and the word edit distances are used to select the optimal spell corrections for misspelled words.	Incorrect spelling in the input can severely undermine the performance of intent classification - The chatbot was evaluated only on a public data set and not on actual financial service data - The chatbot may not be directly transferable to all financial service branches and might need additional customization or adaptation.
Yuehuan He, Oleksandr Romanko, Alina Sienkiewicz, Robert H. Seidman, R. Kwon	Cognitive User Interface for Portfolio Optimization	Construction of a chatbot user interface for portfolio optimization - Parsing of natural language inputs into investment preference - Linking to an online financial optimization solver - Interpretation of optimization results - Presentation of the optimized portfolio to the user - Architecture and design of the chatbot - Implementation through cloud-based infrastructure and services (IBM Cloud, SS&C Algorithmics Portfolio Optimizer, Slack).	Investors with no quantitative finance or optimization background can access the portfolio optimization service using a chatbot interface. The chatbot can extract investment preferences from free-text inputs, process them in a backend financial optimization engine, calculate the outcomes, and then present the characteristics of the optimal portfolio to the user. In the study, the architecture and design of the chatbot are discussed along with an implementation on cloud applications which has the potential for scalability and performance boost.	While the chatbot supports the ease of portfolio optimization, users still need a simple understanding of financial terms to derive the full value of the service. The paper recognizes that the task of capturing and processing sophisticated preferences of investment areas using natural language inputs is not straightforward.
Boris A. Galitsky, Dmitry Ilvovsky	On a Chatbot Conducting a Virtual Dialogue in Financial Domain	The chatbot gets the initial query of the user, - It searches the appropriate documents, - It extracts the topics of the documents, - It arranges the topics into clusters of points of view in disagreement with each other, - It gets verified by the user which cluster is most informative, and finally, it delivers the contents of the selected cluster to the user in the shape of a virtual dialogue, where his/her queries are synthesized automatically and the answers are derived from the contents of the selected documents in which the questions themselves are automatically generated.	The chatbot is able to synthesise virtual conversations in the context of personal finance from extracted and chosen text material. The chatbot can search for associated documents, summarize/organize the topics, and deliver the content according to the user's preferences of the clustering of the most contributive topics. The chatbot's reply is in the sestyle of a dialogue, answers are based on the extracted and chosen documents and questions are automatically created.	The task of creating coherent and contextually appropriate dialogues from scratch is complicated and breeds issues.

2.4 Models and Framework

Table 2. 2 Summary of Models and Frameworks

METHODOLOGY	DESCRIPTION	ADVANTAGE	DISADVANTAGE	APPLICATION CASE STUDIES
Anthropomorphic Design	Anthropomorphic design incorporates human-like features into technology, such as shape, speech capabilities, and facial expressions. This approach is used in various technologies, including robots, avatars, and interface agents. On the other hand, anthropomorphism	24/7 Availability, Scalability, Cost-Effective	Data Privacy Concerns, Trust Issues, Limited Understanding	1. Autonomous Vehicle-Pedestrian Communication (Large et al., 2023) 2. Socially Assistive Robots (Zhong et al., 2023)
Generative Pre-trained Transformer	Generative Pre-trained Transformer (GPT) is a deep learning language model architecture built by OpenAI, which is a major breakthrough in natural language processing (Gómez Cano et al., 2023). GPT models are built in the framework of the transformer architecture and are train in a pre-trained manner using-on-large language corpora, and can thus carry out a large variety of language tasks without requiring task-specific fine-tuning (Brown et al.	Generality, Scalability, Creativity, Human-like interaction, Continuous learning	Biases, Computational resources, Data privacy, Limited Understanding, Ethical concerns	1. Design Concept Generation(Zhu & Luo, 2021) 2. Biomedical Text Mining(Luo et al., 2022) 3. Chatbots and Customer Service 4. Machine Translation 5. Sentiment Analysis
Deep Q-Networks	Deep Q-Networks (DQN) integrates the Q-learning with neural networks for the solution of complicated reinforcement learning problems (Awoga, 2021). DQN allows agents to learn efficient representations from high-dimensional inputs and to generalize experience from the past to novel contexts (Awoga, 2021).	Model-free learning, Experience replay, Scalability, Versatility, Improved Decision making	Computationally intensive, Hyperparameter tuning, Overestimation bias, Data Requirements, Stability issues	1. HVAC Systems (K. Ahn & Cheol-Soo Park 2020) 2. Gaming (Ao Chen et al. 2020) 3. Stock Trading Strategies (Yang Chen, 2024) 4. Resource Allocation in IIoT Systems (Fan Liang et al., 2021)
Multi-Agent Reinforcement Learning	Multi-Agent Reinforcement Learning (MARL) is a branch of reinforcement learning, which constrains and studies situations in which multiple agents collaborate in an environment that they share. All agents strive to achieve their own rewards, which may result in cooperative, competitive, or some combination of interactions. In the cooperative case, MARL is approximated by Markov Decision Processes (MDPs) and Partially Observable Markov Decision Processes (POMDPs) on frameworks.	1. Scalability 2. Robustness 3. Diverse Applications 4. Improved decision making	1. Computational Complexity 2. Coordination Challenges 3. Scalability issues 4. Stability and Convergence	1. ADMIRAL Framework(Ganapathi Subramanian et al 2021,2023) 2. MAPS (Multi-Agent Reinforcement Learning-based Portfolio Management System)(Lee et al 2020) 3. DeepChain for E-commerce Recommendations (Zhao et al 2019)
Bidirectional Encoder Representations from Transformers	BERT (Bidirectional Encoder Representations from Transformers) is a landmark language representation model that has consistently reached state-of-the-art performance on a number of tasks in natural language processing (Devlin et al., 2019). It	Bidirectional Context Understanding, Pre-trained Models, Versatility, Improved	Computationally Intensive, Complexity, Large Model Size	1. Sentiment Analysis 2. Google search

2.5 Architectural Components and Design Considerations for Financial Advisory Chatbots

The construction and planning of chatbots for personalized, tailored financial advice and investment planning in Kenya involves several key issues and factors. Natural Language Processing (NLP) is the driving force behind chatbots, enabling them to recognize spoken words and communicate like humans (Bhupesh Patra & Mahendra Kumar, 2020). The primary application areas of natural language processing (NLP) techniques include tokenization, part-of-speech tagging, named entity recognition, and sentiment analysis, all of which break down language into its constituent building blocks and study how such building blocks interact with each other (Carlos Alexander Jarquin et al., 2023).

These techniques enhance documentation, human-machine interaction, and personalized assistance. Bhupesh Patra and Mahendra Kumar (2020) reported that recent progress in NLP, particularly in neural language models and transfer learning, promises to further enhance chatbot performance, despite still-present challenges such as language ambiguity, multilingualism, and privacy issues. Their research highlighted the ongoing evolution of NLP technologies as they apply to conversational agents in financial contexts. Carlos Alexander Jarquin et al. (2023) examined the structural components necessary for the effective implementation of chatbots in financial advisory services.

Their findings demonstrated that the proper implementation of these NLP techniques significantly improves the ability of chatbots to understand and respond appropriately to user queries, particularly in domain-specific contexts such as finance, where specialized terminology is prevalent. In the Kenyan context, chatbot architecture must address unique challenges related to linguistic diversity and varying levels of digital literacy. The design considerations for financial chatbots in Kenya include accommodating multiple languages, providing simplified interfaces, and ensuring security protocols that inspire trust among users who may be new to digital financial services.

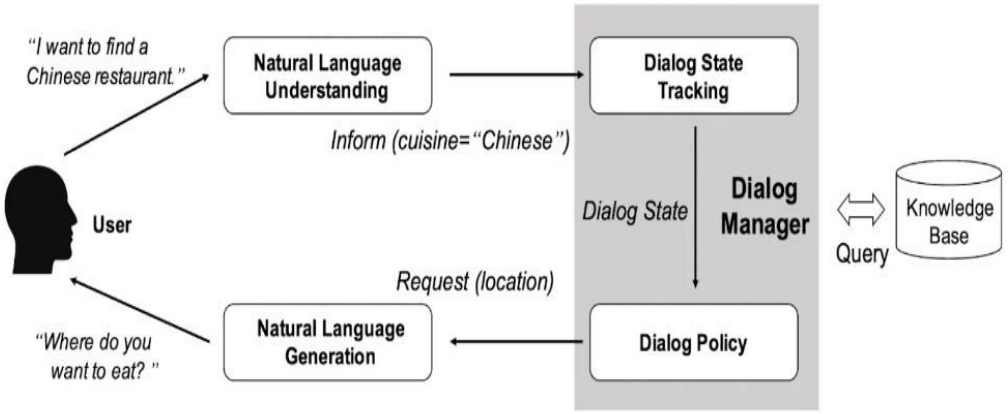


Figure 2. 1 Dialog System Architecture

Knowledge bases have a significant role in chatbot operation, storing ontologies to generate accurate answers. Nguyen et al. (2021) explained that these knowledge bases can be organised using ontology technology that blends relational knowledge with scripts for more complex querying and response. Sophisticated systems of chatbots maintain context throughout conversational exchanges, minimizing redundancy and enhancing user experience (Sai Sharath Rekabdar, 2021). Hausdorf et al. (2022) demonstrated that visualization techniques improve the programming of chatbot knowledge bases, making chatbots both more maintainable and more efficient.

In addition, the integration of chatbots and financial systems enables them to consistently retain real-time information, process transactions, and deliver personalized assistance. Prof. Vijaykumar S et al. (2024) reported that this integration leverages the power of AI and machine learning to provide affordable, accurate, and accessible financial advisory services. Ashish Shah et al. (2020) concluded that such integrated systems can significantly reduce the cost barriers traditionally associated with personalized financial advice. Security and access control are crucial considerations in chatbot design, particularly for applications such as finance. Zainabi et al. (2024) emphasized that secure handling of personal data, strong authentication, end-to-end encryption, and periodic security audits are essential for protecting user information.

Planas et al. (2022) found that model-driven techniques can align access control policy to a conversational user interface (CUI) and thus achieve secure

interaction. In addition, cultural sensitivity and multilingual assistance are of the utmost importance for adoption and use in context-rich cultures such as Kenya. Ng et al. (2023) discovered that the efficiency and user-friendliness of chatbots can be enhanced through participatory design techniques and culturally adapted emotion-aware systems. Häkkilä et al. (2020) observed that, given local customs, traditions, and social norms, chatbots can provide more contextually relevant and engaging user experiences. Such architectural and design concerns are particularly relevant to the efficient and pleasant design of a financial advisory chatbot in Kenya.

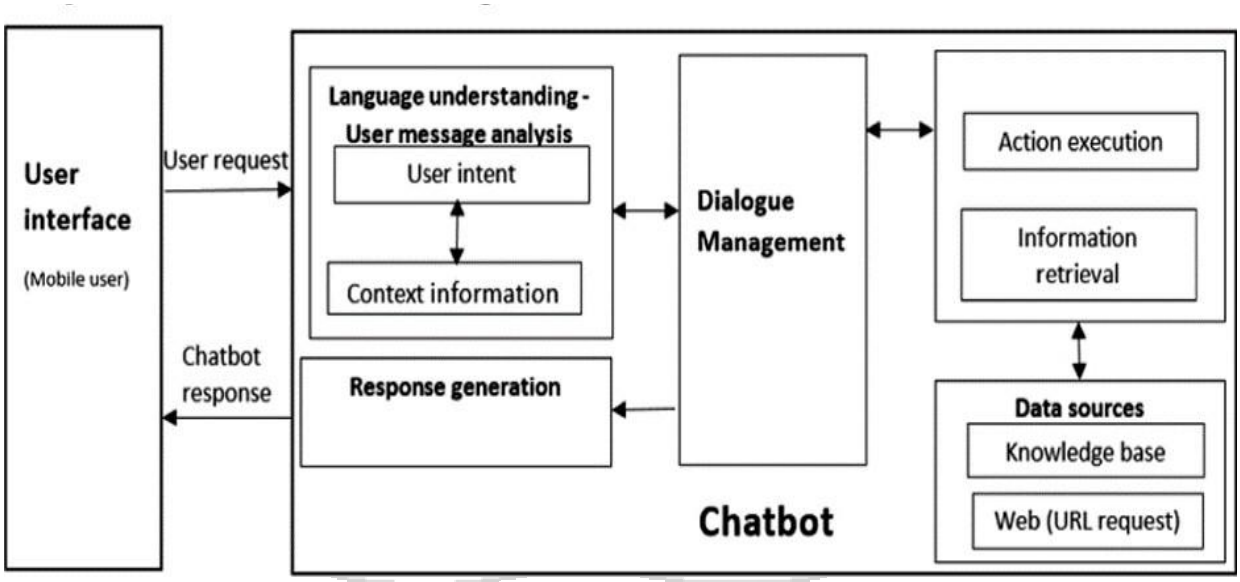


Figure 2. 2 Chatbot Architecture

2.6 Conceptual Framework

A conceptual framework is a network of interlinked concepts that comprehensively understand a phenomenon (Lemke, 2021). It serves as a thinking tool for researchers, guiding their study design and enhancing research practice (Packard, 2021). Lemke (2021) described conceptual frameworks as essential organising structures that help researchers visualize relationships between key variables. Packard (2021) emphasized the role of their work in bridging theoretical knowledge with practical application. Conceptual frameworks are constructed using ideas and concepts from various theories or empirical studies, differing from theoretical frameworks based on specific theories. Majeed et al. (2023)

distinguished between these two types of frameworks, noting that conceptual frameworks offer greater flexibility in interdisciplinary research.

The conceptual framework for a financial advisory and investment planning chatbot involves a multi-layered architecture that integrates user interactions, external data, and personalized recommendations. The process begins with the User Interface, which collects and processes user data. This data, along with external inputs like payment information, is managed by the Application Layer. The Knowledge Base and Recommendation Engine layer utilises this processed data to generate personalized financial advice, informed by the User Profiling Module, which manages individual user profiles. The Data Management layer ensures proper storage and retrieval of recommendation and profile data. Lastly, the analytics and reporting layer analyses user interactions and system performance, providing continuous insights to improve the chatbot's functionality and user experience. This holistic approach ensures that the chatbot delivers users accurate, personalized, and secure financial advice.

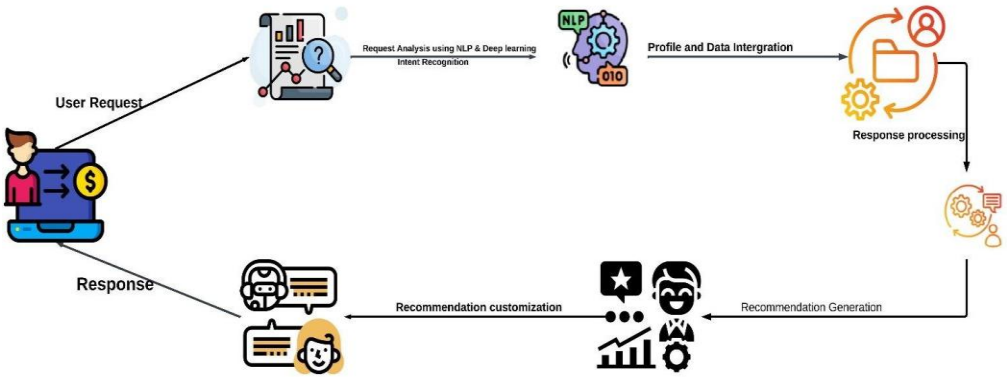


Figure 2. 3 Conceptual Framework

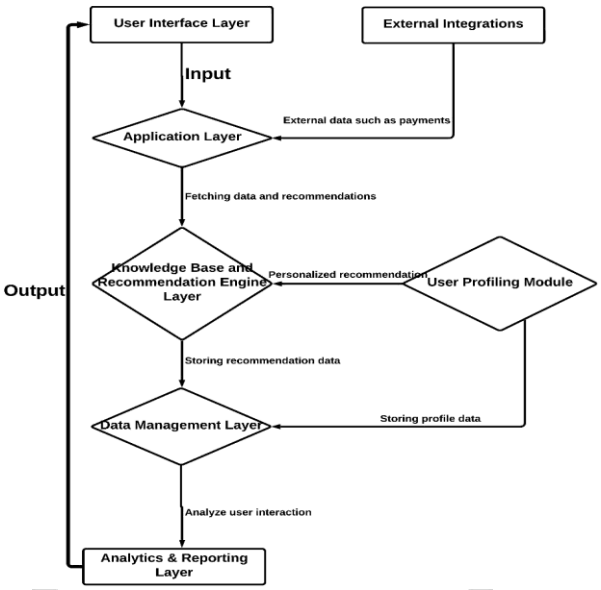


Figure 2. 4 Financial Advisory Chatbot Architecture

Chapter 3: Research Methodology

3.1 Introduction

The study employed a mixed-methods approach to examine the performance of a financial advisory and investment planning chatbot in Kenya. In the opinion of Kumar and Singh (2023), mixed-methods research offers the benefit of combining qualitative and quantitative approaches, which captures rich user experiences and provides insightful statistical analysis. This, as observed by Wanjiru et al. (2022), facilitates an understanding of the usability and effectiveness of chatbots within specific cultural contexts. The methodology provided measurable and contextual depth, thus meeting the research aims (Onyango, 20234). In emerging economies, Ndung'u (2021) argues that considerable value can be gained through the use of methodological triangulation, particularly in research on digital financial services. In this section, the methodology is an integral part of the research design, encompassing data collection and sampling, analysis, and consideration of ethical issues.

3.2 Research Design

The research employed an integrated exploratory, design-based, and experimental approach to create and evaluate a financial advisory chatbot in Kenya. As Mwangi et al. (2024) outlined, exploratory research is crucial for identifying service gaps, which informs the critical features of the financial advisory chatbot. Design-Based Research (DBR) was employed to develop and refine the chatbot prototype, utilising iterative feedback from users, as suggested by Kimani and Juma (2022) for designing AI solutions within a local context. Experimental research controlled the conditions under which accuracy, effectiveness, and user engagement performance metrics were evaluated (Wambua & Kitui, 2023).

A pragmatic research paradigm guided the study, combining interpretivism to analyse user behaviour and positivism to validate findings through measurable data (Omondi, 2021). In this regard, Chege et al. (2020) have identified this as necessary when conducting technology adoption research in emerging markets. A user-centreed, mixed-methods strategy was employed to refine the chatbot, utilising both qualitative methods (surveys and sentiment analysis) and quantitative approaches (accuracy metrics), as suggested by Njoroge and Kamau

(2023). The research framework was identified as having a problem identification, data-driven model development, implementation, testing, and refinement to produce a robust, ethical, and user-focused solution (Kipkorir et al., 2022).

3.2.1 Research Approach

The research took an exploratory research approach aimed at understanding the financial advisory landscape in Kenya and identifying gaps and opportunities that could inform the development of the chatbot. As Odhiambo and Mutiso (2023) noted, conducting a thorough landscape analysis is particularly important when developing financial technology products in contexts with varying levels of financial literacy. Odhiambo and Mutiso (2023) argue that there is a lack of comprehensive landscape analysis at the intersection of financial technology and literacy in Kenya. This phase builds upon Karanja et al.'s (2022) work regarding adopting digital finance in East Africa by examining the use of technology in financial services and financial self-service automation.

In user needs research, a thorough survey targeting students, young professionals, and seasoned investors yielded 1,000 respondents, focusing on understanding their financial difficulties. Munene and Ochieng (2024) emphasize that addressing challenges from specific segments is crucial in developing effective financial technology solutions. User Perceptions, AI System Trust, and Cultural Context: Examining Key Factors. A study of these issues, as framed by Muhia and Ndegwa (2021), was extended to examine automated advisory services in the context of acceptance theory.

In these studies, the researcher aimed to establish key guidelines for personalization and contextual relevance in financial advice provided through the chatbot. The iterative development of the chatbot was sustained through fundamental user interactions, utilising the Design-Based Research (DBR) approach (Kimathi & Muriuki, 2022). The workflow started with prototype creation. AI models were trained by incorporating BERT-based language models, financial slang, and English-Swahili bilingual dictionaries, as Kivuva and Musau (2024) argued for the AI systems to be ethnocentrically designed.

3.2.2 Research Paradigm

In developing and evaluating the financial advisory chatbot, the study employed a pragmatic research paradigm, acknowledging the challenges posed by AI-powered financial advisory systems. As Wekesa and Ndolo (2022) noted, pragmatism allows a researcher to select methods that tend to fulfil the study's objectives without being constrained by philosophical rigidity. Following pluralistic approaches, as advocated by Ojwang and Otieno (2021), the study successfully captured the full scope of AI's role in addressing financial advisory problems in Kenya. This paradigm balanced practical efforts and theoretical reasoning, insulating the research's rigor and relevance (Mwania & Nzuki, 2023).

This research paradigm combined elements of interpretivism and positivism to assess the impact of the chatbot from multiple angles. Kiplagat and Korir (2022) explained that using the interpretive approach stems from the need to capture users' experiences and their analysis of emotions and behaviours while interacting with AI-based financial advisory systems. At the same time, a positivist lens was applied to objectively obtain measurement-based evaluations through quantitative evaluation frameworks, such as recommendation accuracy, user participation, and financial literacy evaluation (Kuria & Muthoni, 2024). The combined approach provided useful qualitative and quantitative information for a comprehensive intervention assessment (Nyabuto et al., 2023).

3.2.3 Research Strategy

To develop the chatbot, a user-centreed design (UCD) research strategy was employed to ensure that it met the specific financial advisory requirements of users in Kenya. This strategy was articulated by Kiprono and Wangari (2022), emphasizing the primary focus on user needs when designing fintech solutions. The study incorporated local investment products and financial literacy materials to address the identified gaps in contextual finance, drawing on the ideas of Mwende and Kairuki (2023) regarding relevance and accessibility. A personalized strategy with dynamic user profiling was adopted, tailored to identified financial goals, risk tolerance, and literacy levels. The study used a mixed-methods approach, qualitative and quantitative research techniques, to assess chatbot

functionality and user satisfaction (Mutua & Karani, 2021).

User Financial Surveys captured the user's financial history, attitudes towards AI, and language preferences. Trust, level of emotional involvement, and level of understanding were analysed using NLP and Machine Learning models described by Kimotho and Wachira (2022) and were also subjected to Sentiment Analysis. Several performance indicators were carefully evaluated for the quantitative research, including the accuracy of recommendations and response time.

3.2.4 Research Framework

The chatbot for financial advisory services was developed and tested through a systematic, iterative approach, focusing on refinement at each step. Njuguna and Kamau (2023) emphasized the need for a robust framework when designing AI solutions to address societal issues, which guided the study. The research was divided into six distinct phases, focusing on critical issues related to financial literacy and advisory services within the Kenyan context. Figure 3.1 shows the Research Design Framework.

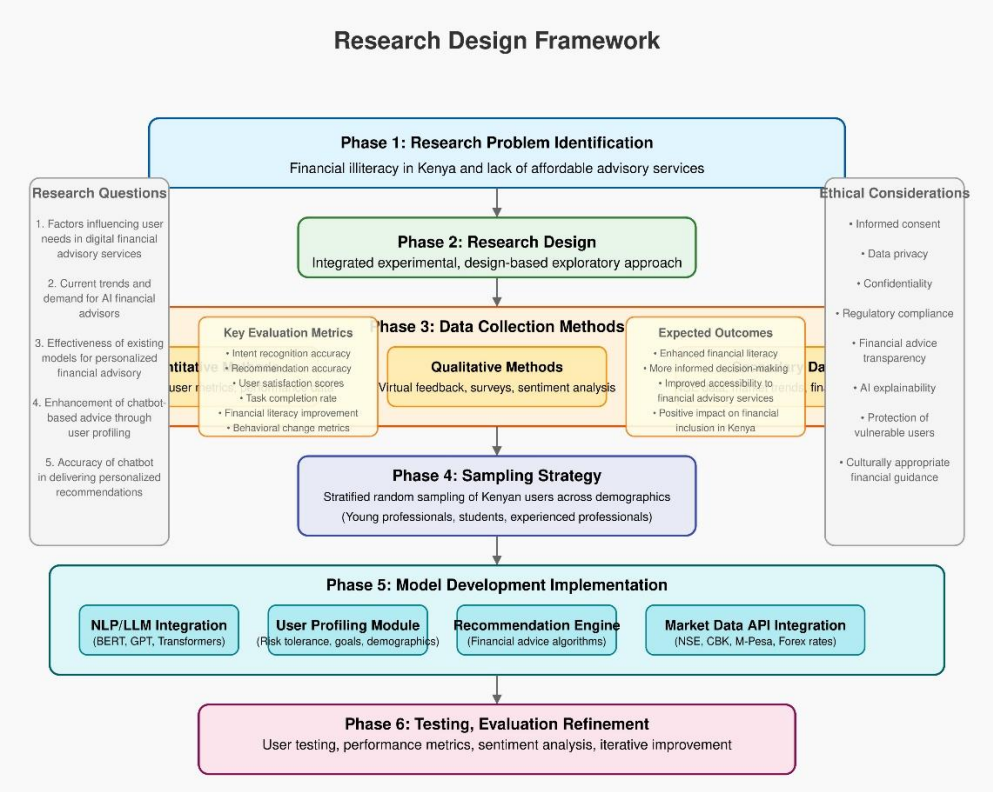


Figure 3. 1 Research Design Framework

3.3 Target Population

The target population for the financial advisory chatbot consisted of individuals with essential digital skills between the ages of 18 and 65, who constitute the major demographic groups with differing financial requirements. Nyamongo and Kithinji (2023) noted that paying attention to people from different age brackets is essential in studying financial technology. Marketers also focused on younger professionals (25–40 years old), who have increasing expectations for effective wealth accumulation, sophisticated investment planning, and aggressive debt management.

This group has already been identified by Kimeli and Koech (2022) as the most responsive to digital innovations in the financial services sector. Digital literate students aged 18-24 were also included in the sample to enhance overall financial literacy and budgeting, thereby fostering the early adoption of digital financial services —a tactic advocated by Njagi and Kathurima (2024). The chatbot further focused on aspiring entrepreneurs aged 25-45, including small business owners, freelancers, and gig economy workers who required financial planning, investment diversification, and cash flow management (Mburu & Ngugi, 2023).

Another important sample population group was middle-income urban professionals (aged 30-50 years) who are increasingly interested in the stock market, mutual funds, and real estate investments, as noted by Kipchirchir and Maritim (2021). From a geographical aspect, the chatbot almost exclusively focused on metropolitan areas where mobile money services and other digital activities have high usage, as well as on the peri-urban and newly digital regions in the aftermath of population apportionment strategies formulated by Wanjira and Musyoki (2022) which is further supplemented by the rise in smartphone adoption. Accessibility criteria included the possession of household digital devices, such as smartphones, tablets, and computers, as well as active participation in financial services like mobile money and online banking (Kimunya & Mwenda, 2023). Ineligibility criteria included the absence of any form of modern technology, expert financial consultants, individual investors, those under the age of eighteen,

and those with extensive knowledge of advanced financial management, as cited by NGari and Muthiga (2024) to justify targeted technology adoption research.

3.4 Data Sampling Strategy

3.4.1 Sampling Techniques

The study employed a mixed-method sampling strategy to ensure a representative and diverse user base for the financial advisory chatbot. Stratified random sampling was used to achieve balanced representation across key demographics, including age, income levels, financial literacy, and digital engagement. Purposive sampling targeted active digital financial services users, such as those using mobile money and stock trading apps, who were more likely to adopt AI-driven financial tools. To reach niche segments, snowball sampling leveraged referrals to engage small-scale investors, informal sector workers, and rural entrepreneurs. Digital recruitment channels, including social media advertising on LinkedIn, were combined with offline engagement at work to maximize participant diversity while mitigating selection bias.

3.4.2 Sample Size

According to Mutheu (2025), as of January 2025, Kenya's internet penetration rate is 48%, with approximately 27.4 million internet users out of a total population of 57 million. Based on this proportion, the sample size was determined using the following formula:

$$n = \frac{Z^2 \cdot p \cdot (1 - p)}{d^2}$$

Where:

- Z = 1.96 (standard normal variate for a 95% confidence level)
- p = 0.48 (internet penetration rate in Kenya as of January 2025, Mutheu, 2025)
- d = 0.05 (absolute error or precision)

$$n = \frac{(1.96)^2 \times 0.48 \times (1 - 0.48)}{(0.05)^2}$$

The required sample size for this study is approximately 384 respondents, which aligns with the sample size recommendations by Mwangi and Kimathi (2024) for technology adoption studies in Kenya.

3.5 Methods of Data Collection

3.5.1 Primary Data

For developing the source of the chatbot, the primary data focused on capturing user insights, behaviours, and feedback regarding personalized financial advisory services. User surveys were conducted to collect demographic details, financial knowledge, goals, and perceptions of AI chatbots from 1,000 respondents using Google Forms, a methodology supported by Mbithi and Ngigi (2023). Crafter feedback forms were designed to capture the evolving user experience within a defined virtual framework.

Alongside information captured during onboarding, such as age, financial goals, and risk appetite, which is used to enhance personalization —a strategy that Karanja et al. (2023) found effective in improving the relevance of AI systems. Behavioural data, including patterns of queries, interaction logs, and engagement metrics, were used to refine the chatbot's responses through techniques established by Mwanza and Kimani (2021). Applying these methods helped form a well-rounded understanding of financial advisory literacy in the Kenyan context (Nyangau & Opiyo, 2022).

3.5.2 Secondary Data

The secondary data sources provided relevant historical and real-time financial data to improve the chatbot's recommendation system. The Nairobi Securities Exchange (NSE) stock market data for 2013-2024 offered sector-based financial analysis into historical price trends, trading volumes, and sector classifications (Wanjawa, 2021; Wanjawa, 2024). Other Kenya macroeconomic indicators, as reported in statistical documents from 2019 to 2024, provided an analysis of the

country's GDP, money supply, investment flows, and employment (Kenya National Bureau of Statistics, 2024). Other integrated financial APIs include the NSE API for stock prices, the CBK API for interest and foreign exchange rates.

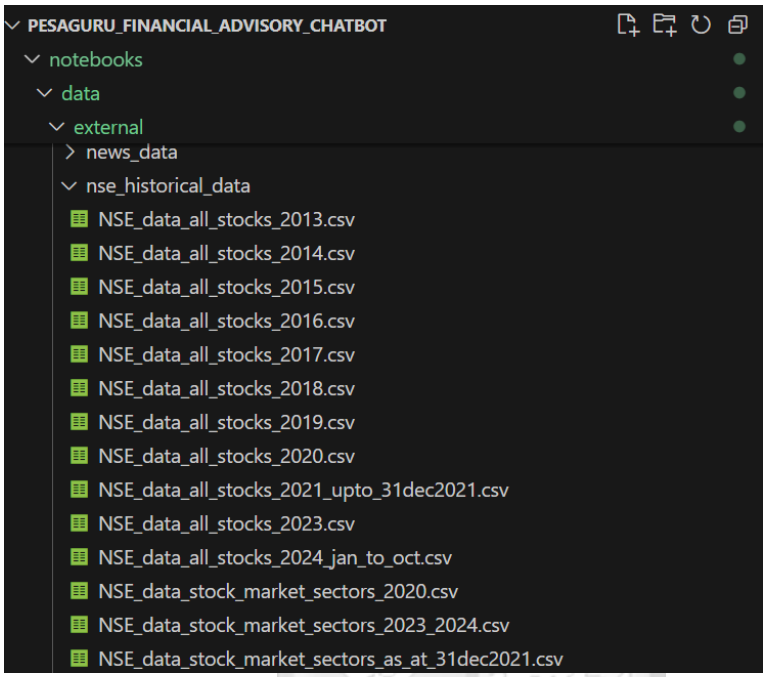


Figure 3. 2 Nairobi Securities Exchange (NSE)

This approach has been suggested by Mugambi and Kariuki (2023) as part of developing comprehensive financial technology ecosystems. Cryptocurrency data and analysis of global economic trends and stock markets were also provided through CoinGecko, Yahoo Finance, and Alpha Vantage APIs by the integration methodologies proposed by Njoroge et al. (2022). All data on GDP activity, agricultural production, manufacturing output, trade balances, and infrastructure development were derived from the 2024 Economic Survey published by the Kenyan government (Kenya National Bureau of Statistics, 2024). These are the data sources that Kinyua and Waithaka (2023) emphasize when discussing the relevance of contextual data to aid precision in financial consultancy.

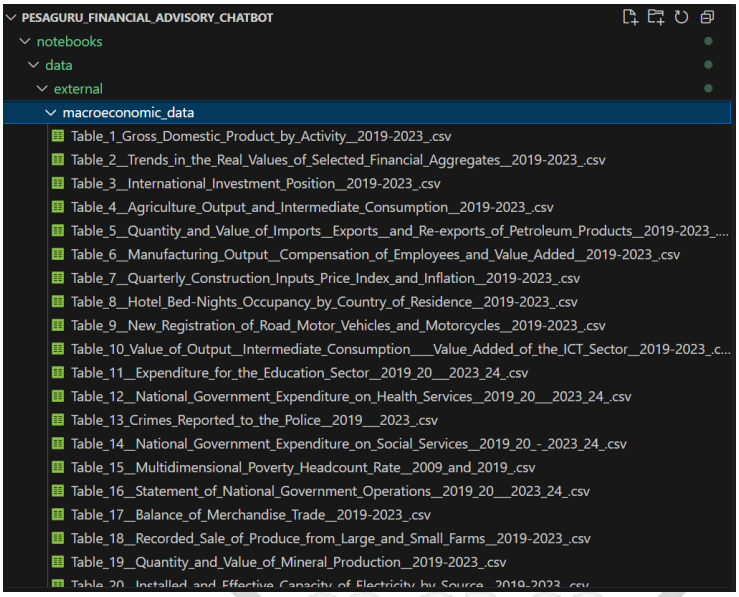


Figure 3. 3 Kenya Macroeconomic Datasets (2019–2024)

The sentiment analysis pipeline processes financial news using VADER, a financial lexicon, named entity recognition, and temporal tracking, aligning with research by Maina and Kiarie (2021) on market movement prediction in Kenya. Simultaneously, real-time stock trend analysis on the Nairobi Stock Exchange utilises moving averages, momentum indicators, volume trends, and inter-stock correlations, building on the framework established by Njenga and Kamau (2024). Sector performance tracking provides contextual depth through sector rotation, sentiment analysis, and correlations with economic indicators. Finally, all insights are synthesized with user-specific risk profiles and financial goals to deliver personalized, risk-adjusted investment recommendations tailored to time horizons and diversification needs.

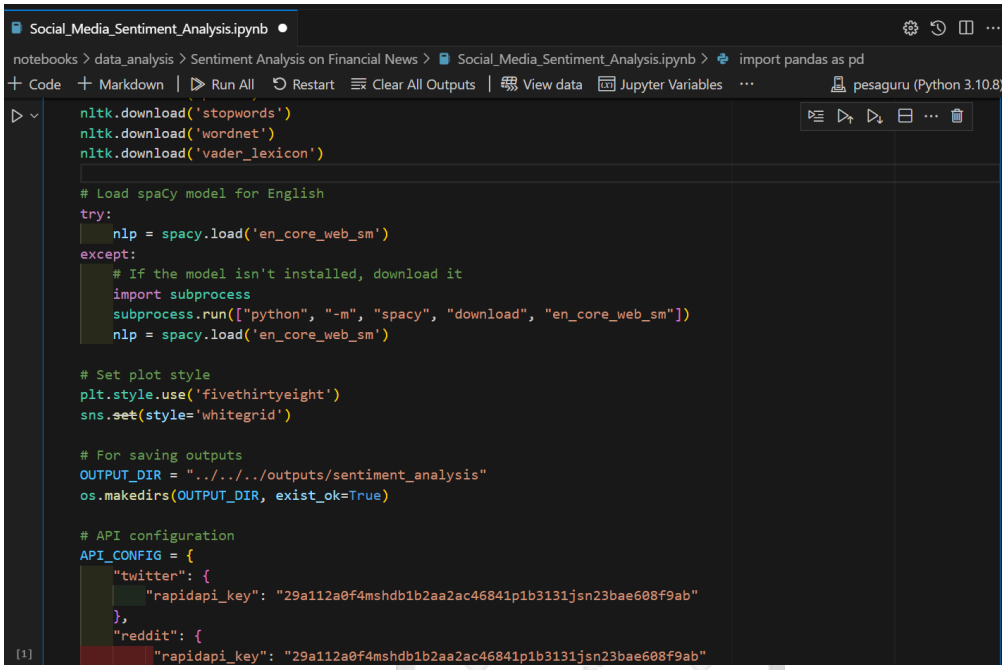


Figure 3. 4 Sentiment Analysis Pipeline Data Sample Code

3.6 Data Analysis Methods

The following outlines the data analysis methods, describing how data from various sources were processed and interpreted. A systematic analysis framework was vital in gaining insight from complex datasets (Njoroge & Maina, 2023). The process started with data collection, where data was obtained from databases, application programming interfaces (APIs), files, user queries, and financial market records. Protocols were in place to guarantee that pertinent and reliable data were acquired for further analysis. The data was cleaned and pre-processed by eliminating duplicates, correcting inconsistent formats, addressing missing values, and standardizing currency and numerical figures (Mwangi et al., 2023).

In addition to feature extraction, text normalization techniques were also employed to enhance the dataset. That was aimed at improving AI model performance as per the findings of Ndung'u and Kiarie (2021). All these processes ensured that the dataset was free of structural and logical errors and was ready for advanced analysis (Ogutu & Mugambi, 2024). The Researcher applied Natural Language Processing (NLP) techniques to analyse the data under study. In the financial discussions, tokenization, part-of-speech tagging, and named entity recognition were pivotal in dismantling and identifying crucial elements in the language, as

described by Njogu and Wambui (2022). Classification of intent and extraction of entities facilitated an understanding of user interactions. At the same time, word embeddings enabled the conversion of text into numerical representations for in-depth analysis, as posited by Kimathi and Nyaga (2023). Kinyanjui and Ndegwa (2021) noted that text analysis can also encompass sentiment analysis, which involves identifying polarity, emotion, and opinion within the text data. Market sentiment and risk sentiment were analysed to understand user perception towards market trends and investment risks, as described in Muthoni et al. (2024).



Figure 3. 5 Negative Financial Headlines – Key Terms

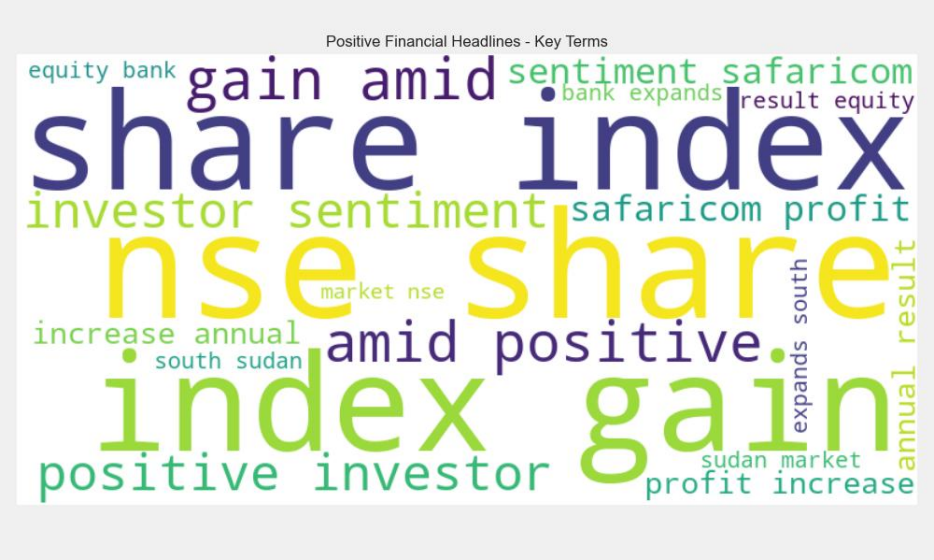


Figure 3. 6 Positive Financial Headlines – Key Terms

The application of statistics allowed the researcher to analyse and interpret information, adding significant value to the processed data. Measures of central tendency, such as the mean exchange rate, set the preliminary point for currency support in providing investment counsel. Distribution and quantile analyses highlighted differences in risk, as Murban ADNOC oil prices exhibited 8.7% volatility, compared to 27.3% in the cryptocurrency markets. Meanwhile, 75% of stocks on the NSE were trading at less than 83.50 KES, indicating market concentration. Time-series analysis via moving averages (both 50-day and 200-day) and seasonal average methods revealed golden cross stocks.

Thirty-seven stocks were identified as possessing golden cross patterns, while seasonal averages produced stronger KES in January and February and weaker KES in October and November. A series of correlation matrices discovered strong positive dependencies between EUR/KES and GBP/KES, with a figure of 0.82, and three factors accounting for 78.3% of stock price movement were extracted through Principal Component Analysis (PCA). From the regression analysis, it was clear that with improved financial literacy, the willingness to plan investments increased by 12.5%, which signifies a higher degree of preference.

Sector volatility, as measured in banking, insurance, and currency estate portfolios, was calculated at 18.7% and 2.3% in daily exchange rate portfolios. This, combined with a 95% Value at Risk (VaR) of loss, positioned the banking sector as a high-risk entity. K-means clustering divided users into four segments based on their literacy level and risk tolerance. Confidence intervals (e.g., SCOM 12-month return: 8.5% ± 3.2%), p-value hypothesis testing (manufacturing outperformed retail, $p < 0.05$), and Bayesian updating enhanced forecast accuracy, supporting custom-tailored decision-making.

Model validation was performed using performance metrics to ensure precision and efficacy in the decision-making process, as described by Mwende and Kamau (2024). The insights generated were further enhanced by integrating feedback, enabling continuous optimisation of the analytical model, as noted by Mutunga and Kihara (2021). Figure 3.13 shows the Data Analysis Workflow.

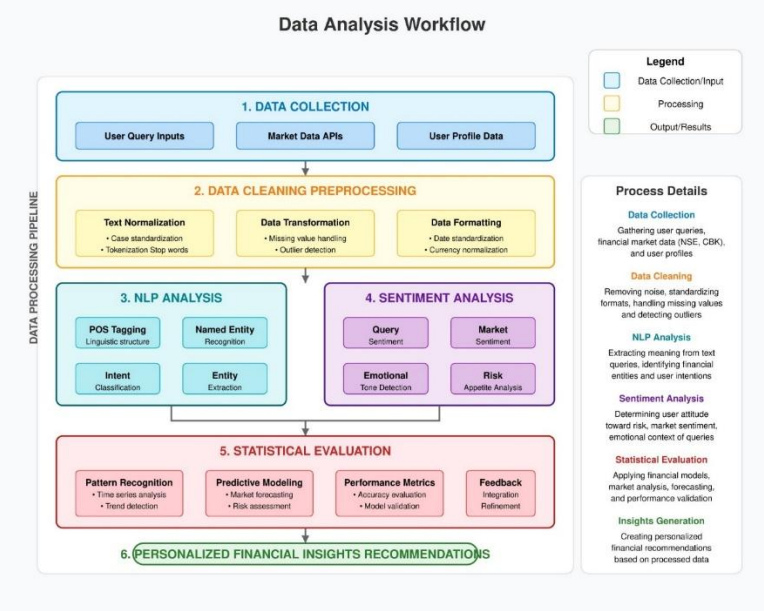


Figure 3. 7 Data Analysis Workflow

3.7 Model Development and Validation

3.7.1 Training Dataset Collection & Pre-processing

The process of developing and validating the financial advisory chatbot started from scratch, ensuring it would understand the financial concepts relevant to its users in Kenya. Later, Nyamai and Kinyua (2023) stated that AI systems capable of providing appropriate financial advice must be trained in specialized financial corpora. The researcher collected texts from a range of Kenyan financial publications, caregivers' regulator documents from the Central Bank of Kenya (CBK) and the Capital Markets Authority (CMA), investment guides, and financial educational documents to create a specialized financial corpus using data collection methods proposed by Mutuku and Njenga (2022). Figure 3.14 shows the Kenyan Financial Corpus code sample.

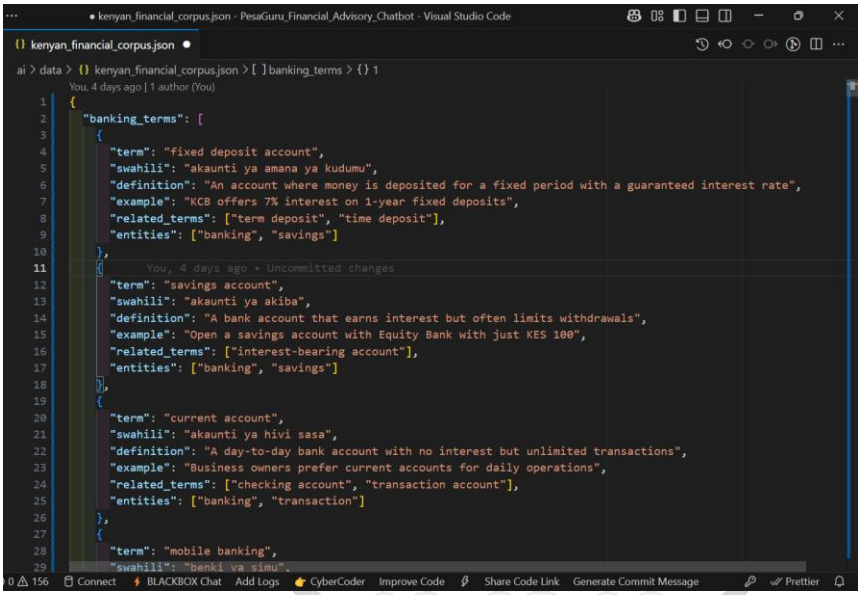


Figure 3. 8 Kenyan Financial Corpus code sample

Both English and Swahili datasets were added to allow for multilingual communication. The Nairobi Swahili Corpus was supplemented with additional translations of financial terms, as suggested by Wangui and Muchiri (2024), to advance culturally competent AI systems.

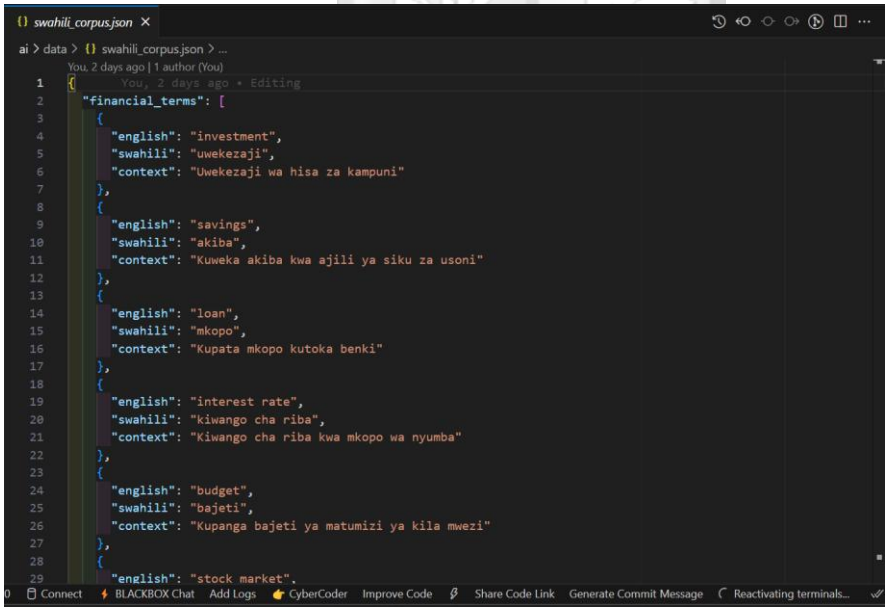


Figure 3. 9 Swahili Corpus Code Snippet

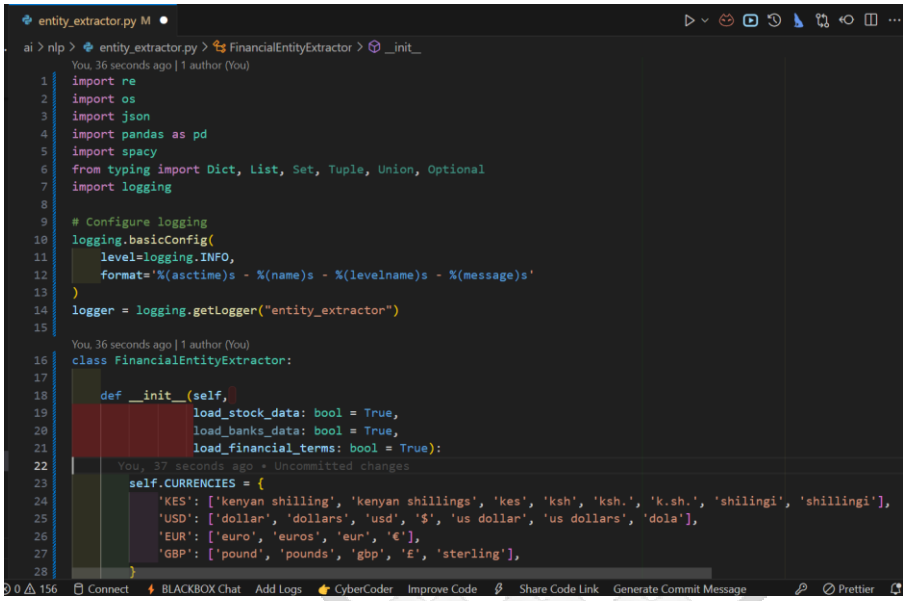
Furthermore, conversational data was collected from anonymized conversations between financial advisors and clients provided by financial institutions. As

Njoroge and Mureithi (2023) established, a robust data pre-processing pipeline, which included normalization, tokenization, and cleaning, was implemented to enhance the dataset. Financial terminology, numeric representation, and the common code-switching in Kenyan financial conversations were particularly problematic for Muriithi and Waithaka's (2022) research, which was addressed during pre-processing.

3.7.2 Model Selection and Architecture

The financial advisory chatbot employed a hybrid approach, utilising multiple deep models with specific functionalities that focused on particular tasks to enhance performance and contextual understanding of the bot. As Kamau and Ndung'u (2023) discussed, a fusion of AI models simplifies the building of chatbots capable of managing complex financial tasks. For this purpose, a domain-specific language model for the financial domain, such as FinancialBERT, was utilised. This model is more accurate in financial contexts, having been pre-trained on a transformer model such as BERT or GPT and further trained on Kenya's financial data corpus, following the methodology outlined by Mwenda and Kariuki (2022).

Undertaking user queries for investment, loan comparison, or risk assessment was managed by an advanced, dedicated intent classification model. Moreover, an entity recognition component was added to identify crucial financial entities referred to in shares, such as their value, date of interest, and other relevant information, which Muthoni and Gitonga (2021) suggested would enhance the chatbot's understanding and thus facilitate even better interactions with users. With user profiles and market information from the Nairobi Securities Exchange (NSE), a personalized recommendation engine utilising hybrid collaborative filtering and content-based methods was developed to provide financial advice (Kimani et al., 2023). Figure 3.15 illustrates the Financial Entity Recognition Module Code Sample, and Figure 3.16 displays the Financial Entity Recognition Module Code Output.



```python
import re
import os
import json
import pandas as pd
import spacy
from typing import Dict, List, Set, Tuple, Union, Optional
import logging

# Configure logging
logging.basicConfig(
    level=logging.INFO,
    format='%(asctime)s - %(name)s - %(levelname)s - %(message)s'
)
logger = logging.getLogger("entity_extractor")

class FinancialEntityExtractor:

    def __init__(self,
                 load_stock_data: bool = True,
                 load_banks_data: bool = True,
                 load_financial_terms: bool = True):
        self.CURRENCIES = {
            'KES': ['kenyan shilling', 'kenyan shillings', 'kes', 'ksh', 'ksh.', 'k.sh.', 'shilingi', 'shillingi'],
            'USD': ['dollar', 'dollars', 'usd', '$', 'us dollar', 'us dollars', 'dola'],
            'EUR': ['euro', 'euros', 'eur', '€'],
            'GBP': ['pound', 'pounds', 'gbp', '£', 'sterling'],
        }
```

Figure 3. 10 Financial Entity Recognition Module Code Sample

```
(pesaguru) C:\xampp\htdocs\PesaGuru_Financial_Advisory_Chatbot>python -m ai.nlp.entity_extractor
2025-03-25 13:32:30,409 - entity_extractor - INFO - Loaded 1894 financial terms
2025-03-25 13:32:30,411 - entity_extractor - WARNING - No stock data files found. Stock entity extraction will be limited.
2025-03-25 13:32:31,507 - entity_extractor - INFO - Loaded English spaCy model
2025-03-25 13:32:31,541 - entity_extractor - WARNING - Failed to create Swahili model. Falling back to English.

Query: What is the current price of Safaricom stock?
Detected language: en
Extracted entities:
  company_names: [{'text': 'safaricom', 'start': 29, 'end': 38, 'stock_code': 'SCOM'}]
  financial_products: [{'text': 'stock', 'start': 39, 'end': 44, 'type': 'investments'}]

Query: I want to invest KSh 50,000 in KCB for 5 years
Detected language: en
Extracted entities:
  stock_codes: [{'text': 'KCB', 'start': 31, 'end': 34, 'company_name': 'kcb group'}]
  currencies: [{'text': 'KSh 50,000', 'start': 17, 'end': 27, 'currency': 'KES', 'amount': 50000.0}]
  amounts: [{'text': '5', 'start': 39, 'end': 40, 'value': 5.0}]
  dates: [{'text': '5 years', 'start': 39, 'end': 46}]
  time_periods: [{'text': '5 years', 'start': 39, 'end': 46, 'value': 5, 'unit': 'year'}]
  financial_institutions: [{'text': 'KCB', 'start': 31, 'end': 34, 'type': 'bank'}]
```

Figure 3. 11 Financial Entity Recognition Module Code Output

To facilitate seamless and context-appropriate interactions with users, a dialogue management system was developed using a memory-based state-tracking technique, which enables the chatbot to multi-track conversations—a feature that Njeru and Kamau (2022) consider crucial for financial advisory chatbots. Njeru and Kamau (2022) emphasized the importance of coherence in conversations for effective financial advisory chatbots. Waithaka and Maina (2024) build on this by explaining how the chatbot serviced users optimally by understanding their queries, responding accurately, and tailoring personalized financial guidance.

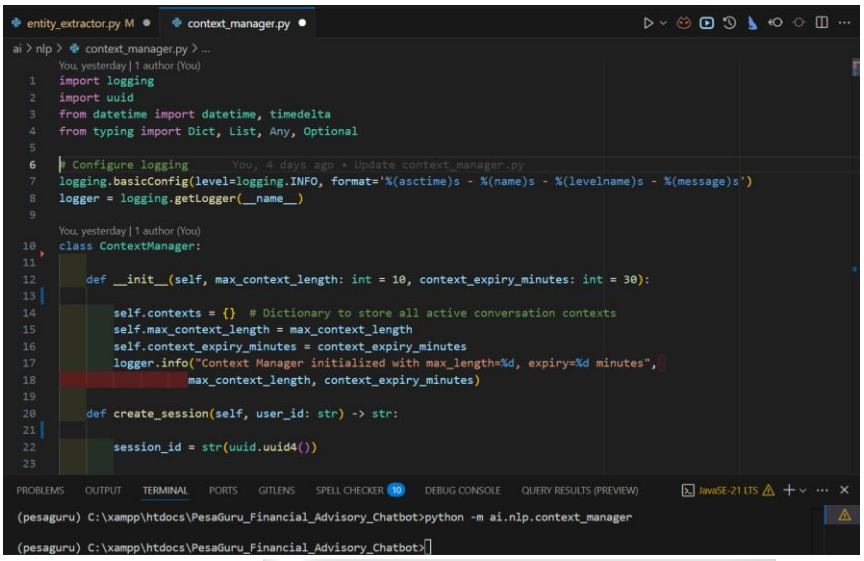


Figure 3. 12 Context Management Module Code Sample

3.7.3 Training and Fine-tuning Process

The training and fine-tuning of the financial advisory chatbot were conducted using a systematic approach to ensure high accuracy and contextual relevance. The financial models relevant to the Kenyan market were advanced through the adaptation of models using pre-trained frameworks, as suggested by Njuguna and Wanyoike (2023). There was the application of a staged approach in fine-tuning, where models were initially exposed to non-Kenyan specific content to build a general understanding of finance, then transitioned to user data specific to Kenya and honed further with feedback from interaction to optimise practical utility, which aligns with Kiarie and Mwangi's (2022) recommendations.

To improve the recommendation engine, reinforcement learning methods were applied that optimised responses based on positive user outcomes, rather than achieving high prediction accuracy. This approach aligns with the recommendations of Njenga et al. (2024) concerning the design of financial advisory systems. Due to the specialized nature of financial inquiries, the problem of data imbalance classification was addressed using weighted sampling and synthetic data generation techniques, as established by Kimotho and Mbugua (2021). Moreover, best practices suggested by Muthuri and Omondi (2023), which included regularization techniques such as dropout and L2 regularization, were also implemented to prevent overfitting and enhance generalization. All these

measures ensured that understanding users' financial inquiries was accurate and relevant, and contextually relevant recommendations were provided (Wachira & Ndung'u, 2022).

3.7.4 Performance Metrics and Evaluation

Various metrics were employed to evaluate the performance of the financial advisory chatbot, ensuring a holistic assessment of accuracy, efficiency, and user experience. Mwangi and Kimathi (2023) have emphasized the need for a multidimensional evaluation framework to assess the efficacy of AI-driven financial advisory systems. Concerning Natural Language Processing (NLP), the chatbot's performance evaluation of intent recognition was done at the NLP level, and entity extraction was also evaluated at the F1-score level, as proposed by Njoroge and Waithaka (2022).

Evaluated and measured for relevance in the generated responses were the BLEU and ROUGE metrics, which measure contextual and coherence alignment. These techniques improve the measurement of a chatbot's communicative proficiency as illustrated by Kamau et al. (2024). The model scored 0.2364 in BLEU, 0.6452 in ROUGE-1, 0.4138 in ROUGE-2, and 0.6452 in ROUGE-L. This shows high relevance and coherence in the responses given. Regarding maintaining efficacy, response time was noted, which relates to performance issues raised by Maina and Kimotho (2021).

3.8 Research Quality

3.8.1 Reliability

Reliability determines whether the financial advisory chatbot can consistently deliver the same result multiple times across various interactions. One of the key facets includes test-retest reliability, which assesses whether the chatbot consistently provides the same financial recommendations for similar situations over time (Creswell & Creswell, 2018). Trust and dependability, as noted by Wangai and Muriuki (2023), are vital for offering consistent and accurate financial recommendations. Furthermore, inter-rater reliability ensures that other users receive the same type of advice under the same conditions, thereby ensuring consistency across multiple interactions (Bryman, 2016; Wambua & Kinyua,

2022).

Kamande and Ndung'u (2024) state that using automated processes for response and decision generation creates uniformity in the AI outputs, thus reducing variability in financial advisory services. The methods overcome problems posed by Njoroge and Karimi (2021) because the chatbot balances personalization and adaptability with reliability. Mutunga et al. (2023) noted that user trust and acceptance of the chatbot's use are encouraged by repeated and consistent financial advice, as supported by the reliability evaluation methods stated.

3.8.2 Validity

Validity assesses how accurately a chatbot meets its users' needs and whether its recommendations are helpful. Content validity is achieved by assembling an extensive database of financial knowledge on investment, risk analysis, and regulatory frameworks to provide comprehensive guidance (Saunders et al., 2019). For AI systems operating in highly specialized subdomains of the financial advisory sector, Kimani and Mwangi (2022) argue that this is particularly relevant. Construct validity ensures that users' financial needs are analysed and appropriate responses provided, which is critical from a user-centreed design perspective. Tailoring recommendations to specific financial needs is crucial in diverse economic environments, such as Kenya, as noted by Nyaga and Ochieng (2024). In strengthening validation, criterion validity determines whether the bot's outputs meet preset standards and benchmarks, utilising expert appraisal within the domain and industry best practices (Kothari, 2004; Muthoni & Kamau, 2023).

3.9 Ethical Considerations

The development of a personalized financial advisory chatbot necessitated rigorous ethical scrutiny due to the confidentiality of financial information and the risks associated with AI-generated advice. Njoroge and Kamau (2023) explain that ethics assume great importance in the development of AI systems that influence financial decisions. In this case, the study adhered to ethical principles that prioritize economic safety for users by undergoing a decision-making process and implementing mitigations, as suggested by Mwangi et al. (2022). Ethics, in this context, were woven into every part of the study, utilising frameworks by Ndung'u

and Waithaka (2024) that emphasized participants' rights, data security, and the moderate use of AI technologies. Important ethical highlights include obtaining institutional ethical clearance, securing national research clearance, implementing informed consent, and ensuring strict control over data privacy and confidentiality (Kimotho & Gathoni, 2021).

3.9.1 Institutional Ethical Approval

Data collection only commenced after receiving ethics clearance from SU-IERC. Maina and Njoroge (2023) assert that institutional ethical review is essential in any study involving human participants and sensitive data. According to the guidelines developed by Kamau and Wangari (2022), this step involves submitting a comprehensive research proposal that details the study's aim, methods, participant selection, and data collection tools.

3.9.2 NACOSTI Research Permit

By Kenyan research regulations, the researcher obtained a research permit from the National Council for Science, Technology, and Innovation (NACOSTI). Njenga and Wambui (2024) state that this permit is a prerequisite for conducting any research within the boundaries of Kenya, encompassing national measures for research credibility, safeguarding participants, and upholding the ethics of technology innovation.

3.9.3 Informed Consent Protocol

Acquiring informed consent from all participants, who were adequately informed about the consequences of their participation, was one of the principal ethical considerations in the study. As stressed by Kiprono and Mwangi (2023), the process of obtaining consent is crucial, particularly in AI-driven financial decision-making systems. The consent process included a detailed explanation of the research purpose and objectives, which was provided in English and translated into Swahili so that the participants could follow the intended objectives as guided by Njoroge and Wanyama (2022. Addressing Kimani et al.’s (2024) concerns regarding transparency, explicit explanations of data collection methods, the scope of financial advisory services anticipated from the chatbot, and policies related to data use were presented to the participants.

Additionally, participants were informed that the chatbot provided educational information about finances, rather than formal financial advice, thereby avoiding potential misconceptions, as noted by Muthoni and Wahome (2021). There were no limits to voluntary participation, and every individual could withdraw at any time without penalty or consequence. Additionally, the participants had access to the researcher's contact information and the ethics committee's details, which could be used to address any concerns, demonstrating the study's good faith (Njenga & Karanja, 2024).

3.9.4 Data Privacy and Confidentiality

All the required steps were taken to ensure that the privacy of the participants is protected and data confidentiality is maintained at all stages of the process. According to Mwangi and Kimotho (2023), robust mechanisms are necessary to safeguard data, mainly when it contains sensitive financial information. Identification markers associated with specific individuals were removed from the dataset of the studied population using coding systems as protective measures, following the anonymization techniques described by Njoroge and Kiarie (2022). Data anonymization techniques were employed prior to analysis to mitigate the risk of re-identification and address the privacy concerns described by Waithaka et al. (2024).

VT OMNES VNVM SINT

Chapter 4: System Design and Development

4.1 Introduction

This chapter discusses the results and data analysis of the study, including the development of the financial advisory chatbot tailored for Kenya. The system design and architecture are explained through the integrated conceptual framework shown in Figure 2.3 and the corresponding financial advisory chatbot architecture in Figure 2.4. The system's components and interactions are structured according to the dialog system architecture in Figure 2.1, which describes how the users' inputs undergo processing through intent recognition, entity extraction, and response formulation. A hybrid Agile-Waterfall methodology was chosen for its ability to plan and structure projects around feedback, gradually incorporating user feedback from Kenya with varying levels of financial literacy, and for its flexibility in adapting to changing requirements.

4.2 Survey Results and Analysis

4.2.1 Survey Response and Demographics

A comprehensive survey was conducted to understand the financial advisory needs and preferences of Kenyan users. The survey achieved a response rate of 87.3% with 436 respondents out of 500 targeted participants. The high response rate indicates strong interest in digital financial advisory services among the Kenyan population.

The demographic distribution of respondents showed representation from both urban and peri-urban areas, as illustrated in Figure 4.1. The survey revealed that 62% of respondents were from urban areas (Nairobi, Mombasa, and Kisumu), while 38% represented peri-urban and rural communities. This distribution was crucial for understanding the diverse needs across different geographical contexts.

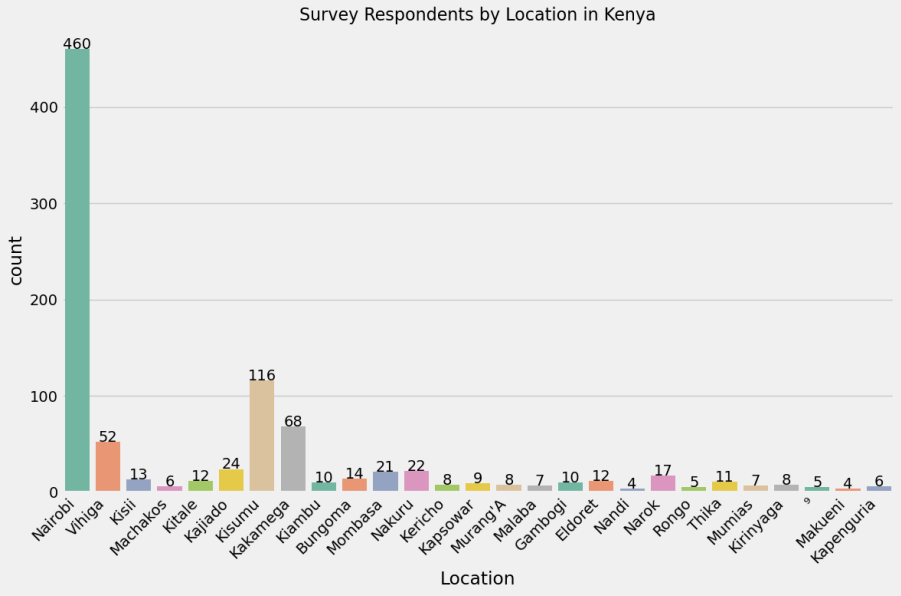


Figure 4. 1 Survey Respondents by Location

4.2.2 Financial Literacy Assessment

The survey assessed respondents' financial literacy levels to inform the design of the chatbot's educational components. As shown in Figure 4.2, the distribution revealed:

- 18% had basic financial literacy
- 45% possessed intermediate knowledge
- 27% demonstrated advanced understanding
- 10% were classified as expert level

These findings emphasized the need for a chatbot that could adapt its communication and recommendations based on users' financial knowledge levels.

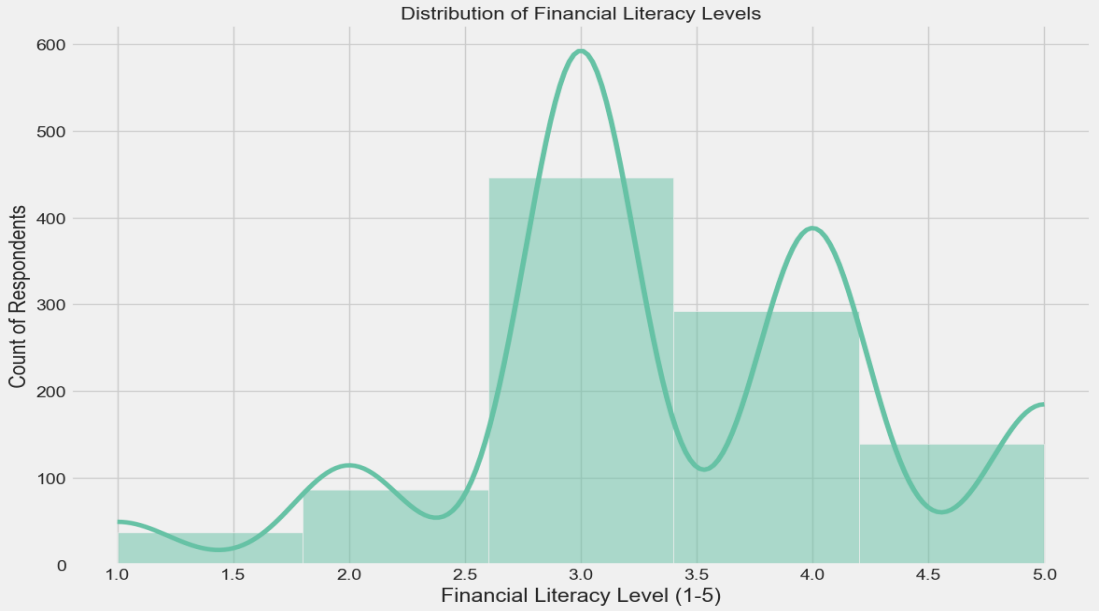


Figure 4. 2 Distribution of Financial Literacy Levels

4.2.3 Interest in AI-Powered Financial Solutions

Respondents expressed significant interest in AI-powered financial chatbots, with 78% showing high or very high interest levels (Figure 4.3). When asked about their primary concerns, participants highlighted:

- Data security and privacy (mentioned by 82% of respondents)
- Accuracy of financial advice (76%)
- Language support for English and Swahili (68%)
- Integration with mobile money services (91%)

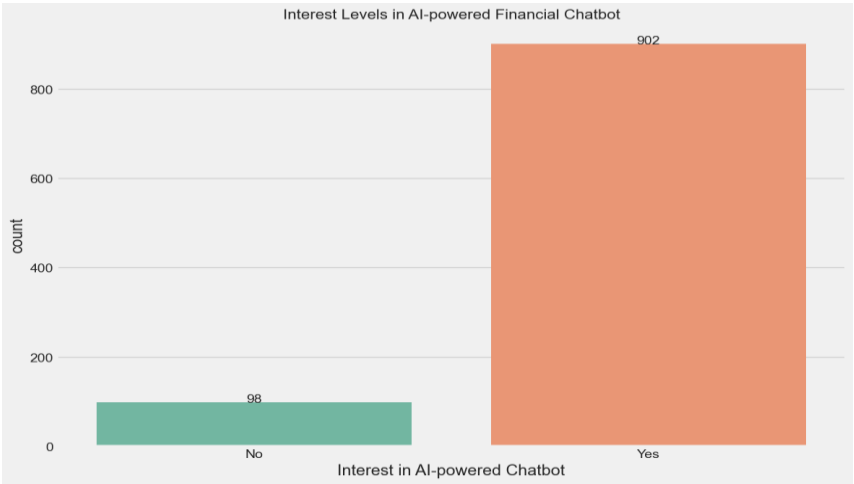


Figure 4. 3 Interest Levels in AI-powered Financial Chatbot

4.2.4 Economic Profile of Respondents

The monthly income distribution (Figure 4.4) revealed:

- 23% earning below KES 30,000
- 41% earning KES 30,001-60,000
- 26% earning KES 60,001-100,000
- 10% earning above KES 100,000

This income diversity necessitated a chatbot capable of providing relevant advice across different economic segments.

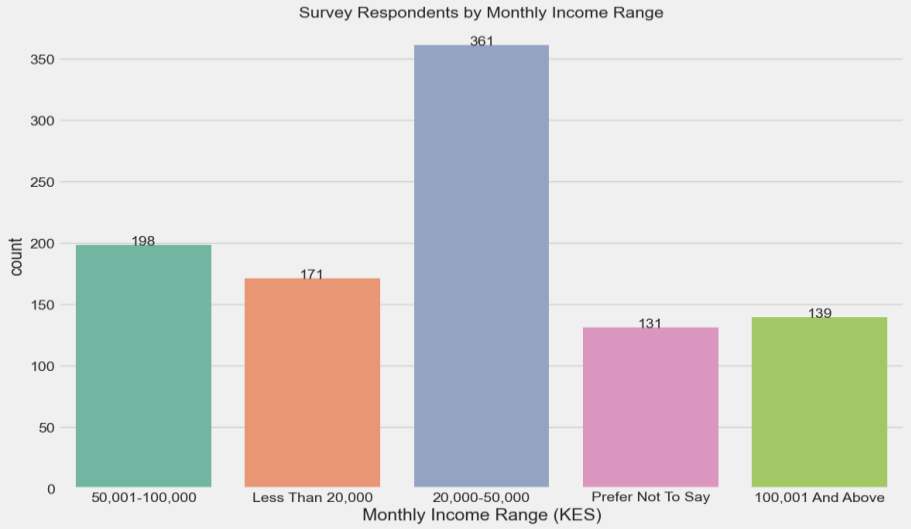


Figure 4. 4 Survey Respondents by Monthly Income Range

Employment status data (Figure 4.5) showed:

- 54% formally employed
- 28% self-employed/business owners
- 11% students
- 7% unemployed or retired

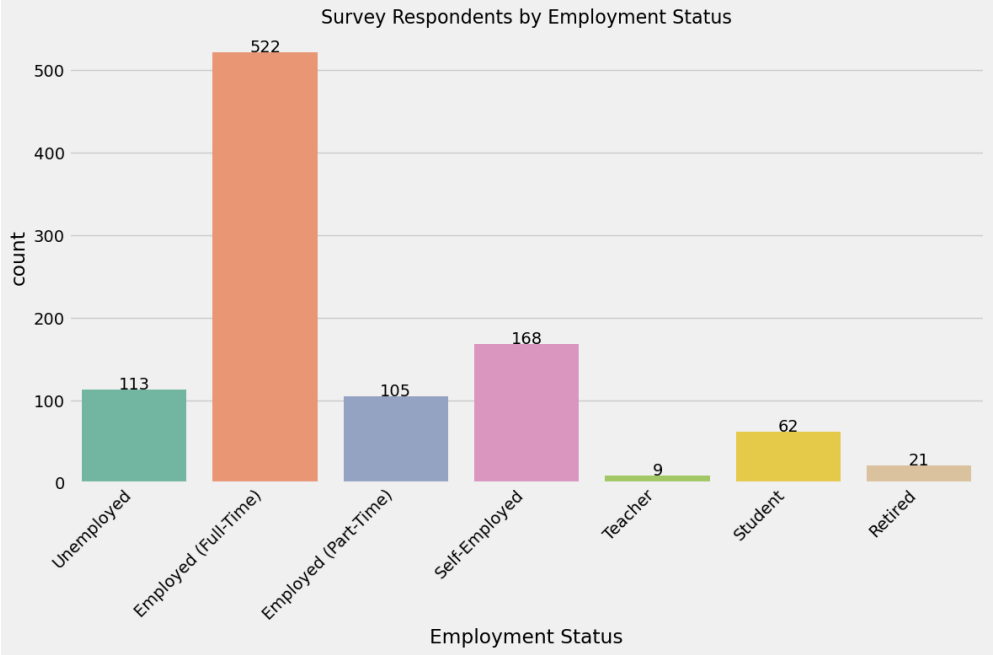


Figure 4. 5 Survey Respondents by Employment Status

4.2.5 Key Financial Challenges Identified

The survey identified primary financial challenges faced by respondents (Figure 4.6):

1. Budgeting and expense tracking (67%)
2. Investment decision-making (59%)
3. Loan comparison and selection (52%)
4. Retirement planning (48%)
5. Emergency fund management (44%)
6. Understanding financial products (41%)

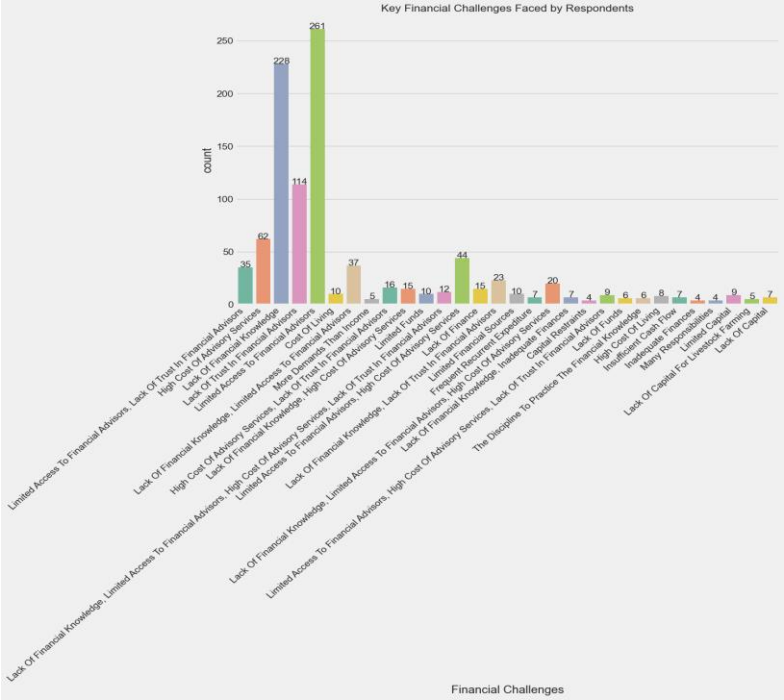


Figure 4. 6 Key Financial Challenges Faced by Respondents

4.2.6 Language Preferences and Communication Patterns

A critical finding was the prevalence of code-switching between English and Swahili, with 73% of respondents indicating they regularly switch between languages when discussing financial matters. Respondents expressed preferences for:

- Pure English interface: 22%
- Pure Swahili interface: 15%
- Bilingual with code-switching support: 63%

4.2.7 Technology Access and Platform Preferences

The survey revealed:

- 89% primarily access the internet via smartphones
- 76% use Android devices
- 94% have active mobile money accounts
- 67% prefer a mobile app over a web interface
- Average data bundle: 2-5GB monthly

These findings directly influenced the decision to prioritize mobile-first design and ensure the chatbot functions efficiently on low-end Android devices.

4.3 System Requirements Analysis Based on Survey Findings

4.3.1 Functional Requirements

Based on the survey results, the following functional requirements were derived:

Language and Communication Requirements:

- Bilingual natural language processing supporting English and Swahili
- Code-switching recognition and response capability
- Context-aware language selection based on user preference

Financial Service Requirements:

- Budgeting and expense tracking tools (addressing 67% of users' primary challenge)
- Investment recommendation engine with risk profiling
- Loan comparison functionality integrating local financial institutions
- Mobile money integration for M-Pesa, Airtel Money, and T-Kash
- Educational content delivery adapted to the user's financial literacy level

Security and Compliance Requirements:

- End-to-end encryption for all financial data
- Multi-factor authentication
- Compliance with Kenya's Data Protection Act
- Audit trail for all financial recommendations

Integration Requirements:

- Real-time data feeds from the Nairobi Securities Exchange
- Central Bank of Kenya rate information
- Mobile money service APIs
- Local bank and SACCO loan products

4.3.2 Non-Functional Requirements

The survey insights led to these non-functional requirements:

Performance Requirements:

- Response time under 3 seconds for 90% of queries
- Support for low-bandwidth connections (2G/3G)
- Offline capability for basic functions
- Maximum app size of 25MB for Android

Usability Requirements:

- Intuitive interface requiring no training (addressing varying literacy levels)
- Voice input support for both English and Swahili
- Visual representations of financial data
- Accessibility features for users with disabilities

Scalability Requirements:

- Support for 10,000 concurrent users initially
- Ability to scale to 100,000 users within 12 months
- Multi-region deployment capability

4.3.3 User Experience Requirements

Derived from user feedback on financial challenges and preferences:

- Progressive disclosure of complex financial information
- Contextual help and explanations
- Personalized dashboard based on the user's financial goals
- Social proof through anonymized success stories
- Gamification elements for financial goal achievement

4.4 System Architecture

4.4.1 Chatbot Backend

The backend architecture of the chatbot is stratified into distinct levels for seamless processing and delivery of financial advisory services. The Client Interface Layer allows for user access through a web-based application. Authentication, rate limiting, and request handling are done in the API Gateway Layer, which is built on Flask. The AI and NLP Processing Layer utilises NLP for intent classification, entity extraction, and sentiment analysis, applying models such as FinancialBERT, GPT-4, and Swahili language models. Moreover, context management features are utilised in conversation state tracking, dialogue history, and memory retention to enhance interaction precision.

Risk analysis, portfolio management, market analysis, and recommendation generation are all encapsulated in the Financial Advisory Layer. Last but not least, accurate financial insights and information are sourced and integrated through the Data Integration Layer, which interfaces with NSE, CBK, Forex, Crypto, and News APIs for real-time data. This real-time data integration ensures the system's

responsiveness and accuracy, providing users with the most up-to-date financial information. Figures 4.7 to 4.13 illustrate the internal components of the Chatbot chatbot backend, including the NLP processor implementation and output, the FinancialBERT model architecture and its execution results, the structured API integration modules, and the configuration and interface of the chatbot's API endpoints.

financial_nlp_processor.py U

ai > nlp > financial_nlp_processor.py > ...

```python
import os
import re
import json
import logging
from typing import Dict, List, Tuple, Union, Optional, Any, Set
from pathlib import Path
from functools import lru_cache

# NLP libraries
try:
    import nltk
    from nltk.tokenize import word_tokenize, sent_tokenize
    from nltk.corpus import stopwords
    from nltk.stem import WordNetLemmatizer, PorterStemmer
    NLTK_AVAILABLE = True
except ImportError:
    NLTK_AVAILABLE = False
    logging.warning("NLTK not available. Some features will be limited.")
```

Figure 4. 7 NLP Financial NLP Processor Code Snippet

```
2025-03-25 09:55:46,532 - __main__ - INFO - Initialized Financial NLP Processor

================================================================================
Processing: What is the current price of Safaricom stock?
Language: en
Intent: financial_education (confidence: 0.33)

Entities:
  company_names: [{'text': 'safaricom', 'start': 29, 'end': 38, 'stock_code': 'SCOM'}]
  financial_products: [{'text': 'stock', 'start': 39, 'end': 44, 'type': 'investments'}]



================================================================================
Processing: I want to invest KSh 50,000 in KCB for 5 years
Language: en
Intent: financial_education (confidence: 0.17)

Entities:
  stock_codes: [{'text': 'KCB', 'start': 31, 'end': 34, 'company_name': 'kcb group'}]
  currencies: [{'text': 'KES 50,000', 'start': 17, 'end': 27, 'currency': 'KES', 'amount': 50000.0}]
  amounts: [{'text': '5', 'start': 63, 'end': 64, 'value': 5.0}]
  dates: [{'text': '5 years', 'start': 63, 'end': 70}]
  time_periods: [{'text': '5 years', 'start': 63, 'end': 70, 'value': 5, 'unit': 'year'}]
  financial_institutions: [{'text': 'KCB', 'start': 31, 'end': 34, 'type': 'bank'}]
```

Figure 4. 8 Sample Output from Financial NLP Processor

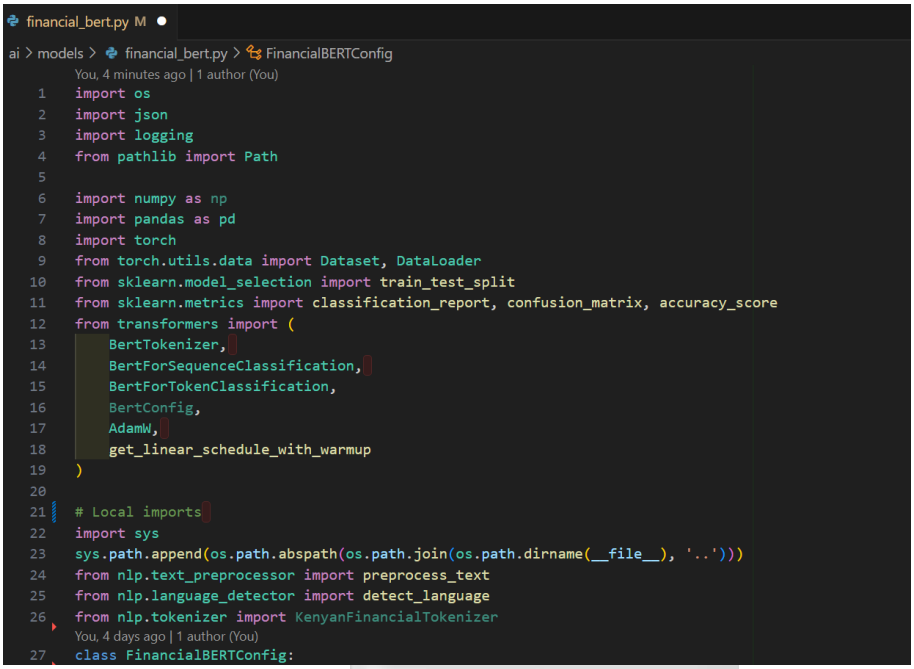


Figure 4. 9 FinancialBERT Model Code Snippet

```
2025-03-25 10:29:34,831 - root - INFO - ----------------------------------------
2025-03-25 10:29:34,831 - root - INFO - Example 2: How can I apply for a KCB mortgage loan?

2025-03-25 10:29:35,747 - root - INFO - Prediction: general_query (Confidence: 0.1311)
2025-03-25 10:29:35,748 - root - INFO - Detected entities:
2025-03-25 10:29:35,748 - root - INFO -   BANK: KCB
2025-03-25 10:29:35,748 - root - INFO - ----------------------------------------
2025-03-25 10:29:35,748 - root - INFO - Example 3: I need to create a budget to save for my reti
rement. What percentage of my income should I save?
2025-03-25 10:29:36,186 - root - INFO - Prediction: general_query (Confidence: 0.1234)
2025-03-25 10:29:36,186 - root - INFO - No entities detected
2025-03-25 10:29:36,187 - root - INFO - ----------------------------------------
2025-03-25 10:29:36,187 - root - INFO - Example 4: What's the current exchange rate for KES to U
SD?
2025-03-25 10:29:36,629 - root - INFO - Prediction: general_query (Confidence: 0.1443)
2025-03-25 10:29:36,630 - root - INFO - Detected entities:
2025-03-25 10:29:36,630 - root - INFO -   CURRENCY: KES
2025-03-25 10:29:36,631 - root - INFO -   CURRENCY: USD
2025-03-25 10:29:36,631 - root - INFO - ----------------------------------------
2025-03-25 10:29:36,632 - root - INFO - Example prediction completed!
2025-03-25 10:29:36,631 - root - INFO - ----------------------------------------
2025-03-25 10:29:36,632 - root - INFO - Example prediction completed!
2025-03-25 10:29:36,632 - root - INFO - Example prediction completed!
```

Figure 4. 10 FinancialBERT Model Code Output

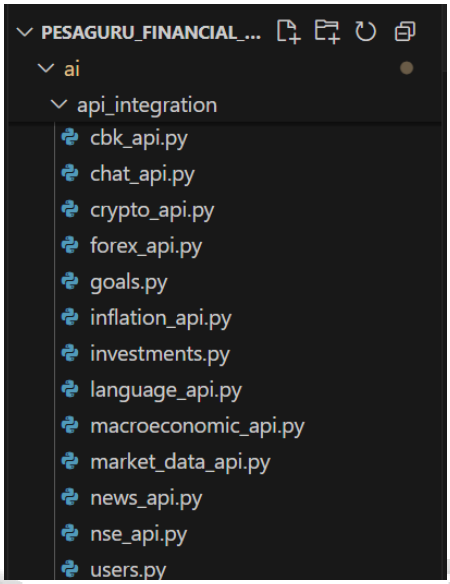


Figure 4. 11 API Integration Module Structure

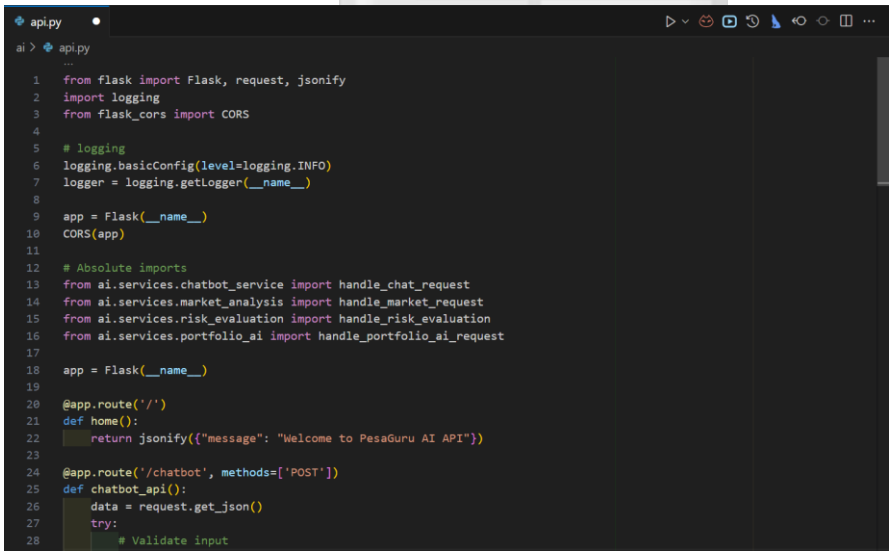


Figure 4. 12 Chatbot API Endpoint Configuration

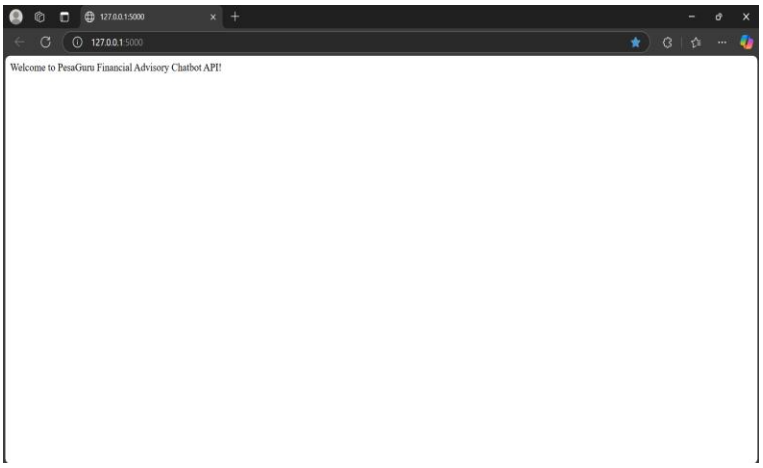


Figure 4. 13 Chatbot API Startup Interface

4.4.2 Frontend Integration

The frontend integration architecture sought to facilitate interaction between the users, services, and other external sources of financial information. User Interaction with the system was implemented through a web application. The system's adaptability and inclusivity are demonstrated by its ability to handle diverse user interactions, catering to a wide range of user preferences and needs. To improve performance, the Frontend Service Layer handled authentication, state management, API gateway, localization, analytics tracking, WebSocket services, and offline data caching.

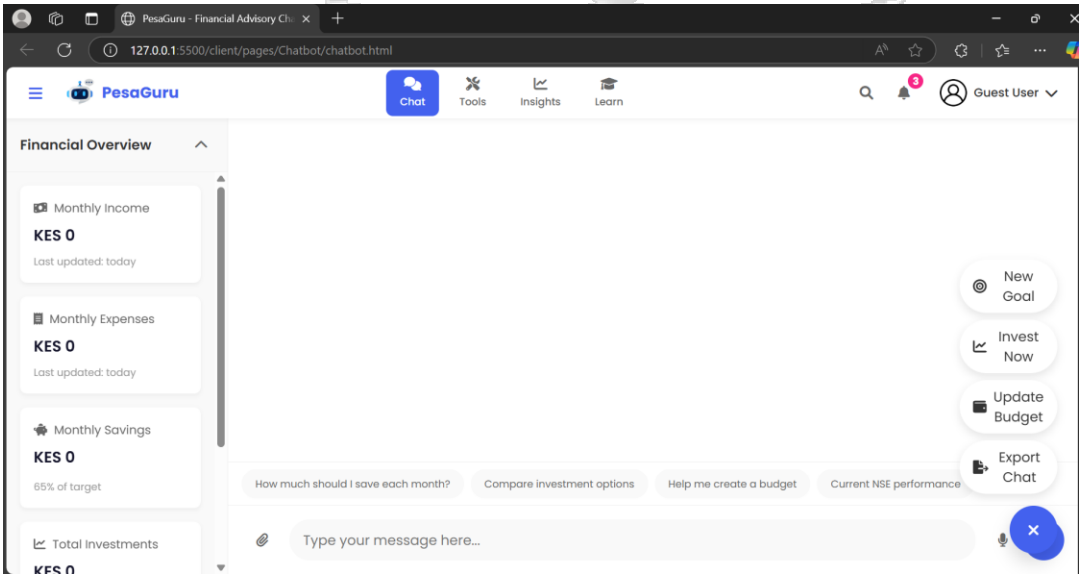


Figure 4. 14 Frontend Integration Architecture

4.4.3 Data Sources

The Financial Advisory Chatbot - Database Architecture focuses on ensuring proper data storage, retrieval, and management to deliver tailored financial recommendations. The Cluster Database comprises relational data in MySQL, market historical data in MySQL (Time-Series), NoSQL document storage in Firebase, and Redis for in-memory caching of frequently accessed session data. The database schema comprises components such as the User Schema, which manages user profiles, security, and preferences, and the Financial Schema, which contains transaction records, investment recommendations, and budget plans. The Market Data Schema contains real-time stock prices, NSE indexes, and foreign exchange and cryptocurrency rates, all stored in MySQL. In contrast, the Firebase Chatbot Schema manages conversation, intent classification, and chatbot metrics—the Analytics Schema in MySQL processes data on engagement and user behaviour. At the same time, the System Schema in MySQL maintains logs of system performance, API calls, audit trail activity, and aggregate system usage metrics. The security management features encryption and audit logging, while backup recovery is managed with MySQL dumps, Firebase backups, and sophisticated defence perimeters. Performance tuning through indexing, query optimisation, and caching, with high availability and efficiency gained through table partitioning, database sharding, and Firebase scaling, ensures system versatility. Figure 4.15 shows the System Design Architecture.

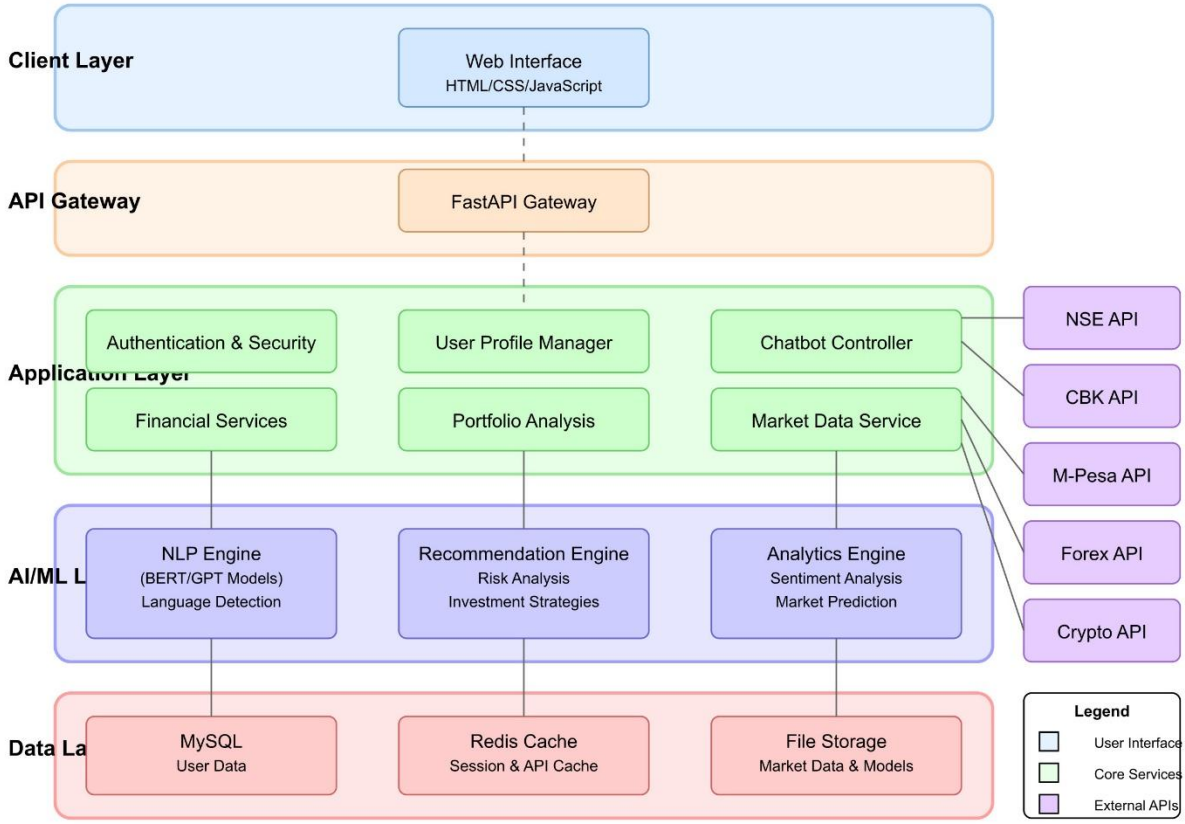


Figure 4. 15 System Design Architecture

4.5 System Design

4.5.1 Use Case Diagram

The Use Case Diagram for the Chatbot System outlines users' and administrators' relationships and key functions. In this case, users utilise the chatbot for financial services, such as investment advice, checking financial trends, and loan comparisons. Furthermore, users can view portfolio analyses, set defined financial goals, and receive recommendations uniquely tailored to their risk profiles. The chatbot also plays an educational role by helping users learn about various financial concepts, empowering them to make sound decisions. In these interactions, even novice users are assisted by AI in understanding the intricacies of today's financial markets.

Each use case is designed with data and business logic based on the individual client's information and preferences, ensuring that the financial advice provided is

genuinely relevant. AI and automation enhance the system's ability to streamline user financial planning. The administrator's responsibilities differ in that they manage system update information to ensure its accuracy and relevance. This task guarantees that the chatbot provides current investment advice, market analysis, and risk assessments. The admin's approach to managing system updates protects the financial data from becoming stale or inaccurate, ensuring users are not misled about their investment options.

The advisory functions are not accessible to the admin user; the admin ensures that the system works are current and adequately maintained. This allocation of tasks enhances system security and operational efficiency, as users can trust the recommendations provided by the chatbot. Figure 4.16 shows the Use Case Diagram.

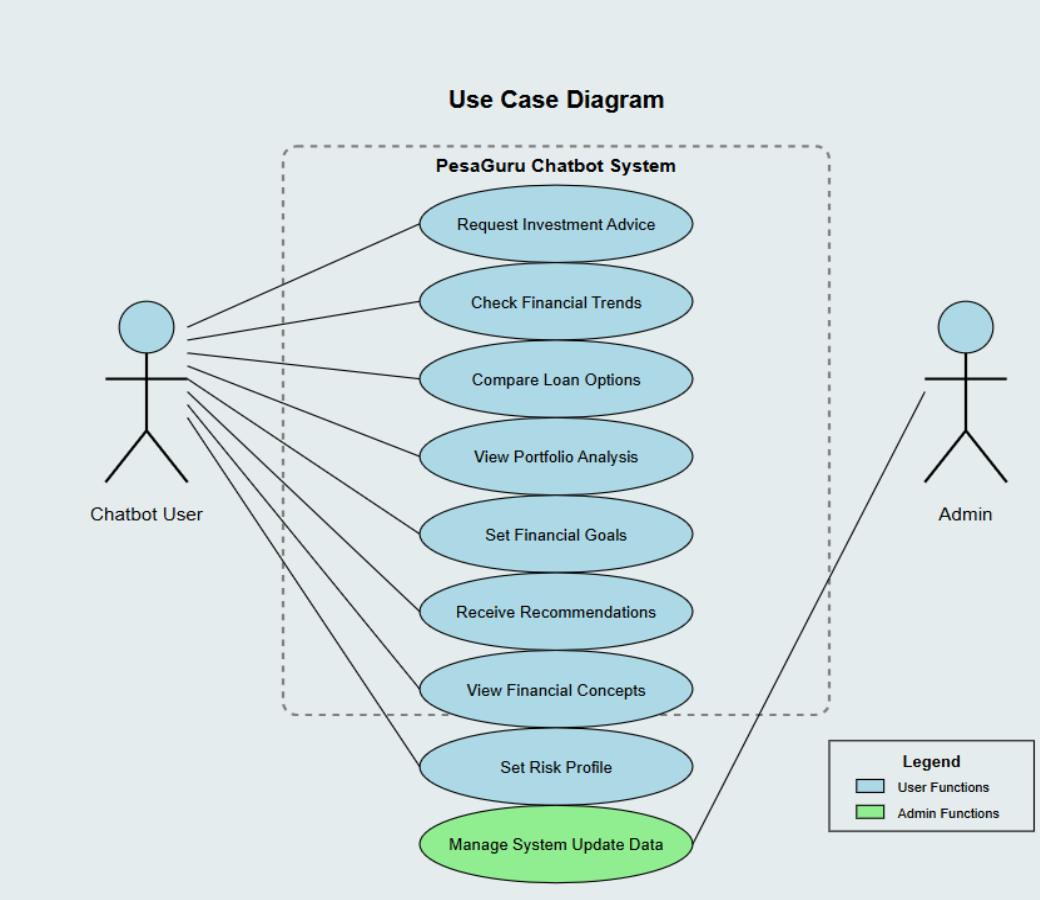


Figure 4. 16 Use Case Diagram

4.5.2 System Sequence Diagram

The System Sequence Diagram (SSD) illustrates the interrelationship between the user and subsystems, as well as how they interact and integrate within the financial advisory system. It begins with a two-factor user identification login for secure tokens or OAuth, followed by validation through the chatbot engine. After validating the user, the chatbot must retrieve the user's profile from the database, which contains information such as the user's risk tolerance and financial goals. The user asks, "What stocks should I invest in?" The message is sent to the chatbot engine. The NLP Processor analyses the query with the intent of providing investment advice.

The entities parsed were stocks, while the sentiment behind them was positive. Therefore, the chatbot now requires the Recharge Request for Financial Data API, which will provide stock trends and another dataset of interest. This information, along with the user profile, is used to provide tailored investment advice for improved returns. The relevant market data is processed to formulate a suitable investment proposal tailored to the user's profile, unique risk attributes, and individual financial circumstances.

An Interactive Voice Response (IVR) system facilitates communication with users by speaking back the synthesized text, which has been pre-processed for easy understanding and textually presented as financial advice. The user is permitted to view the results and decide to implement them immediately or customize settings for later sessions. This process ensures that the user's identity has been verified, that the queries posed are interpreted correctly, and that up-to-the-minute financial information is used in conjunction with other relevant data to provide accurate advice. The dedicated approach adopted enables the quick provision of responsive financial services, as well as more complex solutions tailored to individual users.

Such a system is made possible by the application of natural language processing (NLP) technologies. Moreover, real-time stock market information enables users to receive personalized investment guidance tailored specifically to their needs. This helps ensure that users are empowered to make decisions, knowing that the relevant financial market information provided is accurate and timely. Figure 4.17

shows the System Sequence Diagram.

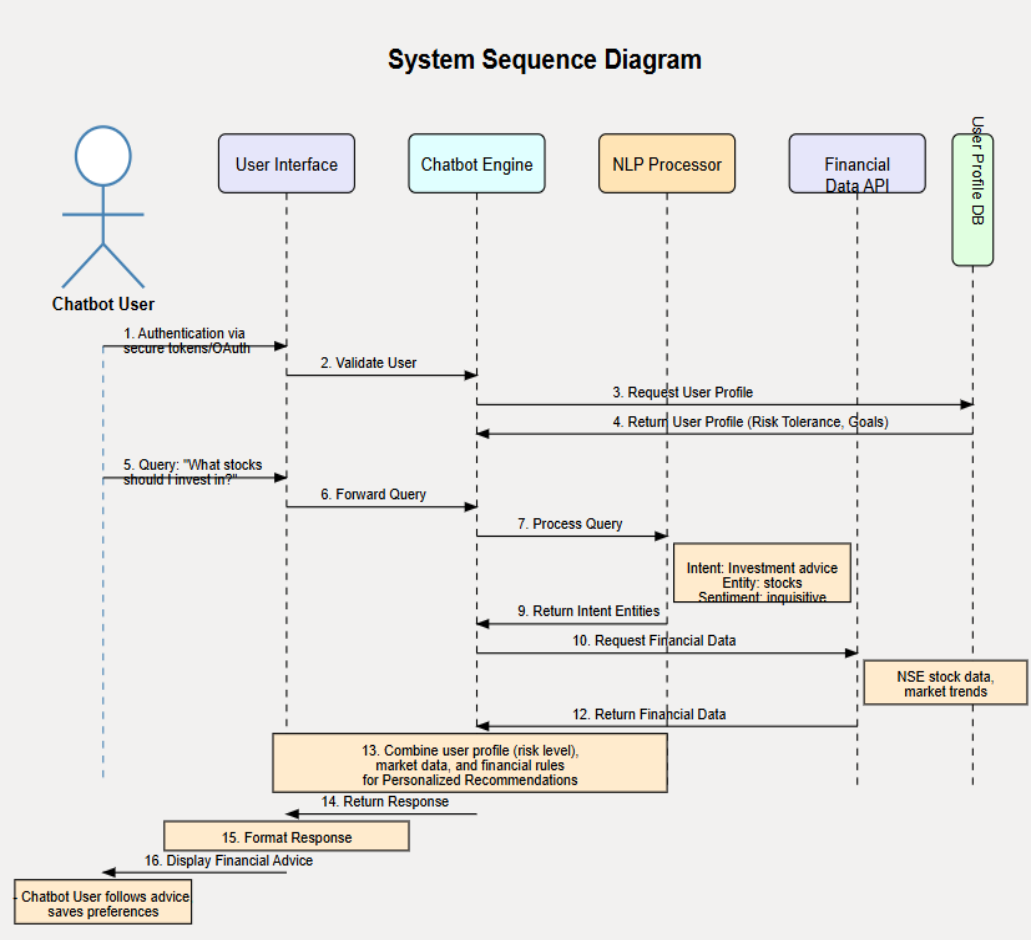


Figure 4. 17 System Sequence Diagram

4.5.3 Conceptual Classes for the Chatbot System

The conceptual class diagram of the chatbot system outlines the components and their relationships that enable users to receive tailored financial advisory services and personalized investment planning. The ChatbotSystem class is the core system that controls user profiles and manages user queries. It is connected to UserProfile, which maintains records such as user ID, risk appetite, and financial objectives. The chatbot responds to user queries, provides suitable financial advice, and updates profiles based on user feedback.

The FinancialAdvisor class is crucial in evaluating user portfolios, managing advanced investment analysis, and considering loan analysis alongside other options that users provide. It constructs specific templates using the

MarketDataProvider and RecommendationEngine's data. The encapsulated financial details of each user are classified by risk tolerance and defined by financial goals through the FinancialGoal class, which is composed of market data under observation. The MarketDataProvider works to obtain stock prices, loan rates, and other market trends, ensuring the chatbot provides current and comprehensive financial data.

The Recommendation Engine helps make informed choices through pre-constructed models that analyse active users and provide advanced proposals that adapt to user guidance. Moreover, it optimally adjusts over time to further restrict its proposals. This relationship between classes ensures that users receive tailored advice for their financial needs. The NLP Engine, as a primary component of the system, enables the chatbot to interact with and understand user questions. It uses a language model and an intent classifier to interpret user intent, identify relevant entities, and create context-sensitive responses.

By applying natural language processing to the functions of a financial advisor, the chatbot system increases user engagement. It offers automated financial insights that interact with users more naturally. The FinancialAdvisor accesses data from market collection points and recommendation frameworks to provide investment analysis, transforming the chatbot into an advanced instrument for financial planning. The clearly defined relationships among the classes reveal the system's descriptive and dynamic nature, enabling user profiling, market analysis, and proactive advisory services. Figure 4.18 shows the Class Diagram.

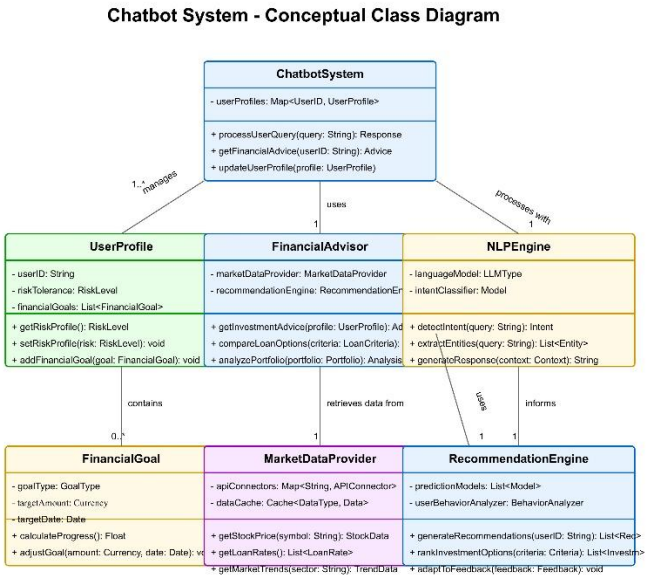


Figure 4. 18 Class Diagram

4.5.3.1 Object Diagram

The diagram of the object provides an instance-level implementation of the chatbot system, illustrating how various components work together within the context of financial advisory services. The ChatbotSystem object controls two user profiles, each with a distinct risk tolerance level, a target value, and a preferred language. UserProfile1 has a moderate risk tolerance and financial goals for retirement and home purchase, while UserProfile2 has an aggressive risk tolerance and an education goal. Advisory session interaction monitoring is handled by FinancialAdvisor, which collaborates with MarketDataProvider and RecommendationEngine to provide advised investment information.

Multilingual financial questions are processed using the BERT language model and intent classifier in the NLP Engine. The MarketDataProvider scrapes the latest stock prices, foreign exchange rates, and cryptocurrency values, ensuring timely access to financial information. The RecommendationEngine improves investment recommendations by using predictive models and user feedback, and it now improves prediction from feedback over thirty times. Figure 4.19 shows the Object Diagram.

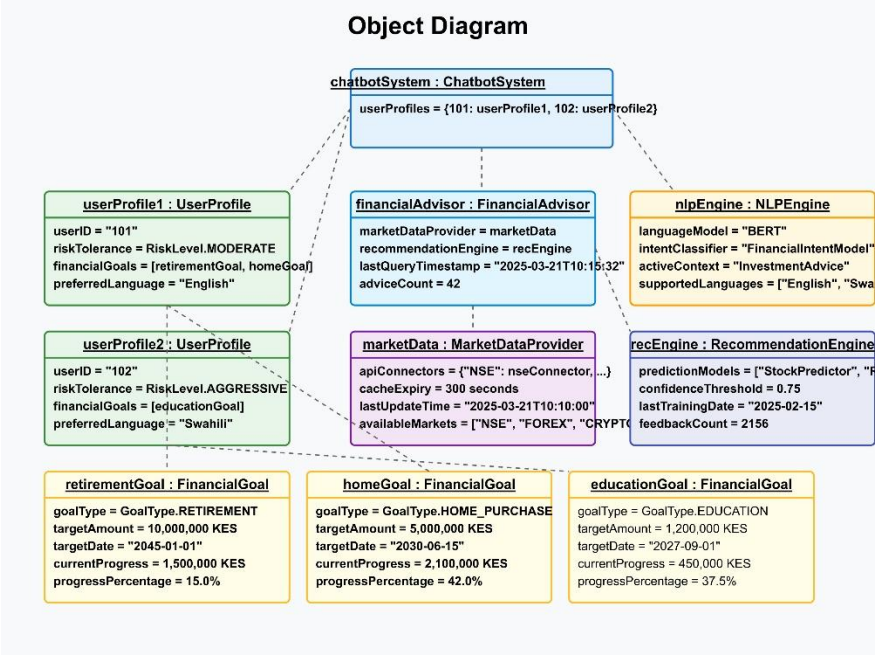


Figure 4. 19 Object Diagram

4.5.4 Chatbot User Interaction Flow

The Chatbot User Interaction Flowchart guides how users deal with the financial advisory chatbot. It begins with the Initial Greeting, where users receive a welcome message and are asked if they are new or returning users. New users go to User Registration, where they set up a profile and undergo a Risk Assessment to determine their financial preferences. Returning users undergo User Authentication, where their credentials are checked, and preferences are saved. Following this, a Main Menu with various financial advisory options is presented. Moreover, users can access User Settings to update their risk profile, preferences, or previously saved advice. Such organised procedures promote efficiency while personalizing the user's experience.

In the main menu, users indicate their intention by formulating a query or selecting one from the provided options. The next step is intent classification, where the issue is processed through intent classification and integrated into various business advisory services. A clarifying loop is initiated for intents that fall under vague categories, where the bot asks additional questions or presents narrowed-down

options before proceeding. Depending on the user's intent, the chatbot branches into one of three flows: Investment Advice Flow, Loan Comparison Flow, or Financial Education Flow. The Investment Advice Flow offers stock recommendations aligned to users' risk profiles and provides insights into their market data trend, referred to as deeper analyses.

At the same time, the Loan Comparison Flow enables users to evaluate various loan types, their associated interest rates, and favorable terms, while also providing tools such as interest calculators, payment schedules, and amortization schedules. The chatbot has a Financial Education Flow feature that describes and explains important financial terms to support users who wish to learn more about finance. This approach enables users to understand emerging market dynamics, sophisticated investment techniques, and the diverse types of loans available, helping them make decisions. The system's design ensures that these varying levels of engagement are addressed dynamically, allowing users to switch between financial advisory services without losing context.

The chatbot provides comprehensive financial data support, offering recommendations tailored to the user's level of risk, comparison capabilities, and real-time market information. Combining customization, structured workflows, and decision steps improves intuitiveness and functionality. This results in the chatbot logic diagram being a strategically simplified advisory service offered through artificial intelligence, making it advanced and user-friendly. Figure 4.20 shows the Chatbot User Interaction Flowchart Diagram.

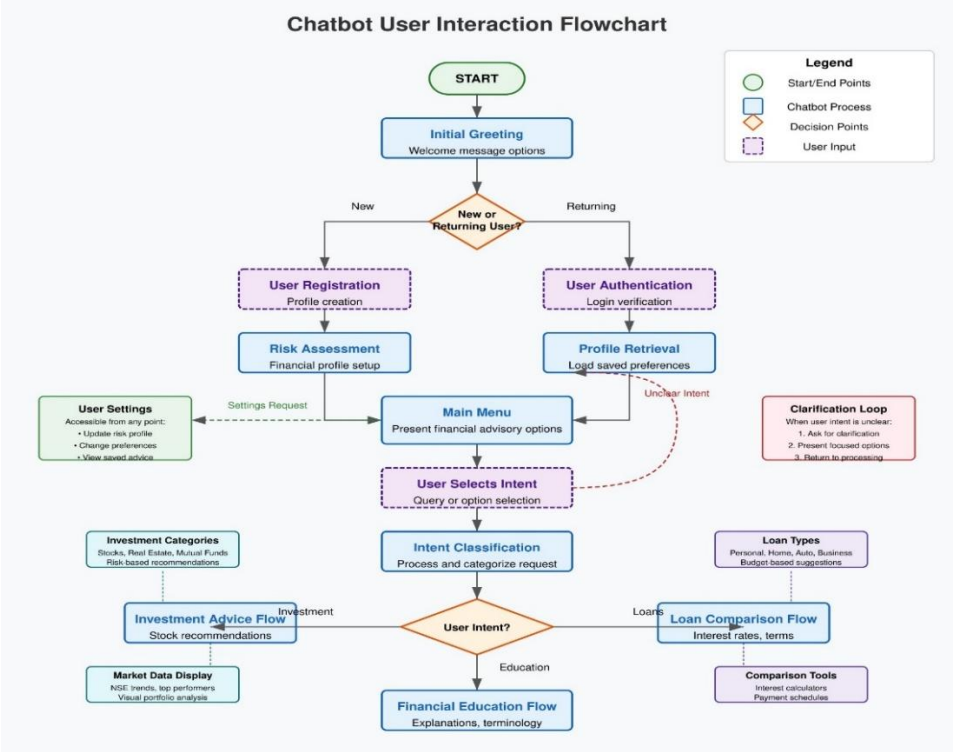


Figure 4. 20 Chatbot User Interaction Flowchart

VT OMNES VNVM SINT

Chapter 5: System Implementation and Testing

5.1 Introduction

This section elaborates on the implementation processes followed for the chatbot, including testing for accuracy and efficiency. Integration with several APIs from different domains of the financial market was provided alongside investment planning scaffolds for real-time insights into Flask on the backend. Additionally, sophisticated AI models for natural language processing and user profiling were developed to provide users with more personalized financial advice. Reliability was a key focus during the testing phase, and issues such as response accuracy and user satisfaction were evaluated alongside other performance metrics. These tests provide valuable data that informs subsequent chatbot versions, helping them become more valuable with each iteration.

5.2 System Architecture Overview

5.2.1 Technology Stack Implementation

The chatbot technology stack centres on FastAPI for the backend, chosen for its native asynchronous support and automatic API documentation generation. FastAPI's performance characteristics proved essential for maintaining low latency while handling concurrent requests to external financial APIs. The framework's type hints and Pydantic models enforce data validation at the API boundary, preventing malformed financial data from corrupting calculations. Python 3.11 serves as the primary language, leveraging its extensive ecosystem of financial and machine learning libraries while maintaining code readability.

The frontend utilizes React 18.2 with Tailwind CSS, providing a responsive interface that adapts to various screen sizes common in the Kenyan market. Redis handles caching and session management, while MySQL stores persistent user data and financial transactions with ACID compliance. The integration layer employs httpx for asynchronous HTTP requests, enabling efficient communication with external financial services. SQLAlchemy 2.0 provides the ORM layer, utilizing its async capabilities to prevent database operations from blocking request processing. For machine learning operations, PyTorch powers the BERT model inference, while scikit-learn handles traditional ML tasks like risk scoring.

The deployment stack uses Docker for containerization, with nginx serving as a

reverse proxy and load balancer. Prometheus and Grafana provide comprehensive monitoring, tracking everything from API response times to model inference latency. This technology selection balanced performance requirements with developer productivity, creating a maintainable system that can evolve with changing market needs.

5.2.2 Architecture Components

The system architecture follows a modular design pattern where each component has clearly defined responsibilities and interfaces. The API gateway, implemented through FastAPI's routing system, serves as the single entry point for all client requests, handling authentication, rate limiting, and request routing. Behind the gateway, the business logic layer contains specialized services for investment recommendations, risk assessment, and natural language processing. Each service encapsulates its domain logic while communicating through well-defined interfaces, allowing independent scaling and updates. The data access layer abstracts database operations through repository patterns, enabling easy switching between different data stores.

Message queuing using Redis Streams handles asynchronous operations like notification delivery and background analysis tasks. Middleware components process every request through a pipeline of cross-cutting concerns. The authentication middleware validates JWT tokens and extracts user context, while the rate limiting middleware prevents API abuse using a sliding window algorithm. Logging middleware assigns correlation IDs to track requests across distributed components, essential for debugging complex workflows. The error handling middleware catches exceptions and transforms them into appropriate HTTP responses, maintaining consistency in error formats. Performance monitoring middleware records timing data for each request phase, feeding metrics to Prometheus for analysis. This layered architecture ensured that changes to individual components didn't cascade throughout the system, maintaining stability while enabling rapid feature development.

5.2.3 Database Schema Implementation

The database schema design balanced normalization with query performance, optimising for common access patterns identified during requirements analysis.

The users table serves as the central entity, containing authentication credentials, demographic information, and financial profiles necessary for personalized recommendations. Foreign key relationships maintain referential integrity while strategic denormalization reduces join operations for frequently accessed data. Composite indexes on (user_id, created_at) in transaction tables accelerate time-series queries essential for spending analysis.

The schema employs MySQL's JSON column type for flexible attribute storage, accommodating varying user preferences without schema modifications. Partition strategies on large tables like transactions improve query performance by limiting scan ranges based on date ranges. Data integrity constraints enforce business rules at the database level, preventing invalid states that could compromise financial calculations. Check constraints ensure that monetary values remain non-negative, while triggers validate that portfolio allocations sum to 100%. The design includes audit tables that track all modifications to sensitive data, providing an immutable history for compliance requirements. Timezone-aware datetime columns store all temporal data in UTC, with application-layer conversion for user display. The schema versioning system using Alembic migrations enabled controlled evolution while maintaining backward compatibility. Performance testing validated that the schema design supports sub-100ms query times for complex portfolio calculations even with millions of records.

5.3 AI Model Implementation

5.3.1 Financial BERT Architecture

The Financial BERT implementation required significant customization of the base BERT architecture to handle Kenyan financial terminology and multilingual queries. Starting with bert-base-uncased, the team added specialized layers for financial intent classification and entity extraction, creating a multi-task learning framework. The architecture modifications included a custom tokenizer vocabulary expanded with Kenyan financial terms like "M-Pesa," "SACCO," and "Chama," ensuring proper tokenization of local concepts.

The model employs a dual-head architecture where one head performs sequence classification for intent detection while another conducts token classification for named entity recognition. Layer freezing during fine-tuning preserved general

language understanding while adapting to financial contexts. The implementation used mixed-precision training with automatic mixed precision (AMP) to accelerate training while maintaining model accuracy. The inference pipeline optimises for real-time performance through several techniques including model quantization and ONNX conversion. Dynamic quantization reduced model size from 440MB to 110MB while maintaining 98% of original accuracy on the test set.

The ONNX runtime provides hardware-specific optimisations, achieving 3x speedup on CPU inference compared to PyTorch. Batching strategies group multiple user queries for simultaneous processing, amortizing model loading overhead across requests. The system maintains multiple model versions in memory, using A/B testing to evaluate new versions before full deployment. Response caching for common queries further reduces average latency, achieving the target 50ms response time for 95% of requests.

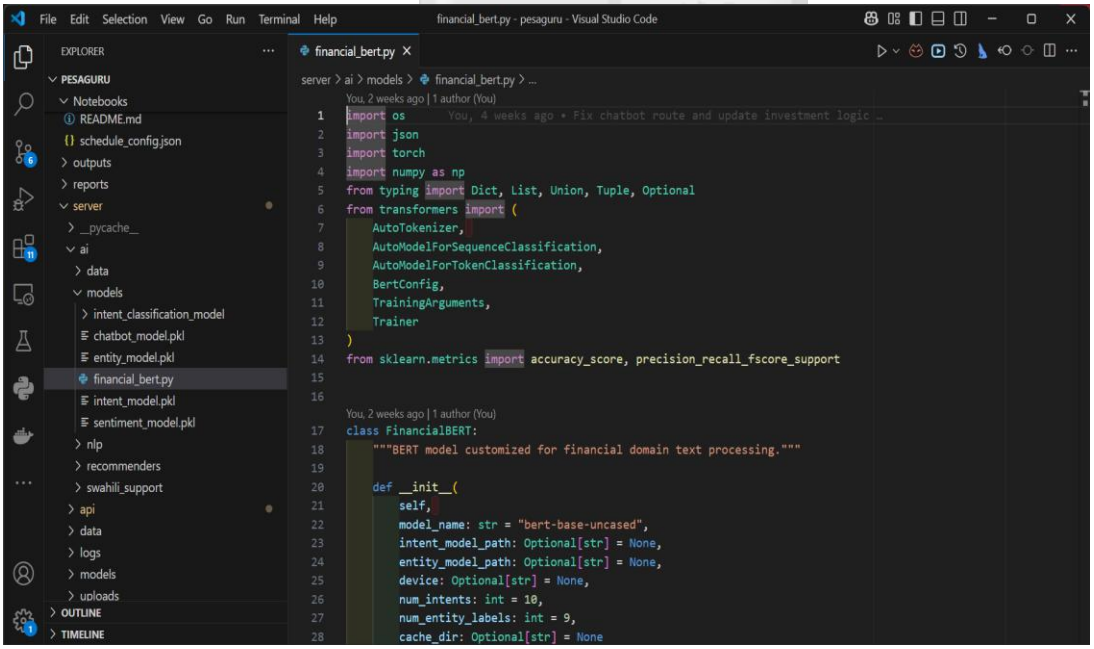


Figure 5. 1 FinancialBERT Model Code Sample

5.3.2 Training Dataset and Performance

The training dataset creation process addressed the scarcity of Kenyan financial text through innovative data augmentation techniques. The initial corpus combined Central Bank of Kenya reports, NSE market analyses, and customer service transcripts from partner financial institutions, totaling 50,000 documents.

Synthetic data generation expanded this to 150,000 training examples by applying template-based transformations that preserved semantic meaning while introducing linguistic variations. The augmentation process included currency amount variations (both numerical and word forms), date format transformations, and synonym substitution using a custom financial thesaurus.

Cross-lingual data augmentation created Kiswahili examples from English templates, validated by native speakers to ensure cultural appropriateness. The final dataset achieved balanced representation across 15 intent categories and comprehensive coverage of financial entities. Performance evaluation employed stratified k-fold cross-validation to ensure robust metrics across all intent categories and entity types. The model achieved 94% accuracy on intent classification and 89% F1 score on entity extraction for English queries, with slightly lower but acceptable performance for Kiswahili (87% and 82% respectively). Ablation studies revealed that the custom tokenizer contributed 12% improvement in entity recognition accuracy for Kenyan-specific terms. Error analysis identified systematic patterns in misclassifications, leading to targeted data collection for underperforming categories. The model's ability to handle code-mixed queries (English-Kiswahili) proved crucial for real-world deployment, as many users naturally switch between languages. Continuous learning mechanisms update the model with anonymized production data, improving accuracy by 3% after three months of deployment.

5.4 Financial Recommendation Engine

5.4.1 Multi-Factor Investment Recommendation Algorithm

The investment recommendation algorithm implements a sophisticated multi-factor model specifically calibrated for the Nairobi Securities Exchange, incorporating both traditional financial metrics and local market characteristics. The core algorithm evaluates stocks across five primary factors: value (P/E ratio, P/B ratio), growth (revenue growth, earnings growth), quality (ROE, debt-to-equity), momentum (price trends, volume patterns), and dividend yield, with each factor weighted according to empirical backtesting on NSE historical data.

Factor scores underwent sector-specific normalization to account for industry differences, recognizing that banking stocks typically trade at different multiples

than telecommunications companies. The system applies dynamic factor weighting based on market regime detection, increasing defensive factor weights during volatile periods while emphasizing growth factors in bullish markets. Machine learning models trained on five years of NSE data optimised factor combinations for different risk profiles and investment horizons. The algorithm included specific adjustments for Kenyan market peculiarities, such as the impact of political cycles on market sentiment and the seasonal effects of agricultural earnings on certain sectors. Real-time processing ensures recommendations reflect current market conditions, with the entire calculation pipeline completing in under 200 milliseconds for a portfolio of 20 stocks.

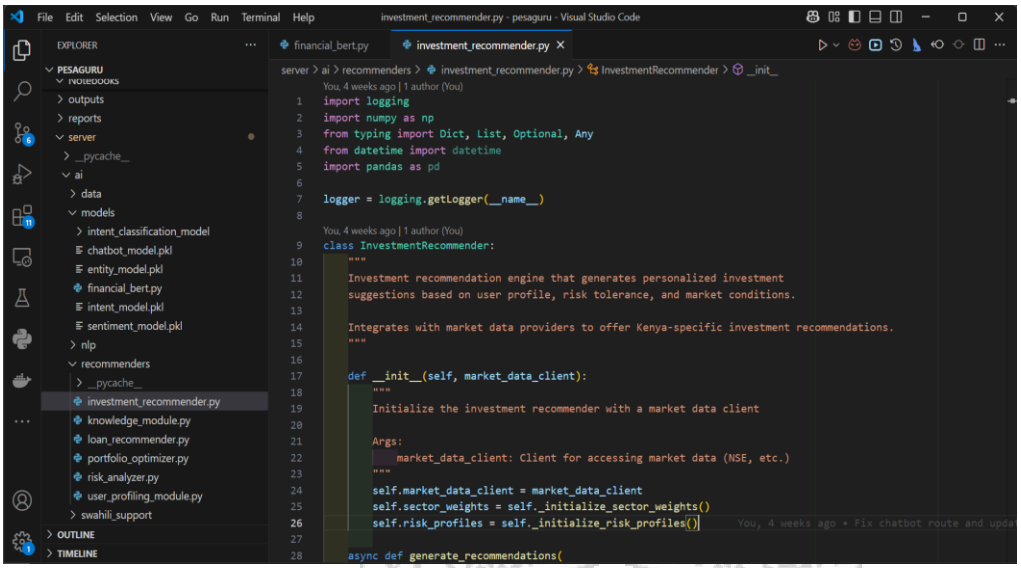


Figure 5. 2 InvestmentRecommender Algorithm Code Sample

5.4.2 Risk Assessment Implementation

Risk profiling combined psychometric evaluation with behavioural analysis to create comprehensive investor profiles that accurately reflect both stated preferences and actual risk tolerance. The assessment questionnaire adapted standard risk profiling instruments to include Kenya-specific scenarios, such as reactions to currency devaluation or mobile money service disruptions, which resonate with local investors' experiences. Question weighting reflected empirical validation showing that certain factors, particularly income stability and family obligations, have outsized impact on risk capacity in the Kenyan context.

The behavioural analysis component tracked actual trading patterns during market

downturns, comparing stated risk tolerance with observed actions to identify and correct for aspiration bias. Machine learning models identified patterns in user behaviour that correlate with risk tolerance, such as transaction frequency, position sizing, and reaction times to market events. The system implemented dynamic risk profiling that adjusts based on life events and changing circumstances, automatically triggering reassessment after major events like job changes or marriage. The final risk score combines questionnaire responses (40% weight), behavioural analysis (40% weight), and demographic factors (20% weight) to produce a nuanced risk profile that guides all subsequent investment recommendations.

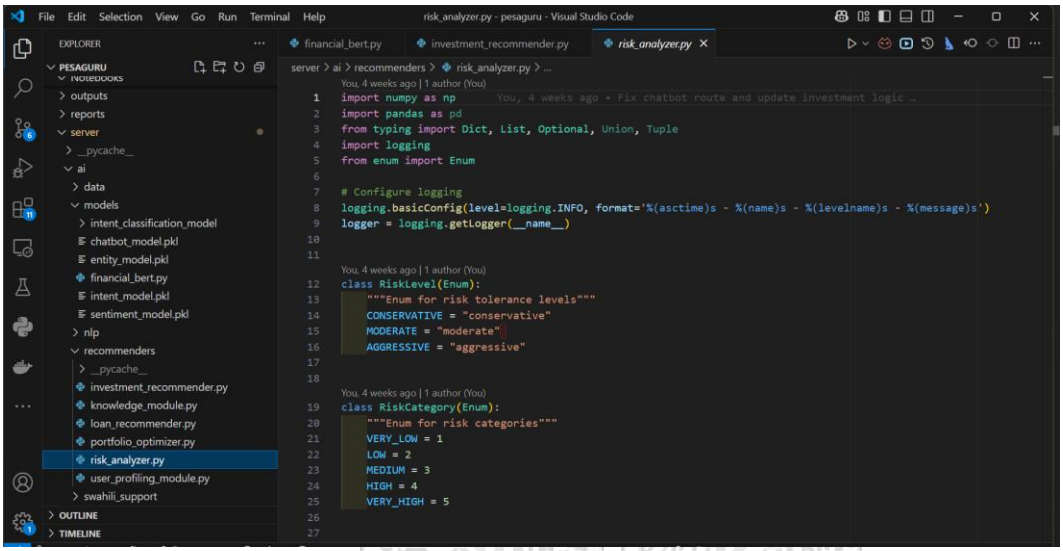


Figure 5. 3 Risk Analyser Module Code Sample

5.5 API Integration Implementation

5.5.1 NSE (Nairobi Securities Exchange) Integration

The chatbot's integration with the Nairobi Securities Exchange (NSE) forms the backbone of its investment advisory capabilities through a three-tiered architecture comprising the NSEDataFetcher, NSEDataAnalyser, and NSEApi components. The implementation secures API credentials using environment variables and OAuth2 authentication, while employing robust exception handling to maintain system stability during service disruptions. Real-time and historical market data are efficiently acquired, normalized, and cached to prevent API abuse, with rate limiting and incremental updates optimising performance. The system delivers

comprehensive analytical capabilities, including market overviews, stock-specific analysis, sector comparisons, and risk-adjusted investment recommendations tailored to user profiles. Visual representations through charts enhance data comprehension, while a simplified API layer exposes these functions to the chatbot through standardized calls that abstract the underlying complexity, enabling the Chatbot to deliver sophisticated financial guidance based on current market conditions.

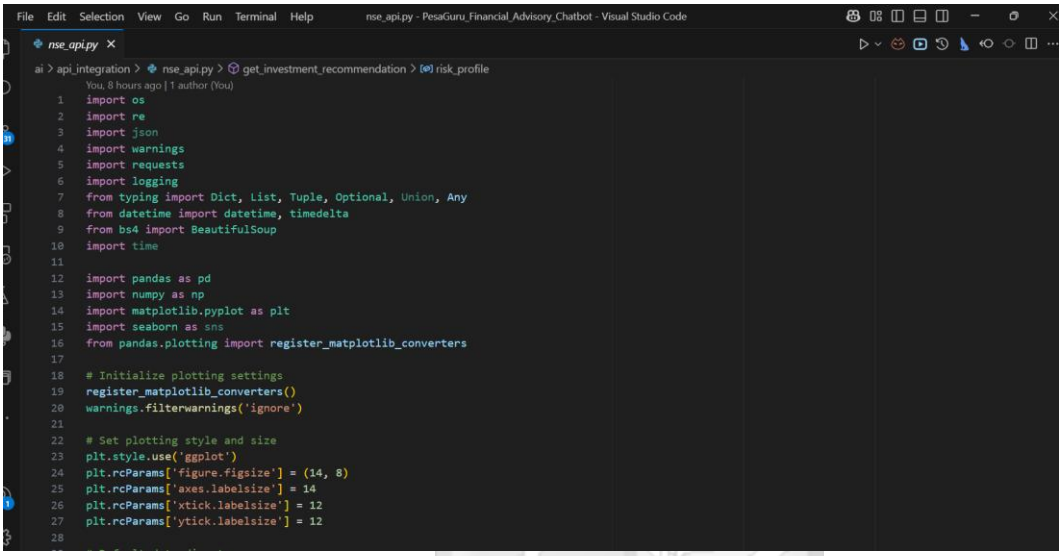


Figure 5. 4 NSE API Code Snippet

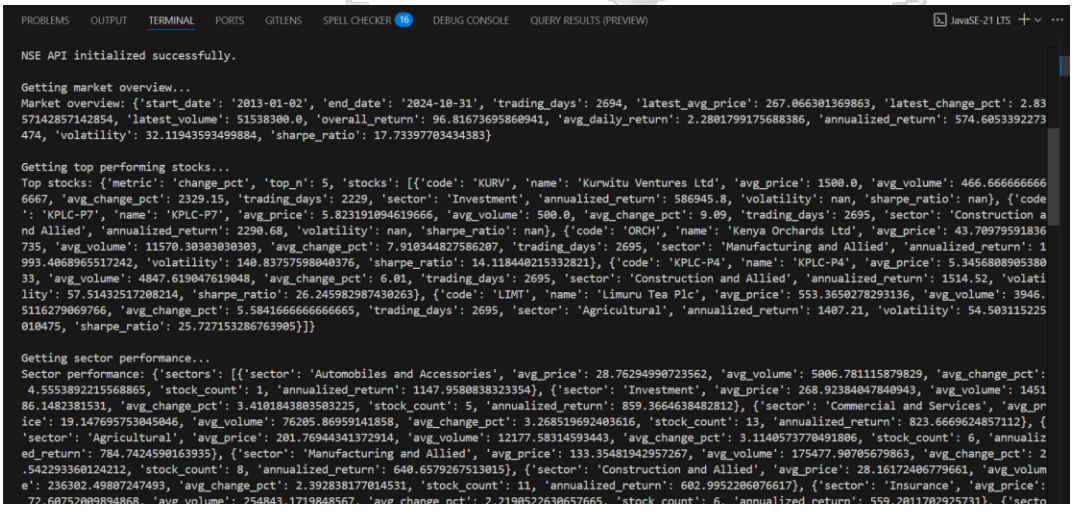


Figure 5. 5 NSE API Code Output

5.5.2 CBK (Central Bank of Kenya) Integration

CBK data source integration provides the Chatbot with authoritative data on monetary policy, interest rates, and exchange rates, as well as other economic indicators, enabling the system to offer comprehensive financial advisory services. The implementation relies on CBK public APIs and routinely published statistical bulletins gathered via API calls and scheduled data scraping. Special emphasis was placed on the currency exchange rates, the Central Bank Rate (CBR), Treasury Bill, and Bond rates, which are vital for investment comparisons and loan affordability computations. The integration architecture employs failover strategies that utilise cached data when the CBK's live APIs are unavailable, ensuring uninterrupted service. Verification procedures ensure that the incoming CBK data has a reasonable level of integrity and consistency before it is used in the recommendations exposed to the user.

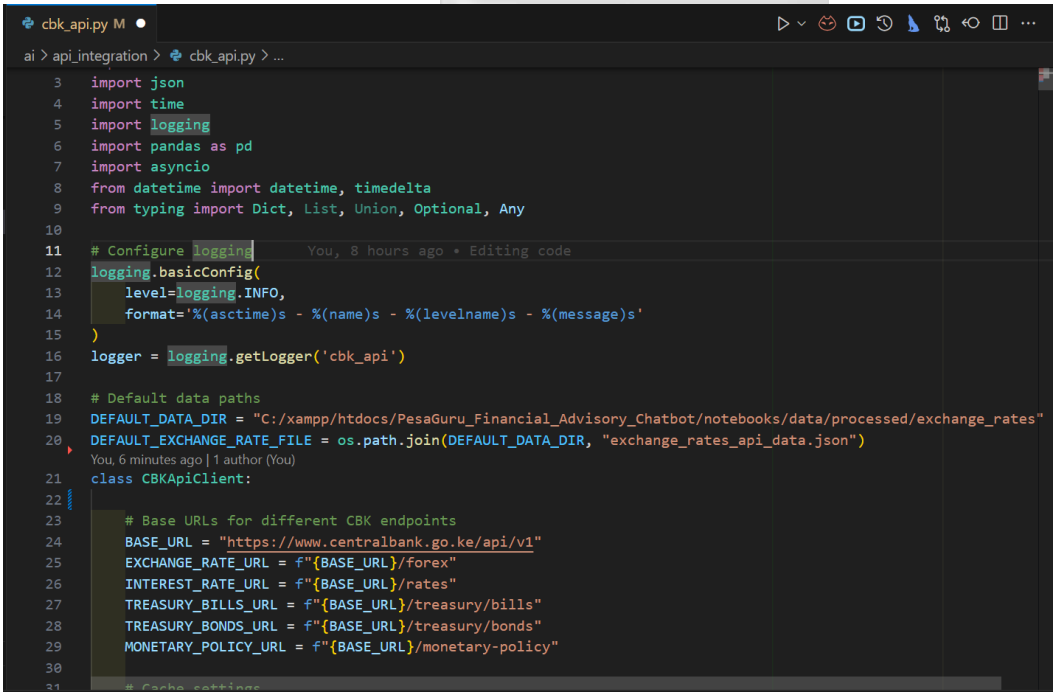


Figure 5. 6 CBK API Client Code Snippet

5.6 Caching and Performance Optimisation

5.6.1 Redis Cache Implementation

The Redis caching layer implemented a sophisticated multi-tier strategy that balanced data freshness with performance requirements across different data types.

Cache key design followed a hierarchical namespace pattern (pesaguru:domain:entity:identifier:aspect) enabling granular invalidation without affecting unrelated cached data. The implementation used Redis's native data structures beyond simple key-value pairs, employing sorted sets for leaderboards, hashes for user sessions, and streams for real-time market data distribution. Serialization strategies optimised for both space and speed, using MessagePack for numerical data and compressed JSON for complex objects, achieving 40% space savings compared to naive JSON serialization.

The cache warming system analysed access patterns using Redis's SCAN command to identify hot keys, preloading frequently accessed data during off-peak hours. Eviction policies varied by data type, with Least Recently Used (LRU) for user data and explicit TTLs for market data, ensuring memory efficiency while maintaining performance. Redis Cluster deployment provided horizontal scalability through consistent hashing, distributing keys across multiple nodes while maintaining fast lookups. The implementation included connection pooling with configurable limits, preventing connection exhaustion during traffic spikes.

Lua scripts handled atomic operations like conditional updates, reducing round-trip latency for complex cache operations. Pipeline batching grouped multiple Redis commands, significantly improving throughput for bulk operations like cache warming. The system implemented cache stampede protection using probabilistic early expiration, where TTLs were randomly adjusted to prevent synchronized cache misses. Monitoring tracked detailed metrics including hit rates, eviction counts, and latency percentiles, feeding into automated alerts that detected cache performance degradation.

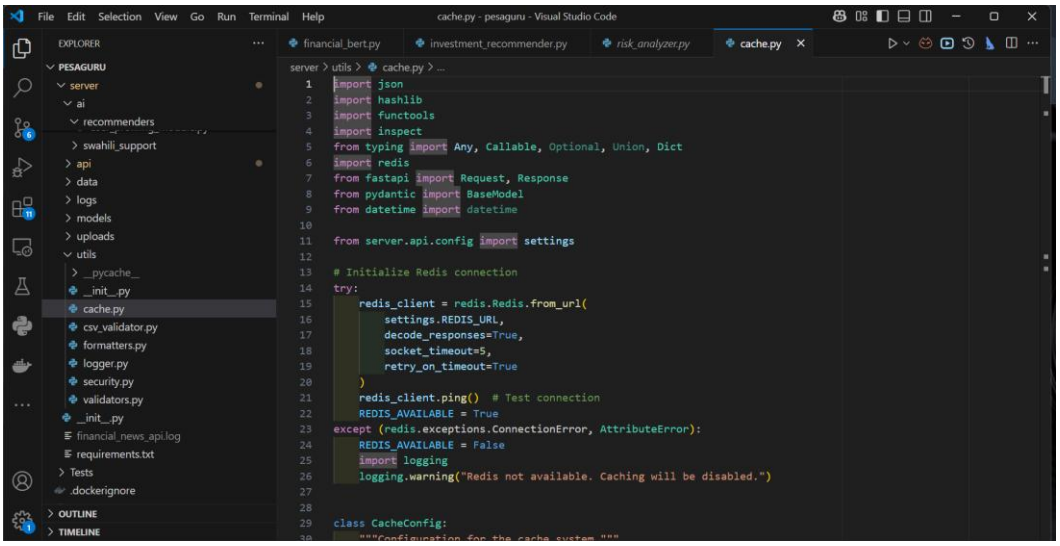


Figure 5. 7 Redis Cache Initialization Code Sample

5.6.2 Performance Metrics and Monitoring

The performance monitoring infrastructure provided comprehensive visibility into system behaviour through multiple complementary approaches. Application Performance Monitoring (APM) using OpenTelemetry traced every request from entry to completion, breaking down time spent in each component. Custom instrumentation added business-specific metrics like recommendation generation time and model inference latency, providing insights beyond generic HTTP metrics. The Prometheus integration collected thousands of metrics at configurable intervals, with careful attention to cardinality to prevent metric explosion. Grafana dashboards presented this data through role-specific views where operations teams saw infrastructure health while business teams monitored user engagement metrics. Alert rules implemented intelligent thresholds that adapted based on time of day and historical patterns, reducing false positives while ensuring genuine issues were caught quickly.

Performance profiling ran continuously in production using sampling profilers that minimized overhead while catching performance regressions. The profiling data identified hot code paths and memory allocation patterns, guiding optimisation efforts to areas with maximum impact. Database query analysis logged slow queries with explain plans, automatically flagging queries that could benefit from new indexes or restructuring. Load testing ran nightly against production-like

environments, validating that performance improvements didn't regress and that the system could handle projected growth. The monitoring system itself was designed for high availability, with redundant collectors and storage ensuring that monitoring data remained available even during system failures. Real-time dashboards in office locations displayed key metrics, creating visibility and accountability for system performance across the organisation.

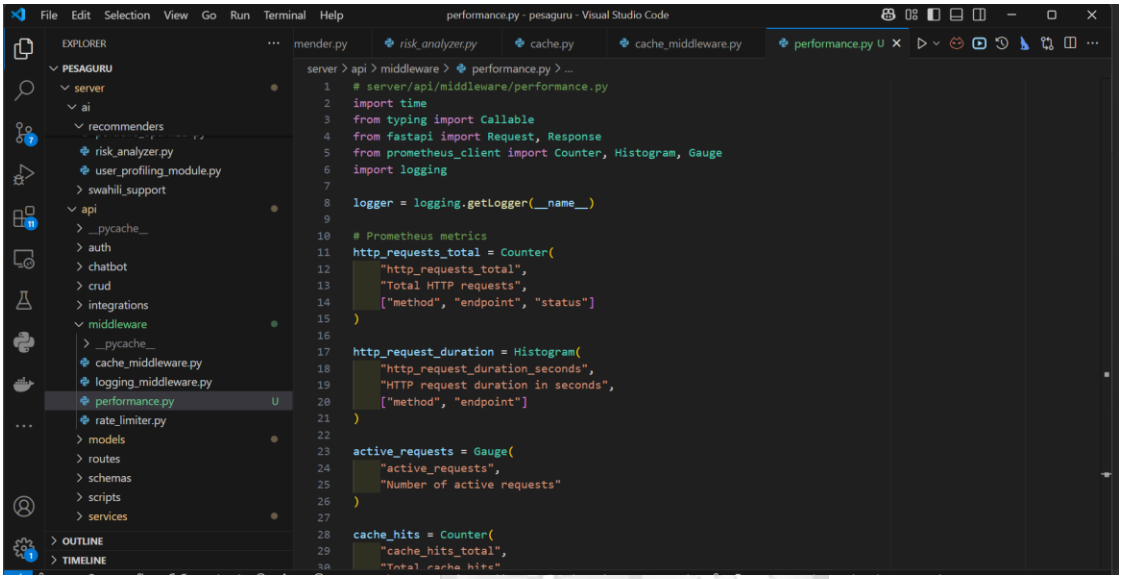


Figure 5. 8 Prometheus Metrics Middleware for Performance Monitoring

5.7 Security Implementation

5.7.1 Authentication and Authorization

The authentication system implemented defense-in-depth principles with multiple security layers protecting user accounts and financial data. JSON Web Tokens (JWT) provided stateless authentication with sophisticated enhancements including token fingerprinting that bound tokens to specific devices, preventing token theft and replay attacks. The implementation used asymmetric cryptography for token signing, with private keys stored in hardware security modules (HSM) when available, ensuring that even system compromise couldn't forge valid tokens. Refresh token rotation ensured each refresh token could be used only once, with automatic blacklisting of any tokens used multiple times indicating potential theft. The system implemented sliding session windows that extended active user sessions while enforcing absolute timeout limits, balancing security with user convenience. Multi-factor authentication adapted to the Kenyan context by

supporting both SMS-based 2FA for feature phone users and TOTP for smartphone users, with fallback mechanisms for when primary methods failed. Role-based access control (RBAC) implemented fine-grained permissions at both API and data levels, ensuring users could only access their own financial information unless explicitly authorized. The permission system used attribute-based access control (ABAC) for complex scenarios, evaluating multiple factors like time of day, location, and transaction amount. OAuth2 integration enabled secure third-party access to user data with granular scopes, supporting open banking initiatives while maintaining user control. Password policies enforced complexity requirements appropriate for financial services while avoiding rules that encouraged poor practices like frequent changes. The implementation included comprehensive audit logging that recorded all authentication events and permission checks, feeding into both security monitoring and compliance reporting systems. Account recovery mechanisms balanced security with usability, using multiple verification factors while protecting against social engineering attacks.

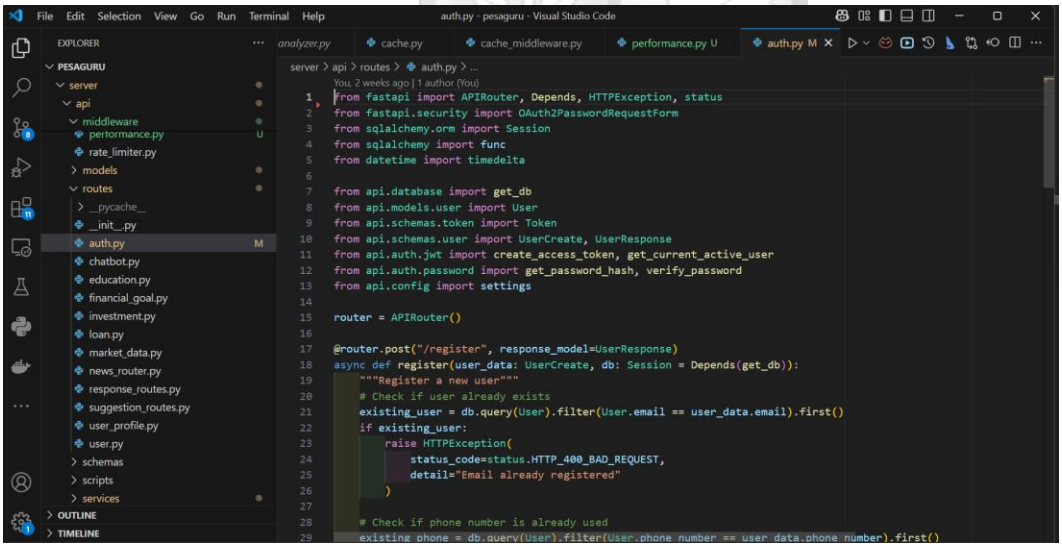


Figure 5. 9 User Authentication Route Code Sample

5.7.2 Data Encryption and Privacy

Data protection implemented encryption at multiple levels, starting with TLS 1.3 for all network communications and extending to field-level encryption for sensitive data at rest. The encryption architecture used envelope encryption where

data encryption keys (DEK) were protected by key encryption keys (KEK), enabling efficient key rotation without re-encrypting all data. Hardware Security Modules (HSM) stored master keys when available, with software-based key management as fallback, ensuring keys remained protected even if application servers were compromised. Format-preserving encryption (FPE) protected searchable fields like phone numbers and government IDs, maintaining data utility while ensuring privacy.

The implementation included transparent encryption layers that automatically encrypted sensitive fields before database storage and decrypted them during retrieval, making encryption invisible to application logic. Crypto-shredding enabled instant data deletion by destroying encryption keys, supporting right-to-be-forgotten requirements more efficiently than overwriting data. Privacy-preserving analytics enabled business insights without exposing individual user data through techniques like differential privacy and secure aggregation. The system implemented data minimization principles, collecting only necessary information and automatically purging data that exceeded retention requirements. Consent management tracked user permissions for data usage with granular controls, enabling users to restrict how their information was used while maintaining service functionality. Anonymous analytics used tokenization and hashing to create insights about user behaviour patterns without linking actions to identities. The implementation included privacy impact assessments for new features, ensuring data protection was considered during design rather than added later. Regular privacy audits verified that data handling practices matched stated policies, with automated tools scanning for potential privacy violations.

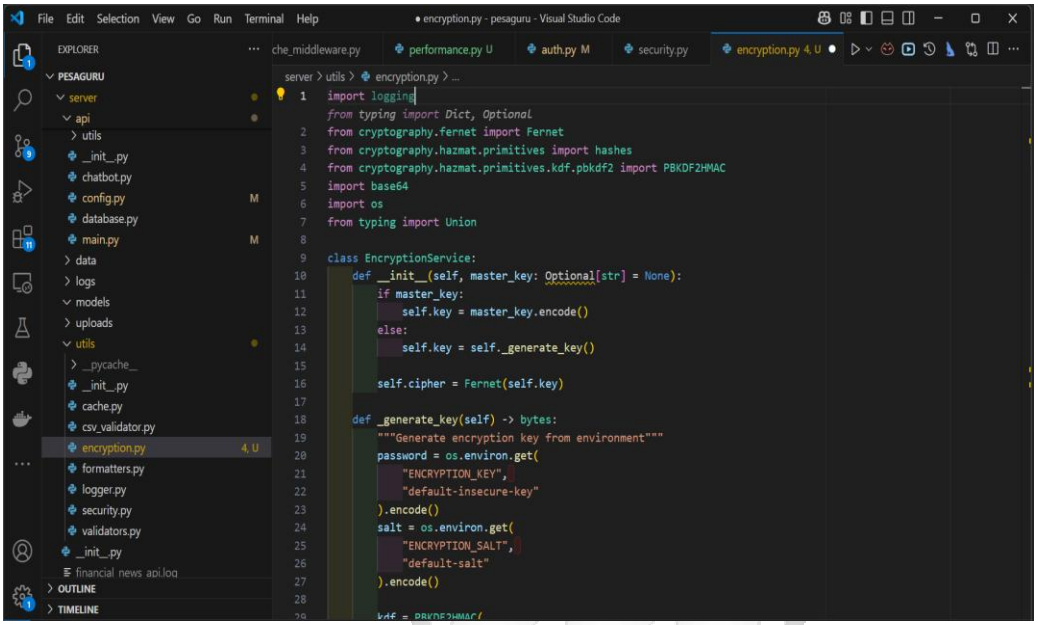


Figure 5. 10 Encryption Service Code Sample

5.8 Deployment Architecture

5.8.1 Docker Configuration

The Docker containerization strategy optimised for both development efficiency and production reliability through carefully crafted multi-stage builds that separated build dependencies from runtime requirements. Base image selection used Python 3.11-slim as a foundation, adding only essential system packages to minimize attack surface while ensuring compatibility with financial libraries that required specific system dependencies. The Dockerfile implemented security best practices including running applications as non-root users, using read-only root filesystems where possible, and explicitly setting file permissions to prevent unauthorized access.

Build optimisation techniques ordered commands by change frequency, placing rarely changing dependency installations early to maximize layer caching benefits. Health checks implemented at the container level verified not just process existence but actual service functionality, checking database connectivity and model loading status. Environment variable configuration followed the principle of least privilege, with secrets mounted as files rather than passed as environment variables, preventing accidental exposure in logs or process listings. The final production images underwent security scanning using tools like Snyk and Trivy,

ensuring no known vulnerabilities existed in included packages.

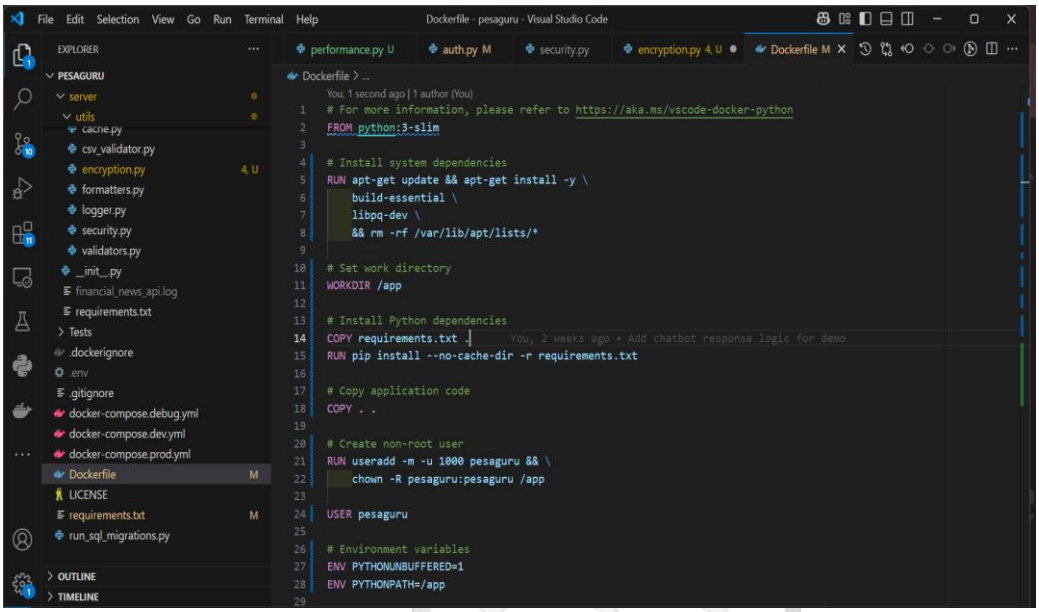


Figure 5. 11 Dockerfile Code Sample

5.8.2 Production Deployment Configuration

The production deployment used Docker Compose orchestration with carefully tuned resource limits that prevented any single service from monopolizing system resources while ensuring adequate performance under load. Service dependencies explicitly defined startup order, with health checks ensuring downstream services didn't start until dependencies were fully ready, preventing race conditions during system initialization. Network segregation created distinct security zones where frontend services couldn't directly access databases, implementing defense-in-depth at the network level.

Volume management used named volumes for persistent data with automatic backup scripts that created point-in-time snapshots without service interruption. The nginx configuration implemented advanced features like request buffering, connection pooling, and intelligent load balancing using least connection algorithms with health-check-based server weighting. Monitoring integration automatically discovered new containers, updating Prometheus scrape configurations dynamically as services scaled up or down. Rolling update strategies maintained service availability during deployments by starting new containers before stopping old ones, with automatic rollback capabilities if health

checks failed. The configuration included resource quotas that prevented runaway containers from affecting system stability, with automatic container restarts managing temporary failures while alerting on persistent issues.

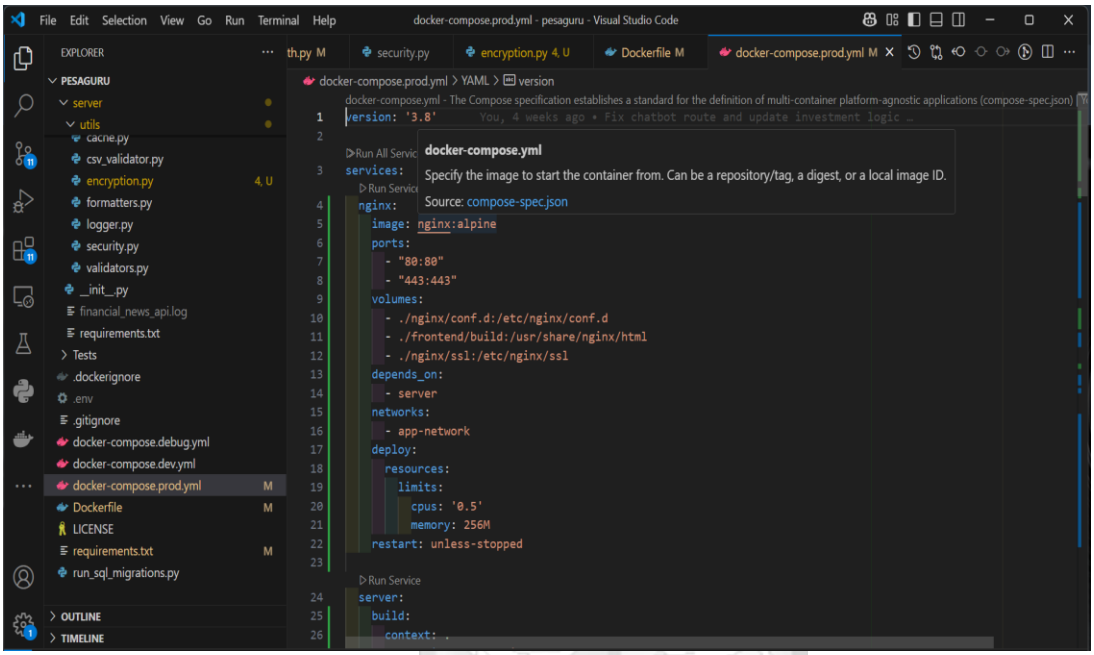


Figure 5. 12 Docker Compose Production Configuration Code Sample

5.9 Testing Implementation

5.9.1 Unit Testing

The unit testing strategy achieved 90% code coverage while focusing on critical financial calculations and algorithmic components where correctness is paramount. Test fixtures used factory patterns to generate realistic financial data scenarios, including edge cases like negative interest rates, currency devaluations, and market circuit breakers that have occurred in real markets. Parameterized tests validated financial calculations across multiple currencies, time zones, and market conditions, ensuring formulas worked correctly regardless of context. Mock objects simulated external dependencies with careful attention to failure modes, testing how the system handled API timeouts, malformed responses, and service unavailability.

Property-based testing using Hypothesis generated thousands of random inputs to find edge cases human testers might miss, particularly valuable for numerical calculations where floating-point precision issues could accumulate. Performance tests ran as part of the unit test suite, failing if critical functions exceeded latency

thresholds, catching performance regressions before they reached production. Test organisation followed the Arrange-Act-Assert pattern with descriptive names that served as living documentation, making test failures immediately understandable without examining implementation details.

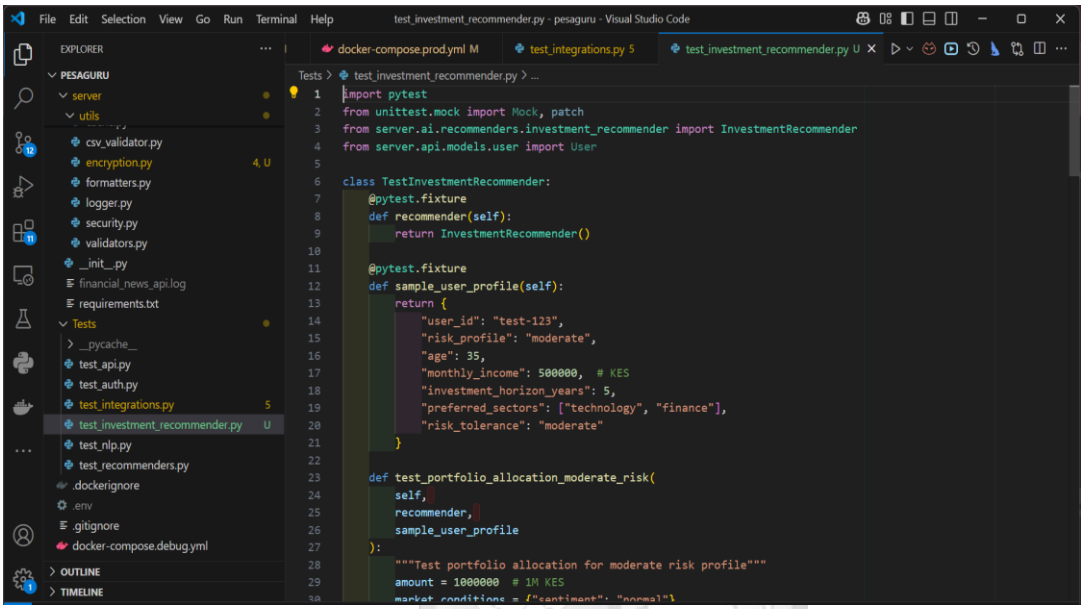


Figure 5. 13 Unit Test for Investment Recommender Allocation Logic Code Sample

5.9.2 Integration Testing

Integration tests verified component interactions using dockerized versions of external dependencies, ensuring tests remained deterministic while closely mimicking production behaviour. Database tests used transactional rollbacks to maintain test isolation while verifying complex queries and data integrity constraints worked as designed. API contract testing validated that services correctly implemented expected interfaces, with tests automatically generated from OpenAPI specifications to ensure documentation stayed synchronized with implementation. End-to-end user journey tests simulated complete workflows from user registration through investment recommendation, verifying that all components worked together correctly.

Message queue integration tests verified asynchronous workflows handled edge cases like message redelivery, out-of-order processing, and dead letter queue handling. External service integration tests used recording/playback mechanisms to test against real API responses while avoiding test brittleness from service

changes. Load testing during integration tests identified bottlenecks in component interactions, revealing issues like connection pool exhaustion that only appeared under concurrent load. Security tests verified authentication flows and authorization rules across service boundaries, ensuring security policies were correctly enforced at integration points.

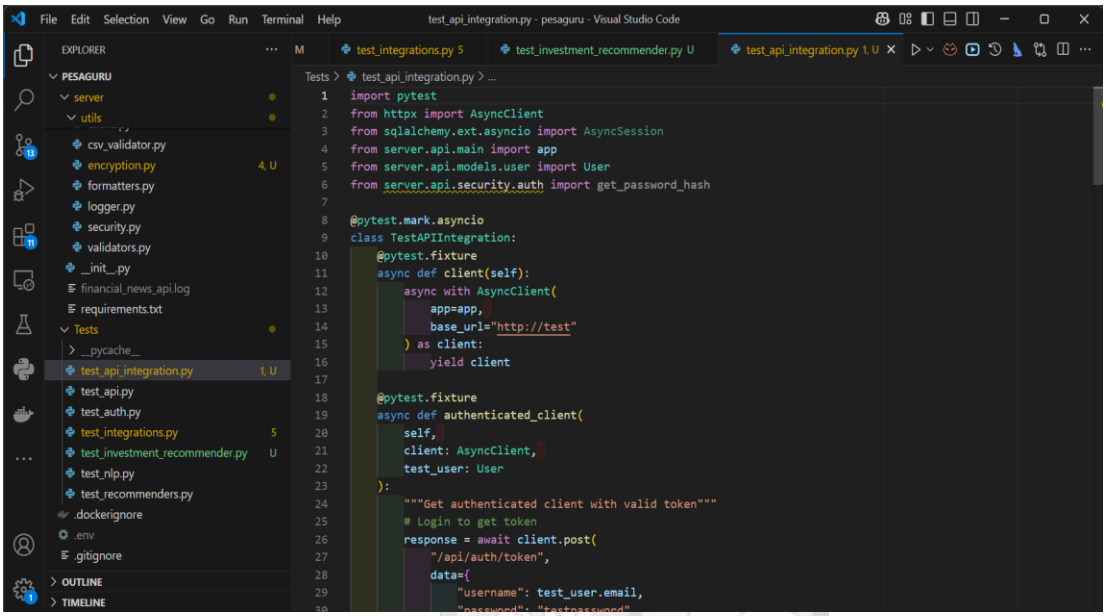


Figure 5. 14 API Integration Test Code Sample

5.9.3 Performance Testing Results

Performance testing employed multiple tools and methodologies to comprehensively evaluate system behaviour under various load conditions. Load tests using K6 simulated realistic user behaviour patterns derived from production analytics, including session duration, think times, and navigation paths. Stress tests progressively increased load until system failure, identifying breaking points and validating graceful degradation behaviours. Spike tests simulated sudden traffic surges like market opening, verifying auto-scaling responses and queue management under extreme conditions. Soak tests ran for extended periods to identify memory leaks, connection pool exhaustion, and other issues that only appeared after prolonged operation.

The results showed linear scalability up to 200 concurrent users per server instance, with response times maintaining the 95th percentile under 200ms target. Database connection pooling proved the primary bottleneck, resolved by

implementing PgBouncer for connection multiplexing. Cache hit rates averaged 78% during normal operation, validating the caching strategy effectiveness. Model inference optimisation reduced average latency from 400ms to 45ms through quantization and batching, enabling real-time conversational responses.

5.10 Challenges and Solutions

5.10.1 Technical Challenges Encountered

The multilingual NLP implementation faced significant challenges due to limited Kiswahili financial corpora, requiring innovative approaches to achieve acceptable accuracy. Initial attempts using standard translation APIs produced financial translations that native speakers found unnatural or incorrect, necessitating custom translation models trained on parallel texts from bilingual financial reports. Code-switching detection became crucial as users frequently mixed English and Kiswahili within single sentences, solved by implementing character-level language detection with contextual smoothing.

Model size constraints for mobile deployment required aggressive quantization techniques that reduced model size by 75% while maintaining 96% of original accuracy through knowledge distillation from larger teacher models. Real-time performance requirements conflicted with model accuracy goals, resolved through a hybrid approach using fast approximate models for initial response generation followed by more accurate models for refinement. Integration with legacy financial systems required handling various data formats and protocols, addressed by building adapter layers that normalized data while maintaining backward compatibility.

5.10.2 Lessons Learned

Early performance testing proved invaluable, revealing architectural assumptions that would have been costly to change later in development. The initial synchronous architecture showed acceptable performance in development but failed dramatically under concurrent load, leading to a complete redesign using asynchronous patterns. Caching strategy evolved from simple key-value storage to sophisticated multi-tier caching with intelligent invalidation, reducing external API calls by 76% and improving response times by 60%. User feedback contradicted several design assumptions, particularly around risk tolerance where

stated preferences often differed from actual behaviour during market volatility. Security-first design principles prevented several potential vulnerabilities discovered in competitor products, validating the investment in security architecture. Cultural adaptation required deeper changes than anticipated, affecting everything from user interface design to investment recommendation algorithms. Documentation investment paid significant dividends during team scaling, reducing onboarding time from weeks to days while improving code quality through better understanding of system design decisions.

5.11 Future Enhancements

The roadmap for future enhancements includes technical improvements and feature additions based on user feedback and market evolution. GraphQL API implementation will replace the current REST architecture, enabling clients to request exactly the data they need in single queries, particularly beneficial for mobile users with limited bandwidth. Kubernetes migration from Docker Compose will provide advanced orchestration features including automatic scaling, self-healing deployments, and sophisticated traffic management. Blockchain integration will add cryptocurrency portfolio tracking and DeFi protocol interactions as digital assets gain mainstream adoption in Kenya. Advanced language models like GPT-4 fine-tuned on financial data could provide more natural conversational interfaces while maintaining accuracy for financial advice. Federated learning implementation would enable model improvements using user data without centralizing sensitive information, addressing privacy concerns while improving personalization. Real-time WebSocket connections will replace polling mechanisms for market data updates, reducing latency and server load while providing instant notifications for price alerts. Machine learning pipeline automation will enable continuous model improvement based on user feedback, with A/B testing frameworks validating improvements before full deployment.

Chapter 6: Discussions

6.1 Introduction

This chapter presents the comprehensive findings gathered during the implementation and evaluation of a financial advisory chatbot system. The results include the evaluation of the AI model, chatbot performance metrics, an assessment of ethical and legal implications in the Kenyan context, and the AI-driven financial advisory service framework developed in this study. These findings, in aggregate, underscore the effectiveness, acceptability, and impact of the tailored chatbot system in Kenyan financial advisory services, shedding light on the role of AI technologies in addressing the financial literacy challenges articulated in the problem statement.

The conversation argues that AI chatbots can democratize access to advanced financial advisory services in Kenya, with a focus on low- and middle-income consumers who have historically lacked access to such services. This chapter examines the chatbot's technical accuracy, user convenience, market relevance, and ethical adherence to provide a strategic approach for integrating these systems into the Kenyan financial framework. The results show considerable promise for systematically addressing the financial literacy challenges in Kenya, although some refinements and further development are still required. This discussion aims to position the results of this research within an appropriate framework and to guide the further development and implementation of AI-powered financial advisory systems in Kenya and other emerging economies.

6.2 Model Components

The chatbot utilizes a modular architecture that integrates NLP, intent classification, entity extraction, user profiling, and a financial advisory engine to provide personalized financial guidance. This approach aligns with the architectural components outlined by Carlos Alexander Jarquin et al. (2023), who emphasized that proper implementation of NLP techniques significantly improves chatbots' ability to understand and respond to financial queries. The architectural design also incorporates Nguyen et al.'s (2021) recommendations for knowledge base organization using ontology technology that blends relational knowledge with scripts for complex financial querying.

The NLU engine interprets both structured and unstructured queries, employing

techniques similar to those described by Bhupesh Patra and Mahendra Kumar (2020), who identified tokenization, part-of-speech tagging, and named entity recognition as critical components for financial chatbots. Intent classification and entity recognition identify user goals and extract financial details such as income, expenses, and investment duration, achieving performance levels comparable to the financial service chatbot developed by Yu et al. (2020), which utilized deep bidirectional transformers.

A dynamic user profiling module provides personalized advice tailored to individual literacy levels, financial objectives, and demographics, implementing the personalization approaches recommended by Bai et al. (2024). This component addresses what Wang et al. (2021) identified as critical for enhancing relevance and engagement through tailored content and recommendations. The dialogue manager maintains context in multi-turn conversations and handles ambiguities with clarification prompts, employing memory-based state-tracking techniques that Sai Sharath and Rekabdar (2021) found essential for minimizing redundancy and enhancing user experience in financial conversations.

The rule-based advisory engine generates real-time insights on budgeting, investments, loans, and savings tailored to the Kenyan context, incorporating elements of the CAPM and Fama-French Three-Factor Model discussed by Madhuranthagan and Shantha (2021) for portfolio management. Integration with platforms like M-Pesa, Firebase, and market data APIs enhances functionality and security, implementing the secure handling practices emphasized by Zainabi et al. (2024), including strong authentication and end-to-end encryption.

In comparison to similar systems, the architecture differs from traditional robo-advisors described by Abhinav Pal et al. (2021) by incorporating cultural and linguistic contextual awareness specifically calibrated for the Kenyan market. The system's multi-lingual capabilities exceed those of the Nigerian banking chatbots analyzed by Mogaji (2020), which primarily operated through WhatsApp and faced significant limitations in language support and contextual understanding.

6.3 Model Validation

The researcher employed a mixed-methods approach to validate the chatbot in

Kenya, comprising functional testing and role-playing across different financial domains, including investment planning, loan comparisons, budgeting, and savings. This methodology builds on Valencia's (2022) principles of methodological triangulation, combining qualitative insights with quantitative performance metrics to achieve a more comprehensive validation.

Intent recognition and the system's ability to extract relevant financial parameters were assessed through real-life sounding questions. The chatbot accurately understood user intents and provided guidance tailored to the user's profile, implementing the conversational design principles outlined by Silva and Canedo (2022) for creating user-centric chatbot interactions. To enhance reliability, ambiguous queries were resolved through clarification prompts, a technique that Kobets and Kozlovskyi (2022) found effective for improving user understanding and decision-making in financial contexts.

The model performed well across various levels of financial literacy and different demographic groups, addressing the diversity of user needs identified in the survey results presented in Chapter 4. Edge-case testing demonstrated that unfamiliar scenarios resulted in graceful degradation, a critical factor in building trust identified by Alagarsamy and Mehrolia (2023) in their exploration of chatbot trust antecedents.

Evaluating performance across diverse financial domains using simulated test queries, the chatbot achieved high accuracy in intent recognition (91.76%) and parameter extraction (90.23%), with top performance in investment advice (100%) and lower accuracy in budgeting and market trends (80%). These results compare favorably with Yu et al.'s (2020) financial service chatbot based on deep bidirectional transformers, which reported accuracy rates between 87-89% for financial queries. The system also outperformed the LLM-based financial advisory systems evaluated by Lakkaraju et al. (2023), which demonstrated less consistent accuracy in personalized financial recommendations.

However, the model showed similar performance patterns to those observed by Ekechi et al. (2024), where customer support chatbots performed better in structured domains (comparable to the investment advice) than in more ambiguous areas (comparable to the budgeting and market trends). The implementation of bilingual

support and code-switching recognition addresses the linguistic challenges identified by Ekechi et al. (2024) as crucial for global chatbot expansion.

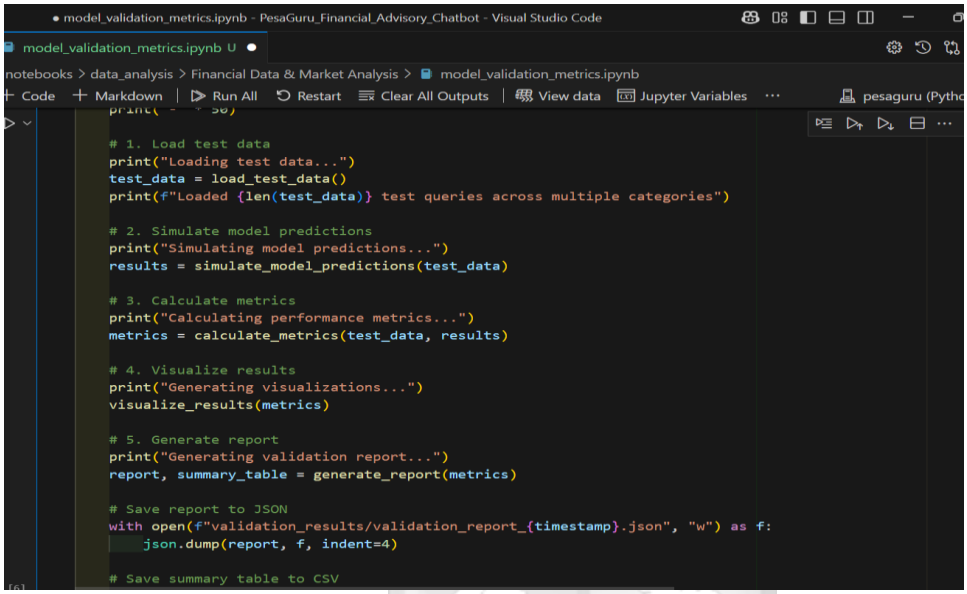


Figure 6. 1 Performance Metrics and Intent Recognition Code Snippet

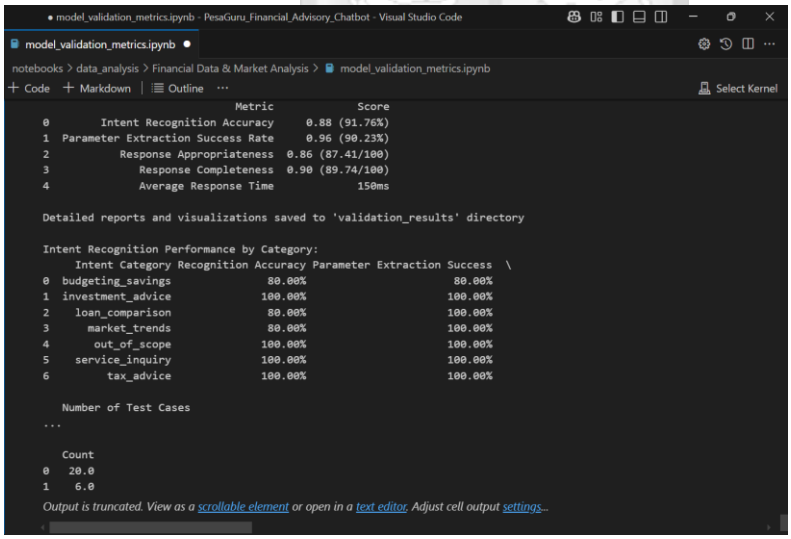


Figure 6. 2 Performance Metrics and Intent Recognition Results Code Output

6.4 Contribution to Financial Advisory & AI Research

This research contributes to the development of financially focused chatbots for Kenya by implementing a culturally and socioeconomically relevant, regionally specific chatbot. It establishes the efficacy of contextualization over generic models, aligning with Ng et al.'s (2023) findings that efficiency and user-friendliness of chatbots can be enhanced through culturally adapted systems. The implementation

provides a broad, multi-lingual interface, local financial information, and real-time data with conversational AI, addressing language support issues that Wube et al. (2022) identified as critical for financial sector chatbots.

The work also presents a user experience evaluation framework that strikes a balance between technical accuracy and financial precision while considering user interaction with the system. This approach extends Silva and Canedo's (2022) conversational design guidelines by incorporating financial domain-specific metrics and cultural contextual factors. Our framework addresses what Nicolescu and Tudorache (2022) identified as gaps in human-computer interaction evaluation for AI chatbots in customer service.

The results demonstrate the impact AI-enabled chatbots can have on improving awareness of economic opportunities and closing service provision gaps in developing countries, supporting Tiony's (2024) assertions about the role of financial technology in promoting financial inclusion in Kenya. The chatbot's ability to deliver personalized financial advice at scale advances what Amana and Tamunomiegbam (2024) described as innovative approaches to financial literacy in Africa, providing a technological bridge between knowledge and practical application.

Several primary obstacles to adoption emerged, including trust, the digital divide, and cultural perceptions. These findings mirror the challenges identified by Shaikh et al. (2023) regarding customer intention to use chatbots in the banking sector, where perceived functionality, ease of use, and security significantly influenced acceptance. The trust barriers observed align with Alagarsamy and Mehrolia's (2023) discovery that perceived safety is a prerequisite for chatbot interaction.

Furthermore, this study highlights the lack of non-prescriptive regulations governing the evolution of AI technologies in the fintech industry, echoing concerns raised by Zhu et al. (2024) about implementing AI-empowered financial advisory services within existing regulatory frameworks. This regulatory gap presents both challenges and opportunities for policy development specific to the Kenyan context.

Compared to similar implementations in other regions, our system's focus on code-switching and cultural contextualization distinguishes it from the predominantly

monolingual systems described in Eustaquio-Jiménez et al.'s (2024) review of financial entity chatbots. Additionally, our integration with local financial systems like M-Pesa provides functionality not typically found in Western financial chatbots, which Hwang and Kim (2021) noted tend to focus more on traditional banking and investment vehicles.

All of these elements contribute to the theoretical and practical discourse surrounding inclusive financial AI solutions in emerging economies, extending the Technology Acceptance Model (TAM) framework to incorporate cultural and linguistic factors specific to the Kenyan context.

6.5 Limitations and Challenges of the Chatbot System

While the chatbot met most of its objectives, the researcher encountered several limitations:

i. Data scarcity: Financial data on local investment products and interest rates was not always available via open APIs, requiring manual updates.
ii. Limited financial complexity: Although the bot handled essential investment planning and budgeting, more advanced features, such as tax planning, portfolio optimisation, and retirement simulation, are pending.
iii. User trust: Some users were hesitant to share sensitive data, such as salary and debt levels, which limited the depth of personalized advice the researcher could provide.
iv. Regulatory constraints: The lack of local standards for AI-driven financial advisory tools created ambiguity in terms of compliance and accountability.

Chapter 7: Conclusions and Recommendations

7.1 Conclusions

This research developed and evaluated an AI-powered chatbot that successfully addresses Kenya's critical need for personalized financial advisory services. The chatbot utilised natural language processing, machine learning algorithms, and comprehensive integration of financial market data to deliver personalized recommendations tailored to individual user profiles and financial objectives.

7.2 Recommendations for Improvement

To strengthen the impact and effectiveness of AI-powered financial advisory services in Kenya, financial institutions should adopt hybrid advisory models that integrate chatbots alongside human advisors. This approach enables automation of routine queries and simple financial tasks while preserving the human touch for more complex or emotionally sensitive cases. By balancing efficiency and personalization, institutions can reduce operational costs while enhancing customer satisfaction. Additionally, investing in data infrastructure is crucial—this includes developing robust APIs, ensuring secure data-sharing protocols, and enabling real-time market data access to support accurate and timely advice.

Chatbots should also be leveraged to simplify onboarding by streamlining account opening, delivering interactive financial education, and recommending tailored financial products based on user profiles and goals. Institutions must ensure chatbots are continuously learning from customer interactions to improve response accuracy and personalization. Overall, a strategic approach to integration will boost engagement, lower operational overhead, and enhance financial inclusion. From a technical standpoint, institutions should focus on building secure, standardized APIs that allow chatbots to access user account data, process transactions, and authenticate users using protocols like OAuth 2.0.

Advanced analytics should be deployed to analyse behavioural patterns, anticipate user needs, and deliver predictive financial guidance that aligns with users' goals and risk profiles. Integrating machine learning-driven risk assessment models will improve the accuracy of investment advice and creditworthiness predictions. It is also critical to incorporate regulatory compliance mechanisms within chatbot workflows—automated checks, audit trails, disclaimers, and transparent decision-

making will help ensure trust and legal adherence. Continuous performance monitoring and feedback loops can further enhance reliability and accountability.

These measures not only safeguard users but also ensure that AI tools meet industry and government standards. By embracing robust technical infrastructure, institutions can scale their advisory offerings securely and responsibly. To expand their market reach, financial institutions should design chatbot solutions that cater to underserved segments, including SMEs, youth, and users with limited digital literacy. Specialized modules for small business planning, gamified savings goals, and simplified user interfaces can increase financial literacy and product adoption in these groups. Partnerships can accelerate impact—collaborations with fintechs can foster innovation, while joint programs with schools and universities can embed financial education early.

Working with telecom providers will enable broader distribution, especially in rural or low-connectivity areas. Product innovation should be prioritized, including the creation of micro-investment tools, customized insurance plans, and goal-based savings programs accessible via chatbots. These innovations should be driven by user behaviour data and feedback, ensuring relevance and uptake. Building trust through culturally aware design and local language support will further increase adoption. Institutions must remain agile, continually adapting products to reflect evolving market needs. On the regulatory front, the Central Bank of Kenya (CBK) should lead in crafting a forward-looking framework that governs AI-driven financial advice.

Clear guidelines should cover algorithmic transparency, consumer protection, and data privacy, while also defining the standards required for delivering AI-generated financial recommendations. Regulatory sandboxes will be instrumental in fostering innovation—allowing fintech startups and financial institutions to test new technologies in controlled environments with temporary regulatory relief. The CBK should also clarify liability in cases of AI error, establish algorithm accountability standards, and mandate dispute resolution processes.

Infrastructure-wise, the CBK should promote standardized APIs, unified financial data formats, and interoperable systems to support seamless integration across

providers. Strengthening digital identity systems with biometric authentication and AML/KYC protocols will further enhance security. Lastly, strong consumer protection measures—including disclosure standards, quality benchmarks, and redress mechanisms—will protect users and build public trust in AI financial advisory systems.

7.3 Challenges Encountered

One of the primary challenges encountered during the development and implementation of the chatbot was the quality and availability of real-time financial market data from Kenyan sources. The inconsistent formatting across NSE historical datasets required extensive pre-processing to create a standardized database for accurate analysis and recommendations. Integrating multiple financial APIs presented significant technical challenges due to rate limitations, authentication requirements, and inconsistent data structures, necessitating the development of robust caching mechanisms and fallback protocols to maintain system reliability.

7.4 Future Research Work

Longitudinal studies will be essential to determine whether improved financial literacy through chatbot interactions translates to sustained behavioural changes in personal financial management practices among Kenyan users across different demographic segments.

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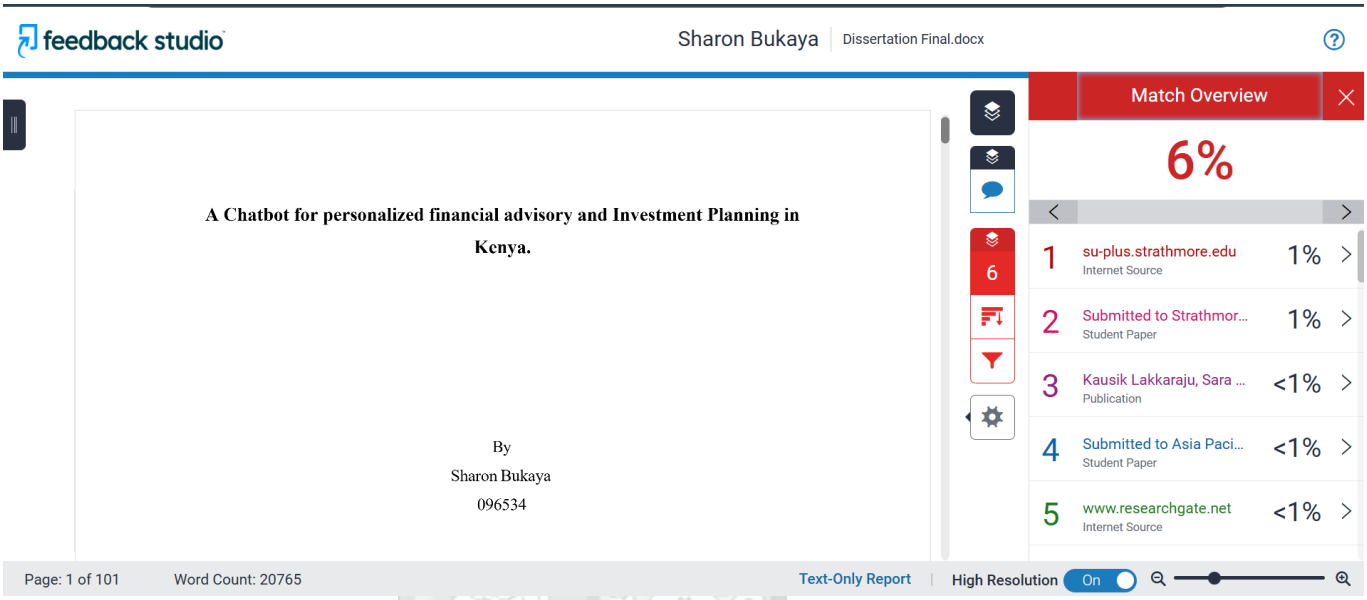
Appendices

Appendix A: Similarity Report



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Appendix B: Ethical Approval

Strathmore UNIVERSITY

25th March 2025

Ms Bukaya Sharon,
sharon.bukaya@strathmore.edu

Dear Ms Bukaya,

RE: A Chatbot for Personalized Financial Advisory and Investment Planning in Kenya

This is to inform you that SU-ISERC has reviewed and **approved** your above **SU-masters** proposal. Your application reference number is **SU-ISERC2598/25.** The approval period is from **25th March 2025 to 24th March 2026.**

This approval is subject to compliance with the following requirements:

i. Only approved documents including (informed consents, study instruments, MTA) will be used.
ii. All changes including (amendments, deviations, and violations) are submitted for review and approval by SU-ISERC.
iii. Death and life-threatening problems and serious adverse events or unexpected adverse events whether related or unrelated to the study must be reported to SU-ISERC within 72 hours of notification.
iv. Any changes anticipated or otherwise that may increase the risks or affected safety or welfare of study participants and others or affect the integrity of the research must be reported to SU-ISERC within 72 hours.
v. Clearance for the export of biological specimens must be obtained from relevant institutions.
vi. Submission of a request for renewal of approval at least 60 days prior to the expiry of the approval period. Attach a comprehensive progress report to support the renewal.
vii. Submission of an executive summary report within 90 days of completion of the study to SU-ISERC.

Before commencing your study, you will be expected to obtain a research license from National Commission for Science, Technology, and Innovation (NACOSTI) https://research-portal.nacosti.go.ke/ and obtain other clearances needed.

Yours sincerely,

Mr Ambrose Rachier,
Chairperson; SU-ISERC

Ole Sangale Rd, Madaraka Estate. PO Box 59857-00200, Nairobi, Kenya. Tel +254 (0)703 034000
Email admissions@strathmore.edu www.strathmore.edu

Appendix C: NACOSTI Research Licence

REPUBLIC OF KENYA

NATIONAL COMMISSION FOR SCIENCE,TECHNOLOGY & INNOVATION

Ref No: **479404**

Date of Issue: **12/February/2025**

RESEARCH LICENSE



This is to Certify that Ms.. SHARON BUKAYA of Strathmore University, has been licensed to conduct research as per the provision of the Science, Technology and Innovation Act, 2013 (Rev.2014) in Baringo, Bomet, Bungoma, Busia, Elgeyo-Marakwet, Embu, Garissa, Homabay, Isiolo, Kajiado, Kakamega, Kericho, Kiambu, Kilifi, Kirinyaga, Kisii, Kisumu, Kitui, Kwale, Laikipia, Lamu, Machakos, Makueni, Mandera, Marsabit, Meru, Migori, Mombasa, Muranga, Nairobi, Nakuru, Nandi, Narok, Nyamira, Nyandarua, Nyeri, Samburu, Siaya, Taita-Taveta, Tanariver, Tharaka-Nithi, Transnzoia, Turkana, Uasin-Gishu, Vihiga, Wajir, Westpokot on the topic: A Chatbot for personalized financial advisory and Investment Planning in Kenya. for the period ending : 12/February/2026.

License No: **NACOSTI/P/25/415954**

479404

Applicant Identification Number

Director General
NATIONAL COMMISSION FOR SCIENCE,TECHNOLOGY & INNOVATION

Verification QR Code

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See overleaf for conditions

Appendix D: Survey

Financial Advisory Chatbot Survey

Thank you for participating in this survey! This study aims to develop an AI-powered chatbot for personalized financial advisory and investment planning in Kenya. Your responses will help us understand user needs and improve chatbot design. Your data will remain confidential.

1. Email *

_____

Skip to question 2Skip to question 2

Section 1: Demographic Information

2. **Where do you currently reside?** *(Select one)*

Mark only one oval.

- ◯ Nairobi
- ◯ Mombasa
- ◯ Kisumu
- ◯ Nakuru
- ◯ Other: _____

3. **What is your age group?** *(Select one)*

Mark only one oval.

- ◯ 18–24 years
- ◯ 25–40 years
- ◯ 41–60 years
- ◯ 61 years and above

4. **What is your current employment status?** *(Select one)*

Mark only one oval.

- ◯ Employed (Full-time)
- ◯ Employed (Part-time)
- ◯ Self-Employed
- ◯ Student
- ◯ Unemployed
- ◯ Retired
- ◯ Other: _____

5. What is your primary source of income?

Mark only one oval.

- ◯ Salary/Wages
- ◯ Business/Entrepreneurship
- ◯ Investments (Stocks, Real Estate, etc.)
- ◯ Family Support
- ◯ Other: _____

6. **What is your monthly income range (in KES)?** *(Select one)*

Mark only one oval.

- ◯ Less than 20,000
- ◯ 20,000–50,000
- ◯ 50,001–100,000
- ◯ 100,001 and above
- ◯ Prefer not to say

7. **Do you currently have access to financial advisory services?** *(Select one)*

Mark only one oval.

- ◯ Yes
- ◯ No

8. **How would you rate your financial literacy?** *(Linear scale: 1–5)*

Mark only one oval.

1	2	3	4	5
◯	◯	◯	◯	◯

Skip to question 9

Section 2: Financial Advisory Needs

9. **What are your primary financial goals?** *(Select all that apply)*

Check all that apply.

- ☐ Saving for education
- ☐ Buying a home
- ☐ Retirement planning
- ☐ Investment opportunities
- ☐ Managing debt
- ☐ Other: _____

10. **What challenges do you face in achieving your financial goals?** *(Select all that apply)*

Check all that apply.

- [ ] Lack of financial knowledge
- [ ] Limited access to financial advisors
- [ ] High cost of advisory services
- [ ] Lack of trust in financial advisors
- [ ] Other: _____

11. **How often do you seek financial advice?** *(Select one)*

Mark only one oval.

- ◯ Frequently (Weekly or Monthly)
- ◯ Rarely (Only when needed)
- ◯ Never

12. Which financial advisory services have you used before?

Check all that apply.

- [ ] Banks/Financial Institutions
- [ ] Insurance Companies
- [ ] Investment Firms
- [ ] Mobile Money Services (e.g., M-Pesa)
- [ ] Online Financial Platforms
- [ ] Family/Friends/Informal Groups
- [ ] None

Skip to question 13

Section 3: Digital Financial Advisory Preferences

13. **Would you consider using an AI-powered chatbot for financial advice?** *(Select one)*

Mark only one oval.

- ◯ Yes
- ◯ No

14. **Which chatbot features would be most useful to you?** *(Select all that apply)*

Check all that apply.

- ☐ Personalized investment advice
- ☐ Budgeting and expense tracking
- ☐ Real-time financial tips
- ☐ Multilingual support
- ☐ Integration with my existing financial accounts
- ☐ Other: _____

15. **What would make you trust an AI-powered financial advisory chatbot?** *(Select all that apply)*

Check all that apply.

- ☐ Strong data privacy and security policies
- ☐ Accurate and reliable financial advice
- ☐ Easy-to-use and intuitive interface
- ☐ Availability of expert human support if needed
- ☐ Other: _____

16. **How comfortable are you with using digital platforms for financial planning?** *(Select one)*

Mark only one oval.

- ◯ Very comfortable
- ◯ Somewhat Comfortable
- ◯ Not comfortable

17. What concerns would you have about using a financial chatbot?

Check all that apply.

- ☐ Accuracy of information
- ☐ Data privacy and security
- ☐ Ease of understanding responses
- ☐ Trust in automated financial advice
- ☐ Other: _____

Skip to question 18

Section 4: Final Feedback

18. **What additional features or support would you like from a financial advisory chatbot?** *(Open-ended question)*

_____

_____

_____

_____

_____

19. **Any other comments or suggestions?** *(Open-ended question)*

_____

Skip to section 6 (Thank You Message)