FinFluent - Personal Financial Advisor

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1 Introduction

People today face an overwhelming number of financial decisions, including budgeting, saving, investing, and long-term planning. Young adults and low-income individuals, in particular, struggle with these challenges due to limited financial literacy, scarce resources, and reliance on misinformation from friends and media. Traditional robo-advisors and financial management systems provide static, one-size-fits-all solutions that fail to engage users with tailored, context-aware guidance.

Large Language Models (LLMs) present an opportunity to bridge this gap by offering intelligent, adaptable, and accessible financial advice. However, existing LLM-based advisors face significant challenges, including hallucinations, unreliable reasoning, and difficulties incorporating real-time financial data. These issues can erode user trust and lead to poor financial decisions.

2 Motivation

To overcome these limitations, we present a Personalized Financial Advisor, a multi-agent system that combines structured financial data and LLM-based suggestions.

The system is made up of three specialized agents that work together to evaluate user financial data, detect anomalies and produce personalized recommendations. Our solution employs Chain of Thoughts (COT) reasoning for logical decision-making, real-time financial data integration for current insights, and ensemble learning models for robust budget forecasting. The primary objectives of our system are: Personalization: Providing financial advice tailored to user preferences, goals, and risk tolerance. Trust and Transparency: Ensuring ethical AI practices, explainability, and security to foster user confidence. By combining AI-driven forecasting, anomaly detection, and ethical financial decision-making, our system aims to empower individuals with responsible and data-driven financial strategies, ultimately improving their financial well-being.

3 Literature Review

The use of Artificial Intelligence (AI) and Large Language Models (LLMs) in personal finance has gained traction, including solutions for budgeting, investment consulting, and anomaly detection. Traditional financial tools make static, rule-based suggestions, but AI-powered solutions may adjust dynamically to their customers' financial behavior and market situations. AI-driven financial modeling has increased budget forecasting accuracy by combining LLMs with economic models. AI-driven financial suggestions fit with user-specific goals, leading to better budget optimization (I. de Zarzà and Calafate (2023)). Forecasting systems like SARIMA, GRU, and LightGBM may accurately anticipate financial trends, leading to better financial planning accuracy (Shuryhin and Zinovatna (2024)). Anomaly detection in financial behavior is a burgeoning study topic, where machine learning techniques such as Isolation Forests and cognitive bias correction assist spot outliers in spending patterns. These strategies target behavioral biases, such as loss aversion and impulsive spending, which influence financial decisions. AI-powered anomaly detection has helped identify fraudulent transactions and strange spending patterns (Suchonwanich et al. (2024)). Investment Advisory Systems that utilize LLMs and financial agents have shown potential in financial decision-making.

Investment Advisory Systems leveraging LLMs and financial agents have demonstrated promise in financial decision-making. The FinCon multi-agent framework (Yu et al. (2024)) has been demonstrated to improve reasoning, decrease information overload, and boost financial suggestions. Research comparing LLM-based financial chatbots (ChatGPT, Bard) to rule-based systems reveals that LLMs deliver tailored and fluent replies, but suffer from inconsistency and mathematical mistakes, needing formal interaction with financial databases (Yang et al. (2024)). FinGPT, an open-source financial LLM, has successfully democratized AI-powered financial decision-making by adding real-time market data.

Further study focuses on the ethical and security problems of AI in finance. To be trustworthy, LLMs should include data privacy safeguards, real-time adaptability, and bias reduction mechanisms (Fieberg et al. (August 06, 2024)). AI-powered financial assistants (Easin et al. (2024)) using Chain of Thoughts (COT) reasoning and hierarchical agent architectures have been shown to increase logical consistency and financial decision-making.

Our proposed Personalized Financial Advisor expands on these developments by including a multi-agent system for financial planning that combines LLM-driven insights, anomaly identification, and stock prediction. Our solution intends to provide customized, adaptable, and trustworthy financial assistance by utilizing real-time data, ensemble learning models, and user feedback mechanisms, overcoming the constraints of current AI-driven financial products.

4 Methodology

The FinFluent Multi-Agent Framework integrates machine learning models and a large language model (LLM) to provide personalized financial insights. The system consists of three key components:

- Budget Forecasting
- Anomaly Detection
- Stock Pattern Prediction

The multiagent system dynamically decides whether to feed data to any of the ML models based on the user's prompt and specific needs. Once a model processes the data, the output is enriched with additional contextual information and passed to the advisor agent - Llama3 (Grattafiori et al., 2024), which analyzes the augmented input and provides the user with tailored financial advice or insights.

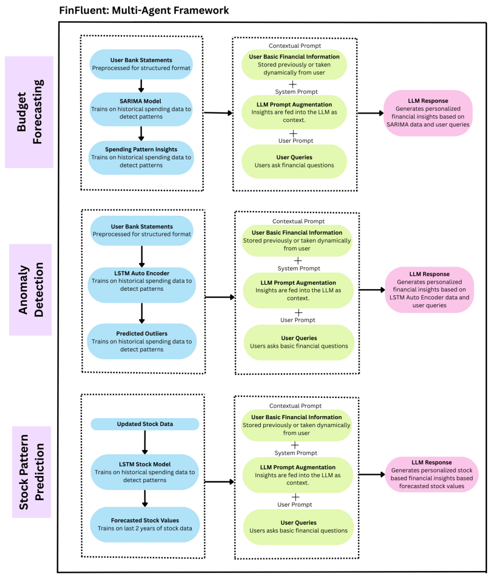

Figure 1: The FinFluent Multi-Agent Framework integrates machine learning models and a large language model (LLM) to provide personalized financial insights.

4.1 Dataset

The dataset is synthetically generated to ensure privacy while maintaining realistic financial patterns. The dataset is of two types one which categorizes spending into seven common areas with transaction details such as date and amount, and another which includes attributes like Age, Region, Category, Amount, Transaction Type, and Account Name. To enhance realism, a seasonality parameter is incorporated, reflecting real-world spending habits. For instance, spending increases in December due to holiday shopping, in June for travel and entertainment, and in March when people receive tax refunds. Monthly spending spikes are predefined for categories such as gym memberships in January, back-to-school shopping in August, and Black Friday purchases in November. Additionally, financial behavior varies based on age and region —users over 35 in urban areas typically have higher incomes and spend more on travel, whereas younger individuals in rural areas exhibit lower discretionary spending. Recurring expenses like gym memberships are designed to repeat over multiple years to add authenticity. The dataset spans over 10 years, allowing for long-term financial trend analysis. To further improve robustness, an anomaly function injects slightly abnormal values to simulate real-world financial outliers, such as sudden large expenses or potential fraudulent transactions. This structured approach ensures a diverse, realistic, and dynamic dataset, optimizing the accuracy of financial models.

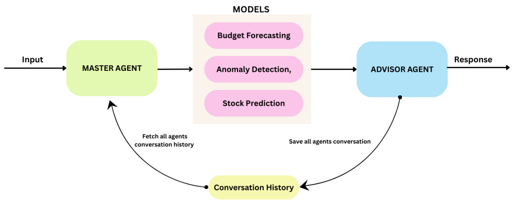

Figure 2: Multi Agent Framework Overview

4.2 Budget Forecasting

We use the SARIMA (Permanasari et al., 2013) model to identify seasonal and trend-based patterns in the user's spending. We then fit the SARIMA model to the data, adjusting for parameters based on the user's financial behavior and forecast future spending trends (e.g., expected spending on rent or utilities) and capture the user's financial habits. The formatted output from the SARIMA model (predicted trends and patterns) is fed it into the LLM (Llama3) to enhance its contextual understanding of the user's finances. The LLM utilizes this context to generate personalized responses to user queries, such as expected spending or budget adjustments. The LLM, informed by the SARIMA model's forecasts, responds to user questions like "How much will I spend on groceries next month?" or "Am I overspending on utilities?" By leveraging the forecasted data, the LLM provides specific, actionable financial advice based on the user's patterns.

4.3 Anomaly Detection

Our anomaly detection system leverages an LSTM Autoencoder, trained specifically on seasonal financial transaction data. Given that spending patterns vary across time (e.g., higher spending during holidays, salary deposits at month-end, recurring bills), our model is designed to learn these periodic patterns and detect anomalies accordingly. We then normalize the transaction amounts and transform data into sequential format.

The LSTM (Hochreiter and Schmidhuber, 1997) Autoencoder for anomaly detection consists of two components: an encoder and decoder. The encoder compresses transaction sequences while learning temporal connections using LSTM layers, while the decoder reconstructs the original sequence. The model is trained solely on routine transactions, learning to detect common patterns. When an abnormal transaction is inserted, the reconstruction error increases, indicating an anomaly. The model is trained utilizing the Mean Squared Error (MSE) loss function and the Adam optimizer, with validation to prevent overfitting.

After training, the model reconstructs normal and anomalous transactions. Normal transactions have low reconstruction errors, while anomalous ones have high errors due to their deviation from learned patterns.

A threshold is set based on the reconstruction error distribution, often using the 95th percentile. Transactions with errors above this threshold are flagged as anomalies, balancing sensitivity to false positives and false negatives.

4.4 Stock Prediction

First, we source the stock data using yfinance (Yahoo Finance library) and extract the close prices of the particular stock for the previous 2 years. We then preprocess this data by reshaping and normalizing the values in the range of 0 to 1. Once preprocessing is complete, we prepare the data by splitting it into lookback and forecast periods. The lookback period helps the LSTM model to capture context about seasonal and short term trends. The LSTM model consists of 2 layers, the first layer, with 80 units, learns the temporal dependencies in the stock price trend. The second layer, with 120 units, outputs only the final hidden state, reducing the dimensionality. The dense layer, which is the dense layer, consists of a fully connected layer that outputs the forecast of the stock prices. The two stacked LSTM layers allow hierarchical learning of temporal patterns and the increase in number of units from layer 1 to layer 2 helps in extracting the features better. The model is trained for 100 epochs, with a batch size of 16.

4.5 Security and Data Privacy

To decrypt the data the Base64-encoded encrypted text is converted back into bytes. The

HMAC-SHA256 (Chen and Yuan, 2012) integrity check is performed to detect tampering. If valid, AES-128 decryption in CBC mode is applied to restore the plaintext. Before sending financial insights to the AI model, the encrypted data is decrypted in a controlled environment to retrieve the original message securely. Given the sensitivity of financial data, we have implemented AES-based Fernet Encryption, to ensure confidentiality and integrity. Fernet encryption was selected due to its balance between strong security and ease of implementation where the financial forecast or user query (plaintext) is converted into bytes. Automatic IV (Initialization Vector) generation, making it resistant to replay attacks and Base64 encoding, allowing safe transmission over APIs and secure storage.

To decrypt the data the Base64-encoded encrypted text is converted back into bytes. The HMAC-SHA256 (Chen and Yuan, 2012) integrity check is performed to detect tampering. If valid, AES-128 decryption in CBC mode is applied to restore the plaintext. Before sending financial insights to the AI model, the encrypted data is decrypted in a controlled environment to retrieve the original message securely.

5 Preliminary Results

When the Enhanced-LLM, which is given contextual data, performs significantly better than when the Base-LLM, to which contextual data is not given to make decisions based on the stock. Integrating the data from the LSTM based stock pattern prediction model helps the LLM model to provide specific forecasted price ranges, for example, the model describes the range in which the stock prices will be in, i.e $220to273$ per stock. The LLM which was not provided with contextual data failed to predict price predictions for the stock. The Enhanced-LLM offers a target entry price to the user, giving the user more understanding of when to take action, whereas the Base-LLM discusses stock performance and keeps its response general.

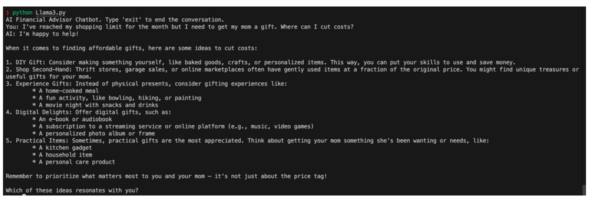

Figure 3: Output from Llama3 without any algorithm

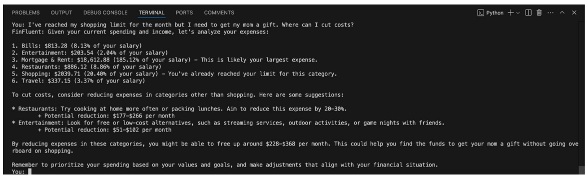

Figure 4: Output from Llama3 with SARIMA Integration

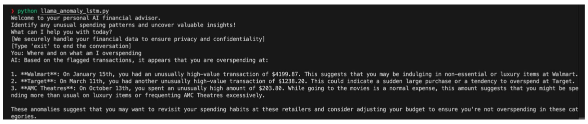

Figure 5: Output from Llama3 with LSTM Autoencoder Integration

Risk consideration based on volatility is an important aspect that the Base-LLM fails to discuss with the user. It provides a broad discussion of market trends, but does not assess short-term price movement. The Enhanced-LLM on the other hand mentions price fluctuations, and also advises the user to diversify his/her portfolio. The user, who is considered financially illiterate, does not receive any information about the stock, rendering the predictions of the model useless to the user. In summary, the Enhanced-LLM is better because it integrates LSTM model predictions, provides precise investment guidance, and offers a more data-driven approach to decision-making.

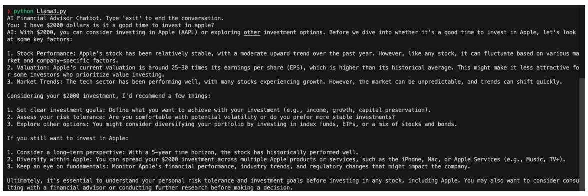

Figure 6: Output from Llama3 without LSTM Stock Predictor

The Enhanced-LLM (here, enhanced using LSTM Autoencoder) analyzes the transaction data and highlights unusual spending patterns. As the model suggests, on certain dates, the user has performed transactions of high value that did not align with the usual spending pattern of the user. Such as, a Walmart order on 15th of January worth 4198.87 USD, a Target order that took place on 11th March that was worth 1238.28 USD. It also flags transactions that do not confine within the normal spending limit of the category and the shopping venue. A potential overspending reminder helps the user to keep their financial transaction in check.

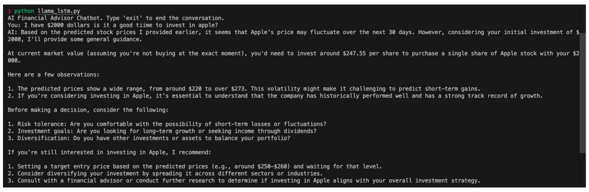

Figure 7: Output from Llama3 with LSTM Stock Predictor

Figure 8: Output from Llama3 with Text Encryption

6 Future Scope

We are actively working on several enhancements to improve the accuracy, usability, and integration of the FinFluent framework. Our key focus areas include: 1. Enhanced Anomaly Detection with Memory-Based Contextual Flagging. We are developing a memory-based contextual flagging mechanism to enhance anomaly detection. This will allow the system to retain historical spending patterns and user interactions, improving its ability to identify suspicious transactions based on long-term behavioral trends rather than isolated deviations. 2. Advanced Prompt Engineering and Tuning Ongoing efforts are focused on refining prompt structures and optimizing LLM interactions to improve response quality and contextual accuracy. By enhancing prompt engineering techniques, we aim to generate more precise and personalized financial insights for users. 3. Agent Integration and Configurable Environment We are working on integrating our individual agents—budget forecasting, anomaly detection, and stock pattern prediction—into a unified and configurable environment. This will enable users to tailor their financial analysis preferences, making the system more interactive and adaptable. 4. OAuth Integration for Secure User Authentication As we develop and prepare to host our front end, we are implementing OAuth authentication to ensure secure and seamless user access. This will allow users to securely connect their financial accounts while maintaining privacy and data protection.

Through these ongoing improvements, FinFluent is evolving into a more intelligent, secure, and user-friendly financial assistant, capable of delivering deeper insights and highly personalized recommendations.

7 Contribution

Amit: LSTM Stock Predictor, Data Generation, Methodology Research, Report writing, Code integration, prompt tuning

Akshata: Related work, introduction, methodology research, Data Generation, Report Writing, Code Integration, Prompt tuning

Suraj: LSTM Auto Encoder Anomaly Detection, Data Generation, Methodology Research, Report Writing, Code Integration, Security Feature integration, Prompt Tuning

Vidya: SARIMA Budget Forecaster, Llama3 integration, Methodology Research, Report Writing, Code Integration, Prompt tuning

References

Fatang Chen and Jinlong Yuan. 2012. Enhanced key derivation function of hmac-sha-256 algorithm in lte network. In *2012 Fourth International Conference on Multimedia Information Networking and Security*, pages 15–18.

Arafat Md Easin, Saha Sourav, and Orosz Tamás. 2024. An intelligent llm-powered personalized assistant for digital banking using langgraph and chain of thoughts. pages 625–630.

Christian Fieberg, Lars Hornuf, and David Streich. August 06, 2024. Using large language models for financial advice. pages 1–5.

Shen Gao, Yuntao Wen, Minghang Zhu, Jianing Wei, Yuhan Cheng, Qunzi Zhang, and Shuo Shang. 2024. Simulating financial market via large language model based agents.

Aaron Grattafiori, Abhimanyu Dubey, and Abhinav Jauhri. 2024. The llama 3 herd of models. *Preprint*, arXiv:2407.21783.

Oudom Hean, Utsha Saha, and Binita Saha. 2025. Can ai help with your personal finances? *Applied Economics*, page 1–9.

Sepp Hochreiter and Jürgen Schmidhuber. 1997. Long short-term memory. *Neural Computation*, 9(8):1735–1780.

Gemma Roig I. de Zarzà, J. de Curtò and Carlos T. Calafate. 2023. Optimized financial planning: Integrating individual and cooperative budgeting models with llm recommendations. *Artificial Intelligence Applications in Financial Technology*.

Kausik Lakkaraju, Sara E Jones, Sai Krishna Revanth Vuruma, Vishal Pallagani, Bharath C Muppasani, and Biplav Srivastava. 2023a. Llms for financial advisement: A fairness and efficacy study in personal decision making. page 100–107.

Kausik Lakkaraju, Sai Krishna Revanth Vuruma, Vishal Pallagani, Bharath Muppasani, and Biplav Srivastava. 2023b. Can llms be good financial advisors?: An initial study in personal decision making for optimized outcomes.

Jean Lee, Nicholas Stevens, and Soyeon Caren Han. 2025. Large language models in finance (finllms). *Neural Computing and Applications*.

Parth Pangavhane, Shivam Kolse, Parimal Avhad, Tushar Gadekar, N. K. Darwante, and S. V. Chaudhari. 2023. Transforming finance through automation using ai-driven personal finance advisors. pages 1–5.

Adhistya Erna Permanasari, Indriana Hidayah, and Isna Alfi Bustoni. 2013. Sarima (seasonal arima) implementation on time series to forecast the number of malaria incidence. In *2013 International Conference on Information Technology and Electrical Engineering (ICITEE)*, pages 203–207.

Kostiantyn Shuryhin and Svitlana Zinovatna. 2024. Recommendation system for financial decision-making using artificial intelligence. *Applied Aspects of Information Technology*, 7:348–358.

Niorn Suchonwanich, Siranee Nuchitprasitchai, and Kanchana Viriyapant. 2024. Enhancing personalized financial advisory application with generative ai and chatbot: A usability study. pages 97–102.

Hongyang Yang, Xiao-Yang Liu, and Christina Dan Wang. 2023. Fingpt: Open-source financial large language models.

Yuzhe Yang, Yifei Zhang, Yan Hu, Yilin Guo, Ruoli Gan, Yueru He, Mingcong Lei, Xiao Zhang, Haining Wang, Qianqian Xie, Jimin Huang, Honghai Yu, and Benyou Wang. 2024. Ucfe: A user-centric financial expertise benchmark for large language models.

Yangyang Yu, Zhiyuan Yao, Haohang Li, Zhiyang Deng, Yupeng Cao, Zhi Chen, Jordan W. Suchow, Rong Liu, Zhenyu Cui, Zhaozhuo Xu, Denghui Zhang, Koduvayur Subbalakshmi, Guojun Xiong, Yueru He, Jimin Huang, Dong Li, and Qianqian Xie. 2024. Fincon: A synthesized llm multi-agent system with conceptual verbal reinforcement for enhanced financial decision making.

Huaqin Zhao, Zhengliang Liu, Zihao Wu, Yiwei Li, Tianze Yang, Peng Shu, Shaochen Xu, Haixing Dai, Lin Zhao, Hanqi Jiang, Yi Pan, Junhao Chen, Yifan Zhou, Gengchen Mai, Ninghao Liu, and Tianming Liu. 2024a. Revolutionizing finance with llms: An overview of applications and insights.

Huaqin Zhao, Zhengliang Liu, Zihao Wu, Yiwei Li, Tianze Yang, Peng Shu, Shaochen Xu, Haixing Dai, Lin Zhao, Hanqi Jiang, Yi Pan, Junhao Chen, Yifan Zhou, Gengchen Mai, Ninghao Liu, and Tianming Liu. 2024b. Revolutionizing finance with llms: An overview of applications and insights.