Personalized Financial Advisor

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1 Motivation

In the complex financial management environment that we have today, people face an overwhelming amount of decisions and options to invest in. People often struggle with budgeting, saving, investments, debt management and long term financial planning. Along with this, the volatile market conditions, uncertainty of future income, and the availability of many options often leave people to make poor financial decisions and rely on others for their investments via friends, news, and relatives who might be inaccurate. Low-income individuals and the young population often do not have the resources to hire expert advice.

Traditional robo-advisors and static financial tools do not engage with the user and provide the user with context-aware advice nor do they provide context-aware advice. LLMs present a way to bridge this gap by making financial advice access easy. For example, after an unprecedented expense for a medical emergency, the user can receive tailored suggestions for adjusting their savings or shift some parts of their investment based on risk-tolerance changes or market fluctuations.

LLMs have a tendency to hallucinate and come up with inconsistent reasoning, which even advanced LLMs such as ChatGPT face. These are usually the factors that reduce user trust and lead to suboptimal, loss making financial decisions. The proposed system integrates structured financial data with LLM driven recommendations, by combining anomaly detection and the user feedback mechanism.

The need to develop a responsible and scalable solution to deliver accurate, personalized, and actionable advice is the primary focus of our project. The core objectives are as follows:

Accessible and inclusive financial advice Continuous improvement and accuracy through feedback and real-time data Promotion of responsible financial behavior and trust

We envision a future where every individual, regardless of their financial literacy, income level, and age, benefits from using AI systems for their financial investments. The proposed financial advisor aims to foster financial well-being for all.

LLMs can engage users through natural language conversations, provide context-aware advice, and adapt to individual financial goals and preferences. For example, a user could receive tailored suggestions on adjusting their savings rate after reporting an unexpected medical expense, or dynamically shift their investment portfolio allocation based on risk tolerance changes or market fluctuations.

However, deploying LLMs in financial advisory roles comes with challenges. Existing models, including ChatGPT and similar systems, suffer from limitations such as hallucinations (generating incorrect or irrelevant information), inconsistent reasoning (providing contradictory advice over time), and difficulty incorporating real-time financial data. These issues could undermine user trust and lead to suboptimal or even harmful financial decisions. To mitigate these challenges, the proposed system will integrate structured financial data with LLM-driven recommendations, combining the predictive capabilities of time series models, anomaly detection, and user feedback mechanisms.

2 Literature Review

Recent study show that the integration of large language models (LLMs) with traditional financial planning approaches improve individual and household budgeting. According to (I. de Zarzà and Calafate (2023)), AI-driven recommendations increase budget optimization by connecting financial advice with individual user goals. The integration of AI with economic models has resulted in more efficient and customized financial planning.

Emerging advances in large language models (LLMs) have demonstrated promise for financial decision-making, particularly in tasks such as reasoning, planning, and risk assessment. Verbal reinforcement techniques and hierarchical agent architectures are useful solutions to improve reasoning and reduce information processing stress. (Yu et al. (2024)) expands on these foundations, combining a manager-analyst hierarchy and dual-level risk control to improve financial job performance.

ASFM uses LLM-based agents to simulate financial markets, therefore overcoming limitations in classic economic models. (Gao et al. (2024)) shows it effectively replicates real market behaviors, aligning with economic theories on policy impacts and trader biases. Modeling complicated financial connections and improving agent decision-making are two major challenges.

(Yang et al. (2024)) examines financial benchmarks for assessing LLMs in finance. It focuses on current benchmarks such as FLARE, MMMU that mainly use multiple-choice questions. These benchmarks focus on sentiment analysis, market forecasting, and risk assessment, but they lack dynamic, user-centered assessments. The paper criticizes their reliance on static datasets, which restricts their real-world significance. To address these drawbacks, it offers the UCFE benchmark.

(Lee et al. (2025)) investigates the evolution of Financial Large Language Models (FinLLMs), following their progression from specialized financial models to general-domain Pretrained Language Models (PLMs) such as GPT. It compares techniques in training, data, and fine-tuning, summarizes performance across benchmark tasks, and highlights advanced financial NLP tasks for further development.

(Zhao et al. (2024))compares the effectiveness of LLM-based chatbots (ChatGPT and Bard) to SafeFinance, a rule-based chatbot, in personal finance. It shows that, while LLMs provide fluent replies, they frequently make mistakes, lack consistency, and struggle with advanced financial thinking. In contrast, SafeFinance provides dependable, traceable solutions, but with limited generality. The findings underscore the need for more dependability in LLMs for financial advice.

LLMs such as GPT-4 are revolutionizing finance by automating reporting, anticipating trends, and evaluating investor sentiment. (Lakkaraju et al. (2023a)) shows that they improve decision-making by extracting insights from enormous amounts of financial data, hence increasing efficiency and consumer satisfaction.

(Hean et al. (2025))evaluates the effectiveness of LLMs in providing personal financial advice, analyzing models like ChatGPT, Gemini, Claude, and Llama on topics such as mortgages, taxes, and investments. The results reveal an average accuracy of 70%, with ChatGPT 4 and Claude 3.5 Sonnet outperforming the rest, but Llama3 70B falls behind. The paper underlines AI's potential to improve financial literacy but cautions against relying solely on AI for financial decision-making.

(Easin et al. (2024)) offers an LLM-powered personalized assistant for digital banking that combines LangGraph for structured data management and Chain of Thoughts (COT) for logical reasoning. The system uses a multi-agent framework to efficiently handle tasks like fund transfers, bill payments, and financial inquiries. The results suggest that the assistant improves banking efficiency, personalization, and transaction accuracy.

(Suchonwanich et al. (2024)) examines the role of Generative AI and chatbots in personalized financial advisory systems, to improve user engagement and investment suggestions. The system achieved 85% precision in classifying user intents and delivered tailored portfolio recommendations based on financial goals and risk choices. Usability testing showed higher satisfaction rates but also raised concerns about trust and security in AI-driven financial advice.

(Pangavhane et al. (2023)) is an AI-powered personal finance adviser that transforms financial management using machine learning and automation to provide personalized suggestions. These systems improve financial decision-making processes, such as investment planning, risk assessment, and budgeting.

(Lakkaraju et al. (2023b)) looks at LLM-based financial advisors, evaluating ChatGPT and Bard on personal finance tasks like credit cards, investments, and banking across different languages. ChatGPT outperformed Bardin in terms of customized replies and quantitative reasoning, but struggled with dialects. Both models faced concerns like mathematical errors, lack of personalization, and language adaptation challenges. The study suggests improvements like numeric solvers and broader demographic testing.

(Shuryhin and Zinovatna (2024)) presents an AI-powered financial recommendation system that uses ML and LLMs to optimize financial behavior, address cognitive biases, and enhance decision-making. It combines anomaly detection (Isolation Forest), budget forecasting (ARIMA, LSTM), and personalized financial advise (LLaMa 3.1) to increase user autonomy. The approach promotes ethics, privacy, and openness, resulting in nonjudgmental, reasonable financial suggestions while preventing manipulation. By combining AI-driven forecasting, anomaly detection, and ethical financial advice, the system promotes responsible financial management and informed decision making.

(Fieberg et al. (August 06, 2024)) evaluates 32 LLMs on 64 investor profiles to assess their ability to provide personalized financial advice. Foundation models like GPT-4 outperformed fine-tuned models, generating more consistent, implementable portfolios aligned with investor risk tolerance and experience. While LLM-generated recommendations performed well historically, they exhibited some bias and potential look-ahead bias due to training on past data. However, LLMs show promise in democratizing financial advice but need refinements for accuracy, trust, and ethical alignment.

(Yang et al. (2023)) introduces FinGPT, an open-source financial LLM designed to democratize financial AI by gathering real-time data from diverse sources instead of relying on costly proprietary datasets. Its modular architecture includes layers for data collection, preprocessing, fine-tuning, and applications like robo-advising, quantitative trading, and fraud detection. Cost-effective fine-tuning methods like LoRA and RLSP enhance adaptability while reducing computational costs. FinGPT fosters open-source collaboration, making financial AI more accessible to researchers and practitioners.

3 Methodology

3.1 Core component

Personalized tailoring of language models for finance advice

LLM choice: We plan to make use of pre-trained financial models such as FinGPT, GPT-4, BloombergGPT, Llama 2 or any other LLM to carry out our tasks.

Fine tuning and specialization: Making adjustments on LLMs using specialized datasets like the Consumer Complaint Database, Yahoo Finance API, and Alpha Vantage API, as well as using XFINBENCH and UCFE benchmark, will guarantee that the LLM is knowledgeable about investment advice, portfolio optimization, and financial jargon.

Chain of Thoughts (COT) Reasoning: COT reasoning will be applied to enhance the logical structure of multistep financial decisions, like computing interest rates, calculation of loan payoffs, choosing optimal investment strategies among others. The COT will guide the LLM through the intermediate steps before recommending an advice to the user, reducing reasoning errors.

We aim to use a multi-agent architecture, inspired by FinCon and hierarchical agent frameworks. The LLM agents will interact to analyze user inputs, process financial data, and generate financial recommendations.

3.2 Agents and Roles

Manager agent: This agent will oversee all financial tasks and oversee the delegation of subtasks to the other analyst and advisor agents. It will also monitor the agents for consistency and endure that the recommendations align with the user's overall financial plans.

Analyst agent: The analyst agent is responsible for analyzing user provided data, utilize anomaly detection techniques and budget forecasting methods.

Advisor agent: The advisor agent fusion agent, which combines user data, real-time market inputs and LLM outputs to recommend personalized financial actions.

The agents will collaborate using an inter-agent communication protocol with message passing and shared context for decision-making, minimizing redundant computations and improving response efficiency.

3.3 Anomaly Detection

To prevent impulsive financial decisions, an anomaly detection module will help identify abnormal spending patterns, and the system will provide warnings or recommendations for corrective action.

Anomaly Detection Using Isolation Forest: Train an isolation forest model using user transaction histories to detect anomalies, such as unexpected deviations from regular spending behavior. We integrate these detections into the LLM's reasoning process to ensure responses account for financial outliers.

Cognitive Bias Detection and Correction: Common biases like loss aversion, overconfidence, and impulsive spending will be addressed by mapping user behavior against known patterns.

3.4 Budget Forecasting

The advisor system will predict future budget trends using an ensemble learning approach to help users plan effectively for both short-term and long-term goals.

SARIMA (Seasonal AutoRegressive Integrated Moving Average): Captures short-term spending trends with a focus on seasonal and cyclical patterns, such as recurring monthly or yearly expenses (e.g., rent, utilities, holiday spending).

GRU (Gated Recurrent Unit) or Time-Series Transformer: Handles non-linear dependencies and dynamic patterns in user financial behaviors, such as sudden spikes or declines in spending and savings.

Random Forest Regressor: Exploits historical patterns, such as user-specific trends in spending, income, or investment allocations.

LightGBM (Gradient Boosting for Variable Dependencies): Can detect patterns where financial behavior depends on multiple inputs and make refined predictions.

Weighted Averaging for Ensemble Forecasts: A dynamic weighting mechanism is assigned to each model based on the financial environment, the weighting is as follows for each model: SARIMA: Higher weight during stable periods with predictable seasonality. GRU/Transformers: Higher weight during volatile periods or when sudden changes in spending patterns occur. Random Forest and LightGBM: Provide consistent baseline forecasts by leveraging historical data.

Based on the outputs obtained, the ensemble model gives out recommendations dependent on the voting.

3.5 Real-Time Data Integration: Dynamic and Up-to-Date Recommendations

To provide accurate financial advice, the system will pull real-time data on investments, stock prices, interest rates, and inflation from external APIs (e.g., Alpha Vantage, Yahoo Finance).

Dynamic Data Pipelines: A data ingestion pipeline uses APIs to provide real-time updates to get apt recommendations from the advisor system by updating portfolio recommendations and risk assessments.

Event-Driven Updates: Significant market changes will trigger updates to user recommendations, such as reallocating investments or modifying savings goals.

3.6 Personalized Recommendations: Adapting to User Needs and Contexts

The LLM will generate personalized advice such as optimal allocation of income to savings, investments, and discretionary expenses, investment strategies such as risk-adjusted portfolio allocations and debt management depending on the user's financial history, preferences, and goals.

Methodology: The LLM will interpret structured financial data and user-provided inputs to generate recommendations using natural language generation (NLG). Human-in-the-loop feedback will validate and refine the recommendations, where users can confirm or correct the advice provided.

Intent Recognition and Adaptive Responses: The system will classify user intents using a natural language understanding (NLU) module based on transformer models. real-time feedback allows the system to adapt to changing user needs over time, improving personalization and user satisfaction.

3.7 Ethical and Privacy Considerations: Building Trust and Compliance

Since financial data is highly sensitive, the system will be designed with a strong emphasis on data privacy, security, and ethical AI practices.

Privacy Measures: Implement OAuth 2.0 authentication and OWASP guidelines for data protection.

Bias Mitigation: Regular audits will be conducted on LLM-generated advice to identify and correct biases.

Transparency: Users will have access to explainable reports showing how decisions were made and the data used in the process.

3.8 Evaluation and Performance Metrics

The performance evaluation is as follows: Precision of recommendations: The accuracy of advice compared to the benchmarks used to evaluate the model.

User engagement: Assess satisfaction levels through user feedback and surveys.

Bias correction: Reducing anomalies and cognitive biases in the decision making process.

Trust metrics: Increase transparency, explainability and data security to Increase user trust.

Efficiency: Reduce average response time and ensure better use of resources in the multi-agent framework..

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