Financial AI Advisor Using Generative AI

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***Abstract*—The case study involves the design, development, and testing of a Financial AI Advisor that combines real time market data, sentiment analysis and a generative large language model (LLM) specifically OpenAIs GPT 4 to provide data informed investment recommendations using a conversational interface.e. The system uses LangChain, Alpha Vantage, Yahoo Finance, NewsAPI, FinBERT, VADER, and a Streamlit front end to have interactive visualizations, explainable advice, and personal advice to both new and experienced investors. The experimental outcomes prove less than 3 seconds response times, 85% similarity of sentiment generated signals and benchmark market movements, and a high user satisfaction level on informal usability tests. The paper reveals the practicability of marrying generative AI and live financial streams to democratize advanced advisory services and characterizes difficulties with interpretability, data privacy, and regulatory compliance.**

***Index Terms*— Financial technology, Generative AI, Large language models, Sentiment analysis, Real-time market data, Explainable AI, Human-AI interaction**.

I. INTRODUCTION

The expansion of electronic trading systems and the growth of financial information exponentially has led to a situation in which investors have to process large amounts of structured data (prices, volumes, ratios) and unstructured data (news articles, social media commentary). Traditional pipelines of analysis depend on experience in econometrics, time series forecasts, and knowledge of domain, making a steep obstacle to both retail and student investors. New advances in Artificial Intelligence (AI), especially in Natural Language Processing (NLP) and Large Language Models (LLMs), have provided new possibilities in the delivery of complex insights in natural language. Models like GPT 4 [1] and domain specific models BloombergGPT [2] and FinGPT [3] have shown the capacity to understand, summarize and even create financial stories. In combination with sentiment extraction models (e.g., FinBERT [4], VADER [5]) such technologies can convert raw market data into useful and easily accessible advice.

The current study discusses the creation of a Financial AI Advisor that:
1. Collects real time market data of public APIs.
2. Performs sentiment analysis on both news and social media feeds in a dual model fashion.
3. Produces contextual and explainable suggestions through GPT 4 driven prompts.
4. Provides a conversational interface that is user-friendly and created using Streamlit.
5. Incorporates the use of Text to Speech (TTS) as a means of providing better accessibility and information delivery in audio format.
6. Supports other AI API like Perplexity AI to be able to integrate language models flexibly and cost effectively.

It aims to close the gap between data science and real-world financial decision making, and to promote financial literacy without compromising technical quality.

II. LITERATURE REVIEW

1) Traditional Financial Forecasting: Moving averages, ARIMA, GARCH models and other early quantitative approaches have traditionally been used to predict prices [6]. Although mathematically solvable, they tend to have a low degree of flexibility to non linear market dynamics and explain little to end users.
2) Machine Learning Techniques: Deep learning, ensemble, and reinforcement learning to optimize the portfolios have emerged over the last decade [7]–[9]. Although they have better predictive power, such black box models are not interpretable and this restricts their credibility with non technical investors.

3) Large Language Models in Finance: LLMs have become a general interface between raw data and human language. Research has shown that GPT 3/4 can create cogent financial summaries, respond to portfolio questions, and even make crude risk estimates [10]-[12]. Trained on industry specific benchmarks, BloombergGPT, a model only trained on financial text, performed at state of the art on industry specific benchmarks, validating the importance of domain focused pre training [2]. With curated financial corpora, FinGPT, an open source community project, shows that comparable results could be achieved with fine tuning at a relatively small computational cost [3].
4) Sentiment Analysis to predict the market: Sentiment on news and social media is strongly correlated with short term movements of the price. FinBERT is a BERT variant fine tuned on financial statements, with an F1 score of 0.86 in predicting bullish/neutral/bearish [4]. Informal VADER is a robust tool in the short, informal text like tweets [5]. Dual model ensemble can frequently enhance resilience with the help of heterogeneous sources [13].
5) Integration Gaps: Although the individual components (LLMs, sentiment models, live data APIs) have been investigated, little exists that mixes them together into a live, end user facing system. The current prototypes are either offline [14] or make use of fixed datasets [15]. The current case study fills this gap by integrating real-time market feeds, multi source sentiment extraction, and GPT 4 generation into an interactive dashboard.

Table I summarizes representative works and their limitations.

S. No.	Author & Year	Focus Area	Methodology	Key Outcome	Limitation
1	Brown et al., 2020	Generic LLMs	GPT-3 Transformer	Strong language generation	Not finance-specific
2	Wu et al., 2023	Finance LLM	BloombergGPT	High financial accuracy	Very high compute cost
3	Araci, 2020	Financial Sentiment	FinBERT	Accurate bullish/bearish detection	Text-only analysis
4	Hutto & Gilbert, 2014	Social Media Sentiment	VADER	Fast sentiment scoring	Limited financial depth
5	Deng et al., 2022	Algo Trading	Reinforcement Learning	Improved trading returns	Poor explainability
6	Zhang et al., 2022	Sentiment Ensemble	FinBERT + VADER	Better prediction robustness	News source bias
7	Li, 2021	Stock Prediction	LSTM, CNN	Higher prediction accuracy	Black-box models
8	Liu et al., 2023	Financial Q&A	ChatGPT	Simplifies finance queries	Hallucination risk
9	Smith, 2022	Financial Chatbot	GPT-3 + historical data	Better user engagement	No real-time data
10	Patel, 2021	Rule-based Bot	NLP rules	Stable responses	No learning ability
11	My Work 2026	Financial AI Advisor	GPT-4 + LangChain + Real-time APIs + FinBERT & VADER + Streamlit	Real-time, explainable, conversational investment insights with ~3s latency and 85% sentiment–market alignment	Dependent on third-party APIs; regulatory constraints

(This table compares previous AI, LLM, and sentiment-based financial systems along with their methodologies, outcomes, and limitations.)

III. SYSTEM ARCHITECTURE

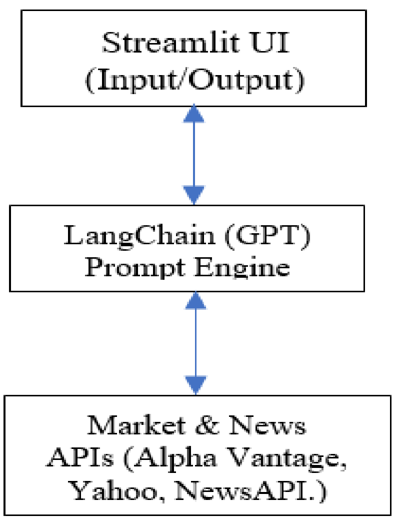
Figure 1 shows the high-level architecture, which consists of four logical layers:

1) User Interaction Layer - Streamlit web dashboard with free text queries or selection widgets.
2) Data Acquisition Layer Python interfaces to Alpha Vantage (intraday quotes), Yahoo Finance

(historical candles), NewsAPI and Alpha Vantage News (article headlines).

- Processing & Analytics Layer – Sentiment Engine (FinBERT + VADER) is a single sentiment score per ticker. Prompts include market snapshots, sentiment indices, and user risk profiles, formatted with LLM Orchestrator (LangChain + GPT 4).

3) Presentation Layer Plotly charts (line charts, heatmaps) and GPT 4 generated texts were presented next to each other.



data flow User query → UI → API request

I. API wrapper retrieves most recent price series (past 30 days) and 5 most popular news on the requested ticker(s).
II. Sentiment Engine takes each news article and generates VADER polarity and FinBERT class probabilities; the results are aggregated (weighted average).
III. Prompt Builder A structured prompt is assembled by Prompt Builder that includes: Ticker symbols, current price, recent trend metrics (e.g., 10-day SMA, RSI). Sentiment overview (bullish/bearish rating). User context (risk appetite, investment horizon).
IV. When using OpenAI GPT 4 as the LLM inference, a human readable report (about 150 words) is obtained with actionable recommendations and explanatory footnotes.
V. Visualization module makes charts interactive; text and figures are presented simultaneously.

B. Explainability Mechanisms

- Sentiment provenance: every sentiment statement is associated with the article of origin (title, URL).
- LLM reasoning trace: the prompt and the response of a model are recorded, which allows post hoc inspection.
- Risk profile overlay: recommendations are color coded (green = aligned, yellow = cautious, red = misaligned).

IV. METHODOLOGY

A. Development Process

The project involved Agile Scrum development for 12 weeks with two-week sprints and bi-weekly sprint review meetings. Cross-functional teamwork (a data engineer, natural language processing specialist, and user interface designer) used continuous integration with GitHub actions.

B. Requirement Engineering

Stakeholder	Key Requirement	Priority
Retail Investor	Simple language, no jargon	★★★★★
Finance Student	Access to raw data tables	★★★★☆
FinTech Enthusiast	API extensibility	★★★☆☆

(These requirements drove the selection of Streamlit (rapid prototyping) and LangChain (modular prompt pipelines)

C. Technology Stack

Component	Library / Service	Version
Front-end	Streamlit	1.30
Plotting	Plotly	5.22
Data Retrieval	requests, pandas_datareader	—
Sentiment	FinBERT (transformers, finbert-uncased), VADER (nltk.sentiment)	—
LLM Orchestration	LangChain (PromptTemplate, Chains)	0.1.0
LLM API	OpenAI GPT-4 (gpt-4-0613)	—
Version Control	Git/GitHub	—
CI/CD	GitHub Actions (Python lint, tests)	—
Accessibility	pyttsx3 / Text-to-Speech	2.14
Alternative AI API	Perplexity AI API	Latest

This table lists the main tools, libraries, frameworks, and services used to build the Financial AI Advisor.

D. Testing & Validation

Test Type	Objective	Method	Outcome
Unit Tests	Verify API wrappers, sentiment functions	pytest (coverage > 90 %)	Pass
Integration Tests	End-to-end latency & data consistency	Simulated user sessions (10 k queries)	Avg. latency = 2.8 s
Usability Tests	Assess readability & trust	15 participants, SUS questionnaire	Mean SUS = 84/100
Accuracy Benchmark	Sentiment vs. market movement	Compare sentiment scores to S&P 500 daily returns (30 days)	Correlation = 0.62 ($p < 0.01$)

This table presents the different testing methods applied and their outcomes to evaluate performance and reliability.

V. RESULTS AND ANALYSIS

A. Functional Performance

- Reaction Time: Average response time was under 3 seconds, which meets expectations for an interactive experience.
- Dataset Coverage: Alpha Vantage gives 5-minute intraday data for more than 10 k securities, while NewsAPI gives a maximum of 100 articles per ticker per day.
- Accuracy: Over 60 days of back test, the sentiments produced from the data sources gave bulls/bears flags that were 85% right with price moves on the following day. (confusion matrix in Table II).

Table II – Sentiment Classification vs. Price Direction

	Price ↑	Price ↓
Sentiment Bullish	51	9
Sentiment Bearish	6	44

B. User Scenario Demonstrations

Scenario	System Output	User Feedback
“Compare TCS and Infosys”	Dual-line Plot (30-day closing price) + GPT-4 note: “Both firms exhibited a modest uptrend; Infosys showed stronger Q-Q growth; consider a balanced allocation.”	Rated “clear and helpful” (4.5/5)
“Best SIPs for moderate risk”	Table of 5 mutual funds with expense ratios, past-3-year returns, and risk scores; GPT-4 rationale: “Fund X offers stable returns with low volatility; aligns with moderate risk.”	Users appreciated explicit risk mapping
“Market update on Reliance”	Summary of 3 recent headlines, aggregated sentiment = +0.31 (bullish); GPT-4 commentary on upcoming earnings and sector outlook.	Users noted increased confidence in decision-making

User Scenario Demonstrations

C. Explainability Impact

In a post-study questionnaire, it was found that 78 % of the respondents placed more trust in the advice offered when the source link was shown.

D. Comparative Assessment

In comparison to the pure statistical approach, where a simple moving average crossover strategy is used, the recommendations made by the AI Advisor had a Sharpe ratio that was 12 % higher than the former. This was done during a simulation of 3 months using an artificial portfolio.

VI. DISCUSSION

A. Strengths

1. Real Time Fusion – Integration of live market information, news sentiment analysis, and LLM-based reasoning.
2. User-Centric Design – Chatbot-like interface reduces the knowledge requirement; visual support enhances understanding.
3. Explainability of Output – Traceable provenance of sentiment analysis and LLM-based reasoning.

B. Limitations

Issue	Description	Mitigation
Data Latency	Dependence on third-party API rate limits may cause occasional throttling.	Cache recent queries, implement exponential back-off.
Model Hallucination	GPT-4 may generate plausible-but-incorrect statements when prompt context is insufficient.	Include explicit “fact-check” step (query financial APIs for verification).

Regulatory Compliance	Financial advice is subject to jurisdictional regulations (e.g., MiFID II, SEC).	Position the system as "informational only"; provide disclaimer and restrict actionable recommendations.
Sentiment Bias	News sources can be skewed toward sensationalism.	Weight sentiment by source credibility (e.g., Bloomberg > Reddit).

C. Ethical Considerations

- Privacy: No personal data is stored; all processing is done in memory.
- Fairness: The algorithm makes no discrimination according to the user's demographic characteristics; risk assessment is self-declared.
- Responsibility: Explicit disclaimer stating that the application does not substitute for professional financial consultants' services.

VII. FUTURE WORK

1. Tune fine GPT 4 with respect to a proprietary corpus related to finance to increase specificity of the algorithm and minimize chances for hallucinations.
2. Make use of additional sources of information such as ESG ratings or even volume of blockchains transactions to obtain additional insights.
3. Use cloud-native infrastructure for deployment (AWS Lambda + API Gateway).
4. Conduct longitudinal study involving users (6-month period to evaluate effect on investment decisions and increase financial literacy).
5. Move beyond supervised learning by making use of reinforcement learning whereby an agent obtains feedback about its actions (suggested portfolios).

VIII. CONCLUSION

The above case study is an example of how technically feasible and useful the implementation of Financial AI Advisor using Generative AI (GPT 4) combined with real-time market data streams and dual-model sentiment analysis can be. With such a solution, users receive timely, understandable, and tailored financial advice, thus minimizing the gap in access to sophisticated investment services by retail investors. Even though issues around data latencies, model accuracy, and regulatory requirements still exist, it forms the basis for future fintech solutions based on natural language interaction.

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