International Journal of Scientific Research in Engineering and Management (IJSREM)
Volume: 10 Issue: 10 | Oct - 2026 SJIF Rating: 8.659 ISSN: 2582-3930

FinSight AI: A Multi-Agent Retrieval-Augmented Generation Framework for Real-Time Financial Analysis and Investment Assistance

Kishan Kumar [1], Amaan Siddiqui [2], Achuta Rao M [3], Shreejal Dash [4], Isanaka Sai Praneeth[5]

[1234]Don Bosco Institute of Technology, Visvesvaraya Technological University, Bengaluru, India. [5]Professor, Computer Science and Engineering, Don Bosco Institute of Technology, Bengaluru, India

Abstract. The rapid growth of data has made it more difficult for individual investors to analyze market information, financial news, social-media sentiment and technical indicators that come from many sources. This paper presents FinSight AI, a financial analysis and investment assistance system that brings together different kinds of financial information into a single conversational platform. The proposed system uses a multi-agent architecture. In this architecture separate components handle market-data retrieval, technical analysis, sentiment analysis, retrieval-augmented generation (RAG) and investment-related recommendations. Real-time market information is gathered from data services. News and social-media sources are examined to find sentiment insights. A RAG pipeline that uses ChromaDB allows the system to pull in financial information and give context-aware answers using the Gemini large language model. The system also gives indicators for example Relative Strength Index (RSI) and moving-average crossover signals. It also includes modules for SIP assistance IPO tracking and paper trading. By putting together market data, unstructured financial information and large language model abilities FinSight AI wants to cut down on information fragmentation. It also wants to give users a decision-support environment, for financial analysis. The proposed framework shows that multi-agent systems and RAG can be mixed with real-time data to build an easy-to-use and intelligent financial analysis platform.

I. INTRODUCTION

The rapid growth of financial markets and digital information has significantly increased the amount of data available to investors. Stock prices, financial news, company information, social-media discussions, technical indicators, and investment-related information are continuously generated from multiple sources. Although this availability of information provides investors with more opportunities for analysis, it also creates the challenge of collecting, processing, and interpreting relevant information efficiently. Traditional financial platforms generally provide specific functionalities such as stock-price visualization, technical indicators, news aggregation, or portfolio management, requiring users to switch between different platforms to obtain a comprehensive view of the market.

Recent advancements in Artificial Intelligence (AI), Large Language Models (LLMs), and Retrieval-Augmented Generation (RAG) provide new possibilities for developing intelligent financial analysis systems. LLMs can understand natural-language queries and generate human-readable responses, while RAG allows relevant external information to be retrieved and incorporated into the generation process. However, general-purpose language models may not have access to current market information and can produce inaccurate or unsupported responses when dealing with rapidly changing financial data. Therefore, combining LLMs with real-time financial data sources, retrieval mechanisms, and specialized analytical components is important for developing reliable financial decision-support applications.

FinSight AI is proposed as an LLM-driven financial analysis and investment assistance system that integrates real-time market data, technical analysis, financial-news analysis, social-media sentiment, and retrieval-augmented generation within a unified platform. The system follows a multi-agent architecture in which different components are responsible for specialized financial tasks. Market data is obtained through financial data services, while financial news and social-media information are processed to generate sentiment insights. Technical analysis is performed using indicators such as the Relative Strength Index (RSI) and moving-average crossover signals. These analytical outputs can be combined with retrieved financial context to provide users with more informative and context-aware responses.

The proposed system also brings in financial tools such as Systematic Investment Plan (SIP) help, Initial Public Offering (IPO) tracking and paper trading. These tools make the system more than a simple question answering tool. They give users a place to look at financial data and try out different investment ideas. The chat style of the interface lets users talk to the system with language. This reduces the need for people to jump from one site to another.

The main goal of FinSight AI is to build an smart platform, for looking at financial data. FinSight AI wants to stop the problem of information being split up in places. FinSight AI also helps people make sense of financial facts. By putting together agents that work together live numbers, feeling-based analysis, technical charts, Retrieval-Augmented Generation (RAG) and big language

models FinSight AI shows a way to mix new AI ideas with analysis of money data. FinSight AI is meant to help people make decisions and learn, not to promise any investment gains. Its success depends on how good how ready and how quick the underlying financial data's.

II. LITERATURE SURVEY

M. Luckianto and A. A. S. Gunawan — MARAG-Fin

Luckianto and Gunawan proposed MARAG-Fin, an intelligent multi-agent RAG-LLM architecture for data-driven trading decision-making. The framework integrates financial news sentiment, macroeconomic indicators, historical stock data, and time-series forecasting. It uses four specialized agents—Dynamics, News, Macroeconomic, and Signal—to independently analyse different aspects of the financial market and then combine their outputs to generate Buy, Hold, or Sell recommendations. The study demonstrates that multi-agent RAG can improve contextual reasoning, adaptability, and investment decision-making in dynamic market conditions. The framework achieved a RAGAS score of 0.92 using ReAct prompting, while its NeuralProphet-based forecasting component achieved MAPE values of approximately 0.038–0.039 for one- and five-day forecasting horizons.[1]

S. Das et al. — FinMSG

Das et al. introduced FinMSG, an order-aware multimodal fusion framework for financial advisory summarization. The proposed system processes text, audio, and video information from financial advisory videos to generate concise and informative summaries. The authors also introduced the Financial Advice Video (FAV) dataset, containing 420 financial advisory videos with gold-standard summary annotations. The framework was evaluated using models such as T5, LLaMA-2, GPT-3.5, and other multimodal approaches. The results demonstrated that appropriate multimodal fusion improves the quality of financial summaries and enables financial information to be presented in a more accessible form. [2]

K. Liagkouras and K. Metaxiotis — Hybrid LSTM and Sentiment Analysis

Liagkouras and Metaxiotis proposed a hybrid LSTM and sentiment-analysis system for stock-market forecasting. The system combines historical stock-price data with sentiment extracted from regulatory news announcements. An LSTM network is used to model temporal dependencies in historical stock data, while a sentiment-analysis component identifies the influence of financial news on stock-price direction. The outputs of both components are combined to generate a more reliable directional trading signal. The study reports that the proposed hybrid configuration outperforms competing configurations, demonstrating the benefit of combining quantitative market data with qualitative financial-news information. [3]

A. Jadhav and V. Mirza — Large Language Models in Equity Markets

Jadhav and Mirza shared an overview of how Large Language Models are used in equity markets. Their work looks at the use of LLMs for predicting stock prices analyzing feelings, in text, managing investments making trades automatically and helping with choices. The overview shows how LLMs can handle both disorganized financial data, like financial reports, news calls about earnings and stuff people post online. It also talks about methods like asking the questions adjusting the models teaching them with rewards and using groups of models. The writers point out a problems, including whether the data is trustworthy if the models are fair if they are easy to understand if they can grow bigger how much they cost, rules that need to be followed and the need to test them in real situations. [4]

N. Srivatsan — LLM-Based Stock Price Prediction

Srivatsan proposed a hybrid stock-price prediction approach that combines social-media sentiment analysis with traditional market-data forecasting models. The study uses VADER and Zero-Shot Text Classification for extracting sentiment from social-media posts and integrates the resulting sentiment features with ARIMA, LSTM, and XGBoost models. The results indicate that sentiment-enhanced models are particularly effective for stocks with high levels of public discourse, with an average prediction-accuracy improvement of 21.6% for high-discourse stocks. However, stocks with low social-media activity showed limited or even negative improvements. The study also found that Zero-Shot Text Classification performed better than VADER because transformer-based models can capture contextual and nuanced sentiment more effectively. [5]

S. No.	Research Paper	Methodology	AI/LLM Integration	Financial Data Integration	Sentiment Analysis	Decision Support	Overall Score
1.	Luckianto & Gunawan (2026) [1	Multi-Agent RAG-LLM + Time Series + Sentiment	Very High	Very High	High	Very High	10
2.	Das et al. (2025) [2]	Order-Aware Multimodal Fusion + LLMs	Very High	High	Low	High	9
3.	Liagkouras & Metaxiotis (2025) [3]	Hybrid LSTM + Sentiment Analysis	High	High	High	High	9
4.	Jadhav & Mirza (2025) [4]	Comprehensive Review of LLM Applications in Equity Markets	Very High	Very High	High	High	9
5.	Srivatsan (2025) [5]	LLM-based Sentiment + ARIMA/LSTM /XGBoost	High	High	Very High	High	9

III. FINDINGS

The literature survey indicates that Artificial Intelligence, Large Language Models (LLMs), sentiment analysis, and Retrieval-Augmented Generation (RAG) have significant potential for improving financial market analysis and investment decision support. The reviewed studies demonstrate that combining multiple sources of financial information generally provides more comprehensive insights than relying exclusively on historical price data.

The study by Luckianto and Gunawan [1] demonstrates the effectiveness of a multi-agent RAG-LLM architecture in financial decision-making. By assigning different analytical responsibilities to specialized agents, the system can process financial news, historical market data, macroeconomic information, and trading signals independently before combining their outputs. This demonstrates the value of modular and collaborative AI architectures for complex financial analysis.

The findings from Das et al. [2] demonstrate that multimodal financial information can be effectively processed to generate concise and informative financial summaries. Their FinMSG framework shows that combining text, audio, and video can improve the accessibility of financial information for users. However, the primary focus of this work is financial advisory summarization rather than real-time stock analysis or investment recommendation.

Liagkouras and Metaxiotis [3] demonstrate that combining historical stock-price information with financial-news sentiment can improve stock-direction forecasting compared with individual approaches. Their hybrid system combines LSTM-based time-series analysis with sentiment analysis of regulatory news, showing that both quantitative and qualitative information can contribute to financial prediction.

Jadhav and Mirza [4] identify the growing role of LLMs in equity-market applications, including sentiment analysis, stock prediction, portfolio management, and algorithmic trading. Their review also highlights important challenges associated with financial LLM applications, particularly data reliability, interpretability, scalability, computational cost, and the need for real-world validation. These findings indicate that LLMs should be combined with reliable external data and specialized analytical components rather than being used as an isolated source of financial information.

Srivatsan [5] further establishes the importance of social-media sentiment in stock-price prediction. The study found that sentiment-enhanced forecasting models produced greater improvements for stocks with high levels of public discourse, whereas stocks with limited social-media activity received little benefit. The results also indicate that transformer-based sentiment classification can provide more contextual information than traditional lexicon-based methods such as VADER.

Based on the analysis three major findings stand out. First hybrid financial-analysis approaches that bring together market data and unstructured information—like news and social-media sentiment—can offer deeper and more complete market insights. Second systems using language models and retrieval-augmented generation provide better understanding of context and allow for natural-language interaction. At the time retrieval mechanisms help overcome the limitations of models that rely on static knowledge. Third multi-agent architectures offer a way to divide financial-analysis tasks among specialized components and then combine their results into one cohesive decision-support system.

These findings form the foundation for FinSight AI. This system brings together time financial data, technical analysis, sentiment analysis, RAG and LLM-based conversational interaction all in one unified platform. The proposed system builds on the ideas found in the reviewed literature by combining financial-analysis functions instead of focusing on just one task—, like forecasting, sentiment analysis or summarization. The literature supports the idea of creating an AI-based financial decision-support platform. It also emphasizes the importance of data quality, model interpretability, system reliability and thorough evaluation.

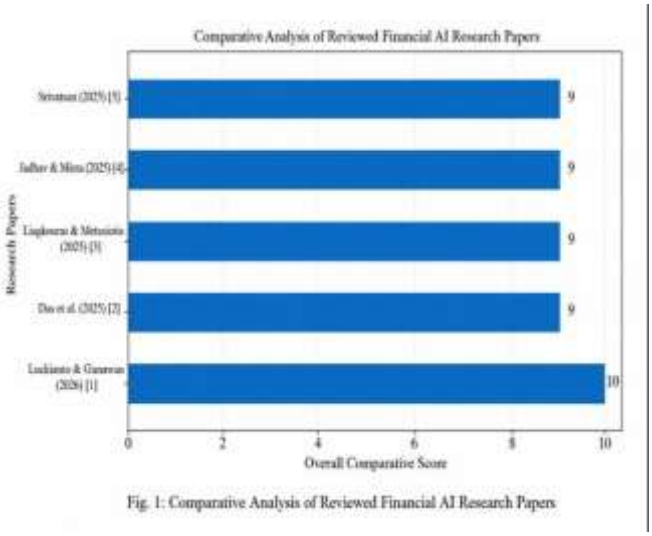


Fig. 1: Comparative Analysis of Reviewed Financial AI Research Papers

Fig 1: Analysis of Existing Project Scheduling Techniques

IV. CONCLUSION

FinSight AI offers an artificial intelligence framework designed for financial market analysis and investment decision support. The platform brings together real-time market data, technical analysis tools, financial news and social media sentiment. It also uses Retrieval-Augmented Generation (RAG) and Large Language Models (LLM) to enable natural-language conversation. All these pieces work together in one

system to help users get financial insights through simple human-like interactions.

The review of existing research shows that combining market data with qualitative inputs—like news articles and social media trends—can give a fuller picture of market movements. Recent studies also point to potential in using Large Language Models, RAG and multi-agent systems for financial tasks. FinSight AI builds on this by combining financial analysis tools with LLM-based reasoning. This allows the system to process kinds of financial data and present results in a way that is easy to understand.

Beyond core analysis FinSight AI adds useful features. These include support for Systematic Investment Plans (SIP) tracking of Initial Public Offerings (IPO) and a paper trading environment. These extras help users explore investment ideas in a simulated setting. The use of RAG ensures that the system can bring in external information when answering questions. At the time technical indicators and sentiment signals add both quantitative and qualitative layers to the analysis.

Overall FinSight AI shows how modern AI technologies can be combined with data to build a smart and user-friendly decision-support platform.. The system's reliability depends on the quality, availability and up-, to-date nature of external financial data. It also depends on the limits of what LLMs can generate. Therefore FinSight AI should be seen as an educational tool—not as a promise of investment success. Future improvements can focus on forecasting methods, more accurate retrieval and sentiment analysis, clearer explanations, wider financial datasets and stronger validation processes.

V. REFERENCES

[1] M. Luckianto and A. A. S. Gunawan, "MARAG-Fin: An Intelligent Multi-agent RAG-LLM Architecture Integrating Financial News Sentiment and Time Series Data for Data-driven Trading Decision-making," *International Journal of Intelligent Engineering and Systems*, vol. 19, no. 1, pp. 738–748, 2026.

[2] S. Das, S. Ghosh, A. Tiwari, R. E. Z. M. Lynghoi, S. Saha, Z. Murad, and A. Maurya, "Presenting an Order-Aware Multimodal Fusion Framework for Financial Advisory Summarization With an Exclusive Video Dataset," *IEEE Access*, vol. 13, pp. 48364–48381, 2025.

[3] K. Liagkouras and K. Metaxiotis, "A Hybrid Long Short-Term Memory with a Sentiment Analysis System for Stock Market Forecasting," *Electronics*, vol. 14, no. 2753, pp. 1–18, 2025.

[4] A. Jadhav and V. Mirza, "Large Language Models in Equity Markets: Applications, Techniques, and Insights," *Frontiers in Artificial Intelligence*, vol. 8, no. 1608365, pp. 1–15, Aug. 2025.

[5] N. Srivatsan, "Using Large Language Models to Predict Stock Price: A Hybrid Model Combining Social Media Sentiment and Market Data," *National High School Journal of Science*, pp. 1–12, Aug. 2025.