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LLM-Based multi-agent system for individual investment in energy and natural resources

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***Abstract*—Recent advancements in large language models and multiagent large language model based systems show that these technologies can be applied to a large number of problems. They can automate complex tasks and perform advanced analyses that would take an expert a significant amount of time. This article describes a multiagent large language model (LLM) based platform for investment advisory in the energy natural resources sector. The system integrates multiple types of investment analyses e.g. technical analysis, fundamental analysis, sentiment analysis and stock price prediction. The approach of integrating multiple types of analyses in one system allows the investor to save significant amount of time on analyzing potential investments.**

***Keywords*—Multiagent systems; Energy Minerals Market; Investment Advisory System; Autonomous LLM Agents; LangGraph**

I. Introduction

THE energy natural resource market is one of the options for individual investors that want to diversify their investment portfolios. This market includes essential natural resources such as oil, natural gas and coal. Coal continues to be a dominant source of electricity, accounting for a significant portion of electricity generation [1], [2]. By participating in the energy natural resource market, investors can potentially benefit from fluctuations in natural resource prices influenced by geopolitical events, supply and demand dynamics, and technological advancements in the energy sector [3]. The oil market, is one of the most significant and strategically manipulated markets. It offers many trading opportunities for individual investors [4]. This market offers opportunities for capital appreciation but also a potential hedge against inflation, as energy prices often move in similar direction as general price levels. Engaging with this sector enables investors to align their portfolios with key components of the global economy, potentially enhancing portfolio performance and resilience. The natural resources sector is further discussed in section "Natural Resources Market".

Individual investors have a variety of ways that they can invest in energy natural resources. Some of these ways include stocks of companies, exchange-traded funds (ETFs), futures, options, and direct commodity purchases [5]. However, this paper focuses specifically on stocks of companies dealing with energy natural resources. It does not talk about forms of investing in energy natural resources other than stocks. For example an investor that wants to profit from crude oil price increase could consider investing in stocks of companies such as: Exxon Mobil (XOM); Chevron Corporation (CVX) and Shell PLC (SHEL). For natural gas the investor could buy stocks of companies such as: Comstock Resources, Inc. (CRK); Ovintiv Inc. (OVV) and Woodside Energy Group Limited (WDS). Similarly for investments in coal the investments could include stocks of coal mining companies like: Peabody Energy Corporation (BTU); Arch Resources, Inc. (ARCH) and Alliance Resource Partners, L.P. (ARLP). Investing in these stocks allows individuals to gain exposure to the sector by owning shares in companies that explore, produce, and distribute these resources. For instance, the dynamics of the oil market offer opportunities for investors that are interested in exposure to energy companies [4].

However, investing in the energy natural resource market has unique challenges that are not as visible in other markets. One of the primary issues is the high volatility of market conditions and rapidly changing natural resource prices [6]. Factors such as geopolitical tensions, supply disruptions, natural disasters, fluctuations in global demand and speculation in the market can lead to significant and unpredictable shifts in the prices of crude oil, natural gas, and coal [7], [8]. This volatility makes it difficult for individual investors to predict market trends and manage risk effectively.

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Fig. 1. Candle chart of Shell PLC stock prices. Screenshot from TradingView [9]

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For instance, the candle chart in Figure 1 of Shell PLC stock prices shows the volatile price movements in the energy market. Factors such as geopolitical tensions, supply disruptions, natural disasters, fluctuations in global demand, and speculation in the market can lead to significant and unpredictable shifts in the prices of crude oil, natural gas, and coal [7], [8]. Additionally, the natural resource market has certain specific characteristics. For example, natural resources are finite , and their scarcity can result in heightened price volatility. Price fluctuations are also influenced by geopolitical events, economic cycles, environmental policies, and exchange rate variations. The the natural resource market often follows long-term cyclical price patterns driven by supply-demand dynamics [10]. These factors make it difficult for individual investors to predict market trends and invest in the sector effectively.

Additionally, the accessibility and usability of investment tools and resources can be limited for individual investors with varying goals and risk tolerances. The energy sector often requires specialized knowledge to understand the nuances of commodity markets, regulatory environments, and technological advancements in energy production and distribution. Financial instruments like futures and options, while offering potential for high returns, are complex and carry higher risks, making them less suitable for inexperienced investors. Furthermore, staying informed about the constant changes in environmental policies and global energy initiatives adds another layer of complexity. These challenges make it imperative for individual investors to seek more sophisticated solutions to navigate the energy natural resource market effectively.

In recent years, Large Language Models (LLMs) have shown significant capabilities in terms of solving problems, generating complex analyses etc. A major development in this area are LLM-powered agents, which integrate LLMs with external tools and software to perform tasks such as research, data analysis, and workflow automation. Multi-agent systems, composed of multiple LLM-powered agents, further enhance these capabilities by enabling collaboration, knowledge sharing, and task coordination to solve complex tasks [12], [13]. An example of a multi-agent LLM system is illustrated in Figure 2. It presents the structure and interactions between agents in such a system. These innovations offer new opportunities for automation in areas such as investment advisory. These

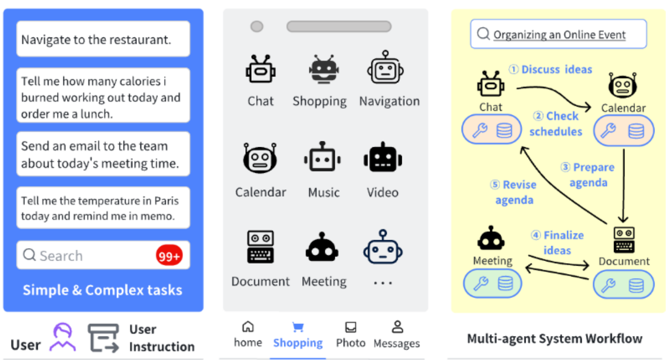


Fig. 2. Multi-agent LLM system [11].

topics, including the applications and implications of LLM-powered agents and multi-agent systems, will be discussed in later sections of the paper.

The aim of this paper is to explore and validate the effectiveness of multi-agent architectures powered by large language models (LLMs) in investment advisory for the energy natural resources market. By using multiple specialized agents working together - each focusing on distinct aspects such as sentiment analysis, technical analysis, fundamental analysis, and trend determination - this paper explores how such systems can enhance decision-making processes for individual investors. The study specifically examines how these multi-agent systems can streamline the analysis of market data, provide comprehensive risk assessments, and deliver personalized investment recommendations tailored to individual investor profiles and goals within the energy sector.

The paper is structured into three main sections. The Preliminaries section provides the background, starting with an overview of the Natural Resources Market, highlighting key trends and challenges, followed by Core Theoretical Concepts like technical analysis, fundamental analysis, and multi-agent systems, which form the foundation of the project. The Experiment section focuses on the system itself, beginning with a System Overview that explains its design and components, followed by Key Functionalities, describing its tasks like data analysis and recommendation generation, and concluding with Testing and Evaluation, where the system's performance is assessed through examples and results. Finally, the Conclusions section summarizes the findings, discusses the system's practical applications and suggests improvements and future research directions.

II. Preliminaries

A. Natural Resources Market

The natural resources market is an important part of the global economy. It offers investment opportunities through instruments such as stocks, ETFs, futures, and options [3], [14]. Its key characteristics include a finite supply of resources, leading to potential scarcity and price volatility. Natural resource prices fluctuate due to geopolitical events, economic cycles, and environmental policies. Long-term cyclical price patterns caused in part by supply-demand dynamics, exchange rate impacts and regulations also have an effect on the market.

Investors can participate in the energy natural resources market in a number of ways e.g.: Investing in stocks of companies engaged in resource extraction and processing, such as oil refineries or mining firms. However, price correlations can be affected by hedging strategies employed by these companies e.g. if the companies are using futures contracts; ETFs - Diversified portfolios of stocks and other financial instruments tracking natural resource indices or their prices; Futures Contracts - Agreements to buy or sell a natural resource at a future date and price. They allow the investor to manage a bigger position than the investor could normally afford through the mechanism of leverage; Options - Derivatives that grant the right, but not the obligation, to buy (call options) or sell (put options) natural resources or futures contracts. Each investment method offers a unique risk-return profile,

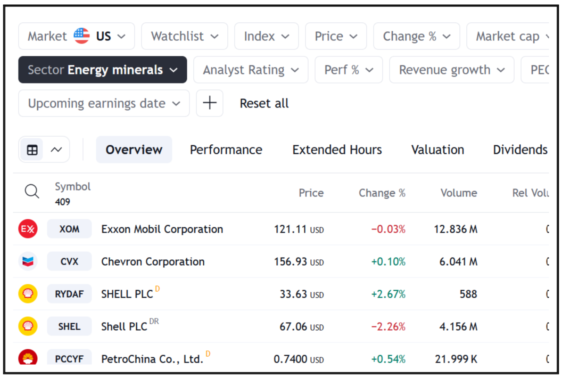


Fig. 3. Examples of energy minerals companies stocks. Screenshot from TradingView [9]

requiring investors to align their choices with their goals and risk tolerance. From straightforward stock investments to leveraged futures and complex options, the natural resources market offers diverse opportunities for individual investors.

Energy minerals like crude oil, natural gas, and coal are particularly significant within the market: Crude Oil - used for fuel, heating, and petrochemicals, with prices influenced by OPEC quotas, geopolitical events, and technological advancements; Natural Gas - Used for heating, electricity, and transportation, with demand tied to weather, economic growth, and competition from renewables; Coal - Used for electricity production. Figure 3 provides examples of stocks from companies in the energy minerals sector. It shows investment opportunities for crude oil, natural gas, and coal.

Price volatility influences how companies manage storage, production, inventory, and pricing. When prices are unpredictable, the value of keeping extra natural resource inventory rises, as it helps stabilize supply and prices in the short term. On the other hand, high volatility can make production more expensive because companies might choose to delay production, hoping for better prices in the future. These connections between storage, productions and natural resource prices shows the importance of price stability for managing the market effectively [15].

B. Fundamental, Technical, Sentiment Analysis of Stock Market

This section highlights some of the concepts integrated into the investment advisory system, focusing on the role of LLM-powered agents, multi-agent systems, and key analytical techniques. It will explore several key concepts used in the investment advisory system: LLM powered AI agents, multi-agent systems, time series prediction, sentiment analysis, technical analysis, and fundamental analysis.

LLM powered agents have advanced thinking and planning skills [17] that help them automate certain tasks. By using methods like tool usage, memory, and planning, they can gather market data, analyze trends, and provide personalized advice. The ReAct [18] (Reason + Act) framework is important because it allows agents to think, act, and learn in cycles.

Using multiple agents together enhances these capabilities even further. Each agent can focus on a specific role, like sentiment analysis, technical analysis, or trend prediction. The multi-agent architecture improves scalability and reliability by dividing tasks and sharing information among agents. Multi-agent systems are robust because even if some parts fail, other agents can continue to function independently.

Fig. 5. Example of the MACD Strategy with Additional Filters on an Exxon Mobil Corporation stock price chart. The stop loss and take profit have been marked on the chart with red and green areas. Chart downloaded from TradingView [9].

Sentiment analysis extracts opinions and attitudes from text to determine how the market feels about a company or resource, which can impact investment decisions [19]. For instance, Figure 4 shows headlines for crude oil from a Google search, which could be analyzed with sentiment analysis to determine market sentiment about crude oil. This process is important for forecasting natural resource prices because it considers the emotional reactions of the market to financial events. Sentiment analysis can be conducted through the use of pre-trained models like FinBERT [20]. FinBERT is a specialized version of BERT that has been fine-tuned on financial texts, making it suitable for classifying sentiments as positive, negative, or neutral. BERT is a language model that uses a bidirectional approach and attention mechanisms to understand the context of words in a sentence, leading to more precise interpretations.

Technical analysis aims to predict market movements by examining historical price and volume data [14]. For example, Figure 5 demonstrates the MACD strategy with additional filters applied to an Exxon Mobil Corporation stock price chart, where stop-loss and take-profit levels are marked in red and green areas, respectively. Analysts use several key indicators including the Exponential Moving Average (EMA) to track price trends, Moving Average Convergence Divergence (MACD) for momentum shifts, Relative Strength Index (RSI) to measure overbought or oversold conditions, Dou-

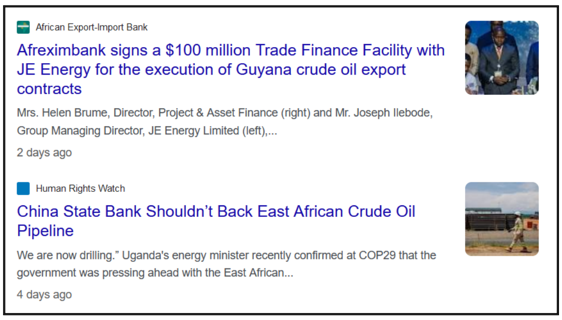


Fig. 4. News headings for crude oil from google search [16].

ble Exponential Moving Average (DEMA) for quick trend identification, and the Supertrend indicator for determining market direction. Traders often combine these tools into strategies. This approach pairs MACD with additional confirmation signals while setting entry and exit points based on EMA levels and risk ratios. Another strategy combines RSI divergence analysis with candlestick patterns, particularly engulfing patterns, to identify trend reversals. A third method leverages both DEMA's responsiveness and Supertrend's signals to identify market moves and optimal trading opportunities. By integrating multiple indicators, traders can develop more robust systems that help filter out false signals and improve their investment decisions.

Fundamental analysis evaluates a company's intrinsic value and based on this value provides buy, sell, or hold recommendations. A complete fundamental analysis involves five steps: analyzing the macroeconomic environment (like GDP growth and inflation), assessing the industry sector for growth prospects and competition levels, examining the company's strengths and weaknesses through SWOT analysis, evaluating financial health via financial statements and ratios, and calculating the stock's intrinsic value to compare with the market price [21].

There are however less complicated ways to conduct fundamental analysis. For quicker assessments, especially suitable for mature companies with stable earnings, multiplier methods [22] like the the Price-to-Earnings (P/E) Ratio method simplify the process by multiplying the company's Earnings per Share (EPS) by a target P/E ratio based on industry averages. This method allows for rapid and effective valuation without extensive data. It is a more practical approach for automated investment advisory systems than a full five step fundamental analysis. P/E Ratio and EPS were ilustrated in Figure 6.

C. LLM Multi-agent systems

LLMs are models that were trained on large amounts of text data. They have shown an ability to understand and generate human-like text, perform complex reasoning and assist with various tasks. The advancements in LLM technology have particularly accelerated since 2022, with models showing increasingly sophisticated abilities [12], [24], [25].

One of the developments in the LLM space have been LLM-powered agents - autonomous or semi-autonomous systems that can perform specific tasks by combining language models with other tools and capabilities [26], [27]. These agents can execute complex workflows, interact with external software, and even make decisions within defined parameters. By integrating LLMs with tools through APIs, databases, and other software applications, these agents can perform tasks like conducting research, analyzing data, and automating repetitive processes. This development has opened up new possibilities for automation and assistance in various fields, from business operations to scientific research. Additionally, multi-agent systems powered by LLMs represent a significant advancement in this field. Figure 7 illustrates various types of graph-based multi-agent architectures used in LangGraph. In these systems, multiple LLM-powered agents collaborate and communicate to solve complex tasks that are beyond the capability of a single agent. By leveraging natural language understanding and generation, these agents can negotiate, share knowledge, and coordinate actions. This collaborative approach enhances efficiency and opens up possibilities for more sophisticated automation solutions [28], [29].

Fig. 6. Earnings per Share and P/E Ratio on a chart of stock prices. Chart downloaded from TradingView [9].

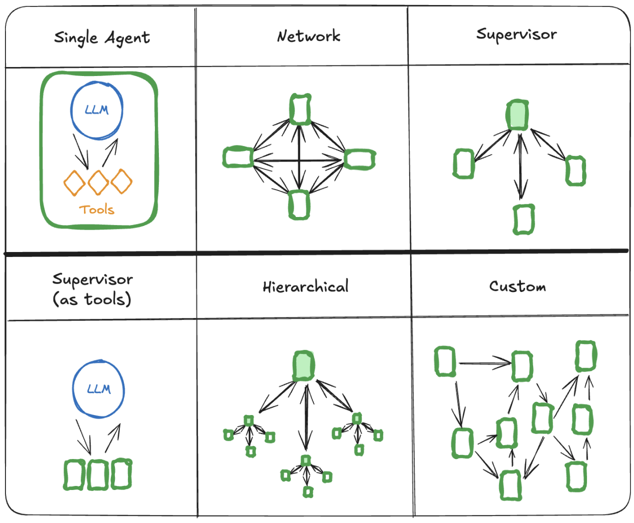


Fig. 7. Types of graph based multi-agent architectures in LangGraph [23].

D. Mathematical tools and components

Mathematical models can be used in financial analysis, making it more accurate. This section focuses on the TinyTimeMixer (TTM) model, a neural network used for time series prediction. Time series prediction involves forecasting future values based on past data, and modern models like the TinyTimeMixer (TTM) [30] have made this process more efficient. TTM is a compact neural network that uses a simple, non-recurrent architecture, unlike traditional models like LSTM and GRU. This design avoids common issues like vanishing gradients, making training more stable and faster while reducing computational costs. TTM can handle multiple types of data at once, which is especially useful in finance where variables like stock prices, trading volumes, and economic indicators all play a role. Preparing the data through normalization and adding features like moving averages and the Relative Strength Index (RSI) helps TTM recognize patterns better, leading to more accurate predictions suitable for real-time applications.

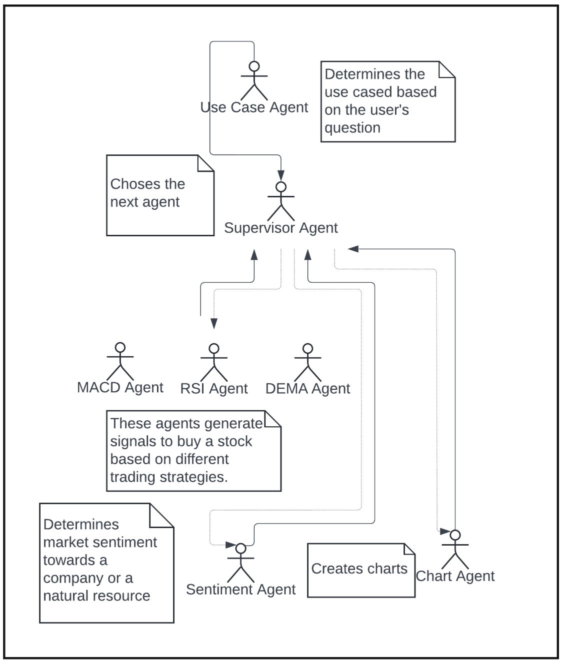


Fig. 8. Diagram of a part of the investment advisory platform.

III. PLATFORM

A. System Overview

The multi-agent investment advisory system was designed with a focus on the energy natural resources market. It is using multiple LLM based agents, each specialized for specific tasks. Figure 8 provides a diagram of part of the system. It shows the relations between its components. The system architecture was implemented using the LangGraph multi-agent framework [31].

The investment advisory system was inspired by cognitive architectures, incorporating elements that mirror various cognitive functions [32]. The design includes components like: perception (for gathering market data and news), declarative memory (for structured storage of financial data), procedural memory (for implementing technical analysis strategies), metacognition (for strategy evaluation through backtesting), emotional processing (for sentiment analysis of market news), and implicit learning (for price prediction using neural networks). Rather than explicitly replicating these cognitive modules, the system uses them as a framework to create an investment advisory tool that combines data collection, storage, technical analysis, strategy optimization, sentiment analysis, and machine learning prediction.

The system utilizes multiple technologies, including: GPT-4o mini LLM; TinyTimeMixer (TTM) for forecasting stock prices; FinBERT for financial sentiment classification; Django web framework for user interaction through a chat-driven interface. The system retrieves data from several external sources which are: Yahoo Finance for historical and fundamental stock data; NewsAPI For retrieving financial news articles for the purposes of sentiment analysis.

The investment advisory system integrates multiple specialized modules to analyze investment opportunities:

- Time Series Prediction module which forecasts future stock prices using TinyTimeMixer (TTM), a pre-trained neural network fine-tuned for multivariate financial data. This module utilizes historical stock data from Yahoo Finance, normalized and preprocessed for prediction.
- Sentiment Analysis evaluates market sentiment using FinBERT, a domain-specific NLP model trained on financial texts. The system then aggregates sentiment scores from news articles to inform investment recommendations.
- Fundamental Analysis assesses stock valuation using the Price-to-Earnings (P/E) ratio to provide buy, sell, or hold signals.
- Technical Analysis implements strategies such as: DEMA + SuperTrend Strategy which combines the Double Exponential Moving Average and SuperTrend indicator; MACD Cross Strategy which uses Moving Average Convergence Divergence to identify trade opportunities; RSI Divergence with Engulfing Pattern Strategy which combines Relative Strength Index and candlestick patterns for trend analysis.

B. Key Functionalities

The investment advisory system has several key functionalities designed to assist individual investors in making investment decisions. Figure 9 shows a use case diagram for the system, depicting the interaction between the investor and the functionalities of the system. One of the primary features is the ability to determine the best investments currently available in the market. Investors begin by selecting their investment goals, such as growth, income, or speculation. Next the investor can ask the system for the best investments available right now. The system accesses up-to-date market data and uses various agents, including technical analysis, fundamental analysis, and sentiment analysis agents to evaluate potential investments. It then filters the recommendations based on the investor's

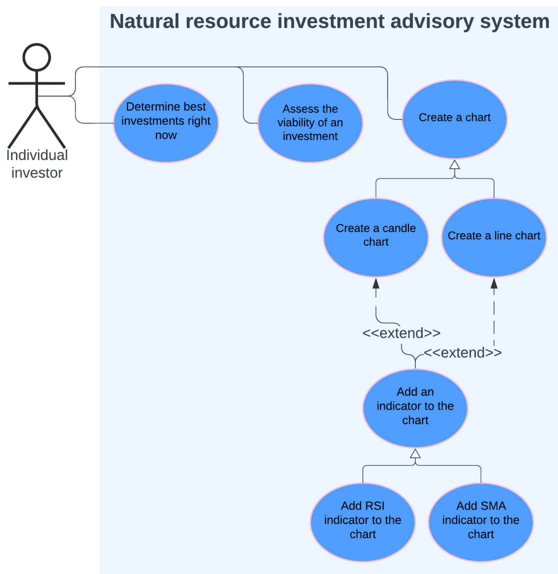


Fig. 9. Use Case diagram for the investment advisory system.

specified goals and presents a curated list of investment opportunities.

Another functionality is assessing the viability of a specific investment. Investors can request an analysis of a particular asset by specifying their investment objectives. The system retrieves the latest market data necessary for the evaluation and utilizes its analytical agents to perform a comprehensive assessment. The investment recommendation is then adjusted according to the investor's goals, and the system provides a detailed evaluation of the investment's potential, helping investors decide whether to buy, hold, or sell.

The system also offers the capability to create customized charts for stock prices. Investors can request the generation of charts for specific stocks and the system will access relevant historical price data to produce the requested visualizations. This feature allows users to visually analyze market trends and patterns.

Additionally, the system enables investors to calculate technical analysis indicators for any given stock. Users can specify the indicators they are interested in, such as the Moving Average Convergence Divergence (MACD) or the Relative Strength Index (RSI) [21]. The system retrieves the necessary historical price data to compute these metrics and presents the calculated indicators to the user. This functionality provides valuable insights into the stock's performance and assists investors in making data-driven decisions based on technical analysis principles.

IV. Experiment

This section describes two experiments that were conducted to evaluate the performance of the multi-agent investment system. It is important to note that this is an experimental platform, designed to explore the integration of technical, fundamental, and sentiment analysis through a multi-agent architecture. The system is not intended for production use or real-world investment decisions, but rather as a proof-of-concept for investigating the potential of combining multiple analytical approaches in an automated investment advisory system.

The first experiment involved a direct comparison between the investment advisory system and GPT-4o, focusing on their responses to an investment-related question: "What should I invest in right now?".

The second experiment focused on the accuracy of the system's stock recommendations for Exxon Mobil Corporation (XOM) during a simulated evaluation period. By analyzing daily predictions against actual stock price movements, this experiment assessed the system's effectiveness in short-term investment decision-making.

A. Data and data engineering

The multi-agent large language model (LLM)-based investment advisory system uses three main types of data: historical stock data, fundamental data, and news data.

Historical stock data for technical analysis is downloaded from Yahoo Finance using the `yfinance` module. It includes time series data such as open, high, low, close prices, and trading volume. This data is well-structured and requires minimal preprocessing, making it directly usable in time series prediction models.

Data for fundamental analysis is also obtained from Yahoo Finance and includes key financial metrics and indicators, such as the Price-to-Earnings (P/E) ratio. The data is structured and requires little preprocessing and can be integrated into analytical models to derive insights about company performance and financial health.

News data for sentiment analysis, relevant to the energy and natural resources sector, is collected using the NewsAPI. For sentiment analysis, because FinBERT model was used, traditional preprocessing steps like tokenization and lemmatization were not necessary.

B. Evaluation

The evaluation of the investment advisory system involved a comparison with GPT-4o and an integrated analysis of investment recommendations for Exxon Mobil Corporation (XOM). This evaluation aimed to determine the system's effectiveness in providing actionable and accurate investment advice.

To assess the practical value of the investment advisory system, both the system and GPT-4o were prompted with the question: "What should I invest in right now?". Figure 10 shows part of an example GPT-4o's response, which provides generic investment principles such as risk tolerance, diversification, and long-term strategies but lacks specific recommendations or tailored analysis.

GPT-4o provided a generic response outlining general investment principles like risk tolerance, diversification, and long-term strategies, without offering specific recommendations or considering external data or user-specific goals.

The investment advisory system provided a tailored response by considering up-to-date market data, news sentiment analysis, and the user's investment goals. It analyzed real-time information and generated specific stock recommendations aligned with the user's profile and current market conditions.

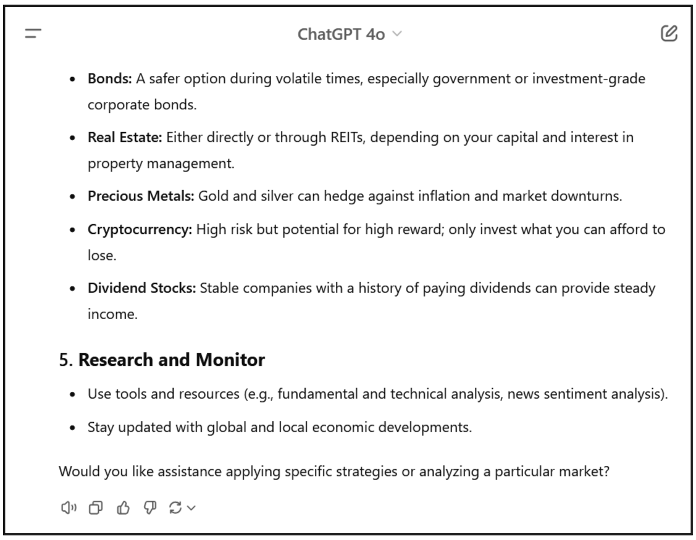
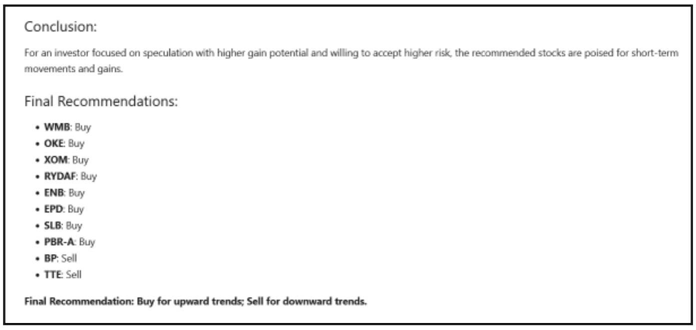


Fig. 10. Part of example of ChatGPT 4o response to question "What should I invest in right now?" [33].



Conclusion:

For an investor focused on speculation with higher gain potential and willing to accept higher risk, the recommended stocks are poised for short-term movements and gains.

Final Recommendations:

- **WMB**: Buy
- **OKE**: Buy
- **XOM**: Buy
- **RYDAF**: Buy
- **ENB**: Buy
- **EPD**: Buy
- **SLB**: Buy
- **PBR-A**: Buy
- **BP**: Sell
- **TTE**: Sell

Final Recommendation: Buy for upward trends; Sell for downward trends.

Fig. 11. Part of example of the investment advisory system response to question "What should I invest in right now?".

Figure 11 shows an example of the system's response to the question "What should I invest in right now?". It demonstrates its ability to provide actionable recommendations.

This comparison highlights a significant advantage of the investment advisory system over a general-purpose language model like GPT-4o. While GPT-4o demonstrates broad knowledge and reasoning capabilities, it lacks the specialized functionality and data integration necessary for generating informed and personalized investment recommendations. By incorporating real-time data sources and investor-specific goals, the investment advisory system provides more valuable and actionable advice to investors.

An integrated analysis was conducted to evaluate the accuracy of the investment advisory system's recommendations for Exxon Mobil Corporation (XOM) over a simulated period from November 5, 2024, to November 15, 2024. The system was asked daily, "Is it a good idea to invest in XOM right now?" The recommendations were then compared against the actual future price movements of XOM stock to assess the system's predictive accuracy.

For each date in the period, the future date was set as the next trading day. The system's recommendation was generated based on the data available up to that date. The correct recommendation was determined by comparing the stock price on the current date with the price on the future date. If the stock price increased from the current date to the future date, the correct recommendation was "Buy"; if the price decreased or remained the same, the correct recommendation was "Sell".

The sample results of the analysis are summarized in the table I. The column "Date" contains dates of prediction generations; the column "Correct Recommendation" contains the correct recommendations for each date based on price differences one day after the prediction; the column "Match" contains information if the recommendation provided by the system was the correct one.

TABLE I
A SAMPLE OF THE RESULTS OBTAINED FROM INTEGRATED ANALYSIS EVALUATION

Date	Correct Recommendation	Match
2024-11-09	Sell	True
2024-11-10	Sell	True
2024-11-11	Sell	True
2024-11-12	Buy	False
2024-11-13	Buy	False
2024-11-14	Sell	True
2024-11-15	Sell	True

The table I presents a detailed evaluation of the investment advisory system's performance in predicting the stock movements of Exxon Mobil Corporation (XOM) over a simulated period from November 5, 2024, to November 15, 2024. Each row in the table corresponds to a specific date within this period and contains the following information:

- Date: The current date on which the investment recommendation was made.
- Correct Recommendation: Determined by comparing the Price and Future Price.
- Match: Indicates whether the system's recommendation matched the correct recommendation based on actual price movement.

The investment advisory system achieved on average a 54% accuracy rate in its recommendations for XOM over the simulated period. The system effectively predicted whether the stock price would increase or decrease the following day. Achieving a 54% accuracy rate indicates the effectiveness of the system in short-term investment decision-making.

These evaluations underscore the system's ability to provide valuable and actionable investment advice compared to a general-purpose language model like GPT-4o. By integrating real-time data, domain-specific knowledge, and user-specific considerations, the system offers tailored and informed investment recommendations. This personalized approach enhances the decision-making process for investors seeking data-driven advice aligned with their individual goals.

By combining multiple analytical approaches, leveraging up-to-date information, and aligning recommendations with specific investment objectives, the investment advisory system delivers a more effective approach to investment decision-making. This represents a significant advancement over general-purpose models, highlighting the importance of specialized systems in domains that require specific expertise and real-time data integration.

V. Discussion

A. Key Findings

This paper evaluated the effectiveness of a multi-agent investment advisory system that uses large language models for decision-making in the energy natural resources sector. Inspired by cognitive architecture modules, the system demonstrated several key contributions. It achieved a 54% accuracy in investment recommendations, outperforming individual analytical methods. The system provided tailored investment advice based on user goals, enhancing relevance to individual financial objectives. By adapting recommendations in real time using market data and periodic backtesting, it enabled timely and informed decisions. The integration of fundamental, technical, sentiment, and time series analyses enhanced decision-making through a comprehensive approach. The effectiveness of multi-agent systems was demonstrated by leveraging complementary strengths to compensate for weaknesses in individual analysis methods. Moreover, the system delivered robust and consistent recommendations even under volatile market conditions.

B. Future Work

Several areas for improvement have been identified to further enhance the system's capabilities. Developing and fine-tuning trading strategies tailored to the energy sector's unique characteristics would optimize sector-specific strategy optimization. Incorporating advanced machine learning techniques, optimizing hyperparameters, and improving sentiment analysis by leveraging a broader range of news sources could enhance the performance of the system. Introducing memory and attention mechanisms, such as long-term memory for storing historical analysis and attention mechanisms to focus on critical market events, would further improve the system's analytical capabilities. Improving data integration by expanding data sources to include additional real-time feeds, news aggregators, and financial metrics would increase accuracy. Enhancing performance in volatile market conditions through dynamic risk management and real-time strategy adjustments could improve volatility adaptation.

VI. Conclusion

The paper described an experimental investment advisory platform in the field of energy natural resources. It provided an introduction into the topic of energy natural resources and it's characteristics as well as the theoretical foundations of the platform. Additionally the paper provided a high level overview of the platform's architecture. Next two experiments were conducted to evaluate the system were presented. One experiment involved a comparison of the platform with a standalone LLM. The other experiment evaluated the performance of the platform in giving investment advice.

In future work, we plan to conduct a series of experiments to evaluate the importance of each component in the multi-agent investment advisory platform. These experiments will involve excluding parts of the platform such as sentiment analysis, fundamental analysis, and technical analysis to assess their contributions to the platform's overall performance. Additionally, we plan to test other sentiment analysis algorithms.

References

[1] L. Schernikau, *Economics of the International Coal Trade*. Springer, 2017.
[2] D. W. Edwards, *Energy Trading and Investing: Trading, Risk Management and Structuring Deals in the Energy Market*. McGraw-Hill Education, 2009.
[3] G. E. Peter Zweifel, Aaron Praktiknjo, *Energy Economics*. Springer, 2017.
[4] S. Watkins, *The Complete Guide To Global Oil Market Trading*. ADVFN Books, 2021.
[5] M. Chrascina, M. VANĚK, and K. Pekarčíková, "Intrinsic value of stocks of "big oil" companies," *GeoScience Engineering*, vol. 70, pp. 67–77, 06 2024.
[6] M. Ezeh, A. Ogbu, A. H. Ikevuje, and E. George, "Optimizing risk management in oil and gas trading: A comprehensive analysis," *International Journal of Applied Research in Social Sciences*, vol. 6, pp. 1461–1480, 07 2024.
[7] S. Obadi and M. Korcek, "The crude oil price and speculations: Investigation using granger causality test," *International Journal of Energy Economics and Policy*, vol. 8, pp. 275–282, 05 2018.
[8] A. Sakkas and N. Tessaromatis, "Factor based commodity investing," *Journal of Banking & Finance*, vol. 115, p. 105807, 2020. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0378426620300741
[9] TradingView, "Tradingview," 2024, accessed: 2024-11-25. [Online]. Available: https://www.tradingview.com/
[10] S. C. Bhattacharyya, *Energy Economics*. Springer London, 2011.
[11] Y. Yang, Q. Peng, J. Wang, and W. Zhang, "Multi-llm-agent systems: Techniques and business perspectives," 11 2024.
[12] D. H. Hagos, R. Battle, and D. B. Rawat, "Recent advances in generative ai and large language models: Current status, challenges, and perspectives," *IEEE transactions on artificial intelligence*, pp. 1–21, 2024.
[13] M. Wawer, J. A. Chudziak, and E. Niewiadomska-Szynkiewicz, "Large language models and the elliott wave principle: A multi-agent deep learning approach to big data analysis in financial markets," *Applied Sciences*, vol. 14, no. 24, 2024.
[14] J. J. Murphy, *Technical Analysis of the Financial Markets: A Comprehensive Guide to Trading Methods and Applications*. New York Institute of Finance, 1999.
[15] R. S. Pindyck, "Volatility and commodity price dynamics," *The journal of futures markets*, vol. 24, no. 11, pp. 1029–1047, 2004.
[16] G. News, "Crude oil news search results," 2024, accessed: 2024-11-09. [Online]. Available: https://www.google.com/search?q=crude+oil&tbm=nws
[17] X. Huang, W. Liu, X. Chen, X. Wang, H. Wang, D. Lian, Y. Wang, R. Tang, and E. Chen, "Understanding the planning of llm agents: A survey," 2024. [Online]. Available: https://arxiv.org/abs/2402.02716
[18] S. Yao, J. Zhao, D. Yu, N. Du, I. Shafran, K. Narasimhan, and Y. Cao, "React: Synergizing reasoning and acting in language models," 2023. [Online]. Available: https://arxiv.org/abs/2210.03629
[19] M. Mäntylä, D. Graziotin, and M. Kuutila, "The evolution of sentiment analysis - a review of research topics, venues, and top cited papers," *Computer Science Review*, vol. 27, 12 2016.
[20] D. Araci, "Finbert: Financial sentiment analysis with pre-trained language models," 2019. [Online]. Available: https://arxiv.org/abs/1908.10063
[21] I. K. Nti, A. F. Adekoya, and B. A. Weyori, "A systematic review of fundamental and technical analysis of stock market predictions," *The Artificial intelligence review*, vol. 53, no. 4, pp. 3007–3057, 2020.
[22] T. Koller, M. Goedhart, and D. Wessels, *Valuation: Measuring and Managing the Value of Companies*. Wiley, 2020.
[23] LangGraph, "Langgraph: Multi-agent systems concepts," 2024, accessed: 2024-12-01. [Online]. Available: https://langchain-ai.github.io/langgraph/concepts/multi_agent/
[24] K. L. Szydlowski and J. A. Chudziak, "Transformer-style neural network in stock price forecasting," in *Proceedings of the 21th International Conference on Modeling Decisions for Artificial Intelligence (MDAI 2024)*, Tokyo, Japan, 2024.
[25] F. Bańka and J. A. Chudziak, "Applying informer for option pricing: A transformer-based approach," in *Proceedings of the 17th International Conference on Agents and Artificial Intelligence (ICAART 2025)*. SciTePress, 2025, pp. 1270–1277.
[26] H. Face, "Transformers agents: Tools and capabilities," 2024, accessed: 2024-11-30. [Online]. Available: https://huggingface.co/docs/transformers/agents#tools
[27] K. L. Szydlowski and J. A. Chudziak, "Toward predictive stock trading with hidformer integrated into reinforcement learning strategy," in *Proceedings of the 36th International Conference on Tools for Artificial Intelligence (ICTAI 2024)*, Herndon, VA, USA, 2024.
[28] X. Li, S. Wang, S. Zeng, Y. Wu, and Y. Yang, "A survey on llm-based multi-agent systems: workflow, infrastructure, and challenges," *Vicinagearth*, vol. 1, no. 1, 2024.
[29] J. A. Chudziak and M. Wawer, "Elliottagents: A natural language-driven multi-agent system for stock market analysis and prediction," in *Proceedings of the 38th Pacific Asia Conference on Language, Information and Computation*, Tokyo, Japan, 2024.
[30] V. Ekambaram, A. Jati, P. Dayama, S. Mukherjee, N. H. Nguyen, W. M. Gifford, C. Reddy, and J. Kalagnanam, "Tiny time mixers (ttms): Fast pre-trained models for enhanced zero/few-shot forecasting of multivariate time series," 2024. [Online]. Available: https://arxiv.org/abs/2401.03955
[31] LangChain, "Langgraph," 2024, accessed: 2024-11-13. [Online]. Available: https://www.langchain.com/langgraph
[32] J. E. Laird, *The Soar Cognitive Architecture*. The MIT Press, 2019.
[33] OpenAI, "Chatgpt," 2024, accessed: 2024-12-01. [Online]. Available: https://openai.com/chatgpt