

Table 3: Ablation analysis on three conference. \checkmark denote the inclusion of components.

MAM	SDM	RAM	ARR(%)	TR(%)	SR	CR	SoR	MDD(%)	VoL(%)	ENT	ENB
\checkmark			40.89	179.66	1.81	5.27	51.23	28.61	1.66	1.73	1.22
	\checkmark		43.25	193.97	1.93	6.27	53.41	24.99	1.63	1.89	1.33
		\checkmark	35.53	148.93	1.88	5.94	52.01	21.73	1.34	1.65	1.19
	\checkmark	\checkmark	48.59	228.07	2.79	8.54	58.85	19.21	1.38	2.37	1.39
\checkmark		\checkmark	46.42	213.94	2.51	7.82	55.21	20.52	1.28	2.18	1.35
\checkmark	\checkmark		52.71	256.12	2.86	9.14	61.46	21.85	1.33	2.55	1.43
\checkmark	\checkmark	\checkmark	58.68	299.55	3.11	11.38	66.94	16.86	1.23	2.97	1.49

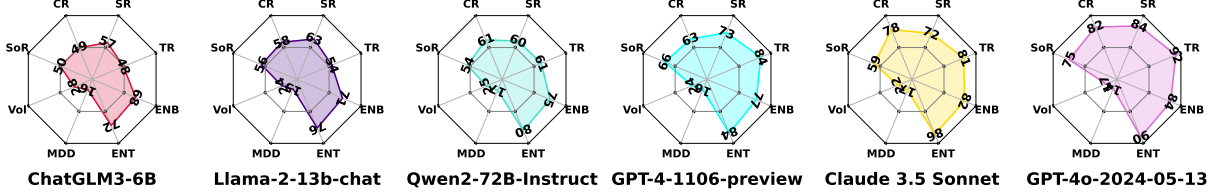


Figure 5: Ablation analysis on several LLM backbones, from open-source to closed-source models. The numbers presented in the figure have been normalized and converted into percentage values.

large-scale language models in financial decision-making. FinAgent achieves an impressive ARR of 45.31% and SR of 2.25, significantly outperforming the top RL-based model, AlphaMix+ (ARR: 32.51%, SR: 1.49). The cumulative returns graph Figure 4 clearly illustrates the superior performance trajectory of LLM-based methods, particularly from mid-2022 onwards.

3) QuantAgents, our proposed multi-agent system, demonstrates superior performance across all evaluation metrics, achieving the highest ARR (58.68%) and SR (3.11), surpassing the best baseline (HedgeAgents) by 19.15% and 30.02%. QuantAgents also excels in risk management with the lowest MDD (16.86%) and VoL (1.43%), while achieving the highest portfolio diversity with ENT (2.97) and ENB (1.49), indicating a more balanced and robust investment strategy. Figure 4 vividly showcases QuantAgents' outstanding performance, with its cumulative returns curve consistently above all other methods, reaching approximately 300% by the end of the test period. This remarkable performance can be attributed to the synergistic collaboration of specialized agents within QuantAgents, each contributing unique expertise in investment management, strategy development, risk control, and market analysis.

4.5 Ablation Study

4.5.1 Effectiveness of Each Meeting

We conducted an ablation study to evaluate the contribution of each meeting module in QuantAgents. Table 3 presents the performance metrics

for different combinations of Market Analysis Meeting (MAM), Strategy Development Meeting (SDM), and Risk Assessment Meeting (RAM). We have the following observations: 1) MAM significantly enhances profitability and portfolio diversity, as evidenced by its high ARR (40.89%) and ENT (1.73) when used alone. Its exclusion from two-meeting combinations reduces ARR and ENT, highlighting its critical role in trend identification and diversification. 2) SDM enhances risk-adjusted returns and portfolio efficiency, with the highest single-meeting SR (1.93) and CR (6.27). Its inclusion in two-meeting setups consistently improves these metrics. The SDM-MAM combination achieves the highest two-meeting SR (2.86) and CR (9.14), demonstrating SDM's effectiveness in strategy formulation. 3) RAM demonstrates strength in risk management and volatility reduction. Despite having the lowest standalone ARR (35.53%), it achieves the lowest single-meeting MDD (21.73%) and VoL (1.34%). In two-meeting configurations, RAM improves risk metrics, notably reducing MDD when combined with SDM. 4) The synergistic effect of all three meetings is evident in our QuantAgents, which outperforms all partial combinations across all metrics. It achieves the highest ARR (58.68%), SR (3.11), and ENT (2.97), while maintaining the lowest MDD (16.86%) and VoL (1.23%).

4.5.2 Effectiveness of LLM Backbone

To evaluate the performance of different LLMs as the backbone, we selected 6 representative

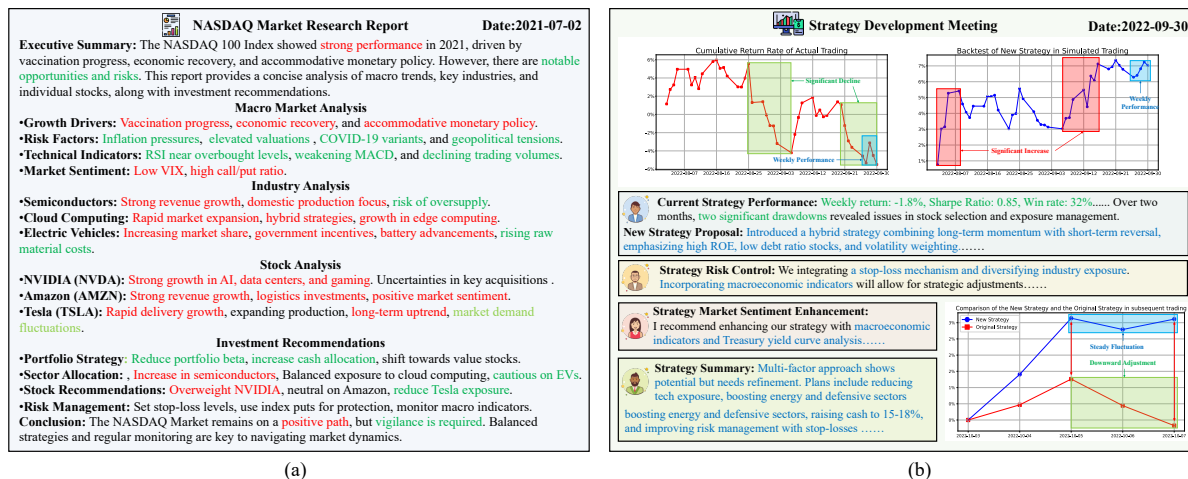


Figure 6: Visualizations of Market Research Report and Strategy Development Meeting.

models, including ChatGLM3-6B (GLM et al., 2024), Llama-2-13b-chat (Touvron et al., 2023), Qwen2-72B-Instruct (Yang et al., 2024), GPT-4-1106-preview (OpenAI et al., 2024), Claude 3.5 Sonnet (Anthropic, 2024), and GPT-4o-2024-05-13 (Wu et al., 2024). Each of these models serves as the brain of QuantAgents, as shown in Figure 5. We have the following observations: 1) QuantAgents achieves consistent performance across diverse LLM backbones, showcasing its adaptability through a robust multi-agent architecture. 2) Larger models, such as Qwen2-72B-Instruct, outperform smaller ones like Llama-2-13b-chat, likely due to their superior capacity to handle complex financial data and detect subtle market patterns. 3) Closed-source models like Claude 3.5 Sonnet outperform open-source ones, such as Qwen2-72B-Instruct, likely due to proprietary training data and advanced fine-tuning techniques enhancing their understanding of financial contexts. Therefore, we select GPT-4o as the core of QuantAgents. Notably, our system has accumulated a total cost of \$180 over the three years, averaging only \$0.17 per day!

4.6 Visualization

4.6.1 Market Analysis Meeting

Figure 6 (a) showcases the visualization of market research report dated 2021-07-02, generated after the market analysis meeting. The report encapsulates key market insights in a structured layout, progressing from an executive summary highlighting the NASDAQ 100 Index’s strong 2021 performance to specific investment recommendations.

4.6.2 Strategy Development Meeting

Figure 6 (b) presents the visualization of a strategy development meeting held on 2022-09-30. The upper left shows the current strategy’s performance, marked by a -1.8% weekly return and significant drawdowns due to issues in stock selection and exposure management. The upper right shows a six-month backtest of the new strategy, yielding 35.3% return and a 1.85 Sharpe Ratio. Dave suggested mitigating risks through stop-loss mechanisms and diversified industry exposure. Emily recommended incorporating macroeconomic indicators and adjusting positions in overvalued tech stocks. Otto summarized the strategy, emphasizing risk management and dynamic adjustments.

4.7 Real-World Investment Performance

We evaluated its live trading performance in the A-stock and HK-stock markets from Q3 2024 to Q1 2025. Figure 11 shows cumulative returns, QuantAgents delivered superior returns of 111.87% (Sharpe Ratio: 2.02, Win Rate: 61.23%) in A-stocks and 97.69% (Sharpe Ratio: 1.76, Win Rate: 59.71%) in HK-stocks, highlighting exceptional profitability and risk management across diverse market conditions.

5 Conclusions

In this paper, we present a sophisticated multi-agent financial system, QuantAgents that incorporates simulated trading, configured similarly to that of human quant traders. Furthermore, our system encourages agents to receive feedback on their performance in the real market and their predictive accuracy in simulated trading. Compared to

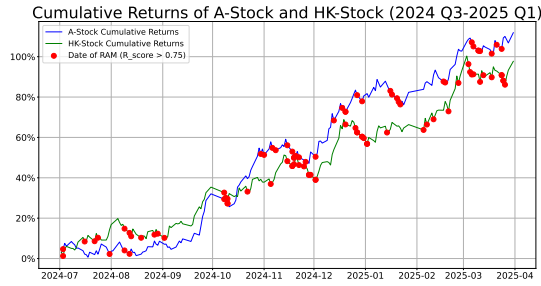


Figure 7: Cumulative Returns of QuantAgents during live trading (24Q3-25Q1). RAM were held 36 times in the A-stock and 46 times in the HK stock market.

baselines and variations in meeting structures, our framework demonstrated strong performance across all metrics, resulting in an impressive overall return of nearly 300%.

Limitations

We still have the following limitations: 1) In terms of generalization, our QuantAgents is modular and flexible, designed to adapt to various market scenarios. We will explore generalization further in future work. 2) Although backtesting may be affected by potential LLM information leakage, QuantAgents’ effectiveness is proven through impeccable live trading performance in A-stock and HK-stock markets over three quarters. We plan to validate it across global markets and report performance periodically.

Ethical Impact

We respect intellectual property rights and comply with relevant laws and regulations. The documents in our dataset are publicly available, and we have taken careful measures to ensure that the documents in our dataset do not contain any personal sensitive information. In addition, our work is only for research purposes, not for commercial purposes.

Acknowledgments

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