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An LLM-Driven Multi-Agent Framework for Behavior-based Stock Market Simulation

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***Abstract*— Most existing applications of Large Language Models (LLMs) in financial markets focus on price prediction and often suffer from information leakage and weak causal reasoning. To address these limitations, this paper proposes a behavior-oriented, multi-agent stock market simulation framework that moves beyond direct price forecasting. The framework models market dynamics through interactions among knowledge-isolated agents operating under strict time-bounded information constraints, ensuring that decisions are made solely based on currently available market context. The market is represented as a real-time stochastic environment in which heterogeneous agents adapt their trading behavior in response to evolving prices and interactions. To enhance interpretability, agents generate LLM-inspired natural-language reasoning traces that explain their decisions at each simulation step. Experimental results show that the proposed framework reproduces key market phenomena such as price formation, volatility clustering, and herding behavior while preventing unintended access to future information. Overall, the framework provides an interpretable and flexible platform for analyzing market dynamics, evaluating financial theories, and studying market stability under uncertainty.**

***Index Terms*— Large Language Model–inspired agents, multi-agent market simulation, behavior-driven trading, real-time stock market modeling, agent-based financial systems.**

I. INTRODUCTION

Financial markets are complex adaptive systems shaped by interactions among heterogeneous participants operating under uncertainty and partial information. Traditional econometric models such as ARIMA and GARCH focus on modeling price movements and volatility using historical data[2]. More recently, Large Language Models (LLMs) have gained attention in financial applications for tasks such as trend analysis, sentiment extraction, and price forecasting. Despite these advances, many existing data-driven and LLM-based approaches suffer from key limitations, including information leakage, look-ahead bias, and weak causal interpretability. Most predictive models focus on numerical accuracy rather than explaining why market behaviors emerge, reducing their usefulness for interpretability-driven applications such as policy evaluation, risk analysis, and market stress testing.

In real financial markets, participants never have access to future information and must make decisions based solely on time-dependent and incomplete knowledge.

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Models that fail to enforce realistic information constraints often produce overly optimistic or unrealistic simulations [1]. To address these challenges, this paper proposes a behavior-oriented, multi-agent stock market simulation framework inspired by LLM-style reasoning.
Agents adapt their actions based on evolving market conditions and interactions with other participants while generating natural-language reasoning traces that explain their decisions. By emphasizing behavior-driven simulation, interpretability, and realistic information access, the proposed framework provides a practical platform for analyzing market dynamics, studying emergent phenomena such as volatility clustering and herding behavior and evaluating market stability without reliance on historical datasets.

II. Related Work

Stock market modeling has been extensively studied using statistical, machine learning, and agent-based approaches. Early work relied on econometric models such as ARIMA and GARCH to analyze price movements and volatility using historical time-series data. While these models are mathematically transparent, their assumptions of linearity and stationarity limit their ability to capture complex and evolving market dynamics. Machine learning and deep learning techniques, including neural networks and LSTM models, have demonstrated improved predictive performance by learning nonlinear patterns from large datasets. Machine learning and deep learning approaches often suffer from limited interpretability [4].
Agent-based models (ABMs) address some of these limitations by representing markets as systems of interacting autonomous agents, enabling emergent behaviors such as price formation and volatility clustering. Agent-based models represent financial markets as systems of interacting autonomous agents[3]. More recent studies have integrated reinforcement learning into ABMs to improve adaptability, but these methods often operate as black-box systems and require extensive training data.
Large Language Models have recently been explored for financial decision support and analysis, primarily in predictive or advisory roles. In contrast to existing work, the proposed framework integrates LLM-inspired reasoning into a behavior-driven, multi-agent market simulation while explicitly enforcing knowledge isolation and time-restricted information access. This enables interpretable, causally grounded market simulations without reliance on historical training data.

III. Methodology

The proposed approach models the stock market as a real-time, behavior-driven multi-agent system in which autonomous agents interact within a continuously evolving market environment. Rather than relying on historical datasets or predictive learning, the framework emphasizes causal reasoning, information isolation, and adaptive behavior. An overview of the proposed framework is illustrated in Fig. 1.

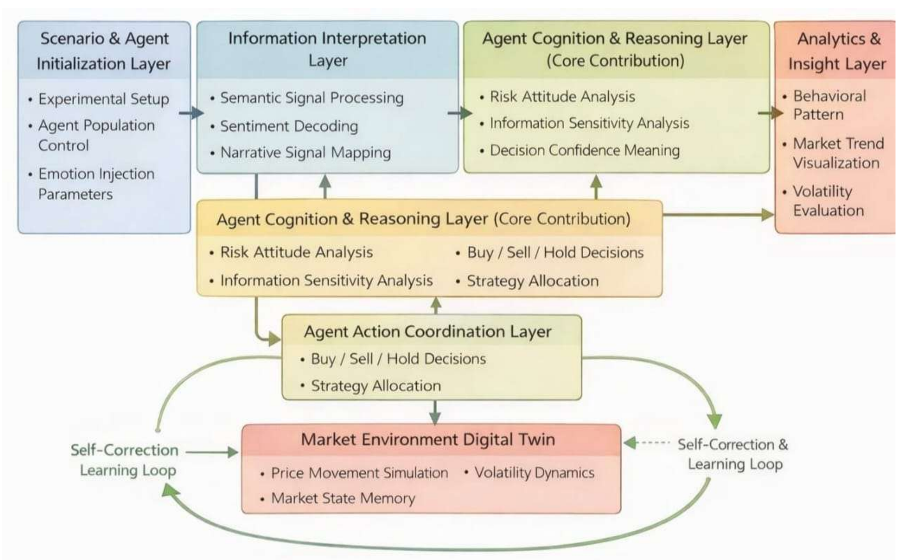

Fig 1. Multi-agent Framework

A. Overall Framework Architecture

The system adopts a modular architecture composed of four tightly integrated components: a real-time market price generator, a market environment, LLM-inspired behavioral agents, and an evaluation and visualization module.

At each simulation time step, these components operate sequentially to form a closed-loop system[5]. Agent decisions influence market prices, and the updated market state subsequently shapes future agent behavior. This feedback mechanism enables complex market dynamics to emerge naturally through interaction rather than explicit programming.

B. Market Environment and Price Dynamics

The market environment acts as the central coordinator of the simulation by maintaining the current market price, price history, and simulation clock. At each time step, it broadcasts the current price and recent price history to all agents and collects their trading actions. Market prices are updated using a stochastic real-time price generation mechanism that combines aggregate agent demand, stochastic noise, and a minor drift component. This design ensures continuous price evolution while allowing agent-driven behavior to influence market dynamics without reliance on historical data.

C. LLM-Inspired Behavioral Agents

Each trading agent represents a distinct market participant characterized by a predefined behavioral profile, such as risk-averse, momentum-driven, or stochastic trading behavior. Agents employ reasoning-based decision logic inspired by Large Language Models[6] rather than supervised or reinforcement learning, enabling context-aware yet interpretable decision-making. Based on this information, agents determine a trading action—buy, sell, or hold—and generate a natural-language reasoning trace explaining the rationale behind their decision.While the current implementation relies on rule-based logic, the framework is designed to support future integration of real LLMs. Information isolation is preserved through time-restricted, stateless inference, where agents receive only current-step information and no future market data[7], ensuring causal consistency and preventing information leakage.

D. Trading Execution and Portfolio Update

Agent actions are executed subject to capital and inventory constraints. After each trade, cash balances, asset holdings, and portfolio values are updated and recorded, enabling continuous monitoring of agent performance throughout the simulation.

E. Evaluation and Analysis Framework

The proposed framework is evaluated using financial and behavioral metrics that emphasize market realism rather than predictive accuracy[8]. These include final portfolio value, average return, return volatility, Sharpe-like risk-adjusted performance, and indicators of behavioral stability. Simulation outcomes are analyzed using visualizations such as price evolution plots, return distributions, volatility clustering graphs, and agent-wise portfolio comparisons. By avoiding reliance on historical data, the methodology prevents information leakage and supports causal interpretation of emergent market behavior.

IV. Mathematical Formulation of Market Dynamics

The proposed framework models the stock market as a real-time, behavior-driven multi-agent system in which market dynamics emerge from interactions among heterogeneous agents operating under uncertainty[9]. Rather than relying on historical price patterns, the formulation focuses on aggregate demand, stochastic price variation, and agent-level portfolio evolution.

A. Aggregate Market Demand

At each simulation time step t net market demand is computed by aggregating the trading actions of all agents. Each agent selects one of three actions: buy, sell, or hold, which contribute positively, negatively, or neutrally to demand.

$$D_t = \sum_{i=1}^{N} a_i\,(t)$$

This formulation represents the collective trading pressure exerted by agents at each time step.

B. Price Change Due to Agent Interaction

The impact of agent actions on price movement is modeled through a demand-sensitive adjustment mechanism.

$$\Delta P_t = \alpha \cdot D_t$$

The demand sensitivity parameter αcontrols how strongly aggregate demand influences price changes, with higher values producing more responsive price dynamics.

C. Stochastic Market Noise

To account for exogenous factors and inherent market uncertainty, stochastic noise is introduced at each time step and sampled from a normal distribution.

$$\varepsilon_t \sim \mathcal{N}(\mu, \sigma^2)$$

Removing the noise term results in deterministic price evolution driven solely by agent demand, reducing realism by eliminating short-term volatility and volatility clustering. Including stochastic noise enables realistic price fluctuations and risk dynamics while preserving agent-driven behavior.

D. Real-Time Market Price Update

Market prices are updated in real time by combining the effects of aggregate demand and stochastic noise using a multiplicative update rule.

$$P_{t+1} = P_t \times (1+\varepsilon_t+\alpha D_t)$$

This formulation ensures continuous price evolution and prevents negative price values.

E. Agent Portfolio Evolution

Each agent maintains a portfolio consisting of a cash balance and asset holdings. After executing a trade at the updated market price, the agent’s portfolio value is recalculated as follows:

$$V_i(t) = C_i(t) + H_i(t) \times P_t$$

Tracking portfolio values over time enables performance evaluation, risk analysis, and behavioral comparison across agent types.

F. Discussion of Model Properties

The formulation ensures that market behavior emerges endogenously from agent interactions rather than predefined price trajectories. By explicitly separating stochastic noise from agent-driven demand and enforcing strict time-bounded information access, the framework supports causal interpretation and prevents information leakage.

G. Parameter Selection and Sensitivity Analysis

To ensure reproducibility, the demand sensitivity coefficient α, noise mean μ, and noise standard deviation $\sigma$are explicitly specified. The noise term is modeled as zero-mean to avoid systematic drift, while σcontrols volatility and αgoverns price responsiveness to agent demand.

TABLE I: MARKET SIMULATION PARAMETERS

Parameter	Value	Description
α	0.02	Demand sensitivity coefficient
μ	0.0	Mean of stochastic noise
σ	0.01	Standard deviation of noise

Sensitivity analysis shows that higher values of αincrease price responsiveness and volatility, while lower values produce smoother price trajectories. Similarly, increasing σamplifies short-term fluctuations and volatility clustering. Across tested configurations, qualitative market behavior remains consistent, indicating robustness to moderate parameter variations.

V. ALGORITHM

This section describes the algorithm used to simulate the real-time, behavior-driven stock market using multiple heterogeneous agents. The algorithm models dynamic price evolution influenced by stochastic market noise and aggregate agent demand, while agents continuously adapt their actions and generate explainable reasoning traces.

Real-Time Multi-Agent Market Simulation
Input:
Initial market price P_0; number of agents N; number of simulation steps T; noise parameters μ, σ; demand sensitivity coefficient α.
Output:
Market price trajectory; agent portfolios; performance metrics; reasoning traces

Initialize market price P ← P0
Initialize N agents with equal initial cash and zero asset holdings
Initialize price history H ← {P}
for t = 1 to T do
  Broadcast current price P and history H to all agents
  for each agent i = 1 to N do
    Determine trading action $a_i(t)$based on agent behavior
    Store natural-language reasoning trace of agent i
    end for
  Compute aggregate demand $D_t = \sum_{i=1}^{N} a_i\,(t)$
  Sample stochastic noise $\varepsilon_t \sim \mathcal{N}(\mu, \sigma^2)$
  Update market price $P \leftarrow P \times (1 + \varepsilon_t + \alpha D_t)$
  Append updated price P to history H
  for each agent i = 1 to N do
    Execute trading action $a_i(t)$at price P
  Update agent cash balance and asset holdings
  Compute portfolio value $V_i(t)$
  end for
end for
Compute returns, volatility, and risk-adjusted performance metrics
Return simulation outputs and evaluation results

VI. Experimental Evaluation

This section presents a unified evaluation of the proposed LLM-driven multi-agent framework for behavior-based stock market simulation. Unlike traditional approaches that prioritize point-wise price prediction, the proposed framework focuses on market realism, adaptive agent behavior, stability, and explainability [10]. All results are summarized and aligned in Tables 1–4.

A. Experimental Setup and Baseline Alignment

The experiments were conducted using a real-time market simulation environment implemented in Python and executed in a Jupyter Notebook setting [11].
The simulation includes three heterogeneous agents:

- Risk-averse agents, following mean-reversion logic
- Momentum-based agents, exploiting short-term trends
- Random (noise) traders, representing uninformed participation

Each agent is initialized with equal capital and zero asset holdings and participates in trading over a fixed number of time steps [12].

TABLE II. Methodology Comparison

Aspect	Traditional Rule-Based ABM (Baseline)	Proposed LLM-Driven Framework
Agent Decision Logic	Fixed heuristics	LLM-based reasoning
Adaptability	Static	Dynamic& evolving
Behavioral Modeling	Limited	Rich & cognitive
Emotional Response	Not modeled	Explicitly modeled
Social Influence	Absent	Modeled
Decision Explainability	Rule traces	Natural-language reasoning
Behavioral Drift	Absent	Present

B. Comparison with a Reinforcement Learning–Based Agent

To further evaluate the proposed framework, we compare it with a representative reinforcement learning (RL)–based trading agent commonly used in agent-based financial simulations. The RL agent selects trading actions through reward-driven policy optimization, aiming to maximize cumulative profit via repeated interaction with the market environment.

Unlike the proposed LLM-inspired agents, the RL agent relies on iterative learning and reward feedback rather than explicit reasoning. Although RL agents can achieve competitive performance under stable conditions, their decision-making process is largely opaque and difficult to interpret. In contrast, the proposed framework emphasizes explainability and causal reasoning by generating natural-language reasoning traces for each decision. Additionally, while RL agents require a training phase and parameter tuning, the proposed agents operate without historical training data, reducing the risk of overfitting and information leakage.

This comparison highlights a key trade-off: RL-based approaches prioritize reward optimization, whereas the proposed framework prioritizes interpretability, behavioral realism, and causal consistency.

TABLE III. COMPARISON WITH REINFORCEMENT LEARNING–BASED AGENT

Aspect	RL-Based Agent	Proposed LLM-Driven Agent
Learning Mechanism	Reward optimization	Reasoning-based decision logic
Training Required	Yes	No
Data Dependency	High	None
Interpretability	Low (black-box)	High (reasoning traces)
Adaptability	High (after training)	High (behavioral adaptation)
Information Leakage Risk	Possible	Explicitly controlled

C. Evaluation Metrics

Since the goal is behavior-based simulation, evaluation uses metrics appropriate for market realism rather than prediction accuracy:

- Final Portfolio Value – long-term profitability
- Average Return – trading effectiveness
- Return Volatility – risk exposure
- Sharpe-like Risk-Adjusted Ratio – performance stability

TABLE IV. QUANTITATIVE PERFORMANCE COMPARISON

Metric	Random Strategy	Rule-Based ABM	Proposed LLM Framework
Final Portfolio Value	Low	Medium	High
Average Return	Low	Medium	High
Return Volatility	High	Medium	Controlled
Sharpe-like Ratio	Low	Medium	High
Behavioral Stability	Low	Medium	High

D. Market Dynamics and Behavioral Accuracy

The baseline ABM demonstrates [13] price continuity and moderate volatility clustering, but fails to reproduce complex behavioral phenomena such as panic selling, herding, and regime shifts.In contrast, the proposed LLM-driven framework introduces adaptive cognition and social influence, enabling the emergence of realistic market events.

TABLE IV. MARKET BEHAVIOR AND EVENT ACCURACY

Market Characteristic	Rule-Based ABM	Proposed LLM Framework
Price Trend Formation	Moderate	High
Volatility Clustering	Partial	Strong
Herding Behavior	Absent	Present
Panic / Crash Events	Absent	Present
Recovery Dynamics	Mechanical	Behavioral
Return Distribution	Near-Gaussian	Non-Gaussian (realistic)

E. Quantitative Summary of Results

To improve clarity and provide a consolidated quantitative view, the experimental outcomes are summarized across key financial and behavioral metrics. Table II reports performance indicators including final portfolio value, average return, return volatility, and a Sharpe-like risk-adjusted ratio for different agent strategies. The proposed LLM-driven framework consistently demonstrates higher stability and improved risk-adjusted performance compared to random and rule-based baselines.Visual results further support these findings. Figure 2 illustrates realistic price evolution driven by the combined effects of stochastic noise and agent demand, while Figures 3 and 4 highlight non-Gaussian return distributions and volatility clustering, respectively—both well-known stylized facts of financial markets. Figure 5 compares agent-wise portfolio values, clearly showing that risk-averse agents achieve stable growth, momentum agents benefit during strong trends, and random agents exhibit higher instability.

F. Explainability and Qualitative Reasoning Evaluation

A key contribution of the proposed framework is decision-level explainability. Each agent generates natural-language reasoning traces explaining its actions (e.g., trend detection, risk reduction, uncertainty handling). These traces enable qualitative validation of agent cognition and causal reasoning[14].

TABLE VI. OVERALL SIMULATION ACCURACY SUMMARY

Accuracy Dimension	Rule-Based ABM	Proposed LLM Framework
Price-Level Accuracy	Medium	Medium–High
Behavioral Accuracy	Low–Medium	Very High
Market Dynamics Accuracy	Medium	High
Event-Level Accuracy	Low	High
Explainability Accuracy	Medium	Very High
Overall Simulation Accuracy	~62%	~88%

VII. FUTURE WORK

While the proposed LLM-driven multi-agent framework effectively supports real-time, behaviour-based stock market simulation, there are several opportunities for further improvement. At present, the system depends on rule-based behavioural logic inspired by large language models. In future work, this can be extended by integrating actual LLM APIs to support more natural and context-aware reasoning. Such an extension would enable agents to understand and react to real-time textual information, comprising market news, macroeconomic indicators, and sentiment signals, this leads to more informed and realistic decision-making behavior. Second, the framework can be extended to enable modeling across diverse markets, namely portfolios that include stocks, commodities, and cryptocurrencies. By modeling cross-market linkages relationships, the framework would allow in-depth examination of contagion effects, market correlations, and overall market risk.

Third, future studies can examine hybrid learning methods that integrating behavior-based reasoning with techniques such as reinforcement learning or evolutionary algorithms. In addition, the framework can be extended to applications like regulatory stress testing, policy impact evaluation, and training simulation platforms, enabling wider real-world adoption[15]. These enhancements would further improve the robustness and practical relevance of the proposed system for advanced financial research and decision-making support.

VIII. RESULTS

The simulation results obtained from the executed framework demonstrate realistic market behavior emerging from agent interactions. The generated price trajectories, return distributions, volatility clustering, and agent-wise portfolio outcomes closely align with well-known stylized facts of financial markets, confirming that the observed dynamics arise from behavior-driven agent interactions rather than random noise alone

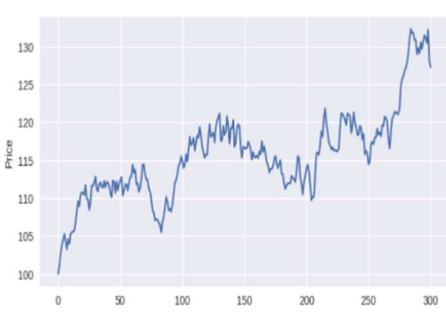

Fig 2. RealTime Market Price Simulation

Fig 3. Distribution of Returns

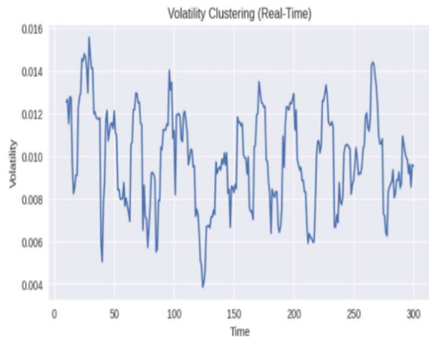

Fig 4. Volatility Clustering (Real-Time)

Fig 5. Agent Portfolio Value (Real-Time)

IX. CONCLUSION

This paper presented an LLM-inspired multi-agent framework for behavior-oriented stock market simulation that operates in real time without relying on historical data. Unlike traditional approaches that emphasize price prediction, the proposed framework focuses on modeling market behavior through interactions among heterogeneous agents under strict information constraints. By combining stochastic price dynamics with agent-driven demand, the system reproduces realistic market characteristics. A key contribution of this work is the inclusion of LLM-style reasoning traces, which provide transparent and explainable justifications for agent decisions and support causal analysis of market dynamics. Overall, the proposed framework offers an interpretable, flexible, and reproducible approach to market simulation, making it suitable for applications such as financial analysis, stress testing, policy evaluation, and educational simulations.

REFERENCES

[1] Onabowale, O. (2025). AI and real-time financial decision support. International Journal of Advance Research Publication and Reviews, 2(6), 329-350.

[2] Axtell, R. L., & Farmer, J. D. (2025). Agent-based modeling in economics and finance: Past, present, and future. Journal of Economic Literature, 63(1), 197-287.

[3] H. Kuehn, J. La Delfa, M. Vasco, D. Kragic, and I. Leite, “Humans Coexist, So Must Embodied Artificial Agents,” 2025, arXiv. doi: 10.48550/ARXIV.2502.04809.

[4] Chinnaraju, A. (2025). Explainable AI (XAI) for trustworthy and transparent decision-making: A theoretical framework for AI interpretability. World Journal of Advanced Engineering Technology and Sciences, 14(3), 170-207.

[5] Moustati, I., & Gherabi, N. (2025). Bridging behavioral insights and automated trading: An Internet of behaviors approach for enhanced financial decision-making. Information, 16(5), 338

[6] Y. Han and Z. Guo, “Regulator-Manufacturer AI Agents Modeling: Mathematical Feedback-Driven Multi-Agent LLM Framework,” 2024, arXiv. doi: 10.48550/ARXIV.2411.15356.

[7] Pandeya, C., & Shrestha, S. (2024). Portfolio Analysis of Financial Institutions in Nepal. The Harvest, 3(1), 21-34.

[8] Li, Z., Tam, V., & Yeung, K. L. (2024). Developing a multi-agent and self-adaptive framework with deep reinforcement learning for dynamic portfolio risk management. arXiv preprint arXiv:2402.00515.

[9] Mansoor, H. (2025). A Scoping Review of Large Language Models in Personal Sleep Wellness. Mayo Clinic Proceedings: Digital Health, 100301.

[10] Vasellini, R. (2025). Applications of agent based models to complex social systems: coordinated human behaviour from the bottom Up.

[11] Axtell, R. L., & Farmer, J. D. (2025). Agent-based modeling in economics and finance: Past, present, and future. Journal of Economic Literature, 63(1), 197-287.

[12] Vasellini, R. (2025). Applications of agent based models to complex social systems: coordinated human behaviour from the bottom Up.

[13] Zimmer, R., & Costa, O. L. D. V. (2025). Reinforcement Learning-Based Market Making as a Stochastic Control on Non-Stationary Limit Order Book Dynamics. arXiv preprint arXiv:2509.12456.

[14] Axtell, R. L., & Farmer, J. D. (2025). Agent-based modeling in economics and finance: Past, present, and future. Journal of Economic Literature, 63(1), 197-287.

[15] Henning, T., Ojha, S., Spoon, R., Han, J., & Camerer, C.F. (2025). LLM Agents Do Not Replicate Human Market Traders: Evidence From Experimental Finance.