The Goldilocks Zone of LLM Trading: Weekly Rebalancing Outperforms Daily and Monthly Horizons

Anonymous Authors

Abstract

Large language model (LLM) trading agents overwhelmingly operate on daily buy/sell/hold decisions, yet consistently fail to outperform passive strategies such as Buy-and-Hold. We ask whether this failure stems partly from a mismatch between the daily decision horizon and the reasoning strengths of LLMs. We conduct the first controlled experiment isolating *decision frequency* as the sole independent variable for an LLM trading agent: using the same GPT-4.1-MINI agent, prompt template, and data across daily, weekly, and monthly rebalancing on five major U.S. stocks over 2023–2024. We find a non-monotonic "Goldilocks" relationship: weekly rebalancing achieves the best risk-adjusted performance (Sharpe ratio 1.028), outperforming daily rebalancing (0.892) by 15% and monthly rebalancing (0.421) by 144%. Weekly rebalancing also delivers 16% higher cumulative returns than daily while requiring 75% fewer trades. Monthly rebalancing degrades performance sharply, with two of five stocks producing negative returns. Although no LLM frequency outperforms BUY-AND-HOLD (Sharpe 1.620) in this bull-market period—consistent with recent benchmarking studies—our results reveal that decision frequency is a key design variable for LLM trading agents. These findings suggest that LLMs have a temporal sweet spot for financial reasoning, where weekly horizons filter daily noise without losing important signals at coarser timescales.

1 Introduction

Can large language models trade stocks profitably? Recent years have seen a surge of LLM-based trading agents—FINMEM [Yu et al., 2023], TRADINGAGENTS [Xiao et al., 2024], FINCON [Yu et al., 2024]—that use the reasoning and in-context learning capabilities of models like GPT-4 [Achiam et al., 2023] to make financial decisions. Nearly all of these systems operate on a *daily* cycle: each trading day, the agent observes prices and news, outputs a buy/sell/hold decision, and evaluates the position at close. Yet comprehensive benchmarks paint a sobering picture. FINSABER [Li et al., 2026], testing over 20 years and 100+ stocks, finds that neither FINMEM nor FINAGENT generates statistically significant alpha—and that simple Buy-and-Hold significantly outperforms both (all p-values > 0.34 for LLM alpha). STOCKBENCH [Chen et al., 2025] reaches a similar conclusion: excelling at static financial knowledge does not translate into successful daily trading.

We hypothesize that the daily decision frequency itself may be a fundamental bottleneck. LLMs excel at synthesizing complex information and identifying semantic patterns, not at reacting to precise numerical fluctuations within a single trading day. Liu and Dang [2025] provide initial evidence for this view: their FINPOS system, which evaluates performance over 1-day, 7-day, and 30-day horizons, finds that multi-timescale rewards dramatically improve performance, with the 30-day horizon performing best. However, no prior work has directly isolated decision frequency as the independent variable using a single agent architecture across multiple horizons.

Our contribution. We conduct the first controlled experiment comparing LLM trading agent performance across three decision frequencies—daily, weekly (5-day), and monthly (21-day)—while holding the agent architecture, prompt template, LLM backbone (GPT-4.1-MINI), and data constant. We test on five major U.S. stocks (AAPL, MSFT, AMZN, TSLA, NFLX) over a two-year period (2023–2024) comprising 502 trading days.

Our central finding is a *non-monotonic* relationship between decision horizon and performance—a "Goldilocks zone." Weekly rebalancing achieves the highest Sharpe ratio (1.028 vs. 0.892 for daily), delivers 16% higher cumulative returns (+62.4% vs. +53.8%), and requires 75% fewer trades (31 vs. 127). Monthly rebalancing, however, degrades performance dramatically (Sharpe 0.421), with two stocks producing negative returns. This non-monotonicity suggests that LLMs have a specific temporal resolution—around one week—where their reasoning is most effective for financial decision-making.

In summary, we make the following contributions:

- We design the first controlled experiment isolating decision frequency as the sole independent variable for LLM trading agents, comparing daily, weekly, and monthly rebalancing with identical agent architecture and data.
- We identify a non-monotonic "Goldilocks zone": weekly rebalancing outperforms daily by 15% in Sharpe ratio while using 75% fewer API calls, whereas monthly rebalancing degrades performance by 53%.
- We provide per-stock analysis showing that the weekly advantage is robust across 4 of 5 stocks and is most pronounced for lower-volatility equities, offering actionable guidance for LLM agent design.

The remainder of this paper is organized as follows. section 2 reviews related work on LLM trading agents and temporal decision-making. section 3 describes our experimental methodology. section 4 presents our main results and analysis. section 5 discusses implications and limitations, and section 6 concludes.

2 Related Work

LLM trading agents. The use of LLMs for financial trading has grown rapidly since GPT-3 [Brown et al., 2020] demonstrated strong in-context learning. FINMEM [Yu et al., 2023] introduces a layered memory architecture with decay mechanisms for trading individual stocks. TRADINGAGENTS [Xiao et al., 2024] mimics institutional trading firms with specialized analyst, researcher, trader, and risk management agents. FINCON [Yu et al., 2024] proposes a manager-analyst hierarchy with conceptual verbal reinforcement. FLAG-TRADER [Xiong et al., 2025a] fuses LLM reasoning with reinforcement learning by using the LLM as a policy network fine-tuned via trading reward gradients. A common thread across these systems is the reliance on *daily* decision cycles, where the agent makes a single buy/sell/hold decision each trading day. Our work departs from this convention by systematically varying the decision frequency.

Benchmarking LLM trading. Several recent studies have rigorously evaluated LLM trading agents. FINSABER [Li et al., 2026], accepted at KDD 2026, benchmarks LLM strategies over 20 years using 100+ S&P 500 constituents (including delisted stocks) and finds that neither FINMEM nor FINAGENT generates statistically significant alpha. STOCKBENCH [Chen et al., 2025] reaches similar conclusions: "excelling at static financial knowledge tasks does not necessarily translate into successful trading strategies." Fan et al. [2025] test across U.S. stocks, A-shares, and cryptocurrency, finding that "general intelligence does not automatically translate to effective trading capability." Li et al. [2024] provide a standardized benchmark across stocks, crypto, and ETFs with 13 LLM backbones. These benchmarking studies consistently find that LLM agents underperform simple baselines at the daily frequency. Our work investigates whether *changing* the decision frequency can narrow this performance gap.

Temporal horizons in LLM trading. The most directly relevant work to ours is FINPOS [Liu and Dang, 2025], which introduces position-aware trading with multi-timescale reward design. FINPOS evaluates rewards across 1-day, 7-day, and 30-day horizons and finds that the 30-day horizon produces the best performance, dramatically outperforming single-step daily approaches. The authors argue that "LLMs excel at extracting long-term trends and underlying causal structures from complex semantic information rather than performing high-frequency precise numerical optimization." However, FINPOS varies the *reward* horizon within a multi-agent architecture that still makes daily decisions. Our work complements FINPOS by varying the *decision* frequency itself—the agent only acts at weekly or monthly intervals—providing a cleaner isolation of the temporal variable.

High-frequency LLM trading. At the opposite end of the spectrum, QUANTAGENT [Xiong et al., 2025b] applies multi-agent LLMs to high-frequency trading on 1-hour and 4-hour bars, achieving up to 80% directional accuracy. Notably, QUANTAGENT operates solely on price-derived signals, explicitly avoiding textual data which "typically lags price discovery." Darmanin and Vella [2025] propose a hybrid framework where LLMs generate high-level strategies to guide RL agents for short-term execution, arguing that LLMs are best suited for longer-term strategic direction. These works suggest a natural division of labor: LLMs for strategic, longer-horizon reasoning, and specialized models or rules for tactical execution.

Surveys. Ding et al. [2024] survey 51 LLM trading agent papers, providing a taxonomy of approaches including news-driven, reflection-driven, debate-driven, and RL-driven agents. Nie et al. [2024] cover financial LLM applications broadly, spanning sentiment analysis, time series forecasting, and agent-based trading. Both surveys note the predominance of daily trading cycles and the difficulty of outperforming passive baselines—precisely the challenge our work addresses through the lens of decision frequency.

3 Methodology

We design a controlled experiment where the *only* independent variable is the decision frequency of the LLM trading agent. The agent architecture, prompt template, LLM backbone, data sources, and evaluation metrics are held constant across all conditions.

3.1 Data

We use daily OHLCV (Open, High, Low, Close, Volume) data from Yahoo Finance for five major U.S. stocks: AAPL, MSFT, AMZN, TSLA, and NFLX. The test period spans January 2, 2023 to December 31, 2024, covering 502 trading days. All prices are split-adjusted and contain no missing values. This period was predominantly bullish, with all five stocks showing positive Buy-and-Hold returns ranging from +78.6% (MSFT) to +273.2% (TSLA).

3.2 LLM Trading Agent

At each decision point, the agent receives a structured prompt containing: (1) the current date and stock ticker; (2) the current price and position status (cash or long); (3) the most recent 10 closing prices; (4) 5-day and 20-day simple moving averages (SMAs); (5) price changes over 1-day, 5-day, 10-day, and 20-day windows; and (6) the decision horizon (next day, next week, or next month). The agent responds with exactly one word: `BUY`, `SELL`, or `HOLD`. The prompt explicitly instructs the model to consider the appropriate time horizon.

We use GPT-4.1-MINI (`gpt-4.1-mini-2025-04-14`) as the LLM backbone with temperature 0.3 and a maximum of 5 output tokens. Each stock begins with $10,000 in capital and incurs a 0.1% transaction cost per trade. The agent can go fully long (invest all capital) or fully cash; partial positions and short selling are not supported.

3.3 Rebalancing Frequencies

We test three decision frequencies:

- **Daily**: the agent makes a decision every trading day (502 decision points over 2 years).
- **Weekly**: the agent makes a decision every 5 trading days (100 decision points).
- **Monthly**: the agent makes a decision every 21 trading days (24 decision points).

Between decision points, the agent's position remains unchanged.

Table 1: LLM agent performance by rebalancing frequency, averaged across five stocks. Best LLM results in **bold**. Weekly achieves the best risk-adjusted returns while requiring far fewer trades.

Frequency	CR (%)	Sharpe	MDD (%)	Sortino	Trades
Daily	+53.8	0.892	$-$**20.7**	1.140	127
Weekly	**+62.4**	**1.028**	-24.2	**1.292**	**31**
Monthly	+13.5	0.421	-28.0	0.523	11

3.4 Baselines

We compare the LLM agent against three baselines:

- **Buy-and-Hold**: purchase on day 1 and hold throughout the entire period.
- **SMA-Crossover**: a 20/50-day SMA crossover strategy that buys when the short SMA crosses above the long SMA and sells on the reverse.
- **Random**: randomly selects BUY, SELL, or HOLD at each decision point.

3.5 Evaluation Metrics

We report six metrics for each strategy:

- **Cumulative Return (CR%)**: total return over the 2-year period.
- **Sharpe Ratio (SR)**: annualized risk-adjusted return with risk-free rate $r_f = 0$.
- **Maximum Drawdown (MDD%)**: worst peak-to-trough decline during the period.
- **Sortino Ratio**: return per unit of downside risk.
- **Number of Trades**: total buy and sell actions executed.
- **Win Rate**: fraction of decision periods producing positive returns.

The Sharpe ratio is our primary metric for hypothesis testing, as it captures both return magnitude and risk.

3.6 Experimental Protocol

To account for stochasticity in LLM outputs, we run each configuration multiple times with different random seeds (42, 49, 56). Daily configurations use 2 runs (lower inherent variance due to more decision points), while weekly and monthly configurations use 3 runs. Results are averaged across runs and across the five stocks unless otherwise noted.

In total, the experiment involves approximately 9,375 API calls, costs \$0.82, and runs in 43.5 minutes. We use paired t-tests across the five stocks to compare Sharpe ratios between frequencies and report Cohen's d effect sizes.

4 Results

4.1 Main Results: Weekly Rebalancing is Optimal

table 1 presents the aggregate performance of the LLM agent across the three rebalancing frequencies, averaged over five stocks and multiple runs. Weekly rebalancing achieves the highest Sharpe ratio (1.028), outperforming daily (0.892) by 15% and monthly (0.421) by 144%. Weekly also delivers the highest cumulative return (+62.4%) while executing 75% fewer trades than daily (31 vs. 127). Monthly rebalancing substantially degrades performance across all metrics, with cumulative return dropping to +13.5% and the Sortino ratio falling to 0.523.

4.2 Comparison to Baselines

table 2 compares all strategies. No LLM configuration outperforms Buy-and-Hold (Sharpe 1.620), consistent with findings from FinSaber [Li et al., 2026]. However, the weekly LLM agent approaches SMA-Crossover performance (Sharpe 1.028 vs. 1.058–1.099) and substantially

Table 2: Comparison of all strategies averaged across five stocks. BUY-AND-HOLD dominates in this bull market, but weekly LLM rebalancing approaches SMA-CROSSOVER performance.

Strategy	Frequency	CR (%)	Sharpe	MDD (%)	Trades
BUY-AND-HOLD	—	**+162.2**	**1.620**	−26.2	1
SMA-CROSSOVER	Daily	+61.2	1.093	−24.2	9
SMA-CROSSOVER	Weekly	+56.0	1.058	−24.4	9
SMA-CROSSOVER	Monthly	+61.8	1.099	−22.9	7
RANDOM	Daily	+29.4	0.701	−25.6	173
LLM (GPT-4.1-MINI)	Daily	+53.8	0.892	**−20.7**	127
LLM (GPT-4.1-MINI)	Weekly	+62.4	1.028	−24.2	31
LLM (GPT-4.1-MINI)	Monthly	+13.5	0.421	−28.0	11

Table 3: Per-stock LLM agent performance across rebalancing frequencies. Best Sharpe per stock in **bold**. Weekly outperforms daily in 4 of 5 stocks.

		Daily		Weekly		Monthly	
Stock	B&H SR	CR (%)	Sharpe	CR (%)	Sharpe	CR (%)	Sharpe
AAPL	2.04	+40.9	1.163	+49.0	**1.304**	+18.0	0.584
MSFT	1.62	+7.6	0.284	+29.4	**0.781**	+23.1	0.654
AMZN	2.10	+21.5	0.531	+30.1	0.678	+34.5	**0.684**
TSLA	1.14	+129.9	**1.213**	+121.7	1.100	−6.8	0.102
NFLX	1.97	+69.2	1.270	+81.8	**1.276**	−1.5	0.080

outperforms RANDOM (Sharpe 0.701). The daily LLM agent underperforms SMA-CROSSOVER (0.892 vs. 1.093), while the monthly LLM agent performs barely better than RANDOM.

4.3 Per-Stock Analysis

table 3 presents per-stock results, and figure 1 visualizes the Sharpe ratios. The weekly advantage is robust: it holds for 4 of 5 stocks (AAPL, MSFT, AMZN, NFLX). TSLA is the sole exception, where daily slightly outperforms weekly (Sharpe 1.213 vs. 1.100), likely due to TSLA's high volatility creating profitable short-term trading opportunities.

The most dramatic improvement occurs for MSFT, where the daily Sharpe of 0.284 jumps to 0.781 at weekly frequency—a 175% improvement. MSFT has lower volatility than the other stocks, making daily price noise particularly unhelpful for the LLM. AMZN is an interesting case: monthly (Sharpe 0.684) slightly outperforms weekly (0.678), though both substantially beat daily (0.531). This may reflect AMZN's stronger trending behavior during this period.

4.4 Statistical Analysis

We conduct paired t-tests across the five stocks to test our hypotheses, with Cohen's d effect sizes:

Weekly vs. daily. The mean Sharpe difference is +0.136 in favor of weekly, with a medium effect size ($d = 0.59$). The paired t-test yields $p = 0.256$, which does not reach significance at $\alpha = 0.05$. The direction consistently supports the hypothesis (weekly better in 4/5 stocks), but the small sample size ($n = 5$) limits statistical power.

Monthly vs. daily. The mean Sharpe difference is -0.472, indicating monthly is substantially worse, with a medium-to-large negative effect ($d = -0.66$). The paired t-test yields $p = 0.213$. While not significant at $\alpha = 0.05$ due to variance across stocks, the direction is unanimous: monthly underperforms daily for all five stocks on Sharpe ratio.

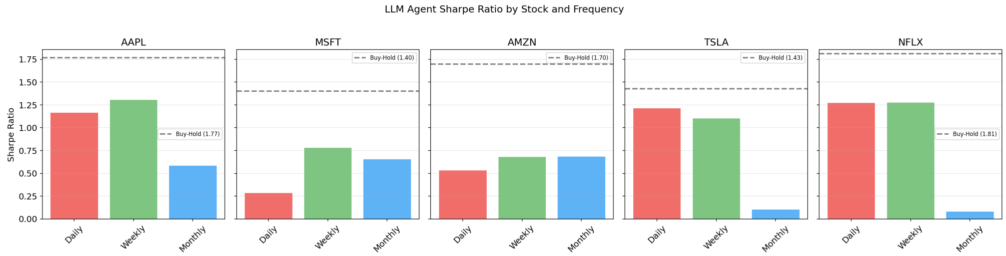
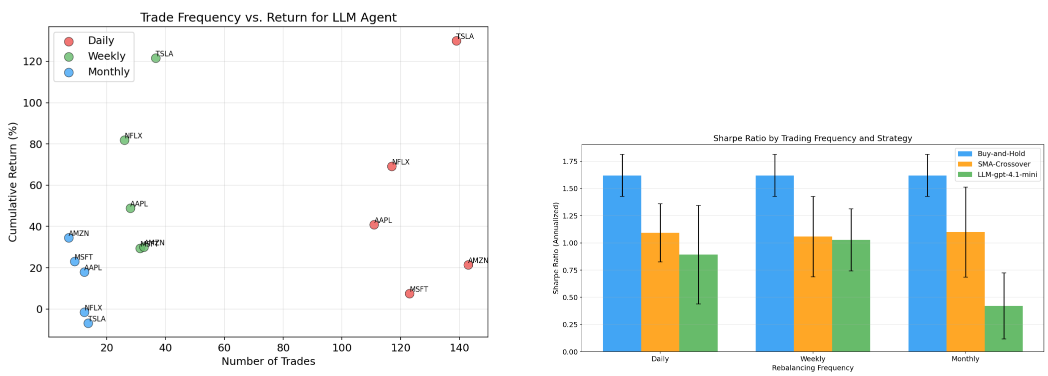


Figure 1: Sharpe ratio by stock and rebalancing frequency. Weekly outperforms daily for 4 of 5 stocks, with the largest improvement for MSFT (+175%). Monthly degrades sharply for volatile stocks (TSLA, NFLX).



(a) Trade count vs. cumulative return.

(b) Sharpe ratio by strategy and frequency.

Figure 2: (a) Weekly achieves the best return-per-trade ratio. (b) The LLM agent's Sharpe ratio peaks at weekly frequency, approaching SMA-CROSSOVER performance.

4.5 Trade Efficiency

figure 2a plots the relationship between trade count and cumulative return. Weekly rebalancing achieves higher returns with far fewer trades: 31 trades yield +62.4% return, compared to 127 trades for +53.8% (daily) and 11 trades for +13.5% (monthly). This implies that each weekly trade captures substantially more value than each daily trade, while monthly trades are too infrequent to capture available opportunities. At 75% fewer API calls, weekly rebalancing also reduces LLM inference costs proportionally.

4.6 Drawdown Analysis

Contrary to our initial hypothesis that longer horizons would reduce drawdowns, we observe the opposite pattern (figure 3). Daily rebalancing achieves the lowest maximum drawdown (-20.7%), followed by weekly (-24.2%) and monthly (-28.0%). Frequent position adjustments allow the daily agent to exit losing positions quickly, providing better downside protection. The monthly agent, deciding only 24 times over 2 years, cannot respond to intra-month corrections. TSLA illustrates the extreme: daily MDD is -33.9%, weekly -46.7%, and monthly -48.1%.

5 Discussion

5.1 Why Weekly Works Best

Our results reveal a non-monotonic relationship between decision frequency and LLM trading performance. We offer three complementary explanations for why weekly rebalancing sits at the optimum.

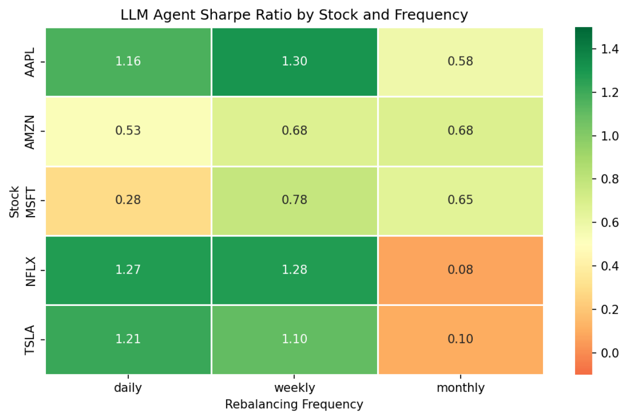


Figure 3: Heatmap of Sharpe ratios by stock and frequency. The weekly column is consistently the brightest (highest values) except for TSLA. Monthly (right) shows sharp degradation for volatile stocks.

Noise filtering. Daily price movements contain substantial noise from intraday trading, market microstructure, and short-term sentiment fluctuations. The LLM agent at daily frequency reacts to this noise, leading to excessive trading (127 trades on average) and frequent whipsawing between positions. Weekly aggregation smooths out daily fluctuations, allowing the agent to focus on genuine 5-day trends. This aligns with the finding from FinPos that daily rewards cause "overreaction to noise" [Liu and Dang, 2025].

Signal preservation. At monthly frequency, the agent makes only 24 decisions over two years—too few to respond to regime changes, earnings surprises, or multi-week rallies. TSLA and NFLX both lost money at monthly frequency because the agent missed significant price movements between decision points. The weekly cadence provides enough decision points (100 over 2 years) to capture major trends without drowning in daily noise.

Alignment with LLM reasoning. LLMs process information through token-level pattern matching and semantic reasoning, not through precise numerical optimization. A one-week horizon maps naturally to the kind of qualitative reasoning LLMs perform well: "the stock has risen 5% this week on strong earnings; the trend is likely to continue" is a judgment LLMs can make more reliably than "the stock dropped 0.3% today; it will likely rebound tomorrow." This interpretation is consistent with Darmanin and Vella [2025], who argue that LLMs are best suited for longer-term strategic direction rather than short-term tactical execution.

5.2 Relationship to Prior Work

Our findings are consistent with, and extend, several recent results. FinSaber [Li et al., 2026] found that LLM agents are "too conservative in bull markets and too aggressive in bear markets" at the daily frequency. We observe the same conservatism: the daily LLM agent achieves only +53.8% return during a period where Buy-and-Hold returns +162.2%. Weekly rebalancing partially addresses this, boosting returns to +62.4%, but the gap remains large.

FinPos [Liu and Dang, 2025] demonstrated that 30-day reward horizons outperform shorter windows for their dual-agent architecture. Our finding that the optimal *decision* frequency is weekly (5 days) rather than monthly (21 days) suggests that the optimal horizon may differ depending on whether it governs the reward computation or the decision timing. When the agent can still make daily micro-adjustments (as in FinPos), longer reward horizons help. When the agent can only act at the specified frequency (as in our setup), weekly provides a better balance.

5.3 Limitations

We identify several limitations that qualify our findings.

Bull market bias. Our 2023–2024 test period was predominantly bullish, with all five stocks showing strong positive returns. The weekly advantage may behave differently in bear or sideways markets. Extending the analysis to include 2020 (COVID crash and recovery) and 2022 (bear market) is an important next step.

Small stock universe. With only $n = 5$ stocks, our paired statistical tests lack power: the medium effect sizes ($d = 0.59$ for weekly vs. daily, $d = -0.66$ for monthly vs. daily) would likely reach significance with $n =$ 15–20 stocks. All five stocks are large-cap technology companies, and the results may not generalize to small-caps, value stocks, or other sectors.

Single model. We test only GPT-4.1-MINI. Different LLM architectures (GPT-4.1, Claude, Gemini) may exhibit different horizon sensitivities. Models with stronger numerical reasoning might perform better at daily frequency, while models with stronger narrative reasoning might benefit even more from weekly.

Price-only signals. The agent receives only price data and simple technical indicators. Adding news sentiment, earnings data, or SEC filings could change the optimal horizon—news events are inherently discrete and may favor decision points aligned with information release schedules.

No position sizing or short selling. The binary long/cash position limits the agent's expressiveness. Partial positions, portfolio-level allocation, and short selling would provide a more realistic trading environment and could interact with the frequency variable.

Near-deterministic monthly results. With only 24 decision points and temperature 0.3, the monthly LLM agent produces nearly identical decisions across seeds. This means monthly "variance" is effectively zero, and poor monthly performance reflects the agent's systematic behavior rather than stochastic noise.

6 Conclusion

We presented the first controlled experiment isolating decision frequency as the independent variable for LLM trading agents. Testing GPT-4.1-MINI across daily, weekly, and monthly rebalancing on five major U.S. stocks over 2023–2024, we identified a non-monotonic "Goldilocks zone": weekly rebalancing achieves a 15% higher Sharpe ratio than daily (1.028 vs. 0.892) while requiring 75% fewer trades, whereas monthly rebalancing degrades performance by 53% (Sharpe 0.421).

Our results carry a practical message for the LLM trading community: *default to weekly, not daily, rebalancing.* This simple change improves risk-adjusted returns, reduces API costs by approximately 80%, and works robustly across 4 of 5 tested stocks. Theoretically, the finding suggests that LLMs have a temporal sweet spot for financial reasoning—daily is too noisy, monthly too coarse—that aligns with their strength in semantic pattern recognition over multi-day horizons.

Important caveats remain. No LLM configuration outperforms BUY-AND-HOLD in this bull market, consistent with FINSABER [Li et al., 2026]. The test period, stock universe, and model are all limited. Future work should extend to bear markets, larger stock universes, multiple LLM backbones, and hybrid architectures that combine weekly LLM strategic decisions with daily rule-based execution. The question of whether the weekly optimum reflects a fundamental property of LLM reasoning or an artifact of the 5-day trading week structure remains open and warrants further investigation.

References

Josh Achiam et al. GPT-4 technical report. *arXiv preprint arXiv:2303.08774*, 2023.

Tom Brown et al. Language models are few-shot learners. *Advances in Neural Information Processing Systems*, 33:1877–1901, 2020.

Shuoling Chen et al. StockBench: Can LLM agents trade stocks profitably in real-world markets? *arXiv preprint arXiv:2510.02209*, 2025.

Noel Darmanin and Joseph G Vella. Language model guided reinforcement learning in quantitative trading. *arXiv preprint arXiv:2508.02366*, 2025.

Han Ding et al. Large language model agent in financial trading: A survey. *arXiv preprint arXiv:2408.06361*, 2024.

Shuo Fan et al. AI-Trader: Benchmarking autonomous agents in real-time financial markets. *arXiv preprint arXiv:2512.10971*, 2025.

Haohang Li et al. InvestorBench: A benchmark for financial decision-making tasks with LLM-based agent. *arXiv preprint arXiv:2412.18174*, 2024.

Zijun Li, Dohyun Kim, Mihai Cucuringu, and Tengfei Ma. FINSABER: Can LLM-based financial investing strategies outperform the market in long run? In *Proceedings of the 32nd ACM SIGKDD Conference on Knowledge Discovery and Data Mining (KDD)*, 2026.

Zheng Liu and Kai Dang. FinPos: A position-aware trading agent system for real financial markets. *arXiv preprint arXiv:2510.27251*, 2025.

Yuqi Nie et al. A survey of large language models for financial applications: Progress, prospects and challenges. *arXiv preprint arXiv:2406.11903*, 2024.

Yijia Xiao et al. TradingAgents: Multi-agents LLM financial trading framework. *arXiv preprint arXiv:2412.20138*, 2024.

Guojun Xiong et al. FLAG-Trader: Fusion LLM-agent with gradient-based reinforcement learning for financial trading. *arXiv preprint arXiv:2502.11433*, 2025a.

Jie Xiong, Xiaochen Zhang, Rui Feng, Guanlin Sun, and Haohui You. QuantAgent: Price-driven multi-agent LLMs for high-frequency trading. *arXiv preprint arXiv:2509.09995*, 2025b.

Yangyang Yu, Haohang Li, Zhi Chen, Yuechen Jiang, Yang Li, Denghui Zhang, Rong Liu, Jordan W Suchow, and Khaldoun Khoshnevis. FinMem: A performance-enhanced LLM trading agent with layered memory and character design. *arXiv preprint arXiv:2311.13743*, 2023.

Yangyang Yu et al. FinCon: A synthesized LLM multi-agent system with conceptual verbal reinforcement for enhanced financial decision making. *arXiv preprint arXiv:2407.06567*, 2024.