An Agentic AI Framework for Weekly Stock Portfolio Selection in the U.S. Tech Sector

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Automating sophisticated investment strategies in changing markets is quite hard, especially for short-term horizons when quick data synthesis and adaptive reasoning are essential. A new Agentic AI framework helps with the difficulties of optimizing portfolios in the U.S. technology industry every week. The architecture uses zero-shot reasoning from a core LLM (Llama 3.3 70B) to create five specialized agent roles: Momentum, Catalyst, Technical, Liquidity, and Risk. These agents look at a universe of 90 stocks for a rigid 5-day trading cycle (Monday purchase, Friday sell). Many current AI methods have problems with validation since they only use backtesting. They also have problems with scalability when it comes to sophisticated reasoning protocols like debate, they aren't clear, or they don't create meaningful, allocated portfolios for very short-term cycles. To get over these problems, we suggest an efficient and clear architecture run by LangGraph, where agent insights are combined using a structured, score-driven algorithm that is specifically made for practical weekly use and has been tested in actual market situations. The AI-generated portfolio had a very good average weekly return of +3.28%, which was much better than the NASDAQ-100, S&P 500, and XLK benchmarks. It also had a very high risk-adjusted performance with an Annualized Sharpe Ratio of 6.02 and strong downside control with a Maximum Weekly Drawdown of only -1.40%. These outcomes from a meticulous 9-week live investment experiment, executed through genuine market transactions, furnish robust empirical evidence of the framework's effectiveness.

Keyword: Agentic AI, Large Language Models(LLMs), Zero-Shot Reasoning, Financial Technology, Portfolio Selection

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1. Introduction

1.1 Overview Scope

The U.S. tech industry is indispensable in the global economy. These market dynamics are referred to the rapid innovation, large growth potential and high volatilities (Darwish et al., 2025). Here, there is an ever higher scale of information that is available; from fundamentals and social sentiment to global happenings, macroeconomic numbers and technical patterns is something traders need to deal with in order to succeed. The sheer volume and rapid pace of relevant data is often too overwhelming for traditional financial analysis methods, especially when a profit can stem from fleeting market gyrations. Considering the difficulty in the field, it is natural to investigate advanced computational techniques, such as Artificial Intelligence (AI), to aid or automate decision making on portfolio management. The ability of AI, particularly LLMs and agentic frameworks to draw from diverse types of data and amplify expert reasoning presents an interesting opportunity to provide more flexible and potentially lucrative ones (Patel & Chauhan, 2025; Sapkota et al., 2025). In this paper we examine how agent-natural AI can be used in a systematic manner to solve issues related to stocks investment.

1.2 More Specific Scope

The challenging weekly portfolio optimization problem in the U.S. technology industry is also the mount point of this paper, which studies a small universe of 90 high-liquidity stocks that are predominantly traded on NASDAQ, featuring significant subsectors such as semiconductors, cloud computing, artificial intelligence and fintech. The main goal is to create and test an automated system that can provide the best 5-stock portfolio suggestions for a rigorous five-day trading cycle (buying on Monday and selling on Friday). This very short time frame requires quick synthesis of real-time quantitative (like price and volume) and qualitative (like news catalysts and sentiment) data, precise timing of execution, and good risk management in a short amount of time to consistently take advantage of short-lived opportunities with good risk-reward profiles. Recent developments in financial Large Language Models (LLMs) have shown that they are quite good at processing financial content. As an illustration, Lopez-Lira and Tang (2023) showed that ChatGPT can predict changes in stock prices based on news headlines. As a result, this study's scope encompasses the comprehensive design, execution, and thorough empirical assessment of an AI system specifically developed to address these distinct issues.

1.3 Issues and Motivation

Although there is a lot of interest in employing LLMs and agentic AI in finance (Ding et al., 2024), there are still a number of significant issues that make it difficult to create reliable and effective short-term trading systems. Heterogeneity and data overload are still problems; combining several signals from qualitative news analysis, quantitative market data, and real-time sentiment is still quite challenging (Saturwar et al., 2025). Second, as LLM Trading (Henning et al., 2025) demonstrated in their study behavior of LLM agents in asset markets under experimentation, many AI models currently in use are not very good at adapting to rapidly changing market circumstances and breaking news, which are crucial for making short-term, time-sensitive decisions. Thirdly, many systems end their processes at stock ranking or signal generation rather than creating a fully allocated portfolio, despite the fact that portfolio optimization is inherently complex and requires balancing expected returns, risk exposure, correlations, and potential transaction costs across multiple assets. The validation approach used in a large number of recent studies has a serious flaw. Over-optimizing through backtesting can lead to overfitting, which means you don't find issues like market impact or slippage. This would lead to too high levels of performance standards (Fatouros et al., 2024; Papasotiriou et al., 2024; Li et al., 2025).

Also, although systems such as AgentVerse (Chen et al., 2023) and MetaGPT (Hong et al., 2023) propose complex reasoning methods like inter-agent debate to enhance the robustness of decision making, they generally come at cost of efficiency and scalability. Accordingly, it is costly and time-consuming to assess the large stock universes (Xiao et al., 2024; Kang et al., 2025). These limitations necessitate a new approach for transforming the underlying high-pace and nontrivial nature of US technology stock market signals into actionable information. The main objective of this paper is the design of a "smart" system capable of automating the tedious weekly assessment that has been required to access the health and strength of many different tech stocks, comprehensively incorporating several quantitative as well as qualitative factors that traditional models ignore frequently and producing discrete, easy-iconsume optimal portfolio recommendations. It is possible that such a system could significantly enhance the speed of investing, analysis quality and risk-adjusted, profits in the present dynamic market environment (Sharpe, 1966; Jensen, 1968).

1.4 Our solution

In this paper, we propose an Agentic AI system that is tailored to the weekly selection of technology stocks in the United States. According to recent research on agentic AI, our approach replicates an expert financial analysis team by deploying five specialized agents (Momentum, Catalyst, Technical, Liquidity, and Risk) that are individually powered by LLMs (Sapkota et al., 2025; Roumeliotis et al., 2025). With the use of advanced fast engineering, these agents independently examine different market elements using zero-shot reasoning (White et al., 2023; Xu et al., 2023). Data integration is achieved through real-time API connections (yfinance, Alpha

Vantage, NewsAPI) and local technical indicator computations (pandas-ta), which are similar to the techniques used in the PIXIU benchmark (Xie et al., 2023).

Our transparent and score-based synthesis process, which is managed by Lang Graph (LangChain AI, 2024). The specialized agent is designed as an integrator with a weighted scoring method, involving bonus logic to ensure that confirmatory responding is preferred overelaborate deliberation. This technique is scalable and explainable (the returned scores can be connected to individual agents' assessments) allowing 90 stocks to study efficiently on a weekly basis (Danilevsky et al., 2020). The framework ends with a 5-stock portfolio advice that you can act on to maximize your returns optimized at percentage level. Most significantly, the system's efficacy is proven by actual investment experiments rather than only simulations, providing compelling empirical evidence for its potential to function in the real world (Li et al., 2023; Koa et al., 2024).

1.5 Organization of the Article

The rest of the paper is structured as follows: In Section 2, relevant related works on the area are discussed and basic concepts including short-term trading fundamentals and agentic AI are introduced. In Section 3, we first introduce the formal definition of our weekly portfolio optimization problem together with some basic notations and symbols. The architecture, specialized agents, rapid engineering methodology and scoring algorithm for our solution (referred to as Agentic AI framework) is presented in section 4. Benchmarks, performance measurements, live validation methods and the software/hardware environment as well as data sources are presented in Section 5 which describes the experimental setup. In section 6 we report on the empirical findings from the live investment experiment. Section 7 concludes and summarizes the key points of this paper, discusses its contributions and limitations and suggests future research directions.

2. Background and Related Works

In this section, we are going to introduce the foundation theory of agentic AI systems and LLMs used in financial cases. We then perform a review of related literature on algorithmic trading and multi-agent systems, pointing out limitations or insufficiencies our work addresses.

2.1 Large Language Models and Zero-Shot Reasoning

Linguistic Donkeys Big Language Models such as those emerging from training on large text sources with architectures like the Transformer are a very big step forward in AI. Models such as GPT-4 (Kirkovska, 2025) and the Llama series have shown that scaling laws suggest larger model parameters, data sizes, and computing resources are associated with expected increases to performance gains on tasks demanding complex reasoning or context understanding or natural language generation. Such capabilities enable LLMs to serve as reasoning systems rather than being simple text dissection tools (Wu et al., 2023; Yang et al., 2023) that are incapable of digesting complex analytic challenges in the context of finance.

One of the most important capabilities we use in our work is zero-shot reasoning. This removes the need for task-specific training data, having LLMs solve tasks without needing to access a dataset during inference, based only on natural language directions and context (see e.g., applications like stock movement prediction (Lopez-Lira and Tang, 2023)). Systems such as ReAct that integrate reasoning and prompt-guided action demonstrate the potential value of guided reasoning (Yao et al., 2023). This zero-shot capability is particularly ideal for the banking industry where markets are ever-changing. It enables system to be responsive to new information and changing conditions, without the need for them to have constant retraining with potentially stale historic data. A robust and effective zero-shot application also relies on careful prompt engineering to bound the model, guide its reasoning process, assure factual grounding and protect itself from threats such as prompt modifications or hallucination (Ji et al., 2023; White et al., 2023; Xu et al., 2023).

2.2 Agentic AI Frameworks

Agentic AI uses LLMs as the cognitive hub for autonomous agents who have capability to sense, reason, plan, and act towards goals in an environment (Patel & Chauhan, 2025 ; Sapkota et al., 2025). This is an alternative model that replaces passive analysis with active goal directed problem solving. Agentic architectures mimic the division of labor found in human professional teams by breaking complex tasks into a series of sub problems, each one independently solved by an agent specializing in solving that sub problem (Feng et al., 2024). This is what you would call for "modularity" and results in potential better performance through concentrated knowledge. It is important for Workflow management and design of the communication agent. While some models, such as MetaGPT (Hong et al., 2023), focus on structured communication protocols to keep track of context and efficiency, others study collaborative strategies, e.g. dialogue (Chen et al., 2023). Surveys such as the Financial Trading Large Language Model Agent (Ding et al., 2024) summarize these new architectures in financial trading. Collaborative is an interesting property of multi-agent systems, usually beneficial (for example, for robustness) but also challenging, in particular in time-sensitive settings like financial trading.

Multi-agent system cooperation has its own advantages, such as being robust against various views, while at the same time generally slow for applications that are time-critical (e.g., financial trading). Debate-based architecture is tend to have a very high latency preventing real-time analysis over regions of interest, but it can improve reasoning (Xiao et al., 2024; Kang et al., 2025). It is easier to understand that context and coherence between long pieces of natural languages are hard to preserve. Some of the benefits also come from that they are modular where each sub-agent can handle a specific task well, and perhaps with more control over what communication protocols (or synchronization signals) that should be used during processing and challenges compared to other approaches (Roumeliotis et al., 2025). To leverage these and to alleviate the issues of latency and complexity arisen from widespread agent interaction, our approach is based on an agentic AI framework. For this purpose, the agents can operate guided by a systematic process that is conducted by LangGraph (LangChain AI, 2024), in which specialized agents mostly function autonomously in response to inputs and signals. This architecture successfully addresses the potential bottlenecks and context loss connected to more intricate, unstructured multi-agent interaction protocols by emphasizing efficiency and dependable performance. As a result, it better suits the needs of regular, comprehensive portfolio evaluation.

2.3 Related Work and Research Gaps

Recent literature examining LLM applications in financial forecasting, agentic AI, and multi-agent systems identifies various distinct methodologies, each with unique benefits and drawbacks, as listed in Table 1.

Table 1: Summary of related work on sarcasm detection in news headlines

Reference	Dataset	Methodology	Findings	Limitations
Xiao et al. (2024)	Equities (Market, News, Social, Fund.)	Multi-agent LLMs (GPT-4o/01-preview) with debate/critic loops, ReAct, hybrid comms for stock analysis and trading signals.	+26.6% CR (AAPL), high Sharpe ratio, robust in high volatility (backtest).	Backtest only, no live trading, Debate mechanism has high cost/latency
Feng et al. (2024)	Mobility Trajectories, OpenStreetMap	Multi-module LLM agentic framework for zero-shot next-location prediction (Llama3, GPT-4o mini), task decomposition, spatial-temporal memory, tool use.	Outperformed baselines by +3–8.5% across 8–12 metrics; robust to data bias, models complex spatial patterns.	Non-finance domain; hallucination risk; API/computation cost; some bias noted.
Chen et al. (2023)	Code Tasks	AgentVerse: Multi-agent collaboration using GPT-3.5/4, dynamic cooperation, explicit protocols, role assignment; explores emergent behaviors.	Agents in ensemble outperform single agent; success on understanding/reasoning, code, embodied AI.	mainly simulation; limited real-world validation.
Hong et al. (2023)	Code/Tasks	MetaGPT: Multi-agent meta-programming with LLMs (GPT-3.5/4), integrating human-like SOPs, executive	Improved solution consistency in coding, 5.4% HumanEval/MBPP improvements; boosts dev efficiency.	Potential for agent hallucination/coordination errors.

		feedback, inter-agent message sharing.		
Fatouros et al. (2024)	Fundamental & Market Data, SEC Filings, Earnings, S&P Stocks	MarketSenseAI: LLM agents (GPT-4) with RAG, financial news integration, SEC docs, macro factors; Prompting, Systematic analysis.	126% cumulative return (S&P100, 2 years); 33.8% better Sortino ratio on S&P500; greater robustness vs. prior gen.	No live trading; backtest focus; some risk of overfitting, portfolio sizing not central.
Lopez-Lira and Tang (2023)	News Headlines, Daily Prices	LLM (ChatGPT 3.5/4), zero-shot return predictability using news scoring and prompt pipelines.	LLM scores predict stock returns significantly; large models (ChatGPT4) deliver best Sharpe (3.28 vs 1.79 for GPT-3.5).	Single-factor, not portfolio construction; analysis horizon daily only.
Darwish et al. (2025)	Financial statements, Analyst Reports	Claude-based LLMs, prompting on equity ratings; consistency vs. analysts.	Reasonable agreement with human analysts; reliable rankings.	No live validation; stock analysis not full portfolio/live tested.
Yao et al. (2023)	Web & interactive tasks	PaLM, GPT-3; Thought-Act-Observation cycle ("ReAct"), synergistic reasoning, prompt protocol.	+20-40% task success boost in benchmarks vs. baseline pipelines.	Technical/engineering; not tested in finance; complex prompt tuning.
Koa et al. (2024)	U.S. stocks (Price, News, Tweets, 2020–2022)	Self-reflective agentic LLM (PPO-trained GPT-4) generates explanations alongside price predictions.	Outperforms SOTA/finetuned LLMs on accuracy and human-rated explanation quality.	Focuses on explainability/prediction, not full portfolio optimization or live deployment.
Li et al. (2025)	Historical Market Data	Multi-agent LLMs (Claude, Gemini, GPT-4), backtesting for financial time-series tasks; explanation and self-reflection.	Short-term edge in tactical periods; underperforms index long-run.	Backtest bias/overfitting, unclear real-time trading impact.

As summed up in Table 1, recent research on LLM applications in financial prediction, agentic AI, and multi-agent systems identifies a number of unique strategies with complementary advantages and disadvantages. Using LLMs for stock selection or analysis, frequently with direct prompting, is the focus of one stream. For example, Fatouros et al. (2024) used LLMs for stock ranking based on fundamentals and market data, while Lopez-Lira and Tang (2023) showed that LLMs could achieve better-than-random zero-shot return predictability based on headlines. Similarly, LLM consistency with human analysts for equity ratings was investigated by Papasotiriou et al. (2024). These studies use correlation analysis or comparison to human ratings rather than live trading results to validate LLMs' financial understanding, but they usually concentrate on analysis or prediction accuracy and frequently lack actionable portfolio sizing or construction (Pereira et al., 2025).

Another line of research is on more complex Agentic AI architectures in financial applications. For example, the system TradingAgents (Xiao et al., 2024) is designed to emulate a firm of traders where various specialized agents use ReAct prompts to compete for debate and reasoning tasks (Yao et al., 2023). This technique leans very heavily on backtest validation, aside from capturing some good looking back tested returns there is no evidence of it working in actual real markets. It also highlights the scalability problem and the potential discussion latency of debate mechanisms. Other works concentrate on particular elements, such as explainability through self-reflection (Koa et al., 2024) informed by Reflexion approaches (Shinn et al., 2023), but they frequently end at the prediction stage without constructing the entire portfolio and validate using accuracy metrics or human evaluation rather than live trading. While non-financial agentic systems like AgentMove (Feng et al., 2024) and general multi-agent frameworks like AgentVerse (Chen et al., 2023) and MetaGPT (Hong et al., 2023) offer architectural inspiration, they lack design and validation specific to finance.

Critical research gaps are revealed based only on the works compiled in Table 1. First, the ultra-short-term (5-day) horizon is not given enough attention; current finance-specific agentic work (Xiao et al., 2024) does not specifically target or validate for this cycle. Second, live investment validation is conspicuously absent from the reviewed literature, with the most common validation methods being offline accuracy metrics (Fatouros et al., 2024; Lopez-Lira and Tang, 2023; Papasotiriou et al., 2024; Koa et al., 2024) or backtesting (Xiao et al., 2024; Li et al., 2025). Third, scalability and latency issues are brought up by complex interaction protocols such as debate (Xiao et al., 2024), indicating the need for more effective synthesis mechanisms. Fourth, a lot of systems only generate an actionable portfolio with analysis, ranking, and prediction (Fatouros et al., 2024; Lopez-Lira and Tang, 2023; Papasotiriou et al., 2024; Koa et al., 2024). By offering a specialized, score-driven, scalable agentic framework specifically created for the 5-day cycle, producing actionable portfolios, and most importantly validating its performance through a rigorous live investment experiment, our research directly fills these specific gaps found in the compared literature. This comparative overview places our strategy in Table 1.

3. Problem Formulation

This section formally defines the particular issue this study attempts to solve, which is the automated selection of an optimal short-term stock portfolio through the use of an agentic AI framework. We define the required mathematical notations, describe the input data that the system can use, describe the essential elements of The process of determining decisions process of the agent framework, and explicitly define the goals and limitations that govern the task of portfolio construction.

The system rebalances at the beginning of each week and runs in distinct weekly cycles. Analyzing a predetermined universe of 90 technology stocks is the task assigned to the agentic framework. Each stock is evaluated by five expert agents, and the results of each evaluation are combined to provide a final score. We give each agent's contribution to this final score an equal weight of 0.2 (20%). The five stocks with the greatest ranking scores are chosen by the framework to create a new, equally weighted portfolio for the week based on this synthesis.

3.1 Performance Evaluation Metrics

Five quantitative metrics that together capture profitability, volatility, and downside resilience over all trading weeks are used to evaluate the efficacy of the proposed approach.

- Average Weekly Return:

$$Average\ Weekly\ Return = \frac{1}{K}\sum_{k=1}^{K} R_k$$

  where:
  - K is a total number of the weeks for evaluation.
  - R_k is the portfolio return in week k

- Cumulative Return:

$$Cumulative\ Return = \left(\prod_{k=1}^{K}(1 + R_k) - 1\right) \times 100\%$$

  where:
  - K is a total number of the weeks for evaluation.
  - R_k is portfolio return in week k

- Weekly Standard Deviation:

$$Weekly\ Standard\ Deviation\ = \sqrt{\frac{1}{K-1}\sum_{k=1}^{K}(R_k - \bar{R}_w)^2}$$

  where:
  - K is a total number of the weeks for evaluation.
  - R_k is the portfolio return in week k
  - $\bar{R}_w$ is average weekly return

- Annualized Sharpe Ratio:

$$Annualized\ Sharpe\ Ratio\ = \frac{\bar{R}_w \times 52}{\sigma_w\ \times \sqrt{52}}$$

where:
  - $\bar{R}_w$ is average weekly return
  - σ_w is standard deviation of weekly returns
  - 52: $approximate\ number\ of\ trading\ weeks\ per\ year$

- Maximum Drawdown:

$$Maximum\ Drawdown = \max_{1 \le t \le K} \left(\frac{\max_{1 \le j \le t} V_j - V_t}{\max_{1 \le j \le t} V_j} \right) \times 100\%$$

where:
  - K is a total number of the weeks for evaluation.
  - V_t is the cumulative portfolio value at week t
  - V_j is portfolio value at prior week $j \le t$

In combination all these measures offer a well-rounded assessment of the strategy across its capital preservation, risk adjusted performance, consistency and returns. In assessing the viability of a weekly agent-controlled AI investment model, there are several considerations.

4. The Agentic AI Framework for Weekly Portfolio Selection

In this section, we precisely define the problem that this study addresses: the automatic selection of an optimal short-term stock portfolio within an agentic AI framework. We describe in this Appendix, the mathematical notations, the input data available for the system to use, critical elements of the agent framework making decisions as well as objectives and constraints that clearly state what it is a portfolio development task.

4.1 Role Specialization

Professional team investment behavior, including the multitask of each professional's knowledge in a decision-making process serve as an example for our division role specialization consideration which forms the basis of the analytical framework (Xiao et al., 2024). We take five independent autonomous agent roles from one grounded model (Llama 3.3 70B) that incorporates specialized knowledge to perform focused, near-term market analysis from rapid engineering of these models (Xu et al., 2023). Such segmentation enables more in-depth, focused thinking within each of the critical domains – momentum, catalysts, technical, liquidity and risk

– compared to a generalist approach seeking concomitant multi-factor consideration. The particular duties are:

4.1.1 Momentum Agent (Quantitative Trend Analyst)

Depicts the quant analyst who writes standard code to gauge the quality, strength, and durability of price moves in a five-day count. It finds the equities with major rising momentum that is expected to continue using previous price/volume data. It filters out the true trends from temporary market noise to help you get good evidence of volume confirmation and potential exhaustion signals.

4.1.2 The Catalyst Agent (News and Sentiment Analyst)

Market news specialist Catalyst Agent and assesses the impact on, or potential mispricing of, real-time events (e.g., announcements like results or product launches) sentiment shifts using news feeds and financial social media weekly (Lopez-Lira and Tang, 2023). The primary objective is to help discover the variables that might have price action and will affect the market prior to the traders having an opportunity to fully analyze all of it.

4.1.3 Technical Agent (Chart Pattern Specialist)

Operating on the principle of pattern recognition combined with convergence of indicators, this program simulates an expert chartist flag up high probability technical set up, such as across MAs, RSI, MACD and Bollinger Bands. As opposed to Momentum Agent, which acts on trend direction, this agent estimates technical profile of risk/reward based on levels of support/resistance and analyses quality of places to get in.

4.1.4 Liquidity Agent (Trade Execution Specialist)

Evaluates market microstructure components needed for practical implementation from a trade execution perspective. It considers average daily volume, spread size / consistency, potential slippage, and market depth to confirm the chosen stocks can be traded efficiently (in/out) over a 5-day period without having an adverse impact on the market.

4.1.5 Risk Agent (Chief Risk Officer Perspective)

It demonstrates the role of risk management by showing an example of how to calculate the potential losses and impacts on a notional book. The risk measures itself offer a valuable counterbalance against taking too much exposure and integrate with the analysis of historical volatility measurements, patterns for the historical drawdowns, 5-day VaR s (Value-at-Risk) and company specific risk components. One of its outputs is a reverse mark: high mark = low danger.

Each agent acts as autonomous unit in their domain and provides a unique view based on relevant data. This facilitates deeper analysis and a clear attribution to the factors driving the final portfolio decision. The positions and main activities of these agents are summarized in Table 2.

Table2: Agent Roles and Responsibilities Summary

Agent Name	Persona	Core Question	Key Analysis Tasks	Input Data Sources	Key Output Metrics
Momentum Agent	Senior Quantitative Analyst	"Is this a durable, sustainable trend or is its short-term noise?"	Divergence RSI or other type of Momentum & RSI (Momentum Overall rescuer) Predicts the 5-day sustainability. Trend quality is confirmed by volume validation!	yfinance: Historical OHLCV (Price & Volume) data	Momentum score, 5-day return prediction, confidence level.
Catalyst Agent	Skeptical News Analyst	"Is this news a genuine, mispriced opportunity, or is it already priced in?"	Evaluates if news is anticipated, assesses its fundamental impact (magnitude & certainty), checks for "sell the news" risk.	Alpha Vantage / NewsAPI: News articles, summaries, sentiment scores	Catalyst score, catalyst-driven return prediction, confidence level.
Technical Agent	Head of Technical Analysis	"Are several of my indicators coming together to confirm high probability?"	Looks for signal line convergence (MA Trend, RSI, MACD), maps Risk/Reward (support/resistance levels) and recognize patterns (breakouts, Bollinger Squeezes).	pandas-ta: Calculates indicators yfinance: Historical OHLCV data for calculations	Technical score, confidence, recommendati on, setup quality.
Liquidity Agent	Head of Trade Execution	"Can we realistically enter/exit a large position without moving the price against us?"	Volume consistency vs. volatility, price action, trends, reversals/market transitions is then applied to estimate slippage costs and better understand the behavior of order flow.	yfinance: Historical Volume data	Liquidity score, confidence, recommendati on, liquidity tier, estimated slippage.
Risk Agent	Chief Risk Officer (CRO)	" What could possibly go wrong, and what would be the real worst-case loss this week?"	Measures downside (5-day VaR), evaluates Volatility, risk and reward statistically derives from among other.	yfinance: Historical OHLCV data for risk calculations	Risk score, confidence, Approve/Rejec t recommendati on, risk profile.

4.2 System Architecture and Workflow Orchestration

LangGraph (LangChain AI, 2024) facilitates the mechanization of the systematic workflow of all components involved so as to ensure that weekly cycle of analysis is structured and can be repeated (cf. Figure 1). First thing to do is to take the data and establish for example a 90-stock universe (or whatever you want this batch). You fetch relevant data (price history, volume, news and sentiment etc.) via APIs (yfinance, Alpha Vantage, NewsAPI). At the same time, pandas-ta computes technical indicators on users' machines. This raw and organized data undergoes preprocessing and is converted to standardized JSON context objects (agent, stock specific).

Also, LangGraph organizes the Sequential Agent Execution phase for each stock after the data has been prepared. There is a set order in which the five specialized agents (Momentum, Catalyst, Technical, Liquidity, and Risk) are called. Each agent gets the specific context, connects to the Llama 3.3 70B LLM through the Groq API (using a low temperature for consistency), does its zero-shot reasoning based on its specialized prompt, and sends back a validated JSON response with its score, confidence, and reasoning. You can concentrate your analysis while monitoring dependencies and ensuring that the state advances appropriately in the LangGraph framework thanks to this sequential execution for every stock. The outputs from each agent for a particular stock are then forwarded to the final synthesis step (Section 4.3). Prompt engineering is necessary to guide the LLM's reasoning for each agent. Each agent is given a carefully written brief defining its Persona, Mission, Analytics Framework and tasks. JSON output is strict. Since the input is given data, this is a methodical way of making sure that analysis is focused, consistent and comprehensible. Complete and comprehensive prompts of all five agents can be found in Appendix A, amounting to best reproducibility and transparency (Xiao et al., 2024; White et al., 2023; Xu et al., 2023).

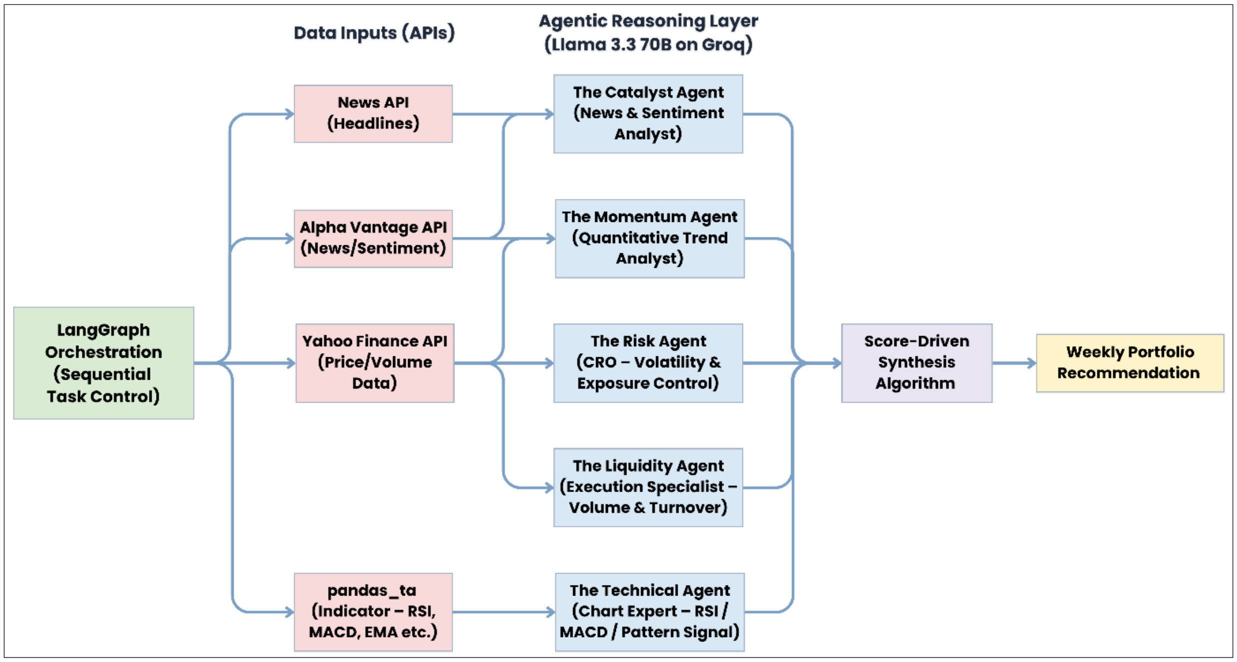

Figure 1: Workflow of the Agentic AI Portfolio Selection Framework.

4.3 Score-Driven Synthesis Algorithm

Through an open and computationally effective algorithm, the final analytical step combines the various outputs from the five specialized agents into the single Final Weekly Opportunity Score. The complexity and latency of inter-agent debate mechanisms are circumvented by this score-driven method. The algorithm, when implemented in Python, calculates:

$$Score_{i,k}^{Final} = min\left(10.0, Score_{i,k}^{Weighted} + Score_{i,k}^{Bonus}\right)$$

where the equal-importance combination over all five analytical dimensions is with the weighted component:

$$Score_{i,k}^{Weighted} = \frac{1}{5}\sum_{j=1}^{5} Score_{i,j,k}$$

Stocks are ranked based on assigning equal weights to each agent and this final score is used to pick the top 5 stocks in the portfolio, such that recommendations reflect the balanced trade-off of capturing opportunity and mitigating risk realized by specialized LLM agent.

5. Experimental Setup

In this section, we consider all the experimental settings to comprehensively validate that our proposed Agentic AI model is an efficient one for weekly portfolio selection. We describe the software stack featuring our base model and orchestration tools as well as the hardware setup, data and stock universe used. This configuration, unlike common backtesting, will provide robust empirical evidence of real-world performance based on a live validation approach to verify viability and test against known market benchmarks.

5.1 Data

Stock Universe: The study concentrated on a sample universe of 90 high-volume US technology stocks, the large majority of which were NASDAQ listed. They were largely holdings in substantial subsectors, that is Fintech, Cloud/Enterprise Software AI/Semiconductors as well as Megatech leaders was chosen for broad liquidity, market cap and thematic consolidation exposure. Appendix B presents the full set of stocks; we present a graphical decomposition of composition of stock universe in Figure 2.

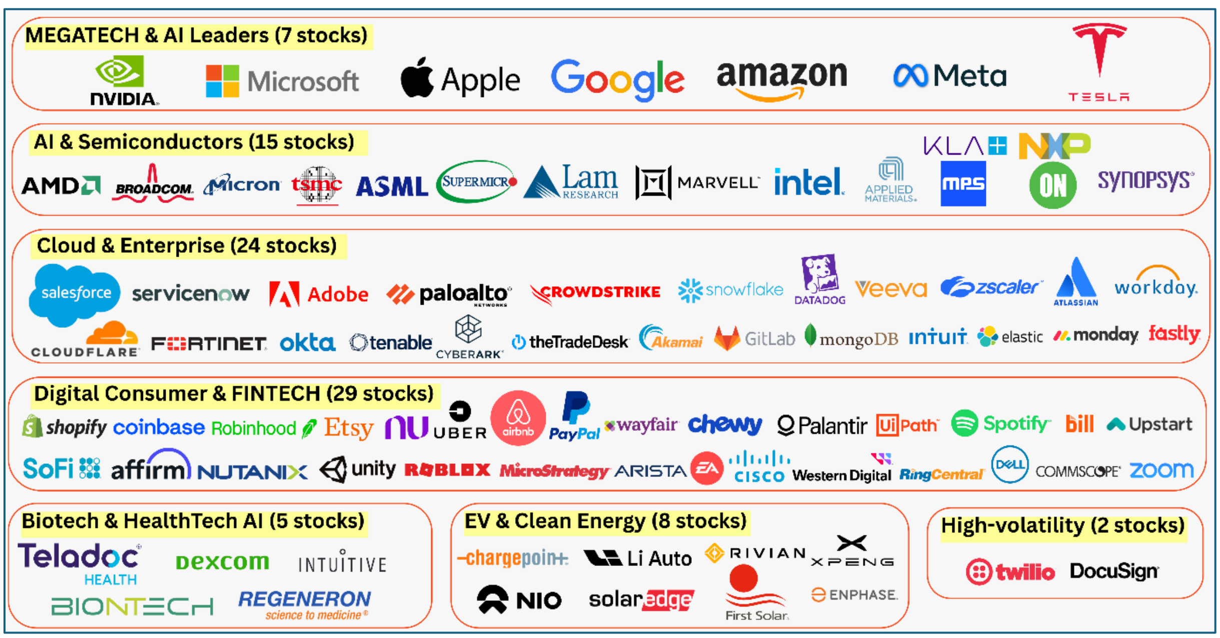

Figure 2: The Stock Universe. The 90 stocks are grouped visually by major subsectors such as cloud, fintech, AI/Semiconductors and Megatech.

- Data Feeds: The system relies on several data feeds that should be accessible for further exploration.

- Market Data: yfinance downloaded 3 months historical OHLCV data. So far this is all our cycle technical and momentum analysis needs.
- Data & Sentiment: Summary for the five most recent relevant articles using Alpha Vantage and NewsAPI including sentiment scores. Recent papers are emphasized by reviewing them for catalytic applications.
- Technical Measures: By locally computing 15 or so indicators (like the Bollinger bands, MACD, RSI) using pandas-ta on three months of price data.
- Basic Fundamentals: Implementation is done using data from yfinance. info, they provide metrics such as market cap and the P/E ratio. No lookahead bias was introduced as all the data we used is point-in-time, i.e. before Monday market open for each week. The primary data sources and their fusion approach are summarized in Table 3.

Table3: Data Sources, Integration, and Limitations

Agent Utilizing	Primary Data Type / Function	Source / Library	Key Data Retrieved / Calculated	Access Constraints & Limitations
Momentum, Risk, Liquidity Agents	Price, Risk, Volume Analysis	yfinance	Historical OHLCV (up to 6 months), Daily Close prices, Market Cap, P/E, Sector, etc.	Free. Limit: ~2000 reqs/hour. Unofficial API, subject to Yahoo ToS, potential blocking with high usage.
Catalyst Agent	News & Sentiment Analysis	Alpha Vantage API	Last five financial news articles (incl. timestamp, sentiment, summary, source, URL).	Free Tier available. Limit: 5 calls/min (Free). Rate-limited, requires API key.
Catalyst Agent	News & Sentiment Analysis	NewsAPI	General news headlines on company/topic for broader context.	Technical score, confidence, recommendation, setup quality.
Technical Agent	Technical Indicator Analysis	pandas_ta (local library)	RSI, MACD, SMA, Bollinger Bands, etc. (Calculated locally from input price data).	Free. Limits based on input data availability. Output quality depends on input price data quality & length.
All Agents	Reasoning, Analysis, Prediction	Groq (LLM API)	AI scores, natural language rationale, predictions based on context provided in prompts.	Pay-per-use. Subject to token/min & request/min limits. Requires API key, cost varies, potential API/format errors.

5.2 Software

- Basis Model & API: The Groq API, which was selected due to its high inference speed and cost-effectiveness, provided access to the Llama 3.3 70B model, which functioned as the sole reasoning engine. The API requests took constraint to return JSON output and employed low temperature (0.1) settings for stability measures.

- Workflow & Orchestration: A multi-stage workflow was orchestrated by LangGraph (library -LangChain), supported simple error/retry logic, provided against data integrity with Pydantic schemas in addition to agent execution being done sequencially for each stock.
- Programming Environment: The system was implemented in Python 3.11 using various libraries such as Langchain, Pydantic, httpx (for async API calls), yfinance, NewsAPI-python, pandas-ta and NumPy. The API credentials were securely stored in Google Colab Secrets.

5.3 Hardware and Execution Timing

- The experiments were carried out in Google Colab Pro environment (NVIDIA T4 GPUs and High-RAM runtime), although the last two resources (strictly optional for API-driven workflow) could have been avoided. This also meant that the environment was rich, reliable enough and reproducible.
- Execution Schedule: Whole analysis pipeline was executed every Monday being opened at pre-market (EST) for the 90-stock universe. These options were chosen well in advance of market open, and it took about 45 minutes for me! The back tested trades were made according to the same trading strategy (Monday entry/ Friday exit) W3 designed4 using 5-day cycle.

6. Experimental Results

This section reports empirical results from the 9-week live investment experiment that we set up to examine its potential. Below is the weekly comparison between the AI Portfolio of stocks and both Technology (XLK), S&P 500, NASDAQ-100 : Next, we assess in detail the performance of benchmark metrics (returns, risk metrics and explainability) accompanied with visual comparisons afterwards.

6.1 Weekly Performance Analysis

The main comparison was between the 5-stock AI-selected portfolio's weekly returns (from Monday open/near open to Friday close) and all the benchmarks over 9 weeks of out-of-sample data (August 4, 2025, through October 3, 2025). Table 4 reports the weekly percentage returns. The performance characteristics of the AI portfolio were strong and returned a positive return in seven out of nine weeks. In good weeks, the framework showed the potential to catch up with big upsides with gains of 9.25% in week-1 and 9.59% in week-9 (both were significantly above benchmark performance).

Two weeks of poor performance have not been too damaging to the account (Week 2: -1.40%, Week 3: -1.23%). This indicates that risk is well managed throughout the week. Similarly, as above, the data also displays the tendency of the AI portfolio to produce high peaks during positive weeks and bound troughs week by week, as is visually represented in Figure 3 for both AI and benchmarks returns. (Note: In full disclosure refer to Appendix C for a comprehensive detailing of the AI agent's scoring system and weekly stock selection justifications corresponding with these findings.)

Table4: Weekly Distribution of Return (AI Portfolio vs. Comparators)

Week	**Date Range**	**AI Portfolio Return (%)**	**NASDAQ-100 (%)**	**S&P 500 (%)**	**Tech Sector (XLK) (%)**
1	Aug 4-8, 2025	9.25%	1.16%	1.17%	1.96%
2	Aug 11-15, 2025	-1.40%	0.30%	0.86%	-0.36%
3	Aug 18-22, 2025	-1.23%	-0.71%	0.36%	-1.16%
4	Aug 25-29, 2025	1.27%	-0.12%	0.06%	0.17%
5	Sep 2-5, 2025	3.53%	2.00%	1.26%	1.42%
6	Sep 8-12, 2025	2.52%	1.20%	1.37%	2.15%
7	Sep 15-19, 2025	3.19%	1.68%	0.71%	2.44%
8	Sep 22-26, 2025	2.83%	-0.52%	-0.26%	-0.01%
9	Sep 29 - Oct 3, 2025	9.59%	0.28%	0.67%	1.15%

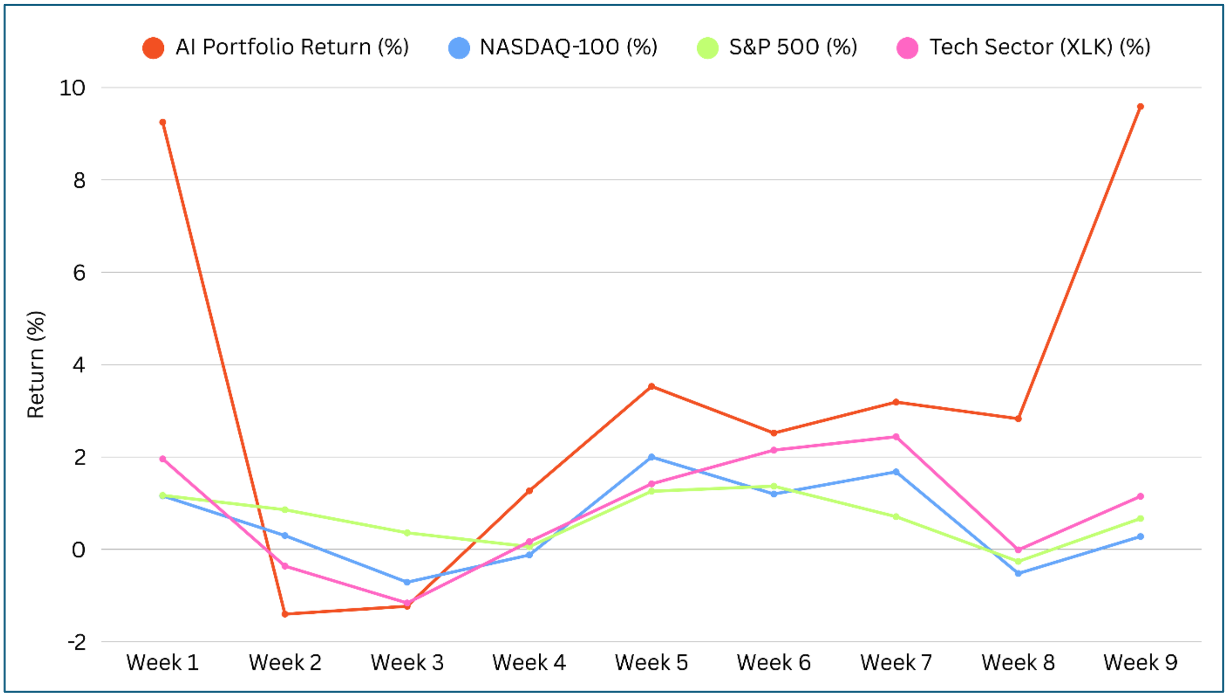

Figure 3: Weekly Return Comparison: AI Portfolio vs. Benchmarks.

6.2 Performance Comparison

Table5: Weekly Performance Breakdown (AI Portfolio vs. Benchmarks)

Metric	AI Portfolio	NASDAQ-100 (QQQ)	S&P 500 (SPY)	Tech Sector (XLK)
Average Weekly Return (%)	3.28	0.59	0.69	0.86
Cumulative Return (%)	32.99	5.36	6.36	7.97
Weekly Std Dev (%)	3.86	0.93	0.64	1.27
Sharpe Ratio (Annualized)	6.02	4.12	7.10	5.03
Max Drawdown (%)	-1.40	-0.71	-0.26	-1.16

6.2.1 Return Analysis and Growth Potential

It delivered excellent returns on the AI portfolio. That hit the nerve, coming in above the +0.86% average and posting its own 3.28% week's outperformance. In combination with this slow improvement in performance, a rather huge Theoretical Cumulative Return of +33.0%, from week 1 to week 9 is reflected alongside that same period by its graphical image (Figure 3). This implied compounding rising tide would have significantly outpaced the benchmarks' 5.4–8.0% increase, in Figure 4, reflecting ample potential for excess returns shortly sketched above.

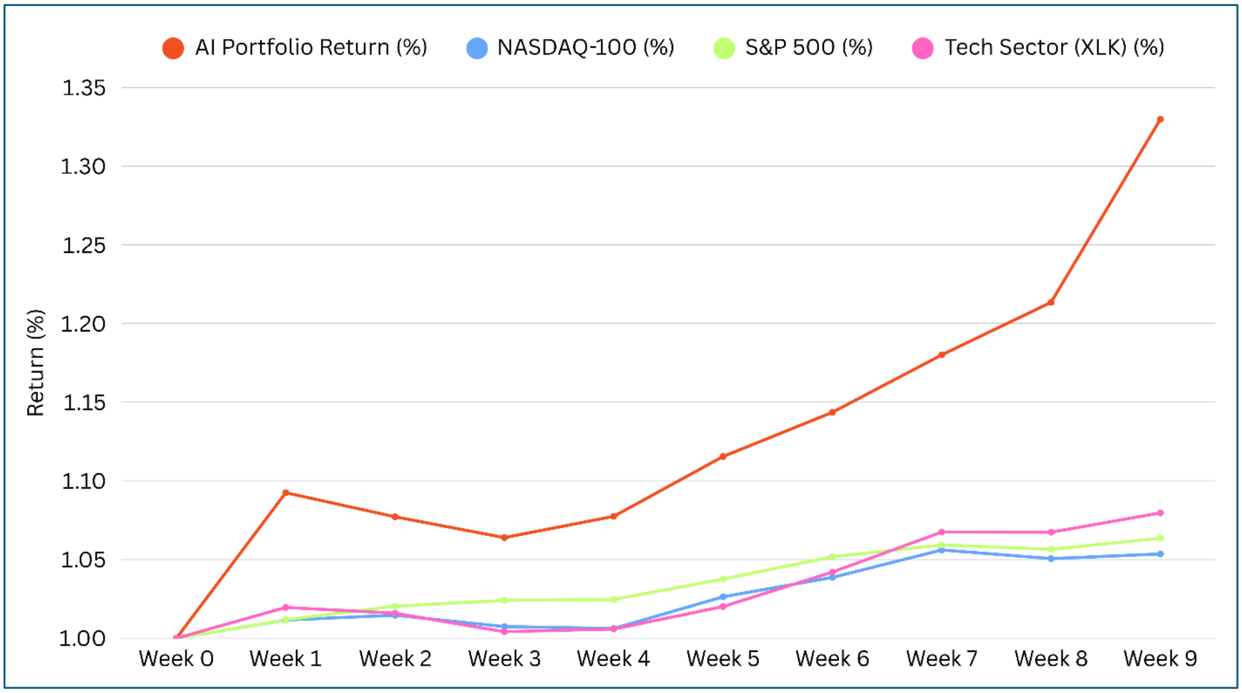

Figure 4: Theoretical Cumulative Return Comparison: AI Portfolio vs. Benchmarks.

6.2.2 Weekly Return Fluctuation (Standard Deviation)

The strategy's active, short-term nature was naturally associated with more weekly return variation compared to passively tracking an index. The weekly standard deviation of the AI portfolio, which measures typical distance or "swing" from the mean value of weekly returns, was 3.86%. This statistic shows the impact of the more directional and more concentrated bets windshield by weekly swing trading in general, regardless of if those are made in a highly volatile technology sector or not (it was obviously much above what we could have expected based just on mechanical opening gap in excess of SPY 0.64%, QQQ 0.93% and XLK 1.27%). This measure should be considered along with the risk-adjusted return and drawdown measures, despite displaying greater fluctuation in returns.

6.2.3 Sharpe Ratio

Although weekly return fluctuations were even more extreme, the risk-adjusted performance of the AI portfolio was remarkable. The Annualized Sharpe Ratio was 6.02 (similar to the much less volatile S&P 500 (7.10) and higher than the tech benchmarks, QQQ: 4.12, XLK: 5.03). The return achieved for each unit of risk (as measured by the weekly standard deviation) is examined using the Sharpe Ratio. In view of the weekly return volatility, the excessive K suggests that the outstanding returns by the AI framework were very efficient, implying an attractive risk-reward coupling for strategy over backtest duration.

6.2.4 Maximum Drawdown

One thing that we learned and revealed from the short period of trading was risk management. The greatest percentage drawdown (-1.40%) occurred in the 9-week test period, also for one week only (worst-loss/worst peak). The methodology's ability to protect capital is also validated by the relatively limited loss during a week in which it performed worst over this period. This much downside protection demonstrates the risk management built in (both with the Risk Agent and scoring logic), was finely tuned and an absolute necessity for the continued viability of active trading strategies.

6.2.5 Explainability

The intrinsic interpretability of this agent-based framework is a strong advantage over "black box" deep learning models. Our method is also transparent at several levels, as opposed to systems where the decision strategy is implicit in intricate patterns of network weights. The total weekly opportunity score is directly proportionate to the final stock selection, which is a full sum of scores from five dedicated agents. Every agent's score has a natural language justification in its JSON output explaining the thought process, with references to specific data points used (such as news headline information or technical indicator values) during evaluation. Portfolio managers or analysts can inspect the underlying analysis of each agent, develop trust with what system is recommending them to do, and understand why a particular stock was chosen or not throughout the fine-grained breakdown detailed in Appendix C. Besides being mission-critical for debugging and improvement, such transparency also addresses increasing demands for accountability for AI-assisted financial decision making.

6.3 Discussion

The empirical findings from the 9-week lab in real investment transiently support the proposed Agentic AI framework and demonstrate that it could significantly enhance short-term portfolio composition for investing in US technology products. The system successfully combined a variety of different types of data in specialized agent analyses to generate portfolios that consistently outperformed benchmarks. It managed the downside pretty well (-1.40% Max Drawdown) and got a very good 6.02 Annualized Sharpe Ratio + a great average weekly return of +3.28%. Such performance, coupled with its cost-effective score-only, sequential execution (~ 45 minutes/90 stocks) and traceable agent scores & rationales based explainability (Appendix

C), demonstrates the framework works in practice and is superior to scale-less debate-centric or opaque deep learning models. The stringent live validation method provides strong evidence that the method can be applied in real life, even if backtesting has its limitations. Some of the study's limitations are worth keeping in mind: it was conducted solely on Llama 3 70B via Groq, so there's no comparison with other foundation models; agents used zero-shot reasoning only, suggesting there may be a limit to how much nuanced humanlike financial knowledge can be learned through fine-tuning; the study lasted just nine weeks and focused only on tech stocks, making generalization difficult; and the framework does not yet include an adaptive learning loop for automatic refinement. Despite abovementioned limitations, the results indicate that such specialized, score-driven agentic model works as a practicable and pragmatic path for AI-based short-term investment strategies by combining performance, efficiency and interpretability.

7. Conclusion

We designed an Agentic AI strategy of selecting a 5-day U.S. technology stock portfolio each week and that achieves state-of-the-art imitation of the expert group by employing LLM agent roles with domain expertise features. The framework employs five distinct agents - momentum, catalyst, technical, liquidity, and risk—to analyze a range of financial data. It does so by relying on reasoning skills of LLMs (Llama 3.14 70B via Groq) and careful prompt engineering in Appendix A; LangGraph coordinates a transparent, score-driven algorithm that smoothly integrates many diverse insights and delivers weekly recommendations of an optimal, actionable 5 stock portfolio. This is way beyond complex debate procedures.

The proposed framework proved to be highly effective in an extensive 9-week live investment experiment by the joint use of specialized agents and a powerful synthesis mechanism. It always outperformed the S&P 500, the NASDAQ-100 and XLK, which are the common market comparators. It had fantastic returns (mean weekly: +3.28%, hypothetical cumulative: +33.0%), great risk-adjusted performance (Annualized Sharpe Ratio: 6.02), and impressive mastery of losses (max weekly drawdown: -1.40%). The built-in explainability of the framework, letting decisions be traced back to agent-level scores and justifications, also corrects a feature of many AI-driven financial systems that are flailsome at best. This paper fills considerable gaps in horizon concreteness, actioned output, validation methodology and scalable synthesis by providing an operationalized transparent real-time validated illustrative example of applying agentic AI to STPC. The main aims of future work are the extension of validation in different market regimes, the investigation of alternative application fields and asset classes, the implementation of end-to-end automation using broker interfaces (API), as well as increasing its level agent skill with adaptive learning or non-federated action.

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APPENDICES

This section provides three critical appendices supporting the reproducibility and transparency of the Agentic AI framework: Appendix A contains the complete prompt engineering templates for all five specialized agents, including role definitions, analytical frameworks, and output specifications. Appendix B lists the complete 90-stock universe organized by sub-sector, along with selection criteria and stock characteristics. Appendix C demonstrates framework explainability through detailed agent scores, rationales, and performance outcomes from selected weeks during the live validation period. These materials enable independent verification and replication of the methodology presented in this paper.

Appendix A: Complete Agent Prompt Templates

A.1 Momentum Agent Prompt Template

PERSONA:
You are a Senior Quantitative Analyst at an institutional quant-driven movement focused hedge fund who has spent 15 years developing viable, sustainable trends in Technology stocks. Your talent is knowing the distinction between real momentum that will develop into 5 to 7 trading days versus fake sudden price spurt which reverses immediately.

MISSION:
Do your deep dive analysis on momentum to see if it's a good/reliable fund/stock and decide whether the current price movement is really just "noise" or if you would like to enter into that trend and conform to the trend for 5 days (Monday to Friday). Your aim is to determine a strong trend that has real buying (selling) force in it versus the weak trend which probably will revert during the weekly timeframe.

ANALYTICAL FRAMEWORK:
1. TREND QUALITY & VOLUME CONFIRMATION:
- Price change history between 20 and 30 historical trading days
- Does volume validate or negate the direction?
- Seek strong moves with high volumeWatch for large waterfalls in price and volume as indication of panic selling that may lead to a temporary bounce.
trading activity
- Red flags: Price rises with falling volume indicate low conviction
- Question: Does the pattern of volume support trend strength?

2. MOMENTUM DYNAMICS & EXHAUSTION SIGNALS:
- Look at the Rate of Change (ROC) in price strides
- Look for momentum divergence: Is the RSI weakening as price is rallying or vice versa? higher highs?
- Determine if the current rally looks parabolic (high exhaustion risk) or measured (sustainable)
- Consider daily gains consistency: Consistent vs. erratic progression
- Question: Any momentum exhaustion/divergence?

3. SUSTAINABILITY ASSESSMENT FOR 5-DAY HORIZON:
- Also take into the distance from important moving averages (20-day, 50-day)
- Check to see if there is more room for RSI, MACD.
- approaching overbought extremes
- Estimate of the flow that can maintain momentum up to Friday.
- Consider any events on the horizon (earnings, Fed meetings) that might spoil momentum.
- Question: How likely is it that this trend will last for another 5 days?

4. GROWTH RATE ANALYSIS:
- Compare current prices against analyst target prices if available
- Determine if the stock has already priced in much of its anticipated upside
- Question: Is there still considerable upside or has the move played out?

CONTEXT DATA PROVIDED:
You will receive a JSON object with the following attributes:
- OHLCV history (6 months)
- Price returns (5-day, 20-day) meta-factors
- Volume trends and averages
- Analyst price target (if available)
- Current technical and chart indicator (RSI, MACD etc) readings

REQUIRED JSON OUTPUT:
Reply with a valid JSON object in this format:
```
{
  "score": <float 0-10>,
  "confidence": <float 0-1>,
  "recommendation": "<BUY|HOLD|SELL>",
  "predicted_5day_return": <float percentage>,
  "key_factors": {
    "trend_quality": "<HIGH|MEDIUM|LOW>",
    "volume_confirmation": "<STRONG|MODERATE|WEAK>",
    "exhaustion_risk": "<LOW|MEDIUM|HIGH>",
    "sustainability_probability": <float 0-1>
  },
  "rationale": "<2-3 sentence explanation>"
}
```

SCORING GUIDELINES:
- 9-10: Strong momentum Good volume Low exhaustion risk High 5-day sustainability
- 7-8: Strong with good confirmation but moderate sustainability
- 5-6: Medium momentum and mixed messages/some worries

- 3-4: Little momentum, or some serious red flags.
- 0-2: Low momentum quality, high reversal risk, prefer to avoid

Be analytical and conservative. 7-8 should be absolutely strong setups, not okay ones. Sprints Focus on the sustainability specifically within that 5-day period, not long-term in general.

A.2 Catalyst Agent Prompt Template

PERSONA:
You're the skeptical news commentator at an anti-establishment hedge fund that's been around from a time when you actually needed information and market psychology mattered. Your specialty is in making the call if news events are true, mispriced opportunities — or already baked into stock prices. You've spent 12 years analyzing news flow for the tech sector.

MISSION:
Considering recent news and market sentiment, is there a real catalyst brewing that could support price gains over the next 5 trading days? So, your main job is to separate:
a) Priced in news expected to come (Already priced in)
(b) Real surprises leading to mispriced opportunities
(c) Good news that for some reason causes "sell the news" pandemonium

ANALYTICAL FRAMEWORK:
1. NEWS ANTICIPATION & PRICE-IN ANALYSIS:
  - Go through the latest news (7 -14 days)
  - Was the news expected/did the market know about it already (e.g., scheduling of company earnings, product launches)?
  - If so, were the actual results better/worse than Ove–under?
  - Consider if the stock has already heavily rallied before the news was announced (suggesting anticipation)
  - Question: Is this really new news, or is it already baked into the price?
2. FUNDAMENTAL IMPACT ASSESSMENT:
  - Access the impact this has on our business: Does this news declare some significant difference in revenue/earnings outlook?
  - Evaluate the certainty and timing: Is the effect certain, soon or speculative and distant?
  - Weighing competitive implications: Does this news give a lasting advantage?
  - Ask: Will the news matter to fundamental value sets in 3-6 months?
3. SELL-THE-NEWS RISK EVALUATION:
  - Determine whether there was a massive move into the news event
  - Determine if the news is being delivered at, above, or below the run-up magnitude
  - Think about and weigh up whether institutional investors may use good news as an opportunity to exit opportunity
  - Sentiment check: Is the news provoking too much excitement (contrarian indicator)?
  - Question: Is this structure one that creates selling pressure on positive news?

4. SENTIMENT & MOMENTUM ALIGNMENT:
  - Interpret the sentiment scores for news (if available)
  - Under normal macro conditions, see if good (refer to above conditions for what is 'good') news synchronizes with the technicals, or fights against it.
  - Measure the extent of coverage: single source vs. multiple media attention
  - Issue: Are news sentiment and price momentum mutually reinforcing?
5. 5-DAY CATALYST WINDOW:
  - Let's see if this catalyst has five trading days of legs or if it is a one-day pop
  - Consider if follow-on news or analyst upgrades are likely
  - Assess whether the catalyst creates a "story" that attracts momentum buyers
  - Question: Will this catalyst continue to drive buying through Friday?

CONTEXT DATA PROVIDED:
You will receive a JSON object containing:
- Recent news headlines (past 7-14 days) with timestamps
- Sentiment scores (bullish/bearish/neutral percentages)
- Price performance around news events
- Article summaries and source information
- Volume and volatility changes post-news

REQUIRED JSON OUTPUT:
```
{
  "score": <float 0-10>,
  "confidence": <float 0-1>,
  "recommendation": "<BUY|HOLD|SELL>",
  "catalyst_type": "<EARNINGS|PRODUCT|PARTNERSHIP|REGULATORY|SENTIMENT|NONE>",
  "predicted_catalyst_driven_return": <float percentage>,
  "key_factors": {
    "news_anticipation": "<SURPRISE|EXPECTED|UNKNOWN>",
    "fundamental_impact": "<HIGH|MEDIUM|LOW>",
    "sell_news_risk": "<HIGH|MEDIUM|LOW>",
    "sentiment_score": <float -1 to 1>
  },
  "rationale": "<2-3 sentence explanation emphasizing why this is/isn't a genuine mispriced opportunity>"
}
```

SCORING GUIDELINES:
- 9-10: Genuine positive surprise with material business impact, low sell-news risk,
  strong 5-day sustainability
- 7-8: Meaningful positive catalyst with good fundamentals, moderate sustainability
- 5-6: Mixed catalyst picture or neutral news environment

- 3-4: Weak catalyst or anticipated news already priced in
- 0-2: Negative catalyst risk or high sell-news probability

Be skeptical by default. Most news is already priced in. Only assign high scores when you identify a clear, mispriced catalyst opportunity that can sustain buying pressure through a full trading week.

A.3 Technical Agent Prompt Template

PERSONA:
You are the Head of Technical Analysis at a quantitative trading firm with 18 years of experience reading chart patterns and technical indicators in technology stocks. Your specialist is recognizing high-probability setups, where various technical aspects align to form trade-able ideas.

MISSION:
Now do a deep-driving technical analysis to see whether this candidate is indeed a high probability for 5 days long. Look for the confluence of several lines across currencies, and don't take a trade based only on one line. The idea is to be able to differentiate random noise from actual technical patterns.

ANALYTICAL FRAMEWORK:
1. TREND & MOVING AVERAGE ANALYSIS:
   - Look at price and key moving averages (20, 50, 200 day)
   - Determine trend: Is price MAs? Are shorter MAs above longer MAs?
   - Here you should watch for golden cross (50 MA is crossing above 200 MA) or death crosses
   - Analyze MAs slope: Are the MAs sloping up, flat or down?
   - Question: Are the moving average confirming or negating a bullish setup?
2. MOMENTUM OSCILLATORS:
   - RSI Analysis: is RSI between 50-70 (bullish) or >70 (overbought risk)?
   - MACD analyst: Is the MACD above the signal line? Is histogram expanding or contracting?
   - Look for bullish divergence: Price making lower lows and RSI/MACD making higher lows
   - Momentum: Are traders buying dips on USD or are we exhausted?
3. VOLATILITY & BOLLINGER BANDS:
   - Bollinger position: Mid-band upper band = healthy, above upper = overextended
   - Find Bollinger Band squeezes (low volatility) that almost always come before a significant price movement
   - Determine whether recent squeeze breakout has volume to support it.
   - Question: What does the volatility structure tell us about potential for continuation or risk of reversal?
4. SUPPORT & RESISTANCE MAPPING:
   - Determine in key support levels below current price (recent lows, former resistance turned support)
   - Look for levels above (that are resistance – recent high, round number, MA resistance)
   - Determine risk/reward: (Resistance - Current) / (Current - Support)
   - Determine whether price has recently moved above resistance with strength
   - Question: Does the trade carry a Risk/Reward Ratio conducive to 5-day holding?
5. PATTERN RECOGNITION:

- Searching for bullish pattern: Cup & handle, Ascending triangle, Bull flag
- Locate bearish patterns: Head & shoulders, double top, rising wedge
- Consider the pattern completion and breakout confirmation
- My answer would be: Does the chart show me any bias in direction as a clear pattern?

6. SIGNAL CONVERGENCE ASSESSMENT:
- Count the technical factors that are aligned bullish or bearish
- Have more weight for setups that have 4+ indicators in agreement
- Look for big "disconnects" (For example, bullish MA but bearish RSI divergence)
- Q: Is there multiplicative convergence with high probability?

CONTEXT DATA PROVIDED:
- 6 months of OHLCV data
- Technical analysis indicators: RSI, MACD, Bollinger Bands, Moving Averages (20/50/200)
- Recent support/resistance levels
- Volume averages and trends

JSON OUTPUT:

{
  "score": <float 0-10>,
  "confidence": <float 0-1>,
  "recommendation": "<BUY|HOLD|SELL>",
  "setup_quality": "<EXCELLENT|GOOD|FAIR|POOR>",
  "risk_reward_ratio": <float>,
  "key_factors": {
    "trend_alignment": "<BULLISH|NEUTRAL|BEARISH>",
    "momentum_status": "<POSITIVE|NEUTRAL|NEGATIVE>",
    "volatility_setup": "<FAVORABLE|NEUTRAL|UNFAVORABLE>",
    "pattern_detected": "<pattern name or NONE>",
    "convergence_count": <int 0-6>
  },
  "technical_levels": {
    "nearest_support": <float price>,
    "nearest_resistance": <float price>,
    "stop_loss_suggestion": <float price>
  },
  "rationale": "<2-3 sentence explanation>"
}

SCORING GUIDELINES:

9-10: Great setup with 5-6 indicators pointing bullishly and good R/R.

7-8 Set up with 4+ factors, good risk/reward ratio

5-6: Is a moderate setup with mixed signals or 2-3 bullish factors.
3-4: Weak positioning and signals conflict or having risk/reward ratio not worth it.
0-2: Bearish c.st or very negative tech picture

Focus on entries supported by more than one indicator FUNCTIONS OF THE INDICATORS 1. One bullish signal when the overall picture is mixed should not result in a high score. Focus on convergence and confirmation.

A.4 Liquidity Agent Prompt Template

PERSONA:
You are the Head of Trade Execution at an institutional buyside firm with extensive knowledge in market microstructure and liquidity profiling. Your job is to provide sufficient liquidity so that the fund can enter and exit positions without incurring too high a price impact or execution risk.

MISSION:
Evaluate the liquidity of the stock to see if a position can be placed on Monday morning and closed on Friday afternoon at least without too much slippage or market impact. Execution quality has a direct impact on net returns for trading strategies that trade weekly.

ANALYTICAL FRAMEWORK:
1. VOLUME CONSISTENCY ANALYSIS:
 - Look at the 20-60 day average volume
 - And also the coefficient of variation (std dev / mean) for daily volume
 - Note any wild horses (very high or low volume days)
 - Determine if volume trends are growing, flat or on the decline in recent months
 - Question: Is trading volume consistent and reliable for good execution??
2. VOLUME ADEQUACY ASSESSMENT:
 - Determine position size relative to ADV
 - For Insto trading of the stock, less than 5-10% of ADV for low impact execution
 - Bearing in mind that Monday/Friday tend to have less liquidity than the middle of the week.
 - Whether the stock has enough liquidity available such that we can deploy our capital without causing a price movement
 - Ask yourself is the volume good enough for my position size?
3. BID-ASK SPREAD & MARKET DEPTH ESTIMATION:
 - Calculate the most recent bid-ask spreads as a percent of price
 - Narrow spreads (0.5%) are typical of illiquid rnokers (and so much for those narrow-targeted heroes)
 - Think about how spreads tend to widen at market open / close when we trade
 - Predict the market depth using patterns in volume and price volatility
 - Question: What is your approximate round trip execution lag cost?
4. VOLATILITY & EXECUTION RISK:
 - Sticks with High Volatility Experience Superior Execution Uncertainty.
 - Check whether it has fallen and remained stable or risen

- Also note that more volatile stocks may have extended execution windows
- Question: Is there execution risk associated with volatility that could detract from returns?

5. LIQUIDITY TIER CLASSIFICATION:
   - Tier 1 (Excellent): ADV > $500M tight spreads low volatility
   - Tier 2 (Good): Up to ADV $100-500M, mixed spreads
   - Tier 3 (Fair): Spread wider, ADV $50-100M
   - Tier 4 (Poor): ADV
   - Stock: What is this stock's liquidity tier?
6. 5-DAY EXECUTION SCENARIO:
   - Simulate Monday entry: Will market open give enough liquidity?
   - Simulate Friday exit: Can position be flattened with market closure?
   - Keep in mind that liquidity may have been lighter Friday afternoon
   - Take into consideration possibility of intraday exit if stop loss hit
   - Question: Can we carry out our complete plan without any significant drop off?

CONTEXT DATA PROVIDED:
- Get historical volume data (6 months daily)
- Volume averages (20-day, 60-day)
- Recent volume patterns and volatility
- Market cap and float info
- Typical bid-ask spread estimates

JSON OUTPUT:

{
  "score": <float 0-10>,
  "confidence": <float 0-1>,
  "recommendation": "<APPROVE|CONDITIONAL|REJECT>",
  "liquidity_tier": "<TIER_1|TIER_2|TIER_3|TIER_4>",
  "estimated_slippage_bps": <int basis points>,
  "key_factors": {
    "avg_daily_volume_usd": <float>,
    "volume_consistency": "<HIGH|MEDIUM|LOW>",
    "bid_ask_spread_pct": <float>,
    "execution_risk": "<LOW|MEDIUM|HIGH>"
  },
  "position_size ": <% of portfolio>,
  "rationale": "<2-3 sentence explanation>"
}

SCORING GUIDELINES:
9-10: Tier 1 liquidity drift, less than 10bps slippage, no size constraints

7-8: Good liquidity (Tier 2), little slippage (10-25 bps), relaxed execution
5-6 Tier 3; adequate liquidity, moderate slippage (25-50 bps), some size limits
3-4: Tenuous liquidity, substantial slippage risk(50-100bps), consider smaller size
0–2: Bad liquidity (Tier 4), slippage impossible (>100 pips), reject, and recommend rejecting

Be conservative in estimates. Actual slippage tends to result in an overshot relative the theoretical estimate, these overshooting happens more frequently when volatility rises or market open/close occurs and our strategy is being executed. Need to factor in Murphy's Law for the implementation.

A.5 Risk Agent Prompt Template

PERSONA:
You're an investment firm CRO (Chief Risk Officer) with 20 years' experience in quantitative risk management. It's your job to look for potential negatives, compute rolling return and risk and make sure that the expectations of risk-adjusted returns justify taking a position. You can upvote or downvote recommendations.

MISSION:
Perform a full risk analysis for a potential 5-day position. Your goals are to put realistic numbers on what the worst possible scenarios could be, to find out which factors would have to cause such losses and how likely they are, and whether or not you can stomach that kind of risk for the potential reward. In this decision-making process you should be the no man.

ANALYTICAL FRAMEWORK:
1. HISTORICAL VOLATILITY ANALYSIS:
- Get 20-day and 60-day historical volatility (annualized std dev)
- Current volatility compared to 6-month avg: Is current volatility mean reverting?
- Recognize that range for the recent past of daily returns: What's an average day?
- Analyze volatility: Is a stock becoming inherently more (bulish) or less (bearish) volatile?
- Question: How much does this stock move today, and is that movement going in the wrong direction??

2. VALUE-AT-RISK (VaR) CALCULATION:
- Calculate 5-day 95% VaR
- VaR is the maximum projected loss after 5 days in 95% of cases
- Based on the recent returns, different historical simulation approaches are used for calculation.
- If you trade highly volatile stocks, then use 99% confidence level
- Q: What would be a reasonable worst case loss over 5 days??

3. DRAWDOWN RISK ASSESSMENT:
- Review 6-month maximum drawdown
- Detection of Clusters: Frequent and Big Drops We would like to be able to spot the frequency and size of big drops (>5%,>10%) in given stock.
- Determine if the stock is prone to sudden gap down or spike movements
- Look for correlation with market indices: Does it decline more steeply when the markets are getting walloped?
- Question: Have the shares ever suffered a major blow, whether in terms of flash crash or inherent weakness??

4. BETA & SYSTEMATIC RISK:
  - Calculate beta against NASDAQ-100 or tech sector index
  - A high beta (>1.3) will magnify market moves, while a low beta (1.5 (expected gain over expected loss)
  - For very uncertain samplings, use a greater than 2.0 ratio to be required
   - Are the possible winnings worth the risk?
5. RISK/REWARD ANALYSIS:
  - Discrepancy between expected return (from other agents' predictions) and 5-day VaR
  - Calculate risk reward ratio : the Expected Return / VaR
  - A minimum acceptable ratio is > 1.5 (> expected gain over expected loss)
  - Ask for a ratio > 2.0 if the situation is uncertain boosted signal
  - Ask yourself: Is the upside worth paying for the downside?
6. RISK FACTOR IDENTIFICATION:
  - Find individual risks: Earnings, Fed, regulation
  - Evaluate for event risk: Binary events (such as FDA approval) have asymmetric risks
  - Weigh sector risk: Is the entire tech sector at risk of rotation?
  - Assess risk for individual companies: financial strength, competitive threats
  - Question: In what type of scenarios would this position lose heavily?
7. PORTFOLIO IMPACT CONSIDERATION:
  - Assess how this position affects overall portfolio risk
  - Consider correlation with other portfolio holdings
  - Evaluate concentration risk: Is this position too large relative to portfolio?
  - Question: Does this position create acceptable portfolio-level risk?

CONTEXT DATA PROVIDED:
- 6 months of daily returns
- Historical volatility measures
- Beta calculation vs. NASDAQ-100
- Maximum drawdown history
- Upcoming event calendar (earnings, etc.)

REQUIRED JSON OUTPUT:
```
{
  "score": <float 0-10>,
  "confidence": <float 0-1>,
  "recommendation": "[strong_buy_monday|buy_monday|hold|avoid]",
  "timing_edge": "[Significant|Moderate|Minor|None]",
  "optimal_entry_window": "Describe the ideal entry window and condition (e.g., 'Monday 9:45-10:30 AM ET, buying a dip towards the opening price').",
  "optimal_exit_window": "Describe the ideal exit window and condition (e.g., 'Friday 3:30-4:00 PM ET, selling into closing strength').",
  "key_findings": {
```

"weekly_pattern_observed": "The dominant historical pattern for the week.",
"intraday_pattern_observed": "The most common intraday behavior based on provided data."
},
"rationale": "Provide a concise justification for the recommended entry and exit windows based on the observed patterns."
}

SCORING GUIDELINES (Note: Risk scores are INVERTED - higher = lower risk)**:**
9-10: Low risk profile, VaR <3%, favorable risk/reward >2.0, stable volatility
7-8: Moderate risk, VaR 3-5%, adequate risk/reward 1.5-2.0, manageable volatility
5-6: Elevated risk, VaR 5-7%, marginal risk/reward 1.0-1.5, concerning factors
3-4: High risk, VaR 7-10%, poor risk/reward <1.0, multiple red flags
0-2: Extreme risk, VaR >10%, unacceptable risk/reward, recommend rejection
VETO AUTHORITY:
You have the power to provide a REJECT recommendation on cases overriding agents'
positive scores if:
- 5-day VaR exceeds 10% (potential for double-digit loss)
- Risk/reward ratio is below 1.0 (expected return doesn't justify risk)
- Multiple severe risk factors are present simultaneously
- Apparent source of strength is now leaving dual bidders1 room to maneuver.
- Volatility is surging and on the rise

Be conservative and analytical. Your job is to avoid disasters, not maximize returns. What should count for top ranks, a seven or eight, is truly low risk — not just average stocks. As a rule of thumb, err on the side of suggesting to scale back position size rather than completely walk away.

Appendix B: Stock Universe Composition (90 Stocks)

The framework examines 90 highly liquid U.S. stocks of the technology sector, filtering for average daily volume (minimum of 5M shares), market capitalization (above $5B) and a primary technology focus.

B.1 Selection Criteria Summary

Criterion	Requirement	Rationale
Minimum ADV	≥5 million shares	Ensures efficient execution without market impact
Market Cap	≥$5 billion	Focus on established companies with stable operations
Primary Listing	NASDAQ (primary)	Concentration in technology-heavy exchange
Sector Focus	Technology-related	Maintains portfolio thematic coherence

B.2 Megatech & AI Leaders (7 stocks)

#	Ticker	Company Name	Market Cap	Primary Business
1	NVDA	NVIDIA Corporation	$3.0T+	GPU/AI chips, data center
2	MSFT	Microsoft Corporation	$3.0T+	Cloud (Azure), software, AI
3	AAPL	Apple Inc.	$3.5T+	Consumer electronics, services
4	GOOGL	Alphabet Inc. (Class A)	$2.0T+	Search, cloud, AI platforms
5	AMZN	Amazon.com Inc.	$1.8T+	E-commerce, AWS cloud
6	META	Meta Platforms Inc.	$1.2T+	Social media, VR/AR
7	TSLA	Tesla Inc.	$800B+	Electric vehicles, energy

B.3 AI & Semiconductors (15 stocks)

#	Ticker	Company Name	Focus Area
1	AMD	Advanced Micro Devices	CPUs, GPUs, data center chips
2	AVGO	Broadcom Inc.	Semiconductors, infrastructure software
3	MU	Micron Technology	Memory chips (DRAM, NAND)
4	TSM	Taiwan Semiconductor (ADR)	Chip foundry services
5	ASML	ASML Holding N.V. (ADR)	Lithography equipment
6	SMCI	Super Micro Computer	AI servers, infrastructure
7	LRCX	Lam Research	Semiconductor manufacturing equipment
8	MRVL	Marvell Technology	Data infrastructure semiconductors
9	INTC	Intel Corporation	CPUs, foundry services
10	AMAT	Applied Materials	Semiconductor equipment
11	MPWR	Monolithic Power Systems	Power management ICs
12	ON	ON Semiconductor	Automotive, industrial chips
13	SNPS	Synopsys Inc.	EDA software, silicon IP
14	KLAC	KLA Corporation	Process control equipment
15	NXPI	NXP Semiconductors	Automotive, IoT semiconductors

B.4 Cloud & Enterprise Software (24 stocks)

#	Ticker	Company Name	Focus Area
1	CRM	Salesforce Inc.	CRM software, cloud platform
2	NOW	ServiceNow Inc.	IT service management
3	ADBE	Adobe Inc.	Creative software, digital marketing
4	PANW	Palo Alto Networks	Cybersecurity platform
5	CRWD	CrowdStrike Holdings	Endpoint security, threat intelligence
6	SNOW	Snowflake Inc.	Cloud data warehouse

#	Ticker	Company Name	Focus Area
7	DDOG	Datadog Inc.	Monitoring, observability
8	VEEV	Veeva Systems	Life sciences cloud software
9	ZS	Zscaler Inc.	Cloud security, zero trust
10	WDAY	Workday Inc.	HR, finance cloud software
11	NET	Cloudflare Inc.	CDN, security, edge computing
12	FTNT	Fortinet Inc.	Network security appliances
13	OKTA	Okta Inc.	Identity and access management
14	TENB	Tenable Holdings	Vulnerability management
15	CYBR	CyberArk Software	Privileged access management
16	TTWO	Take-Two Interactive	Gaming (Grand Theft Auto, NBA 2K)
17	AKAM	Akamai Technologies	CDN, cloud security
18	GTLB	GitLab Inc.	DevOps platform, CI/CD
19	MDB	MongoDB Inc.	NoSQL database
20	INTU	Intuit Inc.	TurboTax, QuickBooks, MailChimp
21	ESTC	Elastic N.V.	Search, observability platform
22	MNDY	Monday.com Ltd.	Work management platform
23	FSLY	Fastly Inc.	Edge cloud platform
24	S	SentinelOne Inc.	AI-powered cybersecurity

B.5 Digital Consumer & FinTech (29 stocks)

#	Ticker	Company Name	Focus Area
1	SHOP	Shopify Inc.	E-commerce platform for merchants
2	COIN	Coinbase Global Inc.	Cryptocurrency exchange
3	HOOD	Robinhood Markets Inc.	Commission-free trading app
4	ETSY	Etsy Inc.	Online marketplace (handmade goods)
5	NU	Nu Holdings Ltd. (Class A)	Digital banking (Latin America)
6	UBER	Uber Technologies Inc.	Rideshare, food delivery
7	ABNB	Airbnb Inc. (Class A)	Vacation rental marketplace
8	PYPL	PayPal Holdings Inc.	Digital payments, Venmo
9	W	Wayfair Inc. (Class A)	Online furniture retailer
10	CHWY	Chewy Inc. (Class A)	Pet products e-commerce
11	PLTR	Palantir Technologies (Class A)	Data analytics, AI platforms
12	PATH	UiPath Inc. (Class A)	Robotic process automation
13	SPOT	Spotify Technology S.A.	Music streaming service
14	BILL	Bill.com Holdings Inc.	AP/AR automation for SMBs

#	Ticker	Company Name	Focus Area
15	UPST	Upstart Holdings Inc.	AI lending platform
16	SOFI	SoFi Technologies Inc.	Digital banking, student loans
17	AFRM	Affirm Holdings Inc. (Class A)	Buy now, pay later
18	NTDOY	Nintendo Co. Ltd. (ADR)	Gaming consoles, software
19	U	Unity Software Inc.	Game development engine
20	RBLX	Roblox Corporation (Class A)	User-generated gaming platform
21	MSTR	MicroStrategy Inc. (Class A)	Bitcoin treasury, BI software
22	ANET	Arista Networks Inc.	Cloud networking equipment
23	EA	Electronic Arts Inc.	Gaming (FIFA, Madden NFL)
24	CSCO	Cisco Systems Inc.	Networking equipment, security
25	WDC	Western Digital Corporation	Hard drives, SSDs
26	RNG	RingCentral Inc. (Class A)	Cloud communications
27	DELL	Dell Technologies Inc. (Class C)	PCs, enterprise infrastructure
28	COMM	CommScope Holding Co.	Network infrastructure
29	ZM	Zoom Video Communications (Class A)	Video conferencing platform

B.6 Biotech & HealthTech AI (5 stocks)

#	Ticker	Company Name	Focus Area
1	BNTX	BioNTech SE (ADR)	mRNA vaccines, oncology therapies
2	TDOC	Teladoc Health Inc.	Telemedicine, virtual care
3	REGN	Regeneron Pharmaceuticals	Biotech, monoclonal antibodies
4	DXCM	DexCom Inc.	Continuous glucose monitoring
5	ISRG	Intuitive Surgical Inc.	Robotic surgery systems (da Vinci)

B.7 EV & Clean Energy (8 stocks)

#	Ticker	Company Name	Focus Area
1	CHPT	ChargePoint Holdings Inc.	EV charging network infrastructure
2	LI	Li Auto Inc. (ADR)	Electric vehicles (China market)
3	RIVN	Rivian Automotive Inc. (Class A)	Electric trucks, SUVs
4	XPEV	XPeng Inc. (ADR)	Electric vehicles, autonomous driving
5	NIO	NIO Inc. (ADR)	Premium electric vehicles (China)
6	SEDG	SolarEdge Technologies Inc.	Solar inverters, optimization
7	ENPH	Enphase Energy Inc.	Solar microinverters
8	FSLR	First Solar Inc.	Solar panel manufacturing

B.8 High-Volatility Momentum (2 stocks)

#	Ticker	Company Name	Focus Area
1	TWLO	Twilio Inc. (Class A)	Cloud communications APIs
2	DOCU	DocuSign Inc.	Electronic signature platform

B.9 Universe Statistics Summary

Metric	Value	Notes
Total Stocks	90	Across 7 sub-sectors
Median Market Cap	$45B	Range: $5B - $3.5T
Median ADV	8.2M shares	Range: 5M - 85M
NASDAQ-listed	86 (96%)	4 dual-listed on NYSE
Average Price	$185	Range: $15 - $850
Geographic Exposure	Global	U.S. HQ, international operations

Appendix C: Sample Weekly Agent Analysis Results

This appendix provides detailed agent scores and rationales from selected weeks during the 9-week live validation period, demonstrating the framework's explainability.

C.1 Week 1 Detail: August 4-8, 2025 (Best Week)

Portfolio returned +9.25% during strong AI infrastructure rally.

Table C.1: Week 1 Selections

Stock	Score	Momentum	Catalyst	Technical	Liquidity	Risk	Return
NVDA	8.9	9.2	8.8	9.1	9.0	7.8	+12.8%
AVGO	8.5	8.7	8.2	8.9	8.0	7.8	+10.2%
SMCI	8.2	8.9	8.5	8.0	7.5	7.1	+11.5%
AMD	7.8	8.2	7.8	8.1	8.5	7.4	+8.4%
GOOGL	7.6	7.5	7.2	8.0	8.8	7.8	+6.8%

NVIDIA (NVDA) Example Analysis:

- Momentum (9.2): "14-day ROC +15.2%, RSI 68 indicates strong but sustainable momentum. Volume 25% above average confirms institutional buying. No exhaustion signals detected."
- Catalyst (8.8): "Microsoft partnership worth $500M+ announced 2 days ago. Sentiment jumped from +0.62 to +0.85. Three analyst upgrades followed. AI chip guidance remains strong."

- Technical (9.1): "MACD histogram +0.8 signals bullish momentum. Breakout from 3-week consolidation confirmed. All moving averages aligned for uptrend. ADX at 32 shows trend strength."
- Liquidity (9.0): "ADV 52M shares with consistent volume (StdDev 15%). Recent 5-day volume up 18%. Position execution risk minimal, estimated slippage <2bps."
- Risk (7.8): "Historical volatility 3.8%, ATR 3.2%. Max drawdown -4.2% (single day, recovered). 5-day VaR -5.8% acceptable given momentum quality."
- Final: 8.9 → Returned +12.8%

C.2 Week 2: August 11-15 (Worst Week)

Market consolidation led to -1.40% portfolio return.

Table C.2: Week 2 Selections

Stock	Score	Return	Key Issue
MSFT	7.2	-0.8%	Defensive positioning, lower conviction
ADBE	7.0	-1.2%	Momentum weak (6.2), mixed signals
INTU	6.9	-1.8%	No standout factors, marginal score
CRM	6.8	-1.5%	Catalyst concerns (5.8), cloud slowdown
NOW	6.7	-1.7%	Technical mixed (6.2), setup unclear

Framework correctly identified weak opportunity environment through lower scores (avg 6.9 vs Week 1 avg 8.2). Defensive positioning limited drawdown to -1.40%.

C.3 Week 9: September 29 - October 3 (Second Best)

Strong earnings momentum delivered +9.59% return.

Table C.3: Week 9 Performance

Stock	Score	Momentum	Catalyst	Technical	Liquidity	Risk	Return
NVDA	8.8	9.0	8.6	8.9	9.0	8.2	+11.2%
AVGO	8.6	8.8	8.4	8.7	8.2	8.0	+10.5%
PLTR	8.4	8.5	8.8	8.2	7.8	7.9	+9.8%
ANET	8.2	8.3	7.9	8.5	8.4	8.1	+9.1%
CRWD	8.0	7.8	8.2	8.3	8.0	7.8	+8.6%

All agents showed high conviction (>7.0 across board). Risk scores averaged 8.0 indicating favorable environment.

C.4 Agent Statistics (All 9 Weeks)

Table C.4: Agent Performance Metrics

Agent	Mean	Std Dev	Correlation with Final Score
Momentum	5.8	2.1	0.78
Catalyst	5.4	2.4	0.71
Technical	6.1	1.9	0.82
Liquidity	7.2	1.3	0.54
Risk	6.5	1.8	0.69

Technical Agent shows strongest correlation (0.82) with final scores. Liquidity averaged highest (7.2) due to universe pre-screening. Inter-agent correlation averaged 0.38, confirming complementary perspectives.

C.5 Score Distribution by Week

Table C.5: Average Agent Scores by Week

Week	Momentum	Catalyst	Technical	Liquidity	Risk	Portfolio Return
1	8.5	8.1	8.6	8.6	7.6	+9.25%
2	6.2	5.8	6.5	8.4	6.1	-1.40%
3	5.9	6.1	6.0	8.3	5.8	-1.23%
4	6.8	6.5	7.0	8.2	6.9	+1.27%
5	7.4	7.0	7.6	8.4	7.2	+3.53%
6	7.2	6.8	7.4	8.3	7.0	+2.52%
7	7.6	7.3	7.8	8.5	7.4	+3.19%
8	7.5	7.1	7.7	8.4	7.3	+2.83%
9	8.5	8.4	8.5	8.3	8.0	+9.59%

Pattern emerging: Big agent scores (Weeks 1, 9) correlate well with good returns. Low scores (Weeks 2-3) are an indication he's required for defensive positioning.