Self-Adapting Financial Agents: Evolution Through Feedback-Driven Meta-Prompt Optimization

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Figure 1: Institutional affiliations

ABSTRACT

Traditional quantitative and deep-learning trading systems are brittle under regime shifts, rely on homogeneous numerical inputs, and often provide limited interpretability. Large Language Models (LLMs) broaden the information scope, through multi-modality capabilities, yet are usually deployed with static prompts, leaving the adaptability problem unresolved. We propose a modular framework for self-adapting LLM-powered agents that integrates (1) a time-aware retrieval-augmented memory, (2) a structured bull-bear debate for deliberative reasoning, and (3) Feedback-Driven Meta-Prompt Optimization (FBPO) that evolves the agent policy from quantitative and qualitative performance feedback through a gradient-free reinforcement-learning approach. The trading task is formalised as a partially observable Markov decision process and evaluated on daily equity data for Apple (AAPL), Amazon (AMZN), and Netflix (NFLX) from 2019 to 2025. Our backtesting results reveal a critical trade-off between reasoning complexity and trading performance. While the full, multi-component architecture proved overly conservative, systematic ablation studies identified the essential drivers of profitability. Disabling the FBPO feedback loop caused performance to collapse (cumulative return of −8.83%), confirming that learning from outcomes is fundamental. In contrast, removing the deliberative debate module produced the most robust configuration, delivering positive alpha against a passive benchmark on AMZN (6.54%) with a maximum drawdown of only 2.93%. This simplified adaptive agent also outperformed a non-adaptive static-prompt baseline by nearly 6 percentage points in cumulative return. Further proving the importance of the adaptive components. The proposed framework provides a blueprint for building robust, interpretable, and genuinely adaptive agents that can navigate dynamic open-world environments by focusing on targeted, feedback-driven learning.

KEYWORDS

Large Language Models, Financial Trading, Adaptive Agents, Meta-Prompt Optimization, Reinforcement Learning, Retrieval-Augmented Generation, Multi-Agent Systems

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1 INTRODUCTION

The recent development of Large Language Models (LLMs) has achieved remarkable results in various natural language processing tasks. The transformer architecture models [1] excel at pattern recognition in high-dimensional textual data and exhibit reasoning capabilities that extend beyond their original training objectives [2]. These models allow for the generation of coherent and contextually relevant text which has led to their use in translation, summarization and question-answering tasks [3]. However, the sophisticated features of these models enable them to perform outside natural language processing domains for decision-making applications. Complex reasoning and nuanced reasoning of these models, now, as they experience increasing performance capabilities, enable their application to solve complex real-world problems including financial trading.

Traditional financial trading systems base their core foundation on quantitative and rule-based approaches [4]. These systems demonstrate inadequate adaptability as they fail to respond well to changes in market conditions [5]. Machine learning (ML) models try to improve their price forecasting abilities through historical data analysis by training on a vast amount of data. However, these models often struggle to generalize well to unseen data and fail to adapt to new market conditions [6]. While online learning techniques, such as Deep Reinforcement Learning (DRL), have been proposed to address this issue, they often lack interpretability and robustness. The complexity of these models makes it difficult to understand their decision-making processes, which is crucial in the financial domain where transparency and trust are key factors. Lastly, traditional methods demonstrate an inability to effectively combine multiple data types, including textual, sound and visual data, which are relevant to model financial markets [6].

The recent emergence of LLM-powered agents shows strong potential to solve these problems [7, 8]. The models achieve detailed reasoning capabilities through their training on extensive datasets [9]. The Transformer architecture built into these models [1] enables them to handle multiple data formats including, numerical time-series as well as textual data feeds, which helps them detect complex market dynamics that traditional numerical-based methods cannot [10]. The initial deployment of LLMs for autonomous financial trading, however, faces ongoing challenges as the experience limited adaptability for the dynamic nature of financial markets. Most LLM implementations lack the capabilities of online learning as they use static prompts or rigid designs

[8]. Retraining the models on new data is often computationally expensive and time-consuming.

The research presents and evaluates an innovative modular and self-adapting LLM-powered financial trading agents framework, as depicted in Figure 2. The process begins with an environment state update (s_{t+1}), which provides the latest market and portfolio data to the system. This information is processed by a multi-agent data pipeline designed to enhance the adaptability of LLMs in dynamic environments. The framework includes a Time-Aware Procedural Memory module, a multi-agent debate protocol, and an innovative Feedback-Driven Meta-Prompt Optimization (FBPO) strategy.

The Time-Aware Procedural Memory module functions as an adaptive procedural memory system that maintains all historical trading activities. Based on the synthesised information from the data agent pipeline, a query (q_t) is generated to retrieve relevant past experiences from the procedural memory, resulting in the output $O_{mem,t}$. This time-decay retrieval method selects the most crucial recent historical data to aid present decision-making.

The multi-agent debate protocol aims to improve reasoning capabilities by allowing agents to present opposing or supportive positions for a specified number of rounds (N_{rounds}). This method performs extensive evaluations of potential strategies before selecting the final choice to detect both risks and opportunities.

Lastly, the Feedback-Driven Meta-Prompt Optimization (FBPO) strategy is a novel approach that employs reinforced optimization cycles to modify prompt templates. The system learns from performance outcomes, which are evaluated by computing a feedback signal ($F_{signal,k}$), and enhances its internal heuristics and decision-making logic dynamically based on market fluctuations and recognized biases. The research evaluates these components in a simulated trading environment by measuring their individual and combined performance.

The system reaches lifetime learning potential through feedback-driven optimization and historical trading experience retrieval which enables autonomous market condition adaptation. The system is designed to excel in dynamic and complex environments through its designed iterative adaptation process where stationary approaches often prove to fail.

The FBPO mechanism is framed as implementing a policy search [11] over the space of prompts within a hidden-markov decision process [12], where performance feedback guides the evolutionary search towards higher-reward prompt configurations. The conceptual foundation enables our adaptive method to be positioned among general optimization principles.

To understand the unique properties defined in this architecture, this research addresses the following central question: **To what extent do the architectural components of a novel, self-adapting agent framework, specifically Feedback-Driven Meta-Prompt Optimization (FBPO), time-aware memory and multi-agent debate, contribute to adaptive behavior and trading performance in dynamic financial markets?** To answer this question, our research is guided by several sub-questions. First, we establish a performance baseline against traditional rule-based, Deep Learning (DL) and Deep Reinforcement Learning (DRL) approaches. Second, we conduct extensive ablation studies to isolate and quantify the individual contributions of the FBPO, Time-Aware Procedural Memory, and multi-agent debate components. Importantly, we address the question of latent-space bias by evaluating the framework's performance across out-of-sample data beyond the training cut-off date of the core Large Language Model (LLM), which is crucial for assessing the adaptability of the agents in unseen market conditions. Finally, and most critically, we investigate how the framework's performance generalizes across different underlying LLMs, revealing that the choice of model introduces a powerful, inherent bias that can be a dominant factor in an agent's success or failure.

The research makes three key contributions through (1) the development of Feedback-Driven Meta-Prompt Optimization (FBPO) as a gradient-free method which enables reinforced adaptation of LLM trading agent behavior through performance feedback, (2) a modular framework that integrates Time-Aware Procedural Memory for contextual memory functions with a multi-agent debate protocol to boost reasoning capabilities for adaptive financial agents, and (3) extensive empirical evidence shows that an LLM's inherent "architectural bias" is a dominant factor in agent performance which often overrides the framework's logic.

The research investigates daily frequency trading using numerical price and textual data yet the modular framework enables analysis of different domains and data modalities. The framework demonstrates its potential to solve complex decision-making problems in open-domains, such as supply chain management and healthcare resource allocation. The scalability of the system requires attention to the computational costs of standard LLM calls particularly for FBPO loop and multi-agent debate operations. The rapid progress of state-of-the-art LLMs in efficiency and decreasing inference costs during the last few years [13] makes adaptive systems more practical.

The remainder of this paper is organised as follows. Section 2 reviews the evolution from traditional quantitative trading models to modern LLM-based agents, identifying the research gaps our work addresses. Section 3 details our proposed framework, including its POMDP formulation, the multi-agent data pipeline, the Time-Aware Procedural Memory module, the multi-agent debate protocol, and the core FBPO mechanism. Section 4 describes the experimental design, covering data sources, evaluation metrics, benchmark models, and the specific configurations used to test our hypotheses. Section 5 presents the empirical findings, where we first establish baseline performance against benchmarks, then conduct extensive ablation studies to isolate the contributions of each architectural component. We follow this with cross-asset and temporal bias tests to assess robustness, and an analysis of how different underlying LLMs affect agent behaviour. Section 6 synthesises these results, discussing their implications and acknowledging the study's limitations. Finally, Section 7 summarises our key contributions and suggests directions for future research.

2 LITERATURE REVIEW

The Transformer architecture, introduced by Vaswani et al. [1], has been pivotal in advancing Large Language Models (LLMs) by providing a more efficient mechanism for processing sequential

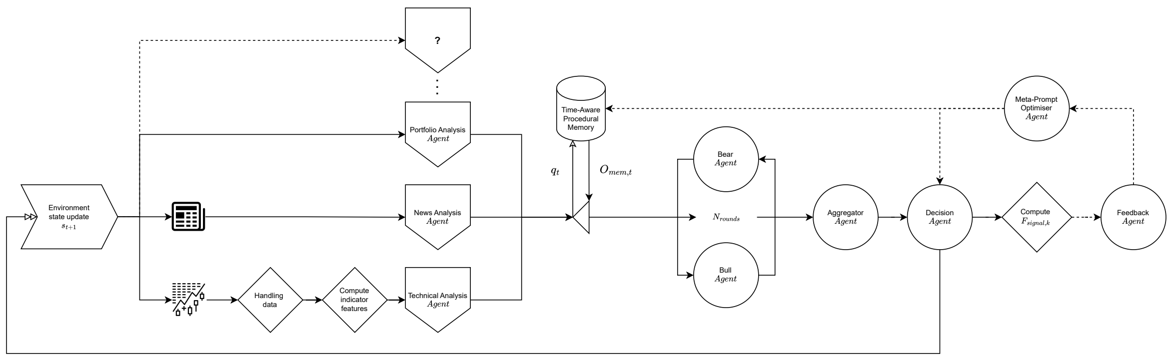

Figure 2: An overview of the self-adapting agent framework. The system is designed as a closed-loop system that continuously learns and adapts from its interactions with the environment. The framework is composed of several specialised agents that work together to analyse data, make trading decisions, and reflect on their performance.

data. This innovative architecture outperformed Recurrent Neural Networks (RNNs) [14] and Convolutional Neural Networks (CNNs) [15]. It handles text dependencies more effectively and addresses the vanishing gradient problem, which initially limited these networks' ability to model long-range dependencies. The self-attention mechanism, combined with parallelization, enabled more efficient training on large datasets. This combination resulted in substantial performance enhancements across various natural language processing tasks. The introduction of scaling laws by Kaplan et al. [16] demonstrated a positive correlation between increasing model size, dataset volume, computational budget, and improved performance. The discovery of these scaling laws has driven the development of progressively larger and more capable models, beginning with BERT's 340 million parameters [17] and extending to Kimi K2's 1 trillion parameters [18].

Subsequent developments focused on enhancing architectural designs alongside training methodologies. The performance of the model exhibited a clear relation with scale. However, changes in architecture and enhancements in training efficiency also yielded significant breakthroughs. The advancement of attention optimizations has led to the emergence of FlashAttention [19], Grouped-Query Attention [20], Multi-Query Attention [21], Sliding Window Attention [22], and Rotary Positional Embeddings (RoPE) [23]. The advancements in attention optimizations facilitated the development of larger, more efficient models that produced text with improved accuracy and speed. Additionally, the introduction of Supervised Fine-Tuning (SFT) of instruction datasets [24] has emerged as a regular post-training procedure, since it improves the model's capacity to adhere to instructions and align with user intent. This development signifies the start of LLM-powered assistants.

Reinforcement Learning from Human Feedback (RLHF) introduced by Ouyang et al. [24] further improved the capabilities of these models by allowing them to learn from human feedback and improve their responses over time. However, despite the apparent dominance of scaling laws driving towards increasingly larger models, a significant counter-trend emerged, focusing on the development of smaller, highly efficient models. This shift came from several key factors. One being the prohibitive computational cost and latency associated with deploying massive models amplified by the metrics tokens per second (TPS) and time to first token (TTFT). Secondly the growing emphasis on task-specific optimization where smaller models can excel, and the realization that sophisticated alignment techniques (like SFT and RLHF) combined with high-quality datasets can enable smaller models to achieve remarkable performance without massive parameter counts. This shift is exemplified by the introduction of models like the Gemma-3 series [25]. Models employing these techniques demonstrate the potential to achieve high performance with fewer parameters, often by emphasizing data quality over sheer quantity, making them more accessible for a wider range of applications on less powerful hardware.

The rapid development of LLMs required reliable evaluation methods due to increasingly larger parameter counts and extensive training datasets. The evaluation of diverse capabilities including, natural language understanding and complex reasoning, as well as knowledge recall, became possible through standardized benchmarks such as GLUE [26], SuperGLUE [27], MMLU [28], and HELM [29]. The performance of models on these benchmarks showed continuous improvement as they scaled up, while recent generations even achieved better results on particular tasks within these suites [30] than average human performance. The advancement went beyond just scale increases as Mixture of Experts (MoE) [31, 32] architectural innovations enabled a key breakthrough in efficient scaling. The MoE system allows networks to scale computation more efficiently by choosing which parts (the so-called experts) to activate for each input, thus enabling larger effective parameter counts without increasing inference computational cost proportionally. The combination of breakthroughs with data curation and scaling, led to LLMs achieving human-level performance across an increasing number of standardized tests, which further demonstrated their advancing capabilities in complex cognitive tasks.

The advanced reasoning and in-context learning capabilities presented new possibilities for using LLMs on complex open-ended problems that extend beyond traditional natural language processing tasks. Agents, which operate in dynamic environments, are entities that explore new skills through autonomous adaptation without requiring human intervention. Voyager [33] shows this new direction by showing an LLM-powered agent that demonstrates lifelong learning in the open-ended Minecraft [34] environment. Voyager uses autonomous exploration to develop a set of skills by interacting with its environment and creating self-generated feedback loops that include code execution to discover new information.

Financial markets, which is an example of an open-world environment, have experienced substantial development in modeling approaches by moving away from traditional quantitative models and adopting more sophisticated machine learning techniques. According to the Efficient Market Hypothesis (EMH), which Fama [35] proposed, financial markets function efficiently when asset prices incorporate all accessible information. The theory has resulted in the development of models that aim to predict future price movements based on increasingly more diverse and large data sources.

Traditionally, financial trading systems relied on quantitative models, such as technical analysis systems, which use historical price patterns and statistical models such as ARIMA and GARCH [36–38] for time series forecasting. However, these traditional models face difficulties with non-stationarity and multiple data sources which restricts their ability to easily adapt to market changes or adhere to the Efficient Market Hypothesis. These models exhibit therefore regidity which makes them less useful when dealing with the dynamic and complex nature of financial markets. For example, the ARIMA model assumes linearity and stationarity which may not be true in real world financial data. Additionally, GARCH models are limited by their dependence on historical volatility patterns which can change rapidly in response to market events. These limitations make it difficult for traditional models to capture the complex relationships between different data sources and to adapt to constantly changing market conditions.

The need to overcome these limitations led researchers to introduce machine learning applications in finance through their work with neural networks for forecasting, as demonstrated by noa [39]. Deep (reinforcement) learning (DL/DRL) models have been proposed to improve price forecasting abilities by analyzing historical data and learning patterns from large datasets. These models, such as Long Short-Term Memory (LSTM) networks [40], have shown promise in capturing complex relationships in financial data. However, they often struggle to generalize well to unseen data and fail to adapt to new market conditions, which is crucial for effective trading strategies. The complexity of these models also makes it difficult to understand their decision-making processes, which is essential in the financial domain where transparency and trust are key factors.

Powerful LLMs have revolutionized the financial sector by leveraging their natural language processing (NLP) capabilities to extract valuable features from text. One such model, FinBERT [41], was developed and trained specifically on financial corpora to enhance the understanding of financial language, thereby improving sentiment analysis of news articles, social media posts, and earnings reports. The BloombergGPT model [42] demonstrated the versatility of large-scale domain-specific models in financial NLP applications, such as generating financial reports, summarizing complex documents, and answering financial questions. Initially, financial LLMs were applied to extract structured information, such as sentiment scores and key financial metrics, from unstructured media streams, enabling analysts to gain essential insights more efficiently. The extracted features, especially sentiment scores, were studied for use as inputs by predictive models that forecast the stock market [43]. The developers of FinGPT [44] created open-source models to make financial LLMs accessible for developing applications like sentiment analysis and financial forecasting.

The initial applications of Large Language Models (LLMs) in financial trading encountered considerable obstacles, especially in understanding complex financial terminology and the subtle dynamics of market activity during their development. The primary problem emerged as general-purpose LLMs and initial finance LLMs were unable to comprehend intricate financial language, market dynamics, and regulatory frameworks, which are crucial for sophisticated market analysis. The text processing capabilities alone failed to produce trustworthy trading signals from only sentiment indicators using extracted text data. They neglected to consider market volatility and the intricate interconnections among many financial indicators. The first approaches lacked models capable of direct reasoning and the incorporation of market data for trading decisions, leading to an inability to identify financial market causation and temporal connections.

Prompt optimiziation emerged as a critical requirement to improve LLMs' performance in financial applications. The potential for such optimization stems from the fundamental mechanism of in-context learning, where the model adapts its behavior based on the prompt's content. Recent work suggests this is a form of implicit fine-tuning [45]. The authors mathematically prove that the standard Transformer architecture, through the interplay of its self-attention and MLP layers, implicitly modifies its weights in response to the provided context, effectively learning without gradient updates. Building on this capability, the early work on prompt engineering in financial applications focused on designing prompts that could elicit more accurate market analysis and trading signals from LLMs. Stock-Evol-Instruct [46] developed high-quality instruction datasets for stock forecasting through market data adaptation of instructions. SPELL [47] utilized Large Language Models (LLMs) to systematically optimize prompts throughout the entire system architecture. In contrast, EVOPROMPT [48] integrated LLMs with evolutionary algorithms to enhance discrete prompt optimization, thereby illustrating the application of evolutionary algorithms in the domain of prompt optimization. TEMPERA [49] conducted a comprehensive study on the utilization of reinforcement learning techniques during the testing phase to generate context-dependent prompts tailored to the specificities of the current query. Self-reflection emerged as a popular concept, which led to the development of systems that evaluate past actions to modify internal behavior [50]. Implementing this self-reflection approach, Li et al. [51] developed a system that adjusted LLMs' trading strategies by analyzing and learning from previous performance data.

Retrieval-Augmented Generation (RAG) [52] proved essential to address the inherent limitations of static LLMs as they exhibited knowledge date-cutoffs and the tendency to produce hallucinations. This online technology gained special importance in financial applications because accurate and current information stands essential for such domains. RAG addresses the limitations of static LLMs by using a retrieval-based generation mechanism that leverages external knowledge vector databases and semantic similarity search to provide accurate and current information. RAG provides relevant text snippets to the LLM which results in more accurate and verifiable outputs that remain up-to-date. RAG's observability feature allows systems to detect and potentially counter hallucinations by enabling the observation of retrieved sources. Standard RAG implementations struggle in the dynamic financial trading domain due to their inability to retrieve and prioritize time-sensitive information necessary for trading decisions. The standard approach to retrieval through semantic similarity therefore fails to retrieve the knowledge required for making trading decisions. Standard RAG systems do not contain built-in functions to properly evaluate information based on its time-sensitive value. According to Horowitz and Plonsky [53] LLMs including those with RAG tend to show recency bias by prioritizing recent information over essential historical data. Automated systems in the financial domain therefore need advanced retrieval methods that can handle time and risk-dependent information to surpass basic semantic similarity approaches.

Multi-Agent Systems (MAS) provide a potential solution to tackle problems in dynamic environments through the distribution of specialized tasks and perspectives among multiple agents. An example of such a system is StockAgent [54], which creates simulations that replicates an investment firm roles, including sector-focused analysts and portfolio managers, who combine insights with risk managers which oversee the process. Another framework, FinCon [8], demonstrated how to model a MAS to boost stock trading and portfolio management in simulated environments, generalising across a set of tasks including stock trading and portfolio management. It utilises both a manager-analyst hierarchy and a dual-level risk-control component to allow for a verbal reinforcement learning approach. Literature concludes that diverse interaction dynamics between MAS agents produce solutions which surpass what a solitary agent could potentially accomplish.

MAS offers the potential of implementing structured interaction protocols, through a debate or critique session. The implementation of structured debate between LLMs [55] together with proposal and critique cycles [56] has proven effective for enhancing reasoning quality and decreasing errors, while also improving the interpretability of LLM outputs and limiting excessive fine-tuning. Incorporating formal debate protocols between agents with different roles in a financial MAS could enhance the reliability and robustness of trading strategies developed by LLMs. The potential benefits and implementation strategies of formal debate protocols between specialized financial LLM agents for real-time trading analysis remain underexplored.

The development of autonomous trading agents based on LLMs became an increasingly more popular research focus after establishing foundational NLP applications. One of those systems is the Summarize-Explain-Predict (SEP) model [9] which fine-tunes self-reflective agents to generate explainable stock predictions. Researchers also investigated direct stock performance forecasting from text sequences while open-source platforms like FinRobot [57] appeared as testing environments. The StockAgent simulation environment [54] was built to analyse realistic trading behaviours of LLM systems. The development of self-reflection capabilities allowed CryptoTrade [58] agents to review their previous actions while improving their future crypto trading approaches. The multimodal systems FinAgent [7] and FinVision [59] combined textual data analysis with visual information from K-Line charts to support decision-making processes.

Research further focused on combining LLM insights with Deep Reinforcement Learning (DRL) agents to utilise LLM reasoning and knowledge while optimising market interaction policies through DRL [60]. Wang et al. [61] introduced a framework with dual-loop architectures which combined internal reasoning components with external feedback mechanisms for autonomous improvement. The development of autonomous trading systems faces significant hurdles despite recent progress [13]. Real-time market volatility continues to be a challenge for numerous systems which fail to adapt continuously. The process of learning from market feedback proves challenging because it contains limited and noisy information. The proper management of memory through RAG mechanisms which integrate historical context with recent events and past trading experiences remains essential and complex [7, 8, 62–64]. Real-time high-stakes financial decision-making requires robust reliable reasoning which multi-agent debate may help overcome [63].

Literature shows that development of LLMs and their applications in finance has made significant progress, but several challenges remain. Traditional quantitative models are limited by the rigidity of their assumptions, while the application of Reinforcement Learning and Evolutionary Algorithms in finance highlights challenges in incorporating diverse data sources and ensuring interpretability. Early adoptations of LLMs in financial trading, while powerful in their language processing capabilities, often lack the necessary adaptability and dynamic strategy refinement required for real-time trading. Several multi-agent system approaches, like FinVision [59], FinMem [62] and TradingGPT [63], have attempted to address these issues, but they often fall short in integrating a continuous feedback loop for prompt and strategy evolution, as well as in providing robust memory management module. Despite these challenges, the emergence of advanced prompting techniques, RAG, and multi-agent systems provides promising avenues for enhancing LLM performance in complex environments. However, the integration of these approaches into a cohesive framework that addresses the unique challenges of financial trading remains an open research question.

3 FRAMEWORK ARCHITECTURE

This section introduces a novel framework featuring a self-adapting, modular architecture tailored for LLM-based financial agents in dynamic environments, highlighting its academic significance and contribution to addressing key challenges in financial markets. The framework addresses key challenges in dynamic financial markets, such as data integration and decision-making, by providing specific solutions where existing LLM capabilities fall short. While LLMs inherently possess reasoning capabilities and can process textual information, our framework specifically contributes, (1) structured multi-modal data integration for financial markets, (2) time-aware memory retrieval that balances semantic relevance with temporal decay, (3) collaborative multi-agent reasoning to mitigate single-agent biases, and (4) automated meta-prompt optimization for continuous adaptation to market dynamics. An overview of the framework is presented in Figure 2.

To formally define the problem, depicted by Kabbani and Duman [65], we formulate the sequential decision-making task of the trading agent as a Partially Observable Markov Decision Process (POMDP), which is crucial for modeling the uncertainty in financial markets. The state space encompasses both observable market data, such as prices, indicators, and news summaries, as well as potentially hidden states, including latent market factors. The agent's actions consist of executing trading decisions, namely taking a long, short, or hold action, within the financial market context. The objective is to learn a policy, guided by the adaptable meta-prompt, that maximizes a predefined financial objective function (e.g., risk-adjusted return) over a given horizon, based on observations and feedback.

3.1 POMDP Formulation

The POMDP is formally defined by the tuple $(S, A, T, R, \Omega, O, \gamma)$, where each element represents a critical component of the decision-making process in our multi-agent system, which operates over time based on incomplete information from a dynamic environment. Here, S, is represented as the true state of the environment, denoted as $s_t \in S$, at time step t. It is important to note that the explicit market state, s_{market}, is not fully observable by the system, which affects the decision-making process. The unobservable market state may include elements such as real asset prices, order book depths, and other market indicators. Latent factors like the underlying market dynamics, investor sentiment, and macroeconomic conditions are also included in the state space. This is due to the inherent complexity and stochastic nature of financial markets, which makes it impossible to fully observe the true state at any given time.

Furthermore, the internal state of the system is part of s_t. This internal state is defined by the current meta-prompt, $prompt_t$, which encapsulates the agent's knowledge, strategies, and decision-making heuristics at time t, and the procedural memory M_t at time t, representing the historical knowledge and past experiences of the system. Thus, a state $s_t \in S$ at time t is a tuple composed of the external market state and the system's internal state:

$$s_t = (s_{market,t}, prompt_t, M_t) \tag{1}$$

The action space, A, consists of the discrete set of possible trading decisions the system can take at time t, which includes our predefined actions $A = \{\text{long, short, hold}\}$. These actions may be seen as mutually exclusive, where the system can only take one action at a time. There is no concept of partial actions or position sizing, as the system is designed to make a single decision at each time step. This makes a_t the action taken at time step t. The transition function, denoted as $T(s'|s, a)$, describes the probability $P(s_{t+1} = s'|s_t = s, a_t = a)$ of transitioning to a new state s' given the current state s and action a. This function is complex and stochastic due to the nature of financial markets and is not inherently known to the system. It consists of the unpredictable market dynamics and internal dynamics of the system.

The reward function $R(s, a)$, which is defined as $R(s_t = s, a_t = a)$, quantifies the immediate reward received after taking action a in state s. This reward function is a critical component of the POMDP, as it guides the agent's learning process, and is defined as a set of performance metrics that guide the learning process. The observation space Ω represents all possible observations o_t available to the system at time step t. These observations comprise the processed information from the multi-agent data processing pipeline ($O_{data,t}$) and the retrieved historical experiences from procedural memory ($O_{mem,t}$). Formally, we define $o_t = (O_{data,t}, O_{mem,t})$, where $O_{data,t} = \{o_{i,t} | i \in \{1, \ldots, N_{agents}\}\}$ represents outputs from N_{agents} specialized data processing agents, and $O_{mem,t}$ contains the top N_{mem} memory entries ranked by the effective score $S_{\text{eff}}(x_i, q_t)$.

The observation function $O(o|s', a)$ represents the probability $P(o_t = o|s_t = s', a_{t-1} = a)$ of observing o given the true state s' and previous action a_{t-1}. Crucially, the partial observations o_t differ from the complete true state s_t, as they represent processed and filtered information rather than the full complexity of the market environment. This observation function captures the inherent information asymmetry in financial markets, where the system's perception of the environment is necessarily incomplete and derived through its data processing pipeline and procedural memory retrieval.

Finally, the discount factor γ represents the importance placed on future rewards relative to immediate ones, though in our implementation this is implicitly handled through the meta-prompt's strategic focus rather than as an explicit parameter. Given this formal definition, the system operates based on belief state $b(s_t)$, which is an internal probability distribution over all the possible true states s_t. The agentic system's actions are determined by a policy $\pi(a_t|b_t, prompt_t)$, which is a mapping from the belief state b_t and the current meta-prompt $prompt_t$ to the action space A. This policy selects an action a_t based on the current belief state and the meta-prompt, which encapsulates the agent's knowledge and strategies, aiming to maximize expected cumulative rewards over the trading horizon. In the framework, the LLM-based reasoning process through a multi-agent debate and aggregation module, guided by the current meta-prompt $prompt_t$, is used to determine the action a_t at each time step t, conditioned on the observation o_t. The system's adaptability is achieved through the feedback-driven meta-prompt optimization (FBPO) process, which continuously refines the meta-prompt based on performance feedback and historical experiences stored in the procedural memory M. It forms the basis for the system's learning and adaptation over time, optimizing the underlying policy over time by adapting the meta-prompt to improve decision-making in the dynamic financial environment.

3.2 Multi-Agent Data Processing Pipeline

The first step of our framework consists of a pipeline designed to ingest, process, and synthesize heterogeneous financial data streams. The pipeline is modular, allowing for the integration of various data sources and types. For example, the pipeline includes specialized agents for processing stock data, news articles, and other relevant information. Each agent is responsible for a specific type of data, ensuring that the information is processed consistently and effectively. The observations of the multi-agent processing pipeline are defined as a structured set, $O_{data,t} = \{o_{i,t} | i \in \{1, \ldots, N_{agents}\}\}$, where N_{agents} is the number of specialized agents in the pipeline. The output of each agent is a structured text summary, which is then passed to the next stage of the pipeline. The system uses Jinja2 [66] templates to provide the LLM with the necessary context and information for each agent. The prompts are designed to be modular and adaptable, allowing for easy updates and modifications as needed. This modularity allows for easy updates and modifications to the prompts as needed, ensuring that the system can adapt to changing requirements and data sources. Appendix A.4 provides ethe prompts used in the pipeline, which consist of a structured Markdown format. One should see the prompts as a key bias for the system. It guides the agent's reasoning process and ensures that the information is processed consistently and effectively, acting as a internal belief state of the system.

Our pipeline consists of three main agents, each responsible for processing different types of data, the Technical Analysis Agent, the Portfolio Analysis Agent, and the News Data Agent. Each agent operates independently and in parallel, processing its respective data streams and generating structured outputs that are then passed to the next stage of the pipeline. This modular design allows for flexibility and scalability, enabling the system to adapt to new data sources and types as needed.

Technical Analysis Agent. This agent processes raw price and volume data, computes technical indicators before summarizing the market's technical information into structured text. Literature shows that LLMs can effectively process and analyze time series data, making them suitable for this task [67, 68], even though there exists a modality gap between numerical price data and the inherent text-based nature of LLMs. The agent's output is a structured text summary that includes key indicators and trends, which is then passed to the next stage of the pipeline. The exact data, such as the exact time-window of the price data and technical indicators, provided as input to the LLM is a key aspect of the agents design. While we want the observations to be as informative as possible, we also want to avoid overwhelming the LLM with too much information, inherently with noise, which could lead to performance degradation as the context length increases.

Portfolio Analysis Agent. This agent assesses the system's internal state, evaluating current portfolio health and any active positions. It analyses metrics such as equity performance, risk ratios (Sharpe, CVaR), and unrealised profit or loss. THis introspective analysis provides critical risk-management context, ensuring that subsequent decisions are made with awareness of the current portfolio's status and risk exposure.

News Data Agent. This agent ingests news feeds and performs sentiment analysis from a dataset of news articles. It extracts key information and entities, summarizes the news into structured text, and provides sentiment scores according to the prompt in Appendix A.4. The agent is designed to handle the noise and variability in news data, ensuring that the information is relevant and actionable. Literature shows that combining price data with textual context, like news headlines, can enhance the performance in task where external factors influence the time series, such as financial markets [69–71]. The agent's output is then passed to the next stage of the pipeline.

Additionally, the system can incorporate other specialized agents, such as those for social media sentiment analysis or macroeconomic data processing, enhancing its adaptability. This modularity ensures that the framework can adapt to new data sources and types, enhancing its robustness and flexibility. Given the parallel nature of the pipeline, the agents can operate concurrently, allowing for efficient data processing and synthesis.

3.3 Time-Aware Procedural Memory Retrieval (RAG)

In order to provide essential context and enable learning from historical performance, the framework incorporates a sophisticated procedural memory module. This module is designed to store and retrieve past experiences, allowing the system to learn from its interactions with the environment. As standard Large Language Models (LLMs) lack inherent long-term memory capabilities, which is required for tracking past actions and outcomes over extended periods, the procedural memory module is crucial for the system's adaptability and performance. Retrieval-Augmented Generation (RAG) offers a potential solution by injecting external, online, knowledge into the decision-making process based on a retrieval mechanism. This retrieval mechanism typically relies on semantic similarity to identify relevant past experiences. This is computed as the cosine distance between the query and the memory entries embeddings, and evaluated based on the highest similarity score. However, this semantic retrieval mechanism often falls short in the financial trading domain, as it typically overlooks the crucial dimension of temporal decay (recency). Trade experiences and decisions are not only contextually relevant but also time-sensitive, as the financial markets are highly dynamic and subject to rapid changes. A memory entry that was relevant a week ago may no longer be applicable today due to shifts in market conditions, making it essential to consider the recency of past experiences in the retrieval process.

Consequently, simple semantic similarity is often insufficient for providing the nuanced historical context needed for effective financial decision-making. We therefore implement a *Procedural*

Memory stored in a vector database, designed to maintain a comprehensive record of the agent's past trading cycles. Each memory entry x_i encapsulates key information from a completed trading cycle. A memory entry consists of the final trade decision, the consolidated reasoning, the prompt used, and any qualitative feedback. Formally, a memory entry from a past time step t' is defined as $x_i = \{a_{t'}, reason_{t'}, prompt_{t'}, feedback_{t'}\}$. The procedural memory is updated after each trading cycle, ensuring that the system retains a comprehensive history of its decisions and outcomes.

The retrieval from this memory utilizes a mechanism enhanced with a scoring function designed to be time-sensitive and relevance-aware. Given a query q_t derived from the current processed data outputs $O_{data,t}$, the effective score S_{eff} for retrieving a past memory entry x_i is calculated as a weighted linear combination of semantic relevance and recency:

$$S_{\text{eff}}(x_i, q_t) = w_{\text{sim}} \cdot \underbrace{\text{sim}(q_t, x_i)}_{\text{Relevance}} + (1 - w_{\text{sim}}) \cdot \underbrace{\exp(-\alpha \Delta t_h)}_{\text{Recency}} \quad (2)$$

Here, $\text{sim}(q_t, x_i)$ represents the semantic relevance score between the query embedding q_t and the memory entry embedding x_i, computed using a normalized cosine distance:

$$\text{sim}(q_t, x_i) = \frac{1}{2}\left(1 + \frac{q_t \cdot x_i}{\|q_t\|\|x_i\|}\right) \quad (3)$$

This equation normalizes the cosine similarity to lie within the range [0,1], where 1 indicates maximum relevance (identical vectors) and 0 indicates minimum relevance (opposite vectors). The term Δt_h represents the time elapsed in hours since the memory x_i was recorded. The weight $w_{\text{sim}} \in [0, 1]$ determines the trade-off between relevance and recency, with $(1 - w_{\text{sim}})$ being the weight for the recency component. The parameter α is the recency decay rate. The top N_{mem} memories, ranked by this S_{eff} score, are retrieved to provide context, according to:

$$O_{mem,t} = \{x_i \in M_t \mid \text{rank}(S_{\text{eff}}(x_i, q_t)) \le N_{mem}\} \quad (4)$$

The number of retrieved memories N_{mem} is a critical hyperparameter. This ensures the utilized historical information is relevant and recent, with the balance determined by the chosen hyperparameters. The query q_t is typically formed by embedding the combined outputs $O_{data,t}$ from the data processing pipeline. Appendix A.5 provides the prompt used to generate the query q_t from the processed data outputs $O_{data,t}$ as well as an example of the memory entries x_i stored in the procedural memory. Our approach allows for the retrieval of memories that are not only semantically relevant but also appropriately recent, enhancing the decision-making process of the agents.

Both the embeddings of the query q_t and the memory entries x_i are computed using a pre-trained embedding model, such as OpenAI's `text-embedding-3-small` [72], which is designed to capture semantic relationships in text. This embedding model is used to transform the textual data into high-dimensional vectors, enabling efficient similarity calculations. The embeddings are stored in a PGVector [73] vector postgres [74] database, allowing for fast retrieval during the decision-making process. The retrieved memories are then used to inform the current decision-making process, providing context and historical insights that can enhance the agent's performance. We set the chunk size of the memories to the maximum context length (C_{max}) of the LLM, which is typically 8192 tokens `text-embedding-3-small`. The memories are chunked to fit within the context window, and any entries that exceed this length are truncated. This chunking process ensures that the retrieved memories are concise and relevant, while still providing sufficient context for the decision-making process. The chunked memories are concatenated on retrieval, ensuring that the retrieved memories are presented to the LLM in a structured and coherent manner. The procedural memory retrieval process is a key component of the framework, enabling the system to learn from its past experiences and adapt its decision-making strategies over time. It allows for the integration of historical knowledge into the current decision-making process, enhancing the agent's performance and adaptability in dynamic financial environments.

3.4 Multi-Agent Debate for Enhanced Reasoning

LLMs are known for their impressive reasoning capabilities, but they can also be prone to biases and limitations in their decision-making processes. One of the challenges with single-agent reasoning is the risk of confirmation bias, where the agent may favor information that supports its initial hypothesis while neglecting alternative perspectives. This can lead to suboptimal decisions and a lack of critical evaluation of risks. Confirmation bias particularly problematic in complex decision-making scenarios where multiple viewpoints and critiques are essential for robust conclusions. Furthermore, the reasoning process of monolithic LLM systems can be opaque, making it difficult to understand the rationale behind their decisions. This lack of interpretability can hinder trust and analysis, especially in high-stakes environments like financial trading.

To enhance the robustness, depth, and interpretability of the trading decisions, the framework utilizes a collaborative reasoning process structured as a debate. This multi-agent debate mechanism is designed to improve the quality of decision-making by allowing multiple agents to engage in a structured dialogue, critique each other's reasoning, and explore alternative perspectives which can lead to more informed and balanced conclusions. In our framework, the debate is structured around two distinct roles which we call the *Bull Agent* and the *Bear Agent*. In the field of financial trading these terms are commonly used to describe opposing market sentiments, with bull means a positive outlook on the market, expecting prices to rise, while bear refers to a negative outlook, expecting prices to fall. Given the processed data and retrieved memories, these agents engage in N_{rounds} rounds of structured dialogue according to the prompts present in Appendix A.4. The *Bull Agent* initiates the debate by proposing a trading action and providing reasoning for that action based on the current prompt ($prompt_t$). The *Bear Agent* then critiques the proposal, highlighting potential weaknesses or alternative perspectives, and proposes a refined action and reasoning. This iterative process continues for N_{rounds} rounds, allowing both agents to refine their arguments and explore different angles of the decision-making process. The effectiveness of this approach is supported by literature, which shows that multi-agent systems can outperform single-agent systems in complex decision-making tasks [55].

A dedicated *Aggregator Agent* receives the full debate transcript and synthesizes the arguments presented by both agents. The Aggregator resolves conflicts based on predefined criteria or through LLM judgment, determining the key arguments. Ultimately, the *Decision Agent* consolidates the final decision by selecting the most appropriate trading action based on the aggregated reasoning. This agent is responsible for formulating the final trading action (a_t) and generating a consolidated, interpretable reasoning ($reason_t$). The action a_t and its corresponding reasoning are direct results of the multi-agent debate, which is guided by the meta-prompt $prompt_t$ and informed by the current portfolio state. This multi-agent debate process not only enhances the reasoning capabilities of the system but also provides a more transparent and interpretable decision-making process, which is crucial in financial trading contexts where understanding the rationale behind decisions is essential. The structured dialogue system allows for a more comprehensive exploration of potential strategies, risks, and opportunities, leading to more informed decisions.

3.5 Feedback-Driven Meta-Prompt Optimization (FBPO)

Our central mechanism consists of the framework's self-adaptation and long-term learning process called Feedback-Driven Meta-Prompt Optimization (FBPO). This module is designed to dynamically refine an agents' guiding meta-prompt, which dictates its high-level strategy and reasoning heuristics. Conceptually, FBPO operates a search algorithm over a high-dimensional parameter state-space of possible meta-prompts ($\mathcal{P}$). Each point in this space represents a unique natural language instruction set defining the agent's policy. The goal is to navigate this space to find prompts that yield superior long-term trading performance.

The core of the FBPO process relies on a performance feedback signal, generated after each complete trading cycle. This signal, denoted $F_{signal,k}$ for the k-th cycle, is a vector of quantitative performance metrics. This multi-faceted feedback allows for a more nuanced assessment of the agent's strategy. Formally, the feedback signal is defined as:

$$F_{signal,k} = [m_{1,k}, m_{2,k}, \dots, m_{N_{metrics},k}] \tag{5}$$

where each $m_{i,k}$ is a specific performance metric, such as the Sharpe Ratio, Maximum Drawdown, or Cumulative Return, which is calculated over the entire duration of the k-th trading cycle. This quantitative vector is the foundation for the subsequent adaptation step. Specifically, it is used by the *Feedback Agent* to generate qualitative feedback, which translates the raw performance numbers into actionable, natural language insights for the *Meta-Prompt Adaptation Agent* to use.

Financially markets exhibit significant non-stationarity and are subject to rapid changes in dynamics. Setting static strategies encoded in fixed prompts can lead to suboptimal performance over time. Explicitly modeling the relationship between prompt text and trading performance is intractable. Therefore, adapting agent behavior requires an effective method to search the vast prompt space ($\mathcal{P}$) using only sparse, delayed, and noisy performance feedback signals, without relying on gradients or explicit models of the prompt-performance landscape. FBPO therefore employs a gradient-free solution to this problem, which is a key novelty of our work. The FBPO process implements an iterative search strategy, similarly to an optimization algorithm, operating directly on the natural language prompts. The objective is to find a prompt $prompt^* \in \mathcal{P}$ that leads to superior long-term performance. The conceptual goal is to find a prompt that yields a desirable trade-off across these metrics over time, which can be expressed as:

$$prompt^* = \arg\max_{prompt \in \mathcal{P}} E\left[U\left(\sum_{k=0}\gamma^k F_{signal,k}\right) \mid \text{policy uses } prompt\right] \tag{6}$$

where $U(\cdot)$ is a utility function that maps the vector of cumulative performance metrics to a scalar value, representing the agent's preferences over different objectives. The expectation $E[\cdot]$ is taken over the stochastic market dynamics. In this objective function, the discount factor γ is a conceptual parameter representing the importance of long-term performance. A value close to 1 prioritizes sustainable, future outcomes. While this equation grounds the theoretical model, our practical implementation does not use γ as an explicit hyperparameter. Instead, the focus on long-term performance is implicitly embedded within the prompt's strategic guidelines. The FBPO process approximates the search for this objective through its iterative, feedback-driven cycle.

First, feedback collection occurs after each trading cycle k, yielding the performance vector $F_{signal,k}$ (defined in Equation 5). This vector is then processed by the *Feedback Agent* to produce qualitative feedback, $feedback_k$. This qualitative summary interprets the quantitative results, providing context for the observed performance. Second, the *Meta-Prompt Adaptation Agent (MPAA)* uses this qualitative feedback $feedback_k$ to generate a new, adapted meta-prompt, $prompt_{k+1}$. Here, the subscript denotes the trading cycle, where the new prompt will be used for all time steps t within cycle $k+1$. This direct generation step serves as a computationally feasible heuristic designed to iteratively move towards the ideal objective defined in Equation 6, mimicking greedy optimization. While this approach allows for continuous adaptation, it prioritizes reactivity to recent feedback over the broader exploration inherent in complex search algorithms. Appendix A.6 provides the specific prompt used for both the direct generation step and the feedback collection step, which guides the MPAA in generating the new meta-prompt based on the performance feedback.

4 EXPERIMENTS

4.1 Data Collection

Our empirical evaluation leverages a comprehensive dataset sourced from the *financialdatasets.ai* [75] platform, which provides extensive financial market data across multiple assets and time horizons. The dataset encompasses daily stock prices, trading volumes, and news data, thereby enabling our framework to process both numerical market signals and textual information sources that characterize modern financial decision-making environments.

To rigorously assess the adaptive capabilities of our proposed framework across varying market dynamics, we deliberately selected a diverse portfolio of three publicly traded companies, technology leader Apple (AAPL), growth-oriented streaming firm Netflix (NFLX), and the diversified e-commerce and cloud computing giant Amazon (AMZN). This selection provides a robust testbed for our framework's adaptability. For instance, AAPL's performance is heavily influenced by cyclical product releases and regulatory news, testing the agent's ability to interpret scheduled events. NFLX, however, operates in the competitive streaming market, is highly sensitive to subscriber revenue data and content performance, presenting scenarios of high volatility and therefore sentiment-driven price swings. Finally, AMZN is a multifaceted business, consisting of e-commerce, cloud and advertising sections, which creates a complex informational environment where the agent must disentangle signals from different economic sectors. This variety ensures our framework is evaluated against a realistic spectrum of market behaviors. The preprocessing pipeline for each asset addresses missing values and ensured temporal consistency across different assets, while preserving the natural market characteristics essential for realistic backtesting scenarios.

Our experimental design addresses four fundamental research questions, as defined in Section 1 that collectively evaluate both the performance superiority and mechanistic understanding of our self-adapting framework:

- Sub-Research Question 1: Does our self-adapting agents outperform industry benchmarks and state-of-the-art trading agents in single-stock trading in terms of cumulative return (CR%), Sharpe ratio (SR) and maximum drawdown (MDD%)?
- Sub-Research Question 2: How do the different components of the self-adapting agents, such as the Time-Aware Procedural Memory Retrieval module, Multi-Agent Debate Protocol, and Feedback-Driven Meta-Prompt Optimization (FBPO) mechanism, impact the overall performance of the agents?
- Sub-Research Question 3: Is there a bias within the selected LLM latent space that influences the performance of the self-adapting agents in stock trading?
- Sub-Research Question 4: How does the choice of LLM impact the performance of the self-adapting agents in stock trading?

4.2 Experimental Setup

Our experimental methodology employs a multi-faceted evaluation strategy designed to comprehensively assess both the absolute performance and adaptive mechanisms of our proposed framework. The experimental design ensures rigorous comparison against established benchmarks while maintaining controlled conditions that enable meaningful attribution of performance differences to our novel architectural components.

To establish the fundamental performance characteristics of our self-adapting framework (addressing SQ1), we conducted an extensive evaluation using Apple (AAPL) as our primary test asset, leveraging the Gemini 2.5 Flash Lite model as our base LLM architecture. The training horizon spans three years (October 3, 2019 to October 4, 2022), providing sufficient historical context for the framework's adaptive mechanisms to learn market patterns while maintaining computational feasibility our experimentation. The out-of-sample evaluation period (October 5, 2022 to June 10, 2023) represents an eight-month window that balances statistical significance with the practical constraints of LLM inference costs, ensuring robust performance assessment while enabling comprehensive ablation studies across multiple configurations. The selection of Gemini 2.5 Flash Lite reflects its demonstrated benchmark performance [76] while offering favorable computational efficiency and cost, and therefore scalability for our adaptive architecture.

To isolate the individual contributions of our framework's core components (addressing SQ2), we implemented a systematic ablation study protocol that selectively disables each major module while maintaining all other system characteristics. These controlled experiments examine the Time-Aware Procedural Memory Retrieval module, the Multi-Agent Debate Protocol, and the Feedback-Driven Meta-Prompt Optimization (FBPO) mechanism in isolation. Alongside the isolations, we also evaluate the performance of the non-adaptive baseline, which employs a static meta-prompt template without the FBPO mechanism and no procedural memory retrieval for online contextualization. This baseline serves as a reference point for understanding the performance impact of our adaptive components.

The ablation studies employ a more concentrated temporal window (January 3, 2022 to October 4, 2022 for training; October 5, 2022 to June 10, 2023 for evaluation) to ensure computational feasibility while preserving the essential market dynamics necessary for meaningful component assessment. This methodological approach establishes a comprehensive baseline incorporating all components, against which individual module contributions can be rigorously quantified.

Our market regime analysis extends beyond single-asset evaluation to encompass the full spectrum of selected stocks (AAPL, NFLX, and AMZN), thereby assessing the framework's robustness across heterogeneous market conditions and sector-specific dynamics. This cross-sectoral evaluation employs identical temporal parameters (January 3, 2022 to October 4, 2022 for training; October 5, 2022 to testing) while utilizing the Gemini 2.5 Flash Lite architecture to ensure consistency across experimental conditions.

To address potential temporal bias concerns inherent in LLM-based financial applications (addressing SQ3), we designed a forward-looking bias study that examines whether our framework's performance derives from inadvertent knowledge of future market conditions embedded within the base model's training corpus. This investigation employs Apple (AAPL) as the test asset over a genuinely out-of-sample period (January 31, 2025 to May 1, 2025), representing market conditions that definitively post-date the LLM's knowledge cutoff. The framework utilizes identical training parameters (October 3, 2019 to October 4, 2022) while being evaluated against this future time horizon, thereby providing definitive evidence regarding the framework's reliance on genuine adaptive capabilities versus pre-existing market knowledge.

Our architectural generalizability study (addressing SQ4) evaluates the framework's performance consistency across diverse LLM architectures, including LLama 4 Maverick [77] (accessed via Groq's optimized API [78]), Qwen3 235B A22B [79], and DeepSeek V3 0324 [80]. This comparative analysis employs the concentrated temporal window utilized in our ablation studies (January 3, 2022 to October 4, 2022 for training; October 5, 2022 to June 10, 2023 for evaluation), enabling systematic assessment of how architectural differences in reasoning capabilities, parameter scaling, and training methodologies influence the framework's adaptive performance characteristics.

4.3 Feature Engineering

Our feature engineering methodology adopts a dynamic, context-sensitive approach by incorporating real-time market signal production directly into the decision-making process. This architectural decision reflects our framework's fundamental principle of adaptive intelligence, where technical indicators function not solely as fixed inputs but as dynamic contextual signals that augment the agents' comprehension of the market structure and momentum dynamics.

The technical indicator suite encompasses a carefully curated selection of complementary metrics designed to capture distinct aspects of market behavior: the 20-day Simple Moving Average (SMA20) and 20-day Exponential Moving Average (EMA20) provide trend identification capabilities, while the Relative Strength Index (RSI) quantifies momentum characteristics. The Average Directional Index (ADX) measures trend strength independent of direction, and the Commodity Channel Index (CCI) identifies cyclical turning points, all originally introduced by [81]. This multi-dimensional approach ensures that our agents receive comprehensive market context spanning trend, momentum, volatility, and cyclical components that collectively characterize price action across different temporal horizons, hence enhancing their decision-making capabilities. Appendix A.1 provides a detailed description of the indicators used in our framework, including their mathematical definitions and implementation details.

The environmental state representation integrates these technical indicators into a comprehensive information architecture, structured into two primary components: market metrics and portfolio metrics. The market metrics component provides a snapshot of the asset's current and historical state, including daily Open, High, Low, and Close prices (OHLC), trading volume. It also includes the latest values and historical trajectories of the technical indicators described previously. The portfolio metrics component tracks the agent's performance and risk exposure in real-time. This includes key performance indicators such as the current equity value, cumulative return, Sharpe Ratio, and maximum drawdown, alongside historical data like daily returns and drawdown history. By combining these two views, the state representation creates a rich contextual foundation that enables our agents to synthesize technical analysis with portfolio management considerations. The resulting information structure ensures that decision-making processes can leverage both immediate market signals and longer-term strategic context, facilitating the nuanced reasoning capabilities. Appendix A.2 provides a detailed description of the state representation used in our framework, including the specific features and their roles and their implementation details.

4.4 Evaluation Metrics

Our evaluation framework employs a comprehensive suite of metrics to assess performance across three key dimensions: portfolio performance, trade-level statistics, and behavioural diagnostics. This multi-faceted approach enables a holistic understanding of the agent's capabilities, from absolute and risk-adjusted returns to the underlying quality of its reasoning and decision-making processes.

4.4.1 Core Portfolio Performance Metrics. These metrics evaluate the overall effectiveness of the strategy from a portfolio perspective.

- **Cumulative Return (CR%)** quantifies the total percentage change in portfolio value over the evaluation period. It is the primary measure of absolute profitability. We aim to maximize this metric.
$$\text{CR\%} = \left(\frac{V_T}{V_{t_0}} - 1\right) \times 100$$
where V_{t_0} is the initial portfolio value and V_T is the final value at the end of the evaluation period.
- **Annualised Sharpe Ratio (SR)** [82] measures risk-adjusted return by normalising the excess return (above the risk-free rate) by the standard deviation of returns. A higher SR indicates better performance for a given level of risk.
$$\text{SR}_{\text{ann}} = \frac{\mathbb{E}[R_p - R_f]}{\sigma_p} \times \sqrt{N_y}$$
where R_p is the portfolio's daily return, R_f is the daily risk-free rate, σ_p is the standard deviation of the portfolio's daily returns, and N_y is the number of trading days in a year (typically 252).
- **Maximum Drawdown (MDD%)** measures the largest single drop from a peak to a trough in portfolio value. It is a key indicator of downside risk and portfolio resilience.
$$\text{MDD} = \max_{t \in [t_0, T]} \left(\frac{\max_{\tau \in [t_0, t]} V_\tau - V_t}{\max_{\tau \in [t_0, t]} V_\tau}\right) \times 100$$
where V_t is the portfolio value at time t.
- **Alpha vs. Buy & Hold (α_{BH})** measures the excess return of the agent's strategy over a passive buy-and-hold strategy. A positive alpha indicates outperformance.
$$\alpha_{\text{BH}} = \text{CR}_{\text{Agent}} - \text{CR}_{\text{B\&H}}$$

4.4.2 Trade-Level Metrics. These metrics provide insight into the tactical execution and efficiency of the trading strategy.

- **Number of Trades (N_{tr})** is the total count of complete trade cycles during the evaluation period. A complete trade cycle is defined as a long, or short, position that is opened and subsequently closed.

- **Total Win Rate (%)** measures the percentage of trades that resulted in a positive profit.

$$\text{Win Rate} = \frac{1}{N_{tr}} \sum_{i=1}^{N_{tr}} \mathbb{I}(P_i > 0) \times 100$$

where P_i is the profit of the i-th trade and $\mathbb{I}(\cdot)$ is the indicator function.
- **Average Win (%)** and **Maximum Win (%)** are the average and maximum profit percentages, respectively, across all winning trades.
- **Average Loss (%)** and **Maximum Loss (%)** are the average and maximum loss percentages, respectively, across all losing trades.

4.4.3 Behavioural and Diagnostic Metrics. These metrics are designed to understand the agent's reasoning, decision-making logic, and potential biases. They are crucial for understanding why an agent performs as it does.

- **Shadow Return (%)** calculates the hypothetical cumulative return if a trade were executed on every single directional signal generated by the agent's reasoning module, irrespective of the final decision mechanism.
- **Gating Efficiency (Δ)** quantifies the value added by the agent's final decision filter. It is the difference between the realised portfolio return and the shadow return.

$$\Delta = \text{CR}_{\text{Agent}} - \text{CR}_{\text{Shadow}}$$

- **Missed Opportunity P&L (%)** is the cumulative profit or loss from high-confidence trades that the agent's reasoning module identified but the model decided not to execute.
- **Hit Ratio (%)** measures the percentage of days where the agent's directional sentiment (bullish/bearish) correctly predicts the direction of the next day's price movement. The associated p-value tests the null hypothesis that the hit ratio is no better than 50%, using a binomial test to assess statistical significance.
- **Sentiment-Price Correlation** is the Pearson [83] correlation coefficient between the agent's daily sentiment score and the market's daily returns. It assesses the alignment between the agent's reasoning and price movements. In optimal conditions, the agent's sentiment should be positively correlated with the market's returns, indicating that the agent's reasoning is aligned with the market's direction.
- **Utilisation Rate (%)** is the percentage of trading days on which the agent holds a non-neutral position (i.e., is long or short the asset). It is a measure of the agent's activity and conviction.
- **Reason-Action Alignment** measures the consistency between the sentiment polarity of the agent's natural-language rationale and its final trading action (e.g., a bullish rationale followed by a long position).

Through this multi-faceted set of evaluation metrics, we aim to achieve a comprehensive understanding of our framework's performance across return generation, risk management, and operational efficiency dimensions.

4.5 Benchmark Comparison

To evaluate our self-adapting framework, we compare it against a diverse set of established trading approaches, including traditional rule-based strategies, machine learning models, and reinforcement learning agents.

The first class, rule-based heuristics, serves as a set of transparent, non-adaptive baselines. This category includes several models, a passive buy-and-hold strategy, a Z-score mean reversion model, a standard Moving Average Convergence Divergence (MACD) crossover strategy, and a KDJ-RSI composite model. The Z-score model initiates trades when the price deviates by ±2 standard deviations from a 30-day moving average, opening a long position below the lower bound and a short position above it, then closing the position upon reversion to ±0.5 standard deviations. The MACD strategy uses conventional (12, 26, 9) parameters, opening a long position when the MACD line crosses above the signal line and a short position when it crosses below. Finally, the KDJ-RSI model combines a 9-day KDJ oscillator with a 14-period Relative Strength Index (RSI), permitting long entries only when the RSI is within the 30-70 range to avoid overbought or oversold conditions.

The second class consists of supervised learning algorithms trained to predict next-day returns. This set features a LightGBM [84] model employing 5- and 10-day lagged returns as predictive features, a Long Short-Term Memory (LSTM) [85] network configured with a 20-day lookback window and 32 hidden units to capture temporal dependencies, and a Transformer-based architecture, also with a 20-day sequence length, composed of two encoder layers and four attention heads to model complex patterns in price data. They are trained to predict the next day's return, and the predicted return is used to determine the trading action. This means, opening a long position if the predicted return is positive, a short position if negative, and holding if zero.

The final category comprises deep reinforcement learning (DRL) agents designed to learn an optimal trading policy directly from market interactions. The state for these agents is represented by a 20-day sequence of returns. This group includes an Advantage Actor-Critic (A2C) [86] agent, a Deep Q-Network (DQN) [87] employing an epsilon-greedy exploration strategy with a decay rate of 0.995, and a Proximal Policy Optimization (PPO) [88] agent, which uses a clipping parameter of 0.2 to ensure stable policy updates. These agents all exhibit the same action space, which consists of the actions long, short, and hold. The agents are trained to maximise the cumulative return over the training period, and the trading action is determined by the agent's policy.

4.6 Configuration Variables

Our simulation environment is a back-testing regime where all trades are executed under a 0% commission schedule, with 0% slippage and 0% borrowing costs, thereby isolating model performance from exogenous frictions. This controlled setting, ensures that comparative results reflect the intrinsic capabilities of the adaptive framework rather than real-world implementation artefacts.

The observation vector ingested by each agent comprises a rolling 30-day window of OHLCV observations augmented by a

20-day history of the engineered technical indicators introduced in Section 4.3. News sentiment features are provided through a sliding 3-day window, preserving short-term informational shocks that frequently catalyse price movements.

To guarantee reproducible language-model behaviour, we fix the sampling temperature at 0.0 and cap the generation budget at 4, 096 tokens per interaction. The upstream data pipeline supports a maximum input context of $128k$ tokens, ensuring that the agents can assimilate extensive historical context when necessary.

Operational robustness is enforced by a structured retry protocol that re-issues failed API calls or malformed responses up to ten and five times respectively. The retry mechanism for API connection errors include an exponentially increasing timeout beginning at 5 and bounded by a $60s$ ceiling; a 10 jitter mitigates synchronisation effects. Secondly, malformed, or unparseable responses trigger a sub-agent attempting to solve the issue by re-querying the LLM with the malfunctioned response and its corresponding error message. This sub-agent is designed to handle up to five retries, ensuring that transient issues do not disrupt the overall decision-making process. The full specification of this mechanism is provided in Appendix A.3.

Procedural memory embeddings are produced via the TEXT-EMBEDDING 3 SMALL model [72], yielding 1 536-dimensional vectors that are persisted in a PGVECTOR-enabled PostgreSQL store [73, 74]. Documents are chunked in 8 191-token segments, which is also the maximum input size for the embedding model. The time-aware retriever employs a similarity function with $\alpha = 0.1$, $\tau = 0.0$, $N_{mem} = 5$, and $w = 0.5$ as described in Section 3.3.

Finally, prompt templates governing each agent's role are parameterised to expose current market context, historical performance statistics, and news items. This design affords the FBPO mechanism a rich action space while maintaining coherent task allocation across the multi-agent pipeline. Detailed template schemas are presented in Appendix A.4.

5 RESULTS

This section presents the empirical findings from our experiments, structured to systematically address the research questions outlined in the introduction. We begin in Section 5.1 by establishing a performance baseline. Section 5.2 then dissects the framework through ablation studies to quantify component contributions. We test the framework's robustness across assets in Section 5.3 and for temporal bias in Section 5.4. Finally, Section 5.5 provides a critical analysis of model-inherent bias, revealing how the choice of LLM fundamentally alters agent behavior.

5.1 Comparative Performance Analysis

This section addresses SQ1 by comparing our framework's performance against the comprehensive suite of benchmarks detailed in Section 4.5. These models serve as a baseline to evaluate the framework's adaptive capabilities and its ability to outperform established trading methodologies.

5.1.1 Key Findings. The cross-method benchmark in Table 1 reveals a foundational insight into our framework's baseline behavior. The most salient finding is the stark underperformance of the full self-adapting agent in this configuration. It registers a compounded loss of −4.15 % and a near-zero Sharpe ratio (−0.17), falling short of the simple buy-and-hold benchmark by over 26 percentage points. The cause is immediately apparent from its trading frequency, as it only executed a single trade ($N_{tr} = 1$). The agent exhibits an extreme risk aversion that results in inaction.

The annualised Sharpe ratio, which measures risk-adjusted return, offers a more nuanced perspective. A value above 1.0 is generally considered strong, while negative values indicate that an investment failed to outperform a risk-free asset. Our agent's Sharpe ratio of −0.17 confirms that its returns did not justify the risk taken. However, its underperformance is relatively small compared to the deeply negative ratios of several rule-based and deep learning models (e.g., Z-score at −1.36, Transformer at −1.13), which suffered significant losses relative to their volatility. In contrast, the LSTM model achieved a Sharpe ratio of 1.15, slightly surpassing the buy-and-hold benchmark (1.10) by generating superior risk-adjusted returns.

This analysis clarifies that while our agent failed to capture market upside, its performance was mixed when compared to other active strategies. It successfully avoided the steep losses of the rule-based methods (e.g., −15.79 % CR for Z-score) and the worst-performing ML models (e.g., −24.71 % for LightGBM). Our method does signal effective risk management, as its maximum drawdown of 4.15 % is significantly lower than the worst-performing strategies, which suffer drawdowns exceeding 30 % (e.g., Transformer at 32.41 %). This suggests that while the agent's ability to generate profitable signals (*alpha*) is impaired, its internal risk-management mechanisms are highly active, providing a safer floor than brittle quantitative systems.

In summary, the baseline performance presents a stark paradox. The framework is demonstrably safer than most traditional strategies but is too conservative to be profitable in this market regime. This initial result reframes our investigation away from pure performance optimisation and towards understanding the source of this emergent, risk-averse behavior. The following diagnostic analysis and ablation studies are therefore critical to disentangling the components responsible for this complex outcome.

These findings must be interpreted cautiously. Each result stems from a single seed per architecture, except for the full system which is averaged over three independent runs. This minimal-seed analysis limits our ability to draw statistically robust conclusions about the framework's performance variability and generalisability across different market conditions. Future work should incorporate multi-seed evaluations to quantify the variance in agent behavior and performance stability [90].

5.1.2 Reasoning Diagnostics. Table 2 summarises key behavioural diagnostics for three independent full-architecture runs (`F0`, `F1`, `F2`) on AAPL. The metrics assess the alignment between the textual sentiment of the final decision agent's rationale, its recommended action, and realised price dynamics.

Table 1: Comparative performance of LLM agents against traditional quantitative strategies. Train metrics cover October 3, 2019-October 4, 2022; test metrics span October 5, 2022-June 10, 2023.

Category	Strategy	CR (%)	Ann. Sharpe		MDD (%)	Avg. Win (%)	Max Loss (%)	Max Win (%)	N_{tr}	α_{BH} (%)
			value	(95% CI)[b]						
Benchmark	Buy & Hold	22.74	1.10	(-1.17, 3.37)	19.81	22.74	–	22.74	1	0.00
Rule-based	Z-score Mean Reversion	-15.79	-1.36	(-3.83, 1.11)	17.34	2.69	-6.75	4.58	11	-37.28
	MACD Crossover	-7.68	-0.23	(-2.50, 2.04)	24.44	4.92	-4.65	20.09	20	-30.42
	KDJ-RSI Filter	-15.74	-1.29	(-3.56, 0.98)	18.77	2.19	-1.02	9.07	40	-38.48
Deep Learning	LSTM	24.04	1.15	(-1.13, 3.42)	20.64	5.90	-4.01	16.91	9	0.41
	Transformer	-23.96	-1.13	(-3.40, 1.14)	32.41	0.00	-32.41	0.00	1	-47.59
	LightGBM	-24.71	-1.18	(-3.45, 1.09)	26.79	1.75	-7.33	9.38	48	-47.45
Deep Reinforcement Learning	DQN	11.33	0.70	(-1.57, 2.97)	24.13	2.71	-6.82	15.51	38	-12.30
	A2C	22.74	1.13	(-1.14, 3.40)	19.81	22.74	–	22.74	1	0.00
	PPO	22.74	1.13	(-1.14, 3.40)	19.81	22.74	–	22.74	1	0.00
Self-Adapting Agents (ours)[a]	Full System	-4.15	-0.17	(-3.94, 3.59)	4.15	1.36	-5.51	1.36	1	-26.88

[a] The "Full System" refers to our complete, self-adapting architecture, powered by the Gemini 2.5 Flash Lite LLM. Metrics represent the mean of three independent runs.
[b] The 95% Sharpe ratio confidence interval is from a non-parametric bootstrap, supplemented by the analytical approximation from Lo [89].

Table 2: Behavioural diagnostics of the full architecture across three independent runs on the AAPL ticker. The metrics assess the alignment between the textual sentiment of the final decision agent's rationale, its recommended action, and realised price dynamics.

Metric	F0	F1	F2	**Mean**
Sentiment Profile				
Sentiment (μ, σ)	-0.043 (0.025)	-0.061 (0.032)	-0.046 (0.026)	-0.050 (0.028)
Bullish / Bearish Days	8/180	4/184	9/179	7/181
Predictive Power				
Sentiment-Price Corr.[a]	0.182	0.086	0.110	0.126
Hit Ratio (1-day)	0.48	0.49	0.52	0.50
p-value (Hit Ratio > 0.5)[d]	0.75	0.64	0.36	0.58
Trading Activity & Performance				
Trades Executed	1	1	1	1
Utilisation Rate [b]	0.5 %	0.5 %	0.5 %	0.5 %
Missed Opportunities	84	86	91	87
Shadow Return (7-days)[c]	−81.0 %	−87.2 %	−84.5 %	−84.2 %

[a] Pearson correlation coefficient.
[b] Percentage of trading days with a non-neutral position.
[c] Cumulative return from acting on every high-confidence signal with a 7-day holding period.
[d] The hit ratio p-value is from a one-sided exact binomial test [91] assessing if the observed accuracy is significantly greater than random chance (50%).

We quantify the sentiment of the agent's reasoning by embedding its natural-language rationales and measuring their cosine similarity to predefined 'bullish' and 'bearish' exemplar statements. This produces a continuous sentiment score for each daily rationale. As shown in Table 2, all three runs exhibit strongly negative average sentiment, with fewer than ten bullish days out of 188. This bias reflects an overly conservative prior that negates long exposure even in an upward-trending market, which also explains the low utilisation observed in Table 1.

Sentiment-price correlations remain low (0.09–0.25) and its lead lag positively correlates one day after price moves, indicating that the decision agent's language reasoning reacts to price rather than forecasts it.

The hit ratio measures the percentage of days where the sentiment of the agent's rationale correctly predicts the direction of the following day's price movement, where positive sentiment is followed by a positive return, or negative sentiment by a negative return. The 1-day hit ratio hovers near 50 %, with p-values far from statistical significance, indicating performance no better than chance. Across longer horizons, accuracy decays further, underscoring the limited predictive content in the decision agent's rationales.

The framework demonstrates flawless internal consistency, with a reason-action alignment score of 1.0 in every run. This metric compares the sentiment polarity of the decision agent's rationale against the final trading action (long, short, hold). However, this perfect score may be misleading. It arises due to the agent execution of a single trade, which was consistent with its reasoning on that specific day. On nearly all other days, the agent exhibited a strong bearish sentiment, yet took a neutral (hold) position. This persistent misalignment between a directional rationale and a non-committal action reveals a critical failure that the agent is unable to act on its own convictions, resulting in its internal reasoning being ineffective for trading.

A shadow backtest, which simulates trading on every directional sentiment signal (short for negative sentiment, long for positive), reveals a crucial insight. This hypothetical strategy would have produced large negative returns (−81.0 to −87.2 %). The single executed trade in each actual run resulted in a near-flat performance, but the framework's internal gating logic successfully shielded capital by filtering out these poor signals. However, in doing so, it suppressed nearly all activity, failing to act on 84 to 91 days where it generated a directional profitable rationale.

Collectively, these diagnostics show a critical tension in the framework. The multi-agent reasoning framework excels at reaching consensus, but the final signals generated by the decision agent are insufficiently informative or timely.

5.2 Ablation Analysis

To isolate the individual contributions of our framework's core components (addressing SQ2), we implemented a systematic ablation study protocol that selectively disables each major module, being Feedback-Driven Meta-Prompt Optimization (FBPO), Time-Aware Procedural Memory, and the Multi-Agent Debate Protocol. For computational feasibility, this intensive analysis was conducted on a shorter, more volatile market period than the benchmark comparison in Section 5.1.

5.2.1 Key Findings. Our ablation study reveals several counterintuitive findings. Most notably, the full architecture (`A0`) executed only one trade over six months, resulting in a minimal loss. In contrast, the non-adaptive baseline (`A4`) delivered a more significant cumulative return (CR) loss of −2.59 %, demonstrating that a static approach is detrimental in the tested market regime.

The critical importance of the feedback mechanism (FBPO) becomes apparent when examining variant `A1`, where its removal triples the trade count but severely degrades performance. Its cumulative return plummets to −8.83 %, a result significantly worse than any other variant, highlighting that a feedback mechanism is essential for generating alpha.

The full system (`A0`) exhibits the most conservative behaviour, executing only three trades and ending with a CR of −1.12 %. This confirms that the combination of all modules leads to a highly cautious agent that avoids most trading opportunities. The agent without FBPO (`A1`) performs the worst, with a CR of −4.26 %, underscoring the critical importance of the feedback loop for adaptation.

Paradoxically, removing either the Time-Aware Procedural Memory Retrieval (`A2`) or the Multi-Agent Debate Protocol (`A3`) improves realised performance relative to the full system. The memory-free variant (`A2`) generates a modest positive return of 1.98 %. However, the debate-free variant (`A3`) is the clear outperformer, producing the study's best cummulative return of 3.20 % across eight trades. This signifies that the debate protocol is the primary source of over-cautiousness, suppressing not only bad trades but also the profitable opportunities identified by the `A3` variant. While all variants significantly underperform the passive buy-and-hold benchmark's CR of 22.74 %, the relative performance differences provide crucial engineering insights.

5.2.2 Behavioural and Shadow Backtest Diagnostics. To understand the source of these performance differences, we conducted a shadow backtest, simulating trades on every directional signal generated by each agent's reasoning module, regardless of whether the final gating mechanism approved the trade. The results are summarised in Table 4.

The analysis reveals a clear insight where only the debate-free variant, `A3`, generated a fundamentally profitable signal. Its reasoning, if followed on every occasion, would have produced a 6.1 % return. This is supported by its statistically significant Binomial test for the hit ratio, which shows a **60%** accuracy rate in predicting price movements, significantly better than chance ($p = 0.003$). This variant also exhibits the highest sentiment-price correlation (0.473), indicating that its rationales are closely aligned with market movements. Its final realised return of 3.20 % indicates its gating mechanism was overly conservative, leaving a further 5.2 % of profit on the table. Its negative gating efficiency (−2.9 %) confirms that its filter actively destroyed value by vetoing profitable signals.

In stark contrast, all other variants (`A0`, `A1`, `A2`) produced signals that, in aggregate, were deeply unprofitable, with shadow returns around −25 %. Their hit ratios were indistinguishable from a coin flip. This reframes the performance of the memory-free (`A2`) variant, where its 1.98 % realised return is not due to good signals, but to an exceptionally effective filtering mechanism. It achieved the highest gating efficiency of the cohort, successfully turning a −25.3 % signal into a positive gain by rejecting the vast majority of trades.

Collectively, the ablation studies clarifies the division of performance among modules and frames the core challenge as a precision-recall trade-off. The FBPO module is the indispensable engine of adaptation, being necessary to generate any alpha. However, the signals it generates are noisy. The Debate Protocol acts as a high-precision filter, screening out almost all signals, which explains why its removal in `A3` unlocks the best performance. The memory module seems to function as an additional filter, further enhancing the overall gating efficiency of the complete system. The primary engineering challenge is not simply to augment layers of reasoning, but to fine-tune them to achieve balance, identifying a position on the

Table 3: Performance and Trade Diagnostics for Ablation Variants. Key metrics are shown for each variant alongside the buy-and-hold benchmark. α_{BH} is the excess cummulative return versus buy-and-hold. Train metrics span January 3, 2022-October 4, 2022; test metrics span October 5, 2022-June 10, 2023.

Category	Strategy	CR (%)	Ann. Sharpe		MDD (%)	Avg. Win (%)	Max Loss (%)	Max Win (%)	N_{tr}	α_{BH} (%)
			value	(95% CI)[c]						
Ablation	A0 (Full System)	-0.55	-1.16	(n/a)	-0.55	0.00	-0.55	-0.55	1	-23.28
	A1 (w/o Feedback)	-8.83	-1.03	(-1.59, 0.76)	11.20	2.67	-10.60	2.67	3	-31.50
	A2 (w/o Memory)	1.98	0.69	(n/a)	0.67	2.67	-0.67	2.67	2	-20.76
	A3 (w/o Debate)	3.20	0.86	(-0.45, 0.96)	1.51	1.02	-1.51	3.42	8	-19.58
	A4 (Static)	-2.59	-0.48	(-1.61, 0.75)	3.13	0.28	-3.13	0.55	3	-25.30
Benchmark	Buy & Hold	22.74	1.10	(-0.07, 0.21)	19.81	n/a	n/a	n/a	1	0.00

[a] 'n/a' intervals indicate fewer than three non-zero daily returns.
[b] Trade statistics for Buy & Hold are not applicable.
[c] The 95% Sharpe ratio confidence interval is from a non-parametric bootstrap, supplemented by the analytical approximation from Lo [89].

Table 4: Shadow Backtest Diagnostics for Ablation Variants. The metrics reveal the quality of the underlying signal before the final trading decision filter is applied.

Metric	A0 (Full)	A1 (w/o FBPO)	A2 (w/o Memory)	A3 (w/o Debate)
Signal Quality				
Shadow Return (1-day)[a]	−25.1 %	−24.4 %	−25.3 %	6.1 %
Sentiment-Price Corr.	0.121	0.214	0.211	**0.473**
Hit Ratio (1-day, p-value)[d]	49% (0.64)	51% (0.47)	48% (0.75)	**60% (0.003)**
Gating and Performance				
Realised Return	−0.55 %	−8.83 %	1.98 %	3.20 %
Gating Efficiency (Δ)[b]	24.6 %	15.6 %	27.3 %	−2.9 %
Missed Opportunity P&L[c]	−25.3 %	−16.5 %	−28.2 %	5.2 %

[a] Cumulative return from acting on every directional sentiment signal with a 1-day holding period.
[b] Gating Efficiency is the difference between Realised Return and Shadow Return, showing value added by filtering.
[c] The P&L of trades the agent considered but did not execute.
[d] The hit ratio p-value is from a one-sided exact binomial test [91] assessing if the observed accuracy is significantly greater than random chance (50%).

precision-recall plane that allows the transmission of high-quality signals while effectively filtering out the bulk of lower-quality ones.

5.3 Cross-Asset Generalisation

To find out whether the behavioural patterns observed in the ablation study (SQ2) generalise beyond a single ticker, we conducted a pilot backtest on two additional assets, Netflix (NFLX) and Amazon (AMZN). For computational efficiency, we tested only the full architecture and the best-performing, less conservative, ablation variant (A3) without the debate protocol over one seed. Table 5 summarises these results.

5.3.1 Key Findings. The cross-asset generalisation study validates a pivotal finding from our ablation analysis, removing the debate protocol results in a more robust and profitable trading system, particularly in non-trending or volatile markets. The performance of the variant without the debate protocol on Amazon (AMZN) provides the clearest evidence (see Figure 6 in Appendix B). It not only generated a positive cummulative return (CR) of 7.71 % but also outperformed its passive buy-and-hold benchmark, delivering an alpha of 6.54 %. Crucially, it achieved this with a maximum drawdown (MDD) of only 2.93 %, starkly contrasting with the benchmark's 32.64 % drawdown. This demonstrates the architecture's ability to generate alpha while maintaining stringent risk control.

In stark contrast, the full system exhibits a systemic bearish bias that proves highly detrimental in upward trending markets. On both AAPL and AMZN, it posted negative returns, failing to capitalise on bullish price trends. The performance on NFLX provides the most compelling evidence of this failure. While the system generated a positive return of 6.78 %, it severely underperformed the buy-and-hold benchmark's return of 76.66 %, resulting in an alpha of nearly −70 %. This result powerfully illustrates the opportunity cost imposed by the debate module's overly conservative or short-biased stance, which prevents the agent from participating in strong bull markets.

Table 5: Preliminary cross-asset performance of the full and debate-free systems. Train metrics span October 3, 2019-October 4, 2022; test metrics span October 5, 2022-June 10, 2023.

Ticker	Variant	CR (%)	Ann. Sharpe		MDD (%)	Avg. Win (%)	Max Loss (%)	Max Win (%)	N_{tr}	α_{BH} (%)
			value	(95% CI)[b]						
AAPL	Full[a]	-4.15	-0.17	(-3.94, 3.59)	4.15	1.36	-5.51	1.36	1	-26.88
	No Debate	-2.15	-1.52	(-3.80, 0.75)	1.52	0.00	-1.52	0.00	2	-24.87
	Buy & Hold	22.74	1.10	(-1.17, 3.37)	19.81	22.74	0.00	22.74	1	0.00
NFLX	Full	6.78	1.73	(-0.55, 4.00)	0.00	2.24	0.00	5.51	3	-69.93
	No Debate	1.28	1.16	(-1.11, 3.43)	0.00	1.28	0.00	1.28	1	-75.38
	Buy & Hold	76.66	1.91	(-0.37, 4.19)	21.17	76.66	0.00	76.66	1	0.00
AMZN	Full	-1.46	-0.12	(-2.39, 2.15)	1.49	0.03	-1.49	0.03	2	-2.56
	No Debate	7.71	1.13	(-1.14, 3.40)	2.93	5.63	-2.47	10.96	5	6.54
	Buy & Hold	1.10	0.25	(-2.02, 2.52)	32.64	1.10	0.00	1.10	1	0.00

[a] Results are the mean of three separate runs, detailed in Table 5. All other agent results are from single runs.
[b] The 95% Sharpe ratio confidence interval is from a non-parametric bootstrap, supplemented by the analytical approximation from Lo [89].

The key insight is that architectural simplification, specifically, the removal of the debate module, directly addresses the value-destructive, over-conservative behaviour observed in the full system. This finding allows us to isolate the debate protocol as a primary source of underperformance and validates the superiority of the leaner configuration without the debate protocol.

Further diagnostic analysis on the AMZN runs reveals the source of this performance difference. For the profitable variant without the debate protocol (A3), the 7-day moving average of its reasoning sentiment closely tracks the normalised asset price, as shown in Figure 7 in Appendix B.1. The agent correctly adopts a negative sentiment during price declines (Figure 8), demonstrating an ability to reason in alignment with market trends. However, this alignment appears to be reactive rather than predictive, suggesting the agent acts too late to fully capitalise on its insights. In contrast, the full system exhibits a persistently negative sentiment bias throughout the period, failing to recognise the upward price trend and explaining its poor performance (Figure 9).

5.4 Analysis of Out-of-Sample Behaviour

To isolate the framework's procedural reasoning from potentially memorised training data in the latent space of the Large Language Model, we conducted a forward-looking diagnostic test on AAPL stock from January 31, 2025, to May 1, 2025. This potential bias is a critical concern, as it can lead to overfitting and poor generalisation in real-world applications. The test period was selected to be beyond the knowledge cutoff of the LLM, which is set at end of 2024 for the Gemini 2.5 models [76].

The objective is not to measure absolute performance, but to diagnose the agent's core behaviour when confronted with a truly novel market environment.

5.4.1 Key Findings. The results from the temporal bias test provide a clear, yet nuanced, answer to SQ3. The agent executed zero trades throughout the entire 93-day period.

Table 6: Key behavioural and performance diagnostics from the forward-looking bias test. The agent was evaluated on market data that post-dates its knowledge cutoff.

Metric	Value
Performance & Trading Activity	
Compounded Return (CR%)	0.0% (NaN)
Annualised Sharpe Ratio	0.0 (NaN)
Trades Executed	0
Buy & Hold Return	-13.39%
Actual Alpha vs. Buy & Hold	+13.39%
Behavioural & Reasoning Diagnostics	
Sentiment (μ, σ)	(-0.053, 0.028)
Bullish / Bearish Days	2 / 91
1-Day Hit Ratio (p-value)[a]	0.52 (0.38)
Peak Sentiment-Price Correlation	0.23 (at lag of -2 days)
Shadow Return (7-day holding)	+37.54%

[a] The hit ratio p-value is from a one-sided exact binomial test [91] assessing if the observed accuracy is significantly greater than random chance (50%).

This inactivity is not due to a lack of market movement, the buy-and-hold benchmark experienced a significant downturn of $-13.39\,\%$ during this time. The agent's decision to refrain from trading resulted in a positive alpha of $13.39\,\%$ compared to the benchmark, but this outcome was purely coincidental, as it did not actively participate in the market.

The behavioural diagnostics in Table 6 reveal the cause of this inactivity. The agent exhibited an overwhelming bearish sentiment on 91 out of 93 days, with very low variance in its conviction ($\sigma = 0.028$), a bias even more pronounced than in previous tests. The peak positive correlation between its sentiment and price occurred with a two-day lag (0.23), meaning its reasoning most strongly reflected what had already happened. Even more revealing, the sentiment showed its strongest negative correlation (-0.22) with prices two days in the future, suggesting its signals were actively misleading. The 1-day hit ratio of 52% was statistically indistinguishable from a random coin flip. Taken together, these diagnostics imply that short-term sentiment is noisy, while the cumulative direction over multi-day windows is informative. The current architecture assesses signals daily and disregards immediately them if instant confidence is absent, therefore preventing potentially profitable medium-term trades.

This can also be concluded by the deep contradiction between the agent's raw signals and its actions. A shadow backtest, simulating trades based on every high-confidence signal, reveals a dramatic trend. The 1-day shadow return was −9.5 %, confirming the poor short-term timing of the agent's signals. However, this performance dramatically reverses as the holding period increases, reaching 37.5 % at 7 days and a remarkable 383 % at 14 days. This suggests that while the agent's timing was flawed, its persistent bearish bias was the correct long-term macro call for this specific falling market. The framework's own internal gating mechanisms, likely the same conservative debate protocol, completely suppressed these profitable, longer-term signals, preventing any capital from being deployed.

This diagnostic test does not rule out the possibility of temporal bias in other backtests, but rather highlights a more immediate architectural problem as the framework defaults to extreme risk aversion when faced with true uncertainty, completely halting the adaptation and learning mechanisms like the FBPO loop. This finding aligns with the results from the ablation study (Section 5.2), where removing the conservative debate protocol led to more robust performance.

5.5 LLM Architecture Generalizability

To evaluate the framework's performance consistency across diverse LLM architectures (addressing SQ4), we benchmarked against several state-of-the-art models. This comparative analysis assesses how differences in reasoning capabilities, parameter scaling, and training methodologies influence the framework's adaptive performance characteristics.

5.5.1 Key Findings. This experiment isolates the LLM as the sole independent variable as all agents began with identical prompts, parameters, and framework configurations. The results, summarised in Table 7, reveal that the choice of LLM introduces a powerful architectural bias that is the dominant factor in driving agent behaviour and performance.

The analysis directly contradicts the assumption that larger, more costly, or notionally smarter (higher AAI score) models yield superior trading results. The best relative performance came from `Deepseek R1 0528 Qwen3 8B`, one of the smallest and the most cost-effective models, which, despite a small loss, demonstrated exceptional risk management (MDD of 0.64 %). In stark contrast, the powerful and expensive `LLama 4 Maverick (Groq)` model was the worst performer, generating catastrophic losses (−28.75 % CR) and the highest drawdown (30.72 %). This demonstrates that performance is not a function of scale but of a model's specific, inherent reasoning style.

Each LLM exhibited a distinct personality, revealing a wide spectrum of risk aversion and activity that is an unpredictable, emergent property of the model itself. This emergent personality likely stems from a combination of the model's pre-training data, its fine-tuning alignment (e.g., the specific RLHF process used to make it a helpful assistant), and fundamental architectural choices like Mixture-of-Experts (MoE). Literature suggests that these factors create an inherent inductive bias that manifests as a distinct approach to risk and uncertainty [93]. The results therefore suggest that the LLM's personality is a core bias that can determine an agent's success or failure before the first trade is ever made.

Most models, including `Gemini 2.5 Flash Lite`, `Deepseek R1 0528 Qwen3 8B`, and `Qwen3 235B A22B`, displayed extreme conservatism. Their personalities prioritized capital preservation above all else, resulting in minimal drawdowns but also an almost complete refusal to trade. This behaviour reached its optimal with `Qwen3 235B A22B`, which was paralyzed into total inaction, executing zero trades. `LLama 4 Maverick (Groq)` represents the opposite personality. It was the only model to overcome the framework's conservative tendencies, executing 12 trades. However, its hyperactivity resulted in a significant loss, indicating that it was generating a high volume of low-quality signals.

No agent, regardless of its personality, could effectively mitigate the framework's internal gating mechanism. This reveals a fundamental mismatch between the LLM's signal generation and the framework's signal filtering. The debate protocol, which is designed to enhance the agent's reasoning capabilities, was simultaneously too restrictive for the cautious models, filtering out the rare signals they did produce, and too permissive for the hyperactive `LLama 4 Maverick (Groq)`, allowing a stream of poor-quality trades to pass through. The framework's static filtering logic failed to adapt to the unique architectural bias of any of the LLMs.

6 DISCUSSION

Our empirical investigation into a novel, self-adapting LLM framework reveals a series of critical, often counterintuitive, insights into the architectural dynamics of such systems. The results challenge common assumptions about agent design, highlighting a paradoxical relationship between complexity and performance, the indispensable role of feedback, and the overwhelming influence of the underlying language model's inherent bias.

The most salient and consistent finding is that increasing architectural sophistication was value-destructive. The full, multi-component system, equipped with advanced modules for memory (Time-Aware Procedural Memory Retrieval) and reasoning (Multi-Agent Debate Protocol), consistently defaulted to a state of extreme risk aversion. This inaction led to severe underperformance against passive benchmarks (Table 1), demonstrating that the system's internal filters, while effective at preventing losses, also systematically eliminated any potential for profit. The ablation studies (Section

Table 7: Comparative performance across different Large Language Model architectures. The training period spans January 3, 2022, to October 4, 2022, and the evaluation period is from October 5, 2022, to June 10, 2023. All models were tested on the AAPL ticker.

LLM Architecture	Size	Cost ($)[d]	AAI Index[e]	CR (%)	Ann. Sharpe value	Ann. Sharpe (95% CI)[f]	MDD (%)	N_{tr}	α_{BH} (%)
Our Framework									
Gemini 2.5 Flash Lite	n/a[a]	~5.83	45.63	-4.15	-0.17	(-3.94, 3.59)	4.15	1	-26.88
Deepseek R1 0528 Qwen3 8B	8B	~1.12	52.19	-0.64	-1.16	(-3.43, 1.11)	0.64	1	-23.38
LLama 4 Maverick (Groq)	17B/400B[b]	~5.28	50.53	-28.75	-1.92	(-4.20, 0.35)	30.72	12	-51.49
Qwen3 235B A22B	22B/235B[c]	~3.28	47.09	0.00	0.00	(n/a)	0.00	0	-22.74
Benchmark									
Buy & Hold	n/a	n/a	n/a	22.74	1.10	(-1.17, 3.37)	19.81	1	0.00

[a] Not publicly available.
[b] Active parameters are 17B, total model size is 400B.
[c] Active parameters are 22B, total model size is 235B.
[d] Cost is approximated for the full experimental run (train + test).
[e] Artificial Analysis Intelligence Index [92].
Metrics for `Gemini 2.5 Flash Lite` represent the mean of three independent test runs, as reported in Table 1.
[f] The 95% Sharpe ratio confidence interval is from a non-parametric bootstrap, supplemented by the analytical approximation from Lo [89].

5.2) confirmed this directly. By removing the debate protocol (A3), we discovered the single most important factor in unlocking a profitable strategy. This simplified agent was the only variant to generate inherently positive signals and deliver alpha in the cross-asset tests (Table 5), confirming that the debate module, intended to enhance reasoning, instead imposed a crippling and overly conservative bias, opposing the intended purpose from literature.

In contrast, the Feedback-Driven Meta-Prompt Optimization (FBPO) mechanism proved to be the indispensable engine of adaptation, providing us with a promising outlook for future research. The ablation study (A1) showed that without FBPO, the agent's performance deteriorated significantly. This underscores that the ability to learn from past performance is not just beneficial but essential for an adaptive agent's success in dynamic environments. The FBPO mechanism allows the agent to refine its internal heuristics based on both qualitative and quantitative feedback, enabling it to adapt its reasoning and trading strategies over time. However, as demonstrated in the temporal bias test (Section 5.4), the framework's conservative gating logic can inhibit the FBPO loop by preventing any trades from being executed when faced with true uncertainty. This highlights a critical area for future research, balancing risk management with the need for exploration and adaptation.

Perhaps the most significant discovery is that the choice of LLM is the dominant factor driving agent behavior, superseding the framework's own logic. Our comparative analysis (Section 5.5) showed that each LLM exhibits a distinct "personality", an unpredictable, emergent property that dictates its approach to risk and uncertainty. This finding contradicts the assumption that larger or notionally "smarter" models yield superior results. Performance is instead a function of the alignment between an LLM's intrinsic reasoning style and the task. The framework's static, one-size-fits-all gating mechanisms were fundamentally mismatched to these diverse personalities, failing to adapt to the unique strengths and weaknesses of each model. This highlights that LLM selection itself is a form of powerful, implicit bias that can determine an agent's success or failure before the first trade is ever made.

6.1 Limitations and Future Directions

The conclusions of this study must be viewed in light of several limitations, many of which stem from the significant computational costs associated with large-scale LLM experiments. These constraints, however, illuminate a clear path for future research.

First, our experiments were conducted on a limited set of assets over a short out-of-sample window, with a single seed for most configurations. This was a necessary concession to cost, but it means our results lack the statistical power to be considered definitive. The sparse trade counts in several variants made the calculation of reliable confidence intervals impossible. While this is a common issue in the field, it is not fully addressed in related works like FinAgent [7] or FinCon [8]. Future work must prioritize large-scale long-term and multi-seed (≥ 30) backtests across a diversified basket of assets (> 20) and varying market regimes to establish robust, generalizable performance estimates to mitigate the impact of potential stock selection bias.

Second, the framework's current design suffers from architectural brittleness. Key hyperparameters for the Time-Aware Procedural Memory Retrieval (RAG) module and the multi-agent debate protocol were not optimised, again due to computational cost constraints. The agent is also constrained by a "short-term memory" effect, where limited context windows for numerical (30-day price, 20-day indicators) and textual (3-day news) data may cause it to neglect longer-term trends. Future work should explore more compact and sophisticated state representations and calibrate memory retrieval and debate hyperparameters through cross-validation or online learning. To counter the observed conservative bias, the framework could be enhanced with richer data modalities, such as real-time macroeconomic indicators or social media sentiment.

Third, while FBPO proved essential, its current implementation is a greedy, reactive process. As noted in Section 3.5, this "prioritizes reactivity to recent feedback over the broader exploration inherent in complex search algorithms." A significant avenue for future research is to evolve FBPO into a more sophisticated search strategy. This could involve using evolutionary algorithms to generate a diverse pool of candidate meta-prompts. These candidates could be evaluated not just on performance, but also on an alignment score on the feedback from a separate evaluation agent, with a potential search regularization based on embedding distance to the current prompt, to balance exploration and exploitation. Additionally, the FBPO reward signal itself could be refined to more explicitly emphasize forecasting accuracy, shifting the agent from descriptive to predictive reasoning.

Finally, the core challenge identified is the tension between an LLM's inherent and emergent personality, and the framework's static logic. Our proposal to explore heterogeneous multi-LLM ensembles and hybrid systems with quantitative meta-models remains a promising path. A crucial next step is to conduct experiments on different LLMs without the debate protocol to isolate the model's raw signal-generation tendencies. The risk of "context rot" [94], where performance degrades as input context grows, also remains a critical, unmeasured concern requiring investigation for agents designed for continuous, long-term operation. This is a newly emerging area of research and should be taken into account in future work as complexity of the system and context length increase.

While our results indicate that a truly autonomous and consistently profitable LLM-based trading agent is not yet a reality, they map out a promising and clear direction for research. By addressing these limitations and exploring these future directions, the path toward building more robust, adaptive, and trustworthy financial agents becomes clearer.

7 CONCLUSION AND CONTRIBUTIONS

This research set out to investigate the promise of a self-adapting, multi-component framework for LLM-powered financial trading. We sought to understand the extent to which architectural components, specifically Feedback-Driven Meta-Prompt Optimization (FBPO), Time-Aware Procedural Memory Retrieval, and a multi-agent debate protocol, could contribute to adaptive and profitable behavior in dynamic markets. Our findings, however, reveal a significant disconnect between architectural intent and empirical reality, leading to three main contributions that reshape our understanding of how to build autonomous self-adapting financial agents.

First, we introduced FBPO as a novel, gradient-free method for reinforced adaptation. Our results confirmed its foundational importance, as without it, the agent's performance collapsed. This validates the core hypothesis that learning from performance outcomes is critical. However, our work also revealed its primary limitation as FBPO is only as effective as the data it receives. When the agent is paralyzed by its own risk-management logic, the feedback loop breaks down, halting adaptation entirely, which is a weakness that became evident as our low trade counts left the agent with insufficient data to learn from.

Second, our modular framework, which combined FBPO with sophisticated memory and reasoning modules, served as a powerful diagnostic tool. Counter to our initial hypotheses, adding layers of sophistication in the form of Time-Aware Procedural Memory Retrieval and the multi-agent debate protocol proved to be value destructive. These components induced a state of extreme conservatism, causing the agent to leave nearly all trading opportunities. The ablation studies were definitive, architectural simplification, specifically the removal of the debate module, is the most effective step toward creating a robust and profitable agent. Yet this insight, is something to be cautious with as it is drawn from a single six-month evaluation window on a handful of equities, so its generalizability remains to be explored as computational costs of LLMs continue to decrease.

Third, and perhaps most critically, this study provides extensive empirical evidence that an LLM's inherent architectural bias is the dominant factor in agent performance, overriding the explicit logic of the framework it operates within. The choice of LLM is not a simple implementation detail but rather the selection of a core component with a distinct, emergent, and unpredictable personality. Performance is not a function of a model's scale or theoretical capability, but of the alignment between its intrinsic reasoning style and the specific task. Although this conclusion emerged consistently across the four models we tested, the limited breadth of the LLM sweep in terms of assets and training and evaluation periods means that further work is required to establish how universal this personality effect truly is.

In answering our central research question, we found that the architectural components contributed to adaptive behavior in unexpected and often contradictory ways. While FBPO provided the engine for learning, the memory retrieval and debate modules halted adaption, while the entire system was ultimately governed by the unpredictable architectural bias of the underlying LLM.

The path forward, therefore, is more regiously testing the framework's components across a wider range of assets and market conditions, as well as longer training evaluation periods and Monte Carlo simulations with multiple seeds,to establish statistical soundness as prices per token continue to fall. Future research should look into heterogeneous multi-LLM ensembles that leverage model personalities and hybrid systems that ground an LLM's qualitative reasoning with the quantitative rigor of high-performing traditional forecasting models to enhance interpretability. By doing so, we can begin to build a new generation of financial agents that are not only intelligent and adaptive but also robust, reliable, and interpretable in the complex and dynamic world of financial markets.

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A APPENDIX

A.1 Technical Indicators

This section details the technical indicators employed within the self-adapting agents framework, especially those used within the environment state accessible to the agents. The indicators are designed to provide a comprehensive view of market conditions, enabling agents to make informed decisions based on both current and historical data. The indicators are computed using the TA-Lib library, which is widely used for technical analysis in financial markets. The set is customisable, yet carefully selected to balance complexity and interpretability, keeping the context length of the underlying agents manageable.

A.1.1 Indicator Definitions. The following indicators are defined to capture various aspects of market dynamics:

- **Simple Moving Average (SMA)**: Averages the closing prices over a specified period, smoothing out price fluctuations. It gives insight into the overall trend by filtering out noise from short-term price movements.
- **Exponential Moving Average (EMA)**: Similar to SMA but gives more weight to recent prices, making it more responsive to new information.
- **Relative Strength Index (RSI)**: Measures the speed and change of price movements, indicating overbought or oversold conditions.
- **Average Directional Index (ADX)**: Assesses the strength of a trend, regardless of its direction.
- **Commodity Channel Index (CCI)**: Evaluates the current price level relative to an average price level over a specified period, indicating potential reversals. Insightful for identifying cyclical trends in the market.

Simple Moving Average (SMA). The Simple Moving Average (SMA) is calculated as follows:

$$\mathrm{SMA}(t) = \frac{1}{n}\sum_{i=0}^{n-1} P(t-i) \tag{7}$$

where $P(t)$ is the price at time t and n is the number of periods over which the average is calculated. For our implementation, we use a 20-period SMA, which is computed using the closing prices of the asset.

Exponential Moving Average (EMA). The Exponential Moving Average (EMA) is calculated using the formula:

$$\mathrm{EMA}(t) = \alpha \cdot P(t) + (1-\alpha)\cdot \mathrm{EMA}(t-1) \tag{8}$$

where $\alpha = \frac{2}{n+1}$ and n is the number of periods. The EMA is more sensitive to recent price changes compared to the SMA, making it useful for identifying short-term trends. Again, we use a 20-period EMA based on the closing prices.

Relative Strength Index (RSI). The Relative Strength Index (RSI) is defined as:

$$\mathrm{RSI}(t) = 100 - \frac{100}{1+RS(t)} \tag{9}$$

where $RS(t) = \frac{\text{Average Gain}}{\text{Average Loss}}$ over a specified period (14 days in our case). The RSI ranges from 0 to 100, with values above 70 typically indicating overbought conditions and below 30 indicating oversold conditions. This indicator helps agents identify potential reversal points in the market.

Average Directional Index (ADX). The Average Directional Index (ADX) is calculated to measure the strength of a trend:

$$\text{ADX}(t) = 100 \cdot \frac{\text{Moving Average of |DI+ - DI-|}}{\text{True Range}} \tag{10}$$

where $DI+$ and $DI-$ are the directional indicators, and the True Range is the greatest of the following:

- Current High - Current Low
- Current High - Previous Close
- Previous Close - Current Low

The ADX is in our experiments calculated over a 14-day period and helps agents understand whether the market either has a strong trend or is ranging. In practice, an ADX value above 25 typically indicates a strong trend, while values below 20 suggest a weak trend or ranging market.

Commodity Channel Index (CCI). Lastly, the Commodity Channel Index (CCI) is computed as:

$$\text{CCI}(t) = \frac{P(t) - \text{SMA}(t)}{0.015 \cdot \text{Mean Deviation}(t)} \tag{11}$$

where $P(t)$ is the price at time t, and the Mean Deviation is defined as,

$$\text{Mean Deviation}(t) = \frac{1}{n} \sum_{i=0}^{n-1} |P(t-i) - \text{SMA}(t)| \tag{12}$$

where n is the number of periods (14 in our case). The CCI oscillates around zero, with values above 100 indicating overbought conditions and below -100 indicating oversold conditions. This indicator is particularly useful for identifying cyclical trends in the market.

A.2 State Representation

The state representation of the environment for the self-adapting agents in this project is designed to capture the essential features of the market environment and the agent's portfolio. Its representation is used to inform the agent's decision-making process in corresponding prompt templates. The state representation includes the following components described in Listing A.1:

```
{
  "current_date": "<ISO_8601_datetime>",
  "current_day_index": <int>,
  "metrics": {
    "market": {
      "ticker": "<string>",
      "open": <float>,
      "high": <float>,
      "low": <float>,
      "close": <float>,
      "price": <float>,
      "volume": <int>,
      "daily_change": <float>,
      "indicators": {
        "SMA20": <float>, "EMA20": <float>, "RSI": <float>, "ADX": <float>, "CCI": <float>
      },
      "indicator_history": {
        "SMA20": [<float>, ...], "EMA20": [<float>, ...], "RSI": [<float>, ...],
        "ADX": [<float>, ...], "CCI": [<float>, ...]
      },
      "historical_data": {
        "daily_open_prices": [<float>, ...], "daily_high_prices": [<float>, ...],
        "daily_low_prices": [<float>, ...], "daily_close_prices": [<float>, ...],
        "daily_volumes": [<int>, ...], "daily_news_history": [<string>, ...]
      }
    },
    "position": {
      "size": <int>, "entry_price": <float>, "current_price": <float>,
      "unrealized_pl": <float>, "is_long": <bool>, "tag": "<string>"
    },
    "portfolio": {
      "equity": <float>, "cash": <float>, "max_equity": <float>,
      "drawdown": <float>, "drawdown_pct": <float>, "equity_curve_pct": <float>,
      "return_1m": <float>, "return_3m": <float>, "return_1y": <float|null>,
      "volatility": <float>, "max_drawdown": <float>,
      "sharpe_ratio": <float>, "sortino_ratio": <float|null>,
      "cvar_1pct": <float|null>, "cvar_5pct": <float|null>,
      "equity_history": [<float>, ...], "drawdown_history": [<float>, ...],
      "cash_history": [<float>, ...], "position_value_history": [<float>, ...],
      "daily_returns": [<float>, ...], "cvar_1pct_history": [<float|null>, ...],
      "cvar_5pct_history": [<float|null>, ...], "max_equity_history": [<float>, ...],
      "drawdown_value_history": [<float>, ...], "equity_curve_pct_history": [<float>, ...],
      "return_1m_history": [<float>, ...], "return_3m_history": [<float>, ...],
      "return_1y_history": [<float|null>, ...], "volatility_history": [<float>, ...],
      "current_max_drawdown_pct_history": [<float>, ...],
      "sharpe_ratio_history": [<float>, ...], "sortino_ratio_history": [<float|null>, ...]
    },
    "trade": {
      "total_trades": <int>, "win_count": <int>, "loss_count": <int>,
      "win_rate": <float>, "avg_profit_pct": <float>, "avg_win_pct": <float>,
      "avg_loss_pct": <float|null>, "max_win_pct": <float>, "max_loss_pct": <float|null>,
      "avg_trade_length_bars": <float>, "avg_win_length_bars": <float>,
      "avg_loss_length_bars": <float|null>, "profit_factor": <float|null>,
      "std_dev_pl_pct": <float>,
      "closed_trades_list": [
        {
          "entry_price": <float>, "exit_price": <float>,
          "entry_time": "<ISO_8601_datetime>", "exit_time": "<ISO_8601_datetime>",
          "entry_bar": <int>, "exit_bar": <int>, "size": <int>, "value": <float>,
          "is_long": <bool>, "pl": <float>, "pl_pct": <float>,
          "trade_duration": <int>, "days_in_position": <int|null>,
          "tag": "<string>", "mfe_pct": <float>, "mae_pct": <float>,
          "realized_risk_reward": <float>, "trade_volatility": <float>
        }, ...
      ]
    }
  }
}
```

Listing A.1: Schema of the JSON state object at a single timestep. Generic placeholders indicate the expected data types for each field.

A.3 Operational Robustness: Retry Protocol

Our agent's retry mechanism consists of two main component, the connection retry protocol and the JSON-fixer. The retry protocol is designed to ensure that the agent can handle transient errors gracefully, while the JSON-fixer addresses issues with malformed responses from the LLM. Together, these components enhance the robustness of the agent's operations, allowing it to recover from errors and maintain a high level of reliability, keeping the system operational even in the face of unexpected issues.

A.3.1 Connection Retry Protocol. The connection retry protocol is a crucial part of the agent's operational robustness, designed to handle transient errors that may occur during API calls to the LLM. This protocol ensures that the agent can recover from temporary issues such as network interruptions, rate limits, or timeouts without losing the context of its operations. When an error occurs when calling the large language model API, the method enters a loop that attempts to reissue the API call up to ten times, with an exponential back-off strategy to avoid overwhelming the server. The timeout starts at 5 seconds and increases exponentially with each retry, up to a maximum of 300 seconds. Additionally, a jitter of 10% is applied to the delay to prevent overwhelming the server with simultaneous retries from multiple agents. This retry mechanism is essential for maintaining the agent's operational integrity, allowing it to handle transient errors without manual intervention.

A.3.2 Fixing Malformed Responses. The JSON-fixer is a specialized component of the agent that addresses issues with malformed responses from the LLM. Each agent is tasked to respond in a strict JSON format, which is essential for us to be able to efficiently and easily parse and utilize the response. In order to ensure that the agent's responses conform to a specific JSON schema, we dynamically compute a JSON schema based on the agent's response model. This schema defines the expected structure of the response, including required fields, data types, and formatting rules. The agent is instructed to strictly adhere to this schema when generating its response. To enforce this, we inject a system prompt into the agent's instructions that outlines the JSON formatting rules and provides an example of the expected output. This prompt is designed to guide the agent in producing valid JSON responses, ensuring that it follows the specified schema and formatting conventions.

However, sometimes the LLM may produce responses that do not conform to the expected JSON schema, which can lead to parsing errors and disrupt the agent's operations. To mitigate this issue, the JSON-fixer is invoked whenever a response is received that does not match the expected schema. It attempts to repair the malformed JSON by applying a set of predefined rules and heuristics, ensuring that the response can be parsed correctly. If this repair process fails, the agent will log the error and invoke a new agent specifically designed to fix JSON issues. This agent will receive the malformed response with its associated error message and will attempt to correct the JSON format with the original prompt in mind. The prompt for the JSON-fixer agent may be seen in Listing A.3.

This approach retries for up to five times, allowing the agent to recover from transient issues while ensuring that the responses remain valid and parsable.

A.4 Agent Prompts

This appendix provides examples of the prompts used in the pipeline. They are stored as Jinja templates (`.j2` files) and appear here exactly as they are passed to the LLMs.

A.4.1 News-Analysis Prompt. Listing A.4 shows the prompt used by the news analysis agent. It instructs the agent to analyze financial news for a specific stock ticker and date, reviewing the daily news history to extract relevant insights that may impact trading decisions.

A.4.2 Technical-Analysis Prompt. The technical analysis agent uses the prompt shown in Listing A.5. It analyzes market metrics to provide insights on price trends, support and resistance levels, volume analysis, key technical indicators, chart patterns, and trading signals.

A.4.3 Portfolio-Analysis Prompt. Next, the portfolio analysis agent uses the prompt shown in Listing A.6. It evaluates the current trading account health and the active position based on the portfolio and position metrics provided in the environment state. The agent provides insights on overall equity performance, risk ratios, cash vs. invested value, unrealised P/L, and actionable insights on portfolio health and potential adjustments.

A.4.4 Bull Debate Agent Prompt. The Listing A.7 shows the prompt for the bull debate agent. This agent is tasked with presenting arguments for why the price will move upward, focusing on the current market analysis and previous debate points. It must evolve its arguments based on the ongoing debate and provide a structured response. It does so by reviewing the market analysis context, previous debate history, and specific instructions to build a compelling case for a bullish position.

A.4.5 Bear Debate Agent Prompt. Subsequent to the bull debate agent, the bear debate agent uses the prompt shown in Listing A.8. This agent is tasked with presenting arguments for why the price will move downward, focusing on the current market analysis and previous debate points. It must evolve its arguments based on the ongoing debate and provide a structured response. It does so by reviewing the market analysis context, previous debate history, and specific instructions to build a compelling case for a bearish position.

A.4.6 Aggregator Prompt. The Aggregator agent uses the prompt shown in Listing A.9. This agent summarizes the debate arguments without making a final trading decision. It provides a balanced overview of the discussion, highlighting the strongest bullish and bearish arguments, and key insights that emerged during the debate analysis. The response is structured into distinct sections for clarity.

A.4.7 Trading Decision Prompt. To make a final trading decision, the trading decision agent uses the prompt shown in Listing A.10. The agent uses the debate outcome, if available, to inform its decision-making process. If no debate outcome is present, it relies on the current market analysis and similar past experiences. The agent is

```
Make sure to respond in JSON format within a code block starting with ```json and ending with ```, STRICTLY respond with the needs of the
      response model with the following schema: {json_schema}

IMPORTANT JSON FORMATTING RULES:
1. Do NOT include trailing commas after the last property in an object or last item in an array
2. All property names must be enclosed in double quotes
3. String values must be enclosed in double quotes
4. Boolean values must be lowercase (true/false)
5. Numbers should not be quoted unless they are part of a string
6. Do not include any other text or formatting in your response
7. ONLY respond with the output needs of the response model and nothing else
EXAMPLE of correct formatting based on your schema: {example_json}
```

Listing A.2: Additional system prompt for the agent to respond in strict JSON format.

```
You are a JSON repair specialist. Fix the following JSON to make it valid according to the schema.

ORIGINAL PROMPT: \% \{prompt\}

MALFORMED RESPONSE: \% \{original\_response\}

ERROR MESSAGE: \% \{error\_message\}

Please provide ONLY a fixed JSON response that follows the schema and formatting rules. Do not include any explanations or additional text.
```

Listing A.3: Prompt for the JSON-fixer agent.

```
You are a financial news analyst. Your task is to analyze the provided news text for the stock ticker {{ ticker }} for the period up to
      today {{ current_date }}.

The following is a history of news items:

News History:
{% if daily_news_history %}
{{ daily_news_history }}
{% else %}
No news history available.
{% endif %}
```

Listing A.4: Prompt for the news analysis agent. The agent analyzes the provided news text for a specific stock ticker and current date. It reviews the daily news history to extract relevant insights that may impact trading decisions.

```
You are a technical analysis expert. Analyze the following market data and provide insights:

## Market Metrics
{{ env_state.metrics.market }}

Based on this information, provide a comprehensive technical analysis including:
1. Price trend analysis
2. Support and resistance levels
3. Volume analysis
4. Key technical indicators
5. Chart patterns
6. Trading signals (bullish/bearish)
```

Listing A.5: Prompt for the technical analysis agent. The agent analyzes the market metrics provided in the environment state and provides insights on price trends, support and resistance levels, volume analysis, key technical indicators, chart patterns, and trading signals. This analysis informs the trading decision-making process.

tasked with making a single trading decision per day, adhering to the simplified position management rules outlined in the prompt.

A.5 Procedural Memory and Query Generation

In this section, we provide the templates used for generating the procedural memory documents and queries. The memory system is designed to store and retrieve past trading experiences, which include the trading decision, reasoning, and feedback on the outcome. This allows the agent to learn from previous decisions and improve its future performance.

```
You are a portfolio analysis expert. Evaluate the current trading account health and the active position.

## Portfolio Metrics
{{ env_state.metrics.portfolio }}

## Position Metrics
{% if env_state.metrics.position %}{{ env_state.metrics.position }}{% else %}No active position.{% endif %}

Provide a concise analysis covering:
1. Overall equity performance (returns, drawdown, volatility).
2. Risk ratios (Sharpe, Sortino, CVaR).
3. Current cash vs. invested value.
4. If a position is open: unrealised P/L and risk-reward outlook.
5. Actionable insights on portfolio health and potential adjustments.
```

Listing A.6: Prompt for the portfolio analysis agent. The agent evaluates the current trading account health and the active position based on the portfolio and position metrics provided in the environment state. It provides insights on overall equity performance, risk ratios, cash vs. invested value, unrealised P/L, and actionable insights on portfolio health and potential adjustments.

A.5.1 Document-Text Template. In Listing A.11, we present the template used to format the trading decision experience documents that are stored in the procedural memory system. Each document captures the decision made, the reasoning behind it, and feedback on the outcome.

A.5.2 Query Generation Prompt. The query generation prompt is designed to create a query that retrieves relevant past trading experiences based on the current market analysis. The template used for generating the memory retrieval queries is shown in Listing A.12. This prompt incorporates the current market analysis, including technical, portfolio, and news analyses when present, along with the current date to formulate a query that can fetch relevant past trading experiences.

A.6 FBPO Prompts

This appendix provides the specific prompts used for the Feedback-Driven Meta-prompt Optimization (FBPO) mechanism as part of the self-adapting agent framework. The FBPO mechanism consists of two main components, the feedback collection prompt and the meta-prompt optimization prompt. These prompts are designed to facilitate the collection of feedback on trading decisions and to optimize the meta-prompt used for generating trading strategies.

A.6.1 Feedback Prompt. First, the feedback collection prompt is used to evaluate past trading decisions based on their outcomes and provide constructive feedback. The prompt present in Listing A.13 is designed to guide the feedback agent in analyzing the trading decision, considering the simplified trading environment's constraints and rules, and focusing on decision timing and market direction accuracy.

A.6.2 Meta-Prompt Optimiser. Next, the meta-prompt optimization prompt is used to analyze past trading decisions, their outcomes, and the feedback received. The prompt present in Listing A.14 is designed to guide the meta-prompt optimiser agent in suggesting improvements to the original meta prompt used for making trading decisions, focusing on enhancing the decision-making process within the simplified trading environment's constraints and rules. It aims to achieve more profitable trades by providing actionable recommendations for optimizing the meta prompt.

```
# Market Analysis Context
{% if data.technical_analysis %}
Technical Analysis: {{ data.technical_analysis }}
{% endif %}
{% if data.portfolio_analysis %}
Portfolio Analysis: {{ data.portfolio_analysis }}
{% endif %}
{% if data.news_analysis %}
News Analysis: {{ data.news_analysis }}
{% endif %}

# Market Context
Ticker: {{ data.ticker }}
Date: {{ data.current_date }}

{% if data.env_state.metrics.position %}
## Position Metrics
{{ data.env_state.metrics.position }}
{% else %}
No active position.
{% endif %}

## Portfolio Metrics
{{ data.env_state.metrics.portfolio }}

# Trading Environment
IMPORTANT: Focus on directional arguments only:
- This is a simplified LONG/SHORT/HOLD environment
- SHORT = Short position (betting price goes DOWN)
- LONG = Long position (betting price goes UP)
- HOLD = Close position and stay flat (cash)
- No position sizing, stop losses, or profit targets available
- Your job: Argue why price will move UP (bullish direction)

# Previous Debate
{% if transcript %}
{{ transcript }}

IMPORTANT: Review the debate above and:
1. Address specific points raised by the bearish agent
2. Build upon your previous arguments (don't just repeat them)
3. Introduce NEW evidence or perspectives that strengthen your bullish case
4. Counter the most compelling bearish arguments with fresh insights
{% else %}
No debate history yet. Present your opening bullish argument.
{% endif %}

# Your Role
You are a BULLISH trading agent arguing for LONG positions. Present compelling evidence for why price will move UPWARD based on the analysis
      provided.

# Instructions
1. **If this is NOT the first round**: Reference and respond to the bearish agent's latest points
2. **Avoid repetition**: Don't just restate your previous arguments - evolve and strengthen them
3. Focus on indicators suggesting UPWARD price movement
4. Highlight factors supporting price appreciation
5. Emphasize catalysts that could drive price higher
6. Address bearish concerns with counter-arguments about upward momentum
7. Keep response focused and under 200 words
8. Be persuasive but factual about directional movement

# Response Format
Provide a clear, structured argument that includes:
1. **Opening**: Brief acknowledgment of previous debate points (if any)
2. **Main thesis**: Your core argument for UPWARD price movement
3. **Supporting evidence**: New or reinforced evidence for price appreciation
4. **Counter-arguments**: Address the strongest bearish concerns raised
5. **Conclusion**: Reinforce the bullish directional call with conviction
```

Listing A.7: Prompt for the bull debate agent. The agent is tasked with presenting arguments for why the price will move upward, focusing on the current market analysis and previous debate points. It must evolve its arguments based on the ongoing debate and provide a structured response.

B SUPPLEMENTARY PERFORMANCE PLOTS

This appendix provides supplementary equity curves for key model variants discussed in the main text. Each figure corresponds to a specific backtest run, offering a visual representation of the agent's trading behavior and its impact on portfolio value over the test period.

B.1 Cross-Asset Diagnostic Plots

This appendix provides detailed diagnostic plots for the cross-asset runs on AMZN, comparing the A3 (w/o Debate) variant with the full system.

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```
# Market Analysis Context
{% if data.technical_analysis is not none %}
Technical Analysis: {{ data.technical_analysis }}
{% endif %}
{% if data.portfolio_analysis is not none %}
Portfolio Analysis: {{ data.portfolio_analysis }}
{% endif %}
{% if data.news_analysis is not none %}
News Analysis: {{ data.news_analysis }}
{% endif %}

# Market Context
Ticker: {{ data.ticker }}
Date: {{ data.current_date }}

{% if data.env_state.metrics.position %}
## Position Metrics
{{ data.env_state.metrics.position }}
{% else %}
No active position.
{% endif %}

## Portfolio Metrics
{{ data.env_state.metrics.portfolio }}

# Trading Environment
IMPORTANT: Focus on directional arguments only:
- This is a simplified LONG/SHORT/HOLD environment
- SHORT = Short position (betting price goes DOWN)
- LONG = Long position (betting price goes UP)
- HOLD = Close position and stay flat (cash)
- No position sizing, stop losses, or profit targets available
- Your job: Argue why price will move DOWN (bearish direction)

# Previous Debate
{% if transcript %}
{{ transcript }}

IMPORTANT: Review the debate above and:
1. Address specific points raised by the bullish agent
2. Build upon your previous arguments (don't just repeat them)
3. Introduce NEW evidence or perspectives that strengthen your bearish case
4. Counter the most compelling bullish arguments with fresh insights
{% else %}
No debate history yet. Present your opening bearish argument.
{% endif %}

# Your Role
You are a BEARISH trading agent arguing for SHORT positions. Present compelling evidence for why price will move DOWNWARD based on the analysis provided.

# Instructions
1. **If this is NOT the first round**: Reference and respond to the bullish agent's latest points
2. **Avoid repetition**: Don't just restate your previous arguments - evolve and strengthen them
3. Focus on indicators suggesting DOWNWARD price movement
4. Highlight factors supporting price decline
5. Emphasize catalysts that could drive price lower
6. Address bullish concerns with counter-arguments about downward momentum
7. Keep response focused and under 200 words
8. Be persuasive but factual about directional movement

# Response Format
Provide a clear, structured argument that includes:
1. **Opening**: Brief acknowledgment of previous debate points (if any)
2. **Main thesis**: Your core argument for DOWNWARD price movement
3. **Supporting evidence**: New or reinforced evidence for price decline
4. **Counter-arguments**: Address the strongest bullish concerns raised
5. **Conclusion**: Reinforce the bearish directional call with conviction
```

Listing A.8: Prompt for the bear debate agent. The agent is tasked with presenting arguments for why the price will move downward, focusing on the current market analysis and previous debate points. It must evolve its arguments based on the ongoing debate and provide a structured response.

```
# Market Context
Ticker: {{ data.ticker }}
Date: {{ data.current_date }}

# Debate Transcript
{{ transcript }}

# Role
You are an impartial trading analyst summarizing a debate between bullish and bearish trading experts. Your role is to analyze and distill
      the key points from both sides WITHOUT making a final trading decision.

# Task
Provide a comprehensive summary of the debate that includes:

1. A balanced overview of the discussion
2. The strongest bullish arguments presented
3. The strongest bearish arguments presented
4. Key insights or unique perspectives that emerged during the debate analysis.

# Response Format
Format your response with these exact sections:

**Summary**: An objective overview of the entire debate, highlighting the main themes and areas of disagreement.

**Bull Arguments**: The strongest points made supporting a bullish position, including specific evidence cited.

**Bear Arguments**: The strongest points made supporting a bearish position, including specific risks highlighted.

**Key Insights**: Important observations, unique angles, or notable patterns that emerged from the debate analysis.

# Important Note
Do NOT provide a trading recommendation (LONG/SHORT/HOLD). Your role is only to summarize the debate arguments objectively, not to make a
      decision.
```

Listing A.9: Prompt for the trading aggregator agent. The agent summarizes the debate arguments without making a final trading decision. It provides a balanced overview of the discussion, highlighting the strongest bullish and bearish arguments, and key insights that emerged during the debate analysis. The response is structured into distinct sections for clarity.

```
{% if debate_outcome and debate_outcome != None %}
# Debate Summary
{{ debate_outcome }}
{% else %}
# Market Analysis Context
{% if technical_analysis %}
Technical Analysis: {{ technical_analysis }}
{% endif %}
{% if portfolio_analysis %}
Portfolio Analysis: {{ portfolio_analysis }}
{% endif %}
{% if news_analysis %}
News Analysis: {{ news_analysis }}
{% endif %}
{% endif %}

{% if similar_experiences and similar_experiences|length > 0 %}
# Similar Past Experiences

Based on analysis of {{ similar_experiences|length }} similar past trading experiences:

{% for experience in similar_experiences %}
## Experience {{ loop.index }} (Importance Score: {{ "%.3f"|format(experience.score) }})
{{ experience.document }}

---
{% endfor %}
{% endif %}

{% if env_state.metrics.position %}
## Current Position Metrics
{{ env_state.metrics.position }}
{% else %}
No active position.
{% endif %}

## Current Portfolio Metrics
{{ env_state.metrics.portfolio }}

# Role and Task
You are a sophisticated trading decision expert responsible for making the final trading decision.
Your task is to analyze the provided information to determine the optimal trading action.
You have the possibility to make a decision once per day. We're not doing intraday trading!

# Position Management Rules
IMPORTANT: Understand how your trading decisions affect positions:

**LONG Decision:**
- Opens a LONG position (betting price will go up)
- If already in a SHORT position, closes the short and opens a long
- If already in a LONG position, maintains the long position

**SHORT Decision:**
- Opens a SHORT position (betting price will go down)
- If already in a LONG position, closes the long and opens a short
- If already in a SHORT position, maintains the short position

**HOLD Decision:**
- Closes any existing position and moves to cash (flat)
- If no position exists, remains in cash
- Does NOT open any new position

# Position Sizing & Risk Management
IMPORTANT: This is a simplified trading environment:

**Position Size:**
- Position size equals 100% of current equity (all-in positions)
- No position sizing control available
- You cannot adjust the amount invested

**Risk Management:**
- No stop loss mechanisms available
- No profit target triggers available
- No partial position exits possible
- Your only controls are: LONG (enter/keep long), SHORT (enter/keep short), or HOLD (close position / stay flat) and you cannot change the position size.

**Decision Simplicity:**
- Focus purely on market direction (up/down/sideways)
- Do not consider position sizing in your analysis
- Risk management comes only from timing of entry/exit decisions

**Positions:**
- You can only have one position at a time.
- By closing your position, you open a new position in the opposite direction.

# Instructions
1. Carefully review and analyze the provided information
2. Consider the position management rules above when making your decision
3. Make an independent trading decision based on the weight of evidence from both current analysis and historical context

<meta_prompt>
Your goal is to maximize the Cumulative Return of the equity curve.
</meta_prompt>
```

Listing A.10: Prompt for the trading decision agent. The agent uses the debate outcome, if available, to inform its decision-making process. If no debate outcome is present, it relies on the current market analysis and similar past experiences. The agent is tasked with making a single trading decision per day, adhering to the simplified position management rules outlined

```
Trading Decision Experience [BAR: {{ bar_index }}] [TIME: {{ decision_time }} on bar {{ bar_index }}]

DECISION [ACTION: {{ decision }}]:
{{ reasoning }}

OUTCOME FEEDBACK:
{{ feedback }}
```

Listing A.11: Template for formatting trading decision experience documents for procedural memory storage. This template structures the decision-making experience, including the decision action, reasoning, and feedback on the outcome. It is used to create documents that can be stored in the memory system for future retrieval and analysis.

```
{{ ticker }} trading analysis:
{% if technical_analysis is not none %}
Technical analysis: {{ technical_analysis }}
{% endif %}
{% if portfolio_analysis is not none %}
Portfolio analysis: {{ portfolio_analysis }}
{% endif %}
{% if news_analysis is not none %}
News analysis: {{ news_analysis }}
{% endif %}
Date: {{ current_date }}.
```

Listing A.12: Prompt for generating memory retrieval queries to retrieve similar trading experiences. The agent uses the current market analysis, including technical, portfolio, and news analyses, along with the current date to formulate the query. This query is then used to fetch relevant past trading experiences that can inform future decisions.

```
You are a trading coach providing feedback on trading decisions. Your task is to evaluate a past trading decision based on its outcome and
    provide constructive feedback.

## Trading Environment Context
IMPORTANT: This is a simplified trading environment. Please respect the following constraints and rules for the decision making agent:

### Position Management Rules
**LONG Decision:**
- Opens a LONG position (betting price will go up)
- If already in a SHORT position, closes the short and opens a long
- If already in a LONG position, maintains the long position

**SHORT Decision:**
- Opens a SHORT position (betting price will go down)
- If already in a LONG position, closes the long and opens a short
- If already in a SHORT position, maintains the short position

**HOLD Decision:**
- Closes any existing position and stays in cash (flat)
- If no position exists, remains in cash
- Does NOT open any new position

### Position Sizing & Risk Management
**Position Size:**
- Position size equals 100% of current equity (all-in positions)
- No position sizing control available
- No ability to adjust the amount invested

**Risk Management:**
- No stop loss mechanisms available
- No profit target triggers available
- No partial position exits possible
- The only controls are: LONG (enter/keep long), SHORT (enter/keep short), or HOLD (close position / stay flat); no ability to change the
    position size.

### Decision Simplicity
- Focus purely on market direction (up/down/sideways)
- Do not consider position sizing
- Risk management comes only from timing of entry/exit decisions

### Positions
- Only have one position at a time.
- By closing the position, the agent opens a new position in the opposite direction.

## Trade Details
- Ticker: {{ ticker }}
- Decision: {{ doc.decision }}
- Confidence: {{ doc.confidence }}
- Reasoning: {{ doc.reasoning }}

## Trade Metrics
{{ trade }}

## Portfolio Metrics
{{ env_state.metrics.portfolio }}

## Market Metrics
{{ env_state.metrics.market }}

## Your Task
Please provide detailed feedback on this trading decision. Consider the following, but not limited to:
1. Was the decision ({{ doc.decision }}) appropriate given the available information?
2. Was the timing of entry and exit optimal given the simplified action space?
3. What could have been done better within the constraints of LONG/SHORT/HOLD decisions?
4. What aspects of the decision-making process were effective?
5. What lessons can be learned from this trade for future directional calls?
6. How might market conditions have changed?
7. Focus on decision timing and market direction accuracy, not position sizing or risk management tools

Provide your feedback in a structured format with clear, actionable insights that can improve future trading decisions within this
    simplified environment.
```

Listing A.13: Prompt for the feedback agent. The agent evaluates a past trading decision based on its outcome and provides constructive feedback. It considers the simplified trading environment's constraints and rules, focusing on decision timing and market direction accuracy rather than position sizing or risk management tools.

```
You are an AI prompt engineer specializing in optimizing prompts for trading decision systems. Your task is to analyze a past trading
      decision, its outcome, and the feedback received, then suggest improvements to the **original meta prompt** used for making trading
      decisions which results in more profitable trades.

## Trading Environment Context
IMPORTANT: This is a simplified trading environment. Please respect the following constraints and rules for the decision making agent:

### Position Management Rules
**LONG Decision:**
- Opens a LONG position (betting price will go up)
- If already in a SHORT position, closes the short and opens a long
- If already in a LONG position, maintains the long position

**SHORT Decision:**
- Opens a SHORT position (betting price will go down)
- If already in a LONG position, closes the long and opens a short
- If already in a SHORT position, maintains the short position

**HOLD Decision:**
- Closes any existing position and stays in cash (flat)
- If no position exists, remains in cash
- Does NOT open any new position

### Position Sizing & Risk Management
**Position Size:**
- Position size equals 100% of current equity (all-in positions)
- No position sizing control available
- No ability to adjust the amount invested

**Risk Management:**
- No stop loss mechanisms available
- No profit target triggers available
- No partial position exits possible
- The only controls are: LONG (enter/keep long), SHORT (enter/keep short), or HOLD (close position / stay flat); no ability to change the
      position size.

### Decision Simplicity
- Focus purely on market direction (up/down/sideways)
- Do not consider position sizing
- Risk management comes only from timing of entry/exit decisions

### Positions
- Only have one position at a time.
- By closing the position, the agent opens a new position in the opposite direction.

## Trade Details
- Ticker: {{ trade_document.ticker }}
- Decision: {{ trade_document.decision }}
- Confidence: {{ trade_document.confidence }}
- Reasoning: {{ trade_document.reasoning }}

## Trade Metrics
{{ trade_document.trade }}

## Portfolio Metrics
{{ env_state.metrics.portfolio }}

## Market Metrics
{{ env_state.metrics.market }}

## Feedback Summary
{{ trade_document.feedback }}

## Your Task
Analyze the provided information and feedback to suggest improvements to the original meta prompt. Focus on enhancing the decision-making
      process within the constraints of the simplified trading environment. Provide actionable recommendations for optimizing the meta prompt
       to achieve more profitable trades.
```

Listing A.14: Prompt for the meta-prompt optimiser agent. The agent analyzes a past trading decision, its outcome, and the feedback received, then suggests improvements to the original meta prompt used for making trading decisions. It focuses on enhancing the decision-making process within the constraints of the simplified trading environment's constraints and rules.

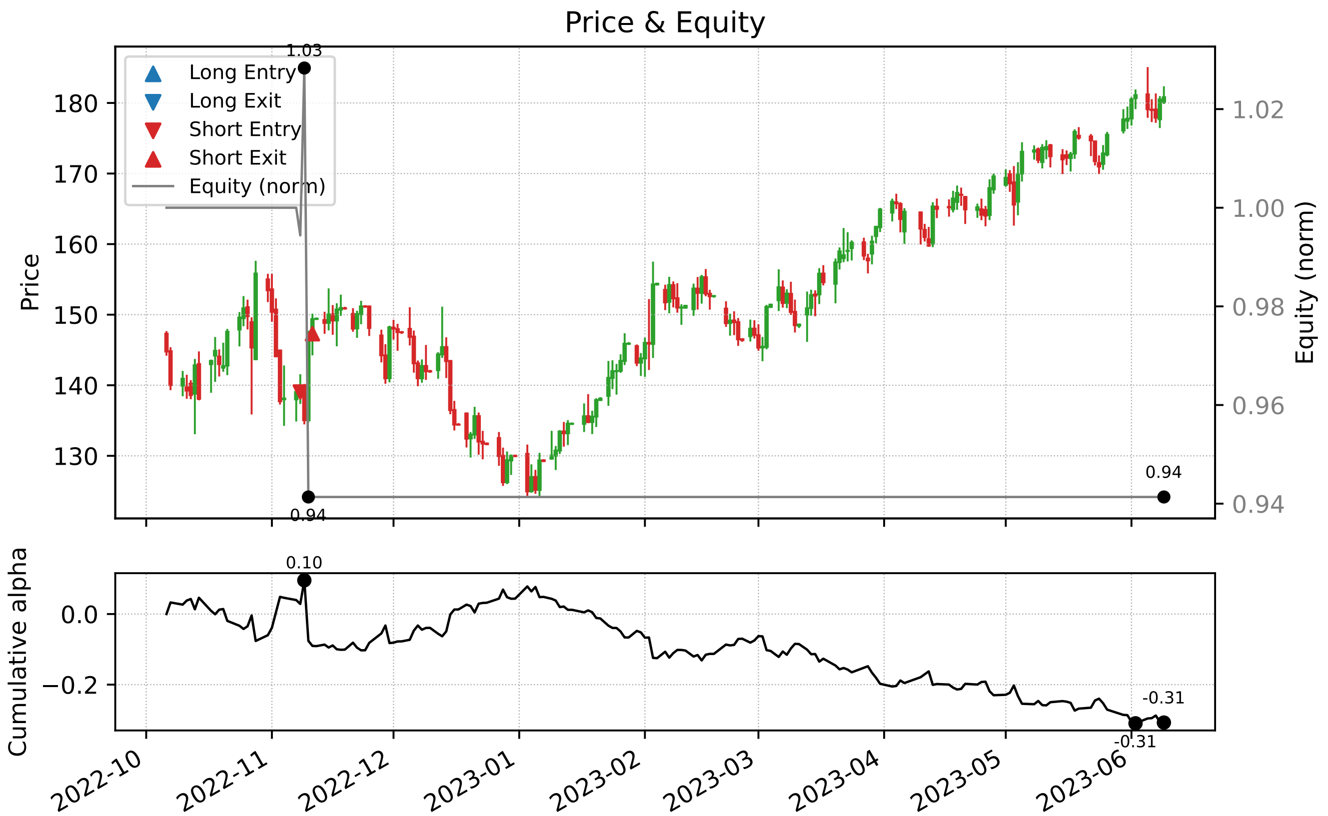

Figure 3: Equity curve and performance metrics for the full system on AAPL (Run `F0`). The plot displays the price as OHLC data, where green indicates an increasing price and red a decreasing price. The solid line represents the normalized equity, highlighting the highest, lowest, and final values. Additionally, the cumulative alpha is shown over time, benchmarked against a buy-and-hold strategy.

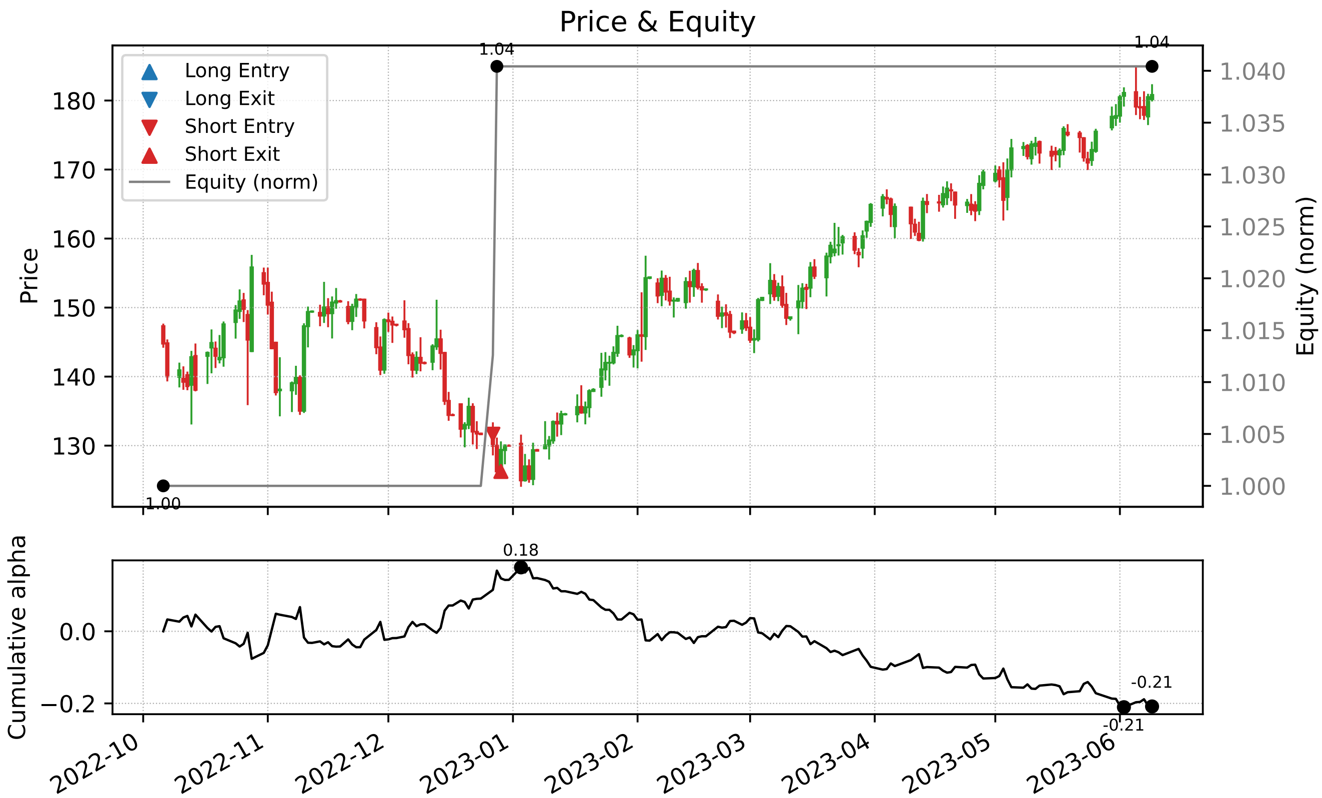

Figure 4: Equity curve and performance metrics for the full system on AAPL (Run F1). The plot displays the price as OHLC data, where green indicates an increasing price and red a decreasing price. The solid line represents the normalized equity, highlighting the highest, lowest, and final values. Additionally, the cumulative alpha is shown over time, benchmarked against a buy-and-hold strategy.

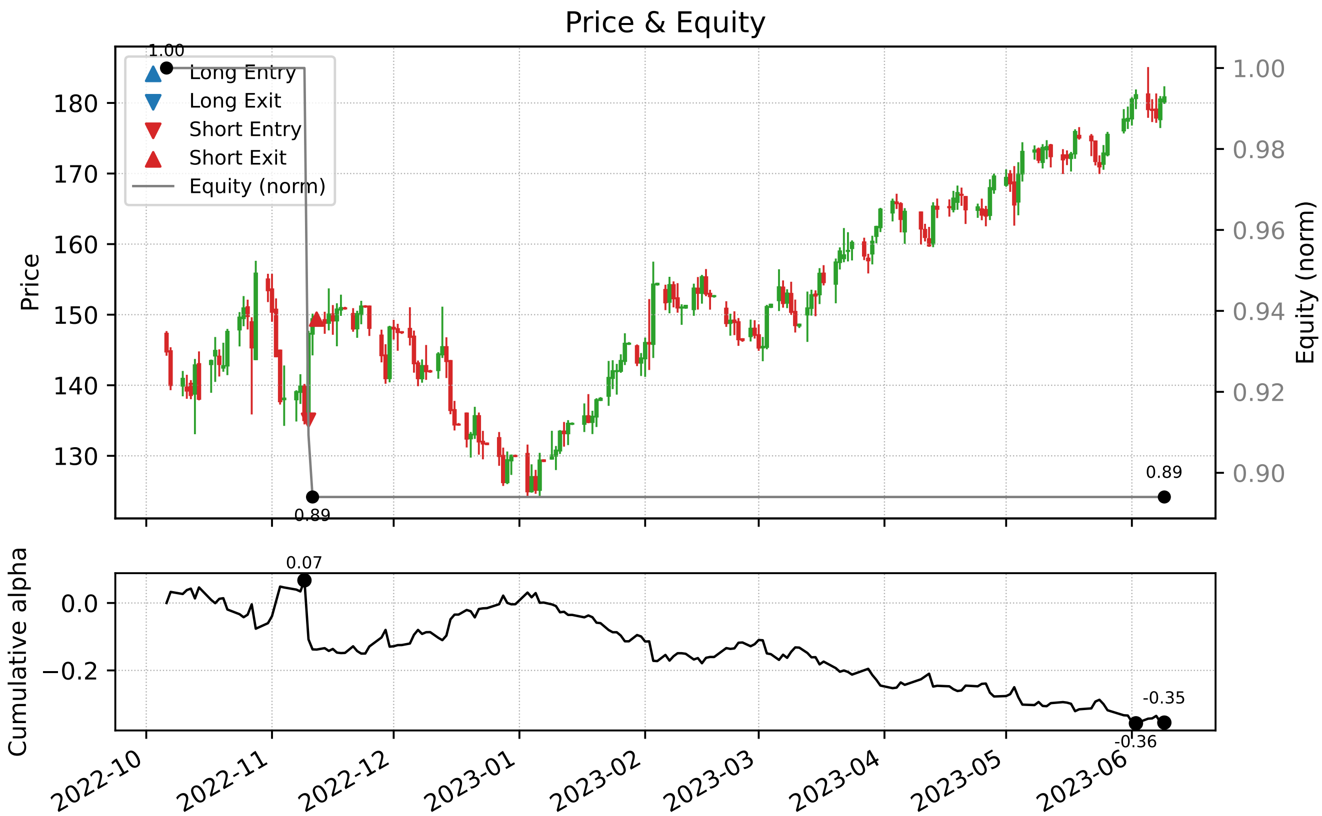

Figure 5: Equity curve and performance metrics for the full system on AAPL (Run F2). The plot displays the price as OHLC data, where green indicates an increasing price and red a decreasing price. The solid line represents the normalized equity, highlighting the highest, lowest, and final values. Additionally, the cumulative alpha is shown over time, benchmarked against a buy-and-hold strategy.

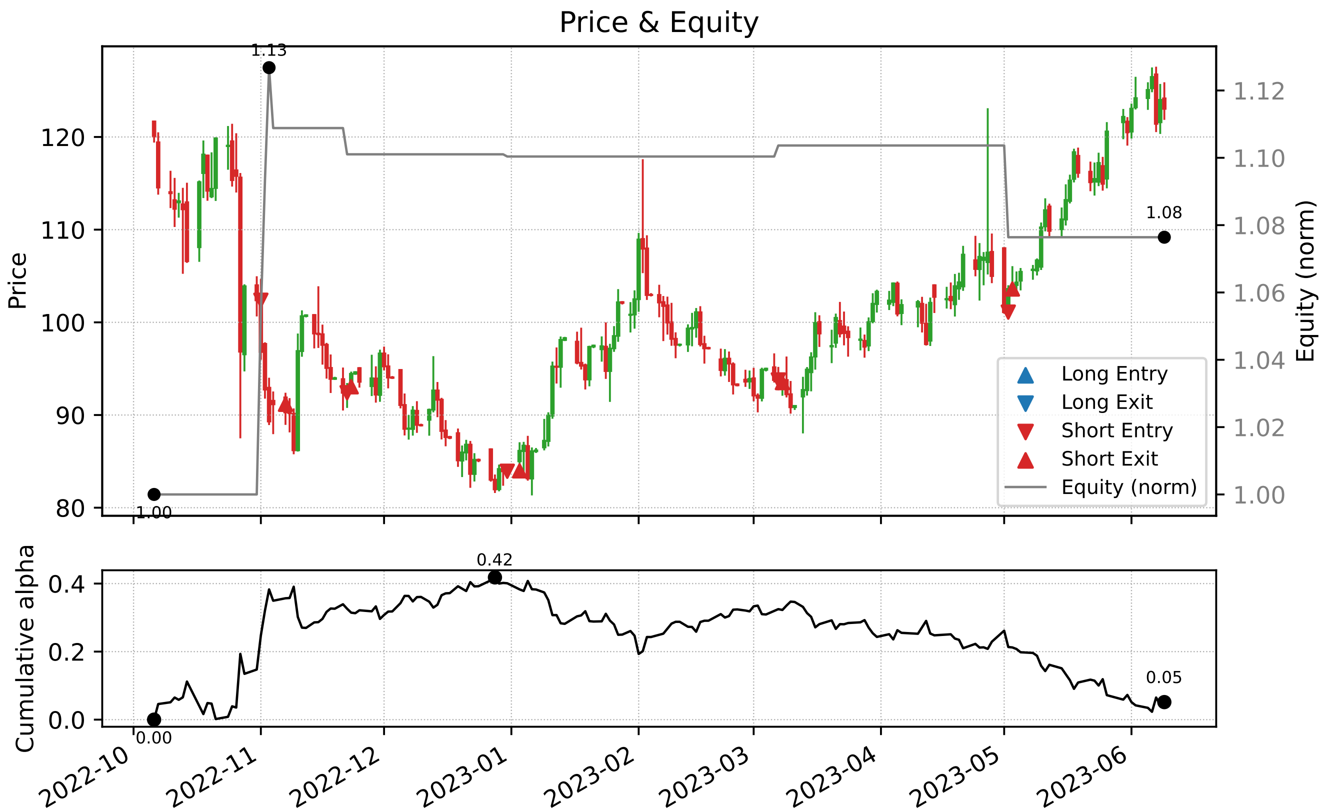

Figure 6: Equity curve and performance metrics for the No Debate variant on AMZN. The plot displays the price as OHLC data, where green indicates an increasing price and red a decreasing price. The solid line represents the normalized equity, highlighting the highest, lowest, and final values. Additionally, the cumulative alpha is shown over time, benchmarked against a buy-and-hold strategy.

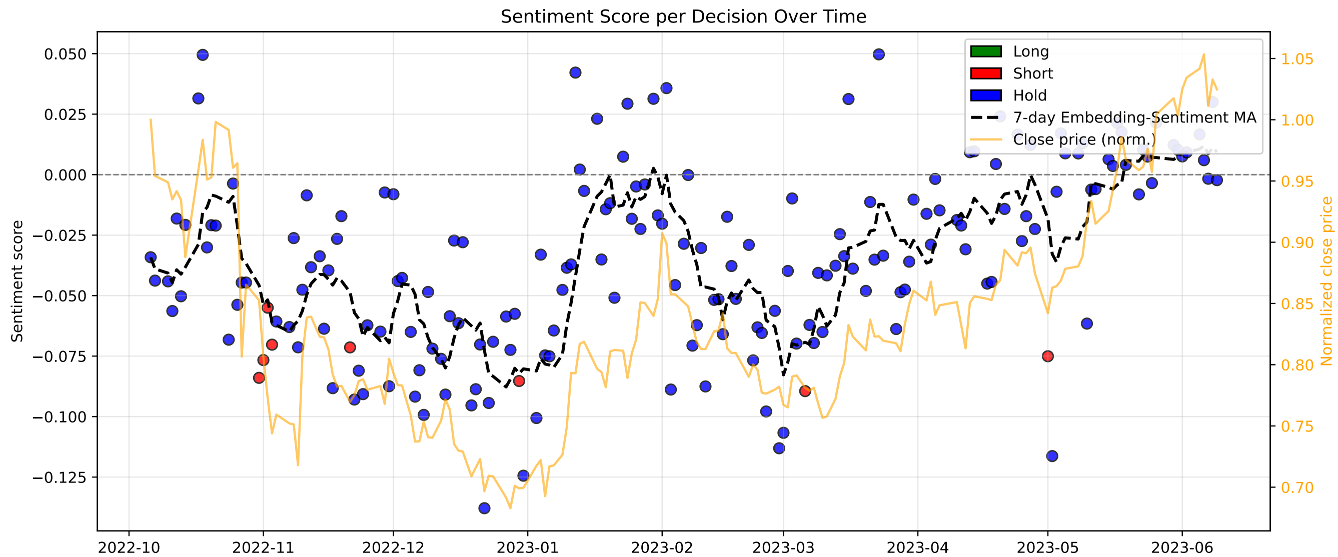

Figure 7: A visualisation of the agent's behaviour on AMZN for the A3 variant. The plot shows the agent's decisions (long, short, hold) against the normalised close price. The plot shows the raw sentiment of the agent's reasoning, with a 7-day moving average that closely tracks the price trend.

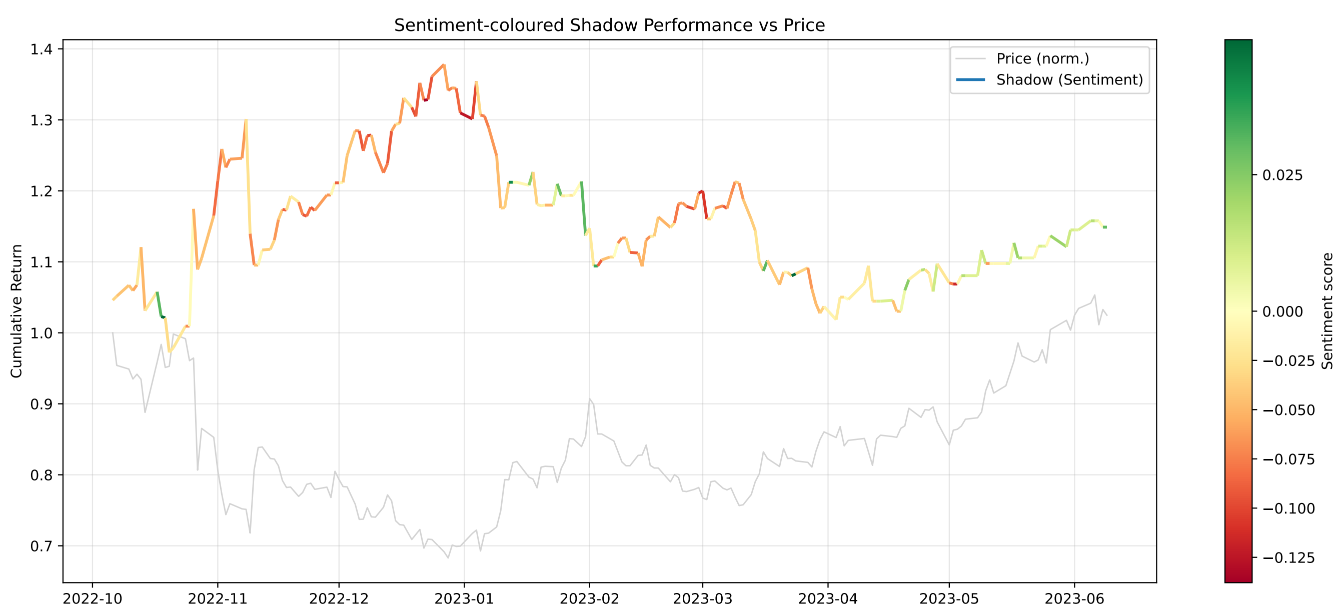

Figure 8: The agent's daily reasoning sentiment plotted against the asset price for the AMZN A3 variant. The sentiment is color-coded (green for bullish, red for bearish), showing a strong correlation where the agent correctly adopts a negative sentiment during price declines and a positive sentiment during price increases. The sentiment gradient line indicates the shadow backtest performance on a single day basis.

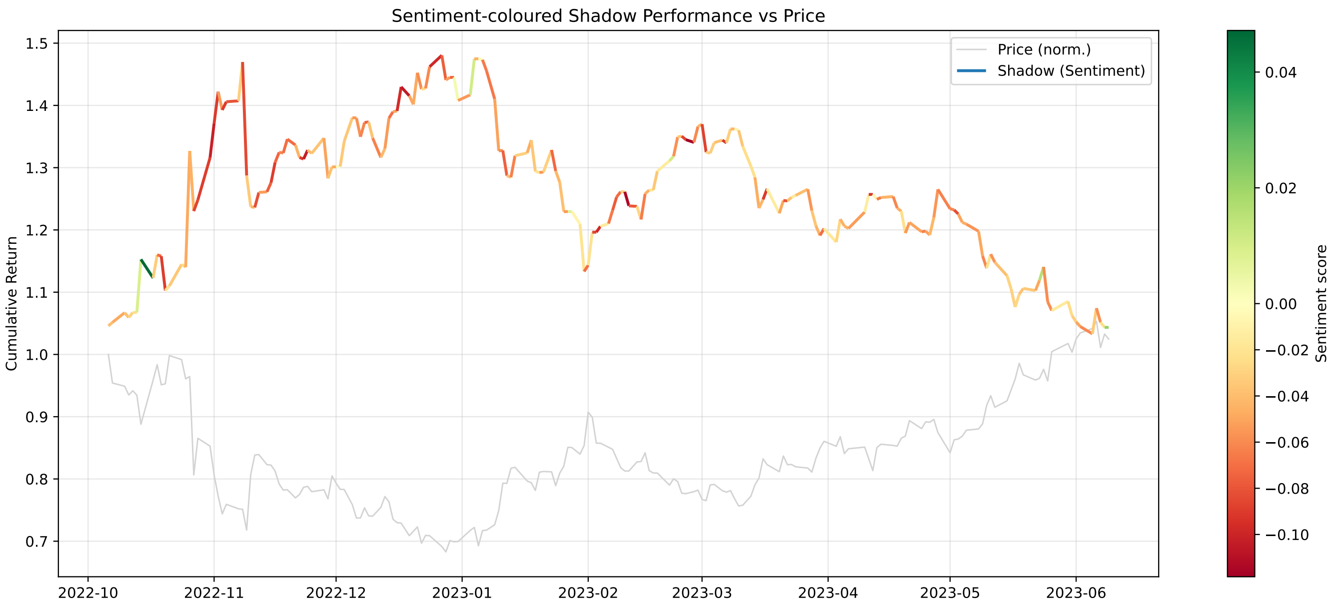

Figure 9: The agent's daily reasoning sentiment plotted against the asset price for the AMZN full system variant. The sentiment is persistently negative, failing to capture the upward price trend and explaining the model's poor performance.