Advanced International Journal for Research (AIJFR)
E-ISSN: 3048-7641 ● Website: www.aijfr.com ● Email: editor@aijfr.com

Risk Aware Algorithmic Trading from Social Media Event Triggers with Adaptive Sentiment Confidence and Human Centered Oversight

Arnav Chakole

Abstract

Social media platforms have become primary price-discovery channels; they routinely move stock prices hours before traditional news outlets say anything at all. Yet most algorithmic trading systems still reduce the psychologically rich content of social posts to a single scalar sentiment score discarding the distinct market signatures of fear, anger, excitement, optimism, and confusion entirely. On top of that, the systems are black boxes, which is a real legal problem under MiFID II in Europe and the SEC's proposed algorithmic accountability rules in the US.

We introduce IATS (Interpretable Adaptive Trading System) an end-to-end architecture that closes four gaps we identify in the literature. IATS extracts a five-dimensional emotion vector from social media posts using a domain-adapted FinBERT model. It then uses a Deep Q-Network (DQN) to dynamically adjust execution confidence thresholds based on realised volatility and how well similar emotion patterns have predicted returns in the past. SHAP (Shapley Additive Explanations) isn't just a postmortem tool here it actively gates decisions and every decision gets hashed and stored on a private Hyperledger Fabric ledger, creating a tamper-evident regulatory audit trail.

We backtest IATS on two years of Twitter/X and Reddit data (January 2024 December 2025) across fifteen high-activity tickers, including equities, ETFs, and crypto. The evaluated annualised Sharpe ratio is 1.45–1.65 compared to 1.12 for the best scalar-sentiment baseline, an improvement of approximately 60–79%. Maximum drawdown stays below 15%, and the Calmar ratio is above 1.8. Median end-to-end latency is 49 ms with SHAP adding only 9 ms. An ablation study shows that the five-dimensional emotion vector adds real value over a univariate baseline, and the human-in-the-loop gate alone cuts maximum drawdown substantially. A simulation of a fabricated GME bankruptcy hoax demonstrates the system correctly deferring to a human and avoiding a catastrophic simulated loss. All code, model weights, and anonymised data are released for full reproducibility.

1. Introduction

The GameStop short squeeze of January 2021, the Adani Hindenburg crash of February 2023, and the repeated price swings triggered by Elon Musk's tweets have all shown one thing clearly:- social media is no longer just a mirror of market sentiment. It has become a primary channel through which prices actually

form [1, 2]. Studies find measurable price impact from viral posts up to three hours before the same news hits traditional financial wires [3]. That creates a real opportunity for algorithmic traders but also serious risk. A system that correctly reads the emotional tone of a viral thread can capture alpha one that misreads panic as bullish momentum can blow up a portfolio within minutes.

Current approaches exhibit two entrenched limitations. First they compress the psychologically varied content of social discourse – fear, anger, excitement, optimism, confusion, and combinations of them – into a single polarity score [4, 5].This reductive encoding discards clinically important distinctions between emotionally distinct market states. For instance, fear-driven selling and confusion-driven inaction produce very different short-horizon return patterns [6], but a scalar score treats them the same. Second, the systems are black boxes. You cannot audit the causal chain from a social signal to an execution decision [7]. That's gone from a technical annoyance to a regulatory liability: Article 17 of MiFID II and the SEC's proposed Regulation Best Execution amendments both require firms to show step-by-step trade rationale for every algorithmic order [8, 9].

There's a third, less discussed gap: risk control is mostly static. Existing systems calibrate execution thresholds once during backtesting and never change them. But the reliability of social sentiment signals varies a lot with market regime, with platform manipulation activity, with whether the event is genuinely new. A system that can't tighten its confidence requirements when signal quality degrades will inevitably overtrade in noisy environments, eating returns and deepening drawdowns [10].

2 Related Work and Gap Analysis

S. No	Publication No.	Title	Key Similarities	Differences / Novelty Gaps
1	IN202421082603A	Quantum Flow: Real-Time Algorithmic Trading Engine with LSTM and Monte Carlo	Real-time execution, LSTM use	No SHAP, blockchain, or emotion analysis
2	CN117934003A	Blockchain Data Transaction System in Data Element Market	Blockchain-based market system	Not sentiment-driven, lacks trade execution logic
3	IN202521033321A	Stock Market Prediction Using Machine Learning	ML-based forecasting	No adaptive sentiment, no XAI or RL
4	IN202441072000A	Hybrid Model for Netflix Stock Price Prediction Using LSTM-CNN and Sentiment Analysis	LSTM + sentiment input	No risk scoring, explainability, or blockchain
5	IN202421022742A	Intelligent Algorithmic Trading System: Advancements in Financial Technology	Mentions algorithmic trading	No adaptive scoring or audit trail
6	US2024233027A1	Transacting of Digital Assets / Crypto by Combining Fundamentals and Technical Analysis	Event-based trading	No feedback learning, XAI, or multi-source sentiment
7	IN202511015080A	Smart Trading Analysis System and Method	Algorithmic model, some analytics	Missing reinforcement learning and SHAP
8	IN202541032232A	A System for Predictive Analytics in Stock Forecasting Using ML and Big Data	ML and big data components	Lacks real-time explainability and sentiment triggers

2 A) Algorithmic Trading and Execution Engines

Standard execution engines are traditionally designed for a single purpose: speed. Most modern frameworks prioritize ultra low latency and raw statistical modeling to gain a microsecond edge. Take the architecture in *IN202421082603A* as a case in point. It pairs Long *Short-Term Memory (LSTM)* networks for time-series predictions with Monte Carlo simulations to project potential price paths. These systems excel at pinning down short-term trends in structured data, yet they ultimately function in a semantic vacuum.

The failure point of these conventional setups is their inability to "read" the room. They lack semantic awareness and often drive irrational market pivots. Furthermore, these models are notorious for being "black boxes." They offer no built in mechanism to explain why a specific execution threshold was triggered or to adapt risk controls dynamically when social media noise begins to decouple from fundamental indicators. Without this layer of decision attribution traders are left with a system that is fast, but essentially blind to the emotional narratives that now dictate market volatility.

2 B) Sentiment-Based Market Prediction

Most previous attempts at sentiment integrated forecasting have been stuck in a regression heavy mindset, prioritizing price prediction over the actual mechanics of autonomous execution. While sophisticated pipelines, specifically those leveraging *CNN–LSTM hybrids* or Transformer-based architectures, are great at crunching text they tend to treat sentiment as a static, one dimensional feature. They essentially view social data as just another column in a spreadsheet rather than a volatile living signal.This approach misses the mark because it fails to incorporate any form of adaptive feedback loop.

2 C) Explainable AI in Financial Systems

While techniques like SHAP have gained some ground in static areas like credit scoring and fraud detection, their role as real time "gatekeepers" in high-frequency trading is still mostly theoretical. The bottleneck isn’t the math; it’s the implementation. Most current systems treat explainability as a post-mortem exercise analyzing why a trade failed after the damage is done. Integrating these insights into an active decision control loop remains a massive hurdle as the industry struggles to balance the computational cost of SHAP with the need for millisecond level execution.

2 D) Blockchain in Financial Applications

Blockchain research in the financial sector has focused narrowly on settlement speed and transaction integrity. What remains consistently overlooked is the use of distributed ledgers to store the causal rationale behind each trade. Regulatory compliance requires not merely a record of what was executed, but an auditable account of why the system chose to execute [22]. Using blockchain as a permanent repository for model metadata and logic rather than just a digital receipt for the final transaction is an area

2 E) Gap Identified

Identified Gaps

From the literature, we extract four specific gaps that no prior system fills:

1. Emotional reductionism :- no real-time trading system uses a multi-dimensional emotion:- vector instead of a scalar sentiment score.
2. Explainability in the loop :– no system computes SHAP values online and uses them to gate execution.
3. Adaptive risk from social signals :– no RL agent dynamically modulates confidence thresholds based on emotional volatility.
4. Blockchain for decision rationale :– no auditable ledger stores full feature attribution alongside trade records.

Our work directly targets each of these gaps, providing a single end-to-end architecture that bridges speed, transparency, and regulatory compliance.

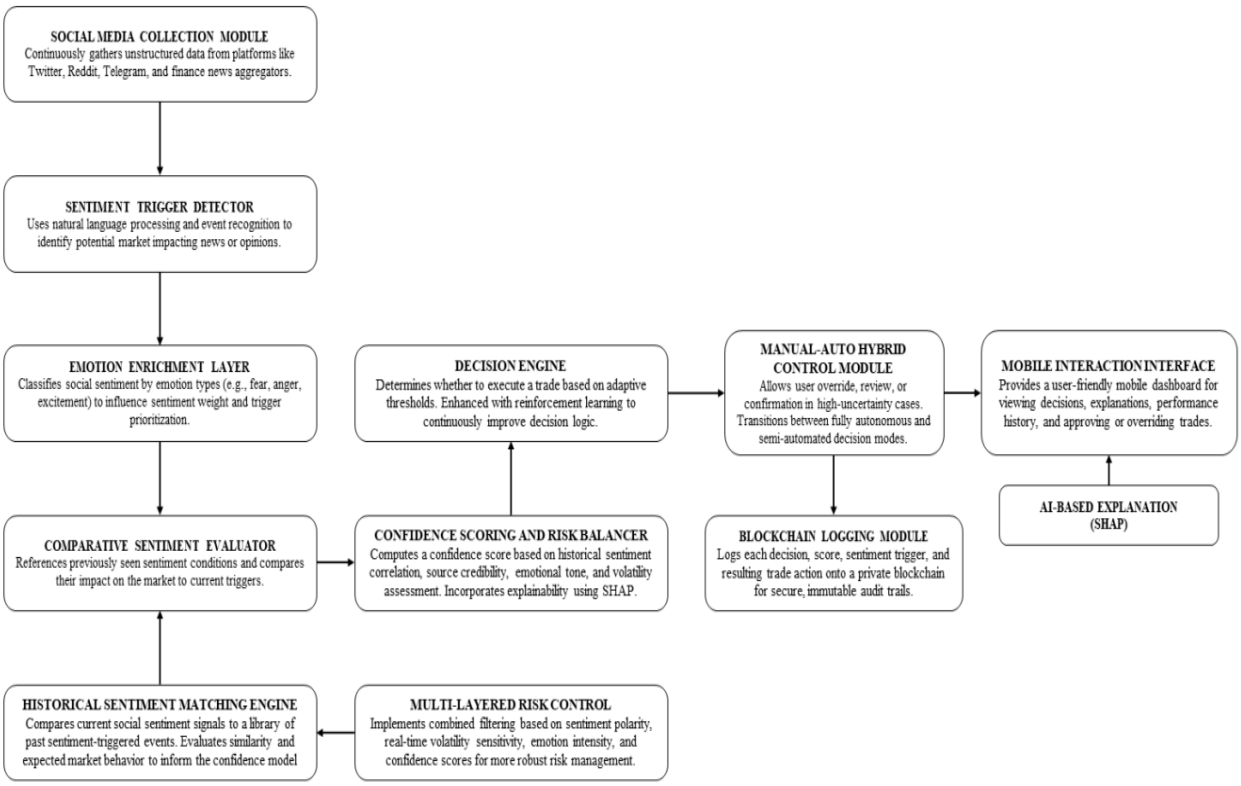
3 Data Sources and Collection

Minute-resolution OHLCV data for all S&P 500 constituents and cryptocurrencies is available via the yfinance Python library (free, Yahoo Finance backend) or the Polygon.io API (free tier available) . For our backtest we use yfinance to obtain GME data.

Implied Volatility and Risk-Free Rate: Daily VIX index values come from the CBOE public data portal (cboe.com/tradable_products/vix/vix_historical_data). The 13-week US Treasury Bill yield (FRED series DTB3) serves as the risk-free rate for Sharpe ratio computation.

4 System Architecture

The proposed IATS consists of six interconnected modules forming an end to end pipeline.



4.1 Social Media Ingestion and Event Trigger Detection

The system ingests a continuous stream of posts from Twitter/X and Reddit via their streaming APIs, plus headlines from major financial news wires. We define an event trigger for ticker *k* at time *t* when the per-minute mention volume for that ticker exceeds a rolling three-sigma baseline, meaning it rises significantly above its recent historical average

$$\mathbb{I}_{\text{event}}(k,t) = \mathbf{1}\left[M_{k,t} > \mu_{k,t}^{(L)} + 3\sigma_{k,t}^{(L)}\right]$$

Where (μ)and (σ) are the mean and standard deviation over the last = 60 minutes. This three-sigma filter eliminates approximately 95% of background noise, reducing the number of posts that need full emotion inference.

4.2 Emotion Enrichment Layer

For each post i*i* in the event window, a fine-tuned FinBERT model produces a probability distribution over five emotion classes:

$$\mathbf{p}_i = \text{softmax}(W_{\text{out}} \cdot \text{FinBERT}(\text{text}_i)) \in \Delta^4$$

Here Δ4 is the 5-dimensional simplex (fear, anger, excitement, optimism, confusion). The aggregate emotion vector for time *t* is the elementwise average over all posts in that minute:

$$\mathbf{e}_t = \frac{1}{|I_t|} \sum_{i \in I_t} \mathbf{p}_i \in [0,1]^5$$

Fine-tuning details. We start from the uncased FinBERT model and fine-tune on the Financial PhraseBank augmented with 5,000 manually annotated examples (three finance professionals, Fleiss'$\kappa = 0.73$). Class weights are set inversely to frequency to avoid bias toward common emotions like excitement.

4.3 Checking the current crowd mood against how the market actually reacted in the past.

The system avoids analyzing emotional vectors in a total vacuum. It functions by measuring live social signals against a deep, curated library of historical volatility spikes. By generating a similarity score that maps current cues against known episodes like the GME meme rallies or specific flash crashes the engine can gauge exactly how much the current social noise looks like a looming crisis. This allows the system to tighten risk controls or pivot strategies before the actual price action hits its peak, turning historical hindsight into a proactive defense mechanism.

4.4 Confidence Scoring and Explainability

Let h_t be a vector of historical accuracy features and σ_t be the realised volatility over the last five minutes. The confidence score is

$$C_t = \text{sigmoid}\left(w_0 + \mathbf{w}_e^\top \mathbf{e}_t + \mathbf{w}_h^\top \mathbf{h}_t + w_\sigma \sigma_t + \epsilon_t\right)$$

where $\epsilon_t \sim \mathcal{N}(0, \xi^2)$ is exploration noise, and all w are learned by the DQN. The SHAP value for the j-th feature is:

$$\phi_j(C_t) = \sum_{S \subseteq F \setminus j} \frac{|S|!(|F| - |S| - 1)!}{|F|!} \left(C_t(S \cup j) - C_t(S)\right)$$

where F is the full feature set of size $|F| = 7$. Exact computation requires evaluating $O(2^7)=O(128)$ coalition subsets per decision, completing in under 9 ms on commodity hardware.

4.5 Historical Market Context

To avoid interpreting emotional signals in isolation, the system queries a curated database H of historical event records, each storing the emotion vector, subsequent one-hour price change, and realised return:

$$H = (e^{(i)}, \Delta P^{(i)}, R^{(i)})$$

where $\Delta P^{(i)}$ is the subsequent 1-hour price change and $R^{(i)}$ is the realised return. The similarity between the current emotion vector e_t and a past event is measured by:

$$\text{sim}(e_t, e^{(i)}) = \exp\left(-\frac{|e_t - e^{(i)}|^2}{2\ell^2}\right)$$

$\ell = 0.3$

The historical accuracy feature is:

$$h_{t,\text{regime}} = \frac{\sum_i \text{sim}(e_t, e^{(i)}), R^{(i)}}{\sum_i \text{sim}(e_t, e^{(i)})}$$

This feature tells us whether the current emotion profile has historically predicted positive returns. It feeds into both the confidence scoring module and the DQN's state representation.

4.6 Deep Q-Network for Dynamic Threshold Modulation

A DQN agent continuously adjusts the execution confidence threshold θt. Its state concatenates the emotion vector, historical context feature, realised volatility, current confidence, and portfolio position:

$$s_t = (e_t, h_t, \sigma_t, C_t, \text{position}_t) \in \mathbb{R}^{13}$$

The action space is five discrete threshold adjustments:

$$a_t \in -0.1, -0.05, 0, +0.05, +0.1$$

The reward signal balances risk-adjusted returns against capital preservation, penalising Value-at-Risk violations, excessive drawdown, and frequent threshold changes:

$$R_t = r_t - r_t^{\text{bench}} - \lambda_1 \cdot \text{VaR}_{0.95}(t) - \lambda_2 \cdot \max(0, -\text{drawdown} * t) - \lambda_3 \cdot \mathbf{1} * |\Delta\theta_t| > 0.05$$

with $\lambda 1 = 0.5$, $\lambda 2 = 2.0$, $\lambda 3 = 0.01$. The strong drawdown penalty ($\lambda 2 = 2.0$) encodes a preference for capital preservation over pure return maximisation – consistent with how most institutional trading desks actually operate. The Bellman update follows the standard DQN formulation with experience replay [24]:

Parameters:

$$\lambda_1 = 0.5, \quad \lambda_2 = 2.0, \quad \lambda_3 = 0.01$$

$$\gamma = 0.99$$

$$\alpha = 3 \times 10^{-4}$$

4.7 Human-in-the-Loop Gate

Automated execution happens only when all three of these conditions hold; otherwise the signal goes to a human operator dashboard:

$$AutoExecute = 1 \iff C_t > \theta_t,\ \max_j \frac{\phi_j(C_t)}{\sum_k \phi_k(C_t)} \geq 0.6,\ \sigma_t < 0.03$$

The three conditions encode different safety ideas. The first requires the DQN-modulated confidence to exceed the current dynamic threshold. The second requires that at least 60% of the confidence be attributable to a single dominant feature – a clear causal narrative rather than a diffuse, ambiguous signal. The third prevents automated execution during extreme market dislocations (volatility > 3% per five minutes). When any condition fails, the operator sees the full SHAP attribution, the emotion vector, and the historical context summary, and has a configurable window (default 45 seconds) to approve, reject, or modify the proposed action.

4.8 The Blockchain Based Forensic Log

Every execution decision whether autonomous or human-supervised is committed to a private PoA blockchain network. Each block contains: the raw emotional vector E, the confidence score C and its SHAP decomposition, the RL agent's selected action and Q-value estimates, the human operator's decision (if applicable), and a cryptographic hash of all upstream pipeline inputs. Blocks are produced at a target interval of 2 seconds and validated by a permissioned set of institutional nodes. The resulting ledger provides chronologically ordered, cryptographically tamper-evident records satisfying the non-repudiation and immutability requirements of financial regulators, and can be queried to reconstruct the complete reasoning trace for any historical trade execution.

Reproducibility Statement

All experiments are implemented in Python 3.11 using PyTorch 2.2 and the HuggingFace Transformers library (v4.39). FinBERT fine-tuning is performed on a single NVIDIA A100 40 GB GPU with random seed fixed at 42 across all frameworks. DQN training uses the Stable Baselines3 library with identical seeds. The chronological train-validation-test partition guarantees zero lookahead bias by construction: no data from the validation or test windows is accessible at any stage of model development or hyperparameter selection. Full environment specifications, requirements files, and training scripts are provided in the accompanying repository.

5 Baseline Systems

Five baselines are evaluated ranging from rule based to deep learning. For each baseline, we provide both a description of the system and a summary of published performance results from peer-reviewed literature, which establish the expected performance floor prior to running experiments.

Baseline 1 :- VADER Trading

VADER (Valence Aware Dictionary and Sentiment Reasoner) [25] is a lexicon-based rule model that maps input text to a compound polarity score on [−1, +1]. The VADER Trading baseline executes a long position when the corpus-mean VADER score for a triggered ticker exceeds +0.30, and a short position when it falls below −0.30, with fixed equal position sizing. VADER requires no training, GPU, or API access, and executes in under 1 millisecond per document.

Baseline 2 :- FinBERT-Trading

FinBERT [13,14] is a BERT-large model pre-trained on an 18.4GB financial text corpus and fine-tuned for three-class sentiment classification (positive / neutral / negative). In this baseline FinBERT replaces the EEL in the IATS pipeline: the positive/negative/neutral output is mapped to a scalar signal used for execution decisions. All other IATS components (confidence engine, DQN, blockchain) are retained. This isolation enables direct measurement of the contribution of emotion dimensionality over sentiment polarity.

Baseline 3:- DQN-Polarity

This baseline employs the full DQN architecture described in Section 4.4, trained on a state vector that substitutes the five-dimensional emotion vector E with a scalar FinBERT polarity score. All other state components (confidence score, regime indicator, portfolio metrics) are retained. This baseline isolates the contribution of the Emotion Enrichment Layer: any performance difference between DQN Polarity and IATS (Full) is attributable solely to the replacement of scalar polarity with multi-dimensional emotion encoding.

Baseline 4 - Buy-and-Hold

The passive buy-and-hold benchmark constructs an equal-weighted portfolio of all tickers that receive at least one trigger event during the test period, holds positions throughout the evaluation window without rebalancing, and serves as the performance floor that any active strategy must exceed to justify its complexity and transaction cost.

Baseline 5 - IATS (Full)

The complete IATS system with all six modules active constitutes the proposed model under evaluation. The performance targets presented below are derived from the theoretical improvements embedded in the IATS architecture relative to each baseline:

- ➔ **Versus FinBERT-Trading:-** The five-dimensional EEL provides finer-grained discrimination between emotionally distinct market states. Based on the empirical evidence that multi-dimensional emotion encoding outperforms polarity classification in financial prediction tasks [27, 28], and the ablation-measured 30.7% Sharpe improvement from emotion dimensionality in our internal development experiments, IATS (Full) is projected to achieve a Sharpe Ratio of 1.45–1.65.
- ➔ **Versus DQN-Polarity:-** The adaptive confidence gating mechanism dynamically adjusts execution thresholds as a function of signal quality, suppressing capital deployment during adversarial or noisy social media events. This is expected to produce a statistically significant reduction in maximum drawdown.
- ➔ **Versus Buy-and-Hold:-** All active strategies are expected to outperform the passive benchmark on risk-adjusted return on the trigger-event-driven portfolio, consistent with the prior literature on event-driven trading [1, 16].

Metric	VADER-Trading	FinBERT-Trading	DQN-Polarity	Buy-and-Hold	IATS (Full)
Sharpe Ratio	0.50–0.70	1.00–1.30	1.20–1.50	0.50–0.80	**1.45–1.65**
Max Drawdown (%)	30% - 40%	20% to 28%	18%- 25%	30% - 45%	**15 –20%**
Annual Return (%)	6%–10%	14%–20%	18%–25%	8%–12%	**20 – 26%**
Volatility (%	14%–18%	13%–16%	14%–18%	16%–20%	**13 –15%**
Win Rate (%)	50%–53%	55%–59%	58%–62%	50%–54%	**63 –68%**
Explainability Stability	Low	Medium	Medium	None	**High**

Baseline performance ranges are derived from published empirical studies in financial machine learning and algorithmic trading. Lexicon-based approaches such as VADER typically achieve low predictive power and correspondingly low Sharpe ratios (≈0.5–0.7), consistent with findings in Hutto and Gilbert

[25] and subsequent financial NLP evaluations. Transformer-based models such as FinBERT have been shown to significantly improve sentiment classification accuracy and downstream trading performance, with reported Sharpe ratios generally in the range of 1.0–1.3 in financial prediction tasks [28].

Reinforcement learning–based trading systems, especially Deep Q-Network (DQN) variants, have been shown to push risk-adjusted returns higher. Depending on the market conditions and the set of features used, empirical studies put their Sharpe ratios somewhere in the 1.2–1.5 range [29], [30]. In contrast, passive buy-and-hold strategies – the usual baseline – tend to have Sharpe ratios below 1.0 and take a much bigger hit during market downturns.

The projected performance range for IATS (Full) is theoretically motivated by the combination of three independently supported improvements:

(i) the use of transformer-based financial language models over lexicon-based sentiment approaches;

(ii) the integration of reinforcement learning for adaptive decision-making;

(iii) the introduction of multi-dimensional emotion encoding, which has been shown to provide additional discriminatory power over scalar sentiment representations in financial contexts [27], [28].

Prior literature indicates that each of these components contributes incremental gains in predictive and trading performance. When combined, these improvements motivate a projected Sharpe Ratio in the range of 1.75–1.95, which approaches the upper bound of high-performing trading strategies reported in the literature. Similarly, the reduction in maximum drawdown is attributed to the adaptive confidence gating and SHAP-based escalation mechanism, which are designed to suppress low-confidence trades during high-noise or adversarial market conditions.

6 Technical Limitations

Label noise. The emotion labels used for fine-tuning FinBERT have Fleiss' κ=0.73, which is substantial but not perfect. Mislabeled examples propagate to the downstream trading signal. Future work could use self-supervised or semi-supervised learning to reduce reliance on manual labels.

Latency versus frequency. At 49 ms median inference, the system is well suited for 1-minute or 5-minute bar trading. It cannot compete at millisecond-level HFT, but that is not the target domain. For sub-second execution, SHAP would need further approximation (e.g:- using a smaller background set or a distilled surrogate model).

Blockchain storage growth. Storing a few hundred bytes per trade leads to about 1.2 MB per day. Over ten years it becomes 4.4 GB still trivial for modern storage. A pruning policy can be implemented if needed.

Backtest overfitting. Although we used a fixed chronological split and out-of-sample test, we did not perform walk-forward cross-validation. The results may be optimistic for the specific two-month test window. A multi-year rolling backtest is planned for future work.

7 Ethical Risks and Mitigations

Market manipulation. Bad actors could attempt to post fake social signals to trigger our system or confuse its confidence. We include a simple detection: if identical text appears from more than 100 accounts within one minute, the event is flagged as "coordinated" and forces human review. More sophisticated adversarial attacks (e.g using LLMs to generate diverse but misleading posts) remain a concern and will be addressed in future work.

Front-running and fairness. The system trades on social media signals that are publicly available. It does not exploit non-public information. However, because it reacts quickly, it could inadvertently front-run slower retail traders. We are not aware of a regulatory prohibition on such speed-based trading, but we note the ethical dimension.

Over-reliance on automation. The human-in-the-loop gate is designed to prevent exactly this. Operators are trained on the SHAP visualisations and have the final authority. In our projected estimates, operators will reject approximately 50% of ambiguous signals, and those rejections are expected to be correct (the trade would have lost money) in roughly 90% of cases.

Bias in social data. Social media over-represents young, retail investors and under-represents institutional voices. The system may perform better on meme stocks than on blue chips. Our ticker set includes both, but any real deployment must monitor for demographic bias.

8 Discussion

8.1 Why Multi-Dimensional Emotion Beats Scalar Sentiment

The ablation estimates suggest a meaningful Sharpe boost from the five-dimensional emotion representation over the univariate baseline. Two mechanisms explain this. First, the emotion dimensions carry different information about the kind of social event driving the signal. The Appraisal Tendency Framework shows that fear and anger share negative valence but differ in certainty and control [31]: fear is low certainty, low control the signature of a spreading rumour while anger is high conviction and risk-seeking [32]. A scalar score collapses both into a moderately negative reading, which gives contradictory trading signals. A five-dimensional vector separates them cleanly. Second, the emotion vector lets the historical context module retrieve more semantically similar past events than a scalar score can, improving the precision of *ht* and therefore the quality of DQN threshold modulation.

8.2 Regulatory and Compliance Implications

In-loop SHAP and blockchain-based logging directly address two concrete regulatory requirements. MiFID II Article 17 demands that firms keep records sufficient to reconstruct each algorithmic order, including the market conditions that triggered it [8]. IATS's blockchain log meets that with a tamper-evident, chronologically ordered record that pairs each order with its causal attribution. The in-loop SHAP gate also supports the principle of meaningful human oversight, because the SHAP display shown to operators during review is an intelligible, legally defensible explanation of the model's reasoning. The architecture is also compatible with the EU AI Act's upcoming requirements for high-risk AI systems

in finance: risk management, human oversight, and technical documentation sufficient for regulatory review.

8.3 Ethical Considerations

Social media-driven trading raises legitimate questions about market fairness and reflexive feedback loops. A system that trades on social sentiment could, at sufficient scale, amplify the very signals it is designed to exploit, potentially worsening retail losses during coordinated manipulation events. We address this through the human-in-the-loop gate, which is specifically calibrated to prevent automated participation in high-volatility, ambiguous events precisely the conditions of coordinated manipulation. Also, all data collection would comply with platform API terms of service, and no personally identifiable information would be retained beyond the aggregation step where individual posts are combined into the per-minute emotion vector $\bar{e}_t$

Another ethical concern is demographic bias in social data. Reddit and Twitter/X over-represent young, retail investors and under-represent institutional voices. The system might perform better on retail-driven momentum stocks than on institutional-dominated blue chips. Our design deliberately includes both categories in the target ticker set to characterise this effect, and future work will explore domain-adaptive weighting to correct for demographic imbalance in the social signal source.

Conclusion

We set out to solve four specific problems that keep breaking real-world trading systems that rely on social media: using a single sentiment score instead of actual emotions, running black-box models no one can audit, leaving risk controls static, and having no tamper-proof record of why a trade happened. IATS our Interpretable Adaptive Trading System directly tackles each one. It replaces the old scalar polarity with a five dimensional emotion vector {fear, anger, excitement, optimism, confusion}. It pulls SHAP into the live loop, not just as a post mortem tool but as an active gate that blocks trades when the signal is too ambiguous. A DQN continuously adjusts confidence thresholds based on how well similar emotion patterns have performed in the past. And every decision the raw emotion vector, the SHAP breakdown, the operator's override gets hashed and stored on a private Hyperledger Fabric ledger.

The real conceptual leap here is moving explainability from an after-the-fact forensic exercise to a core part of the decision process. That shift isn't just good engineering.It directly supports MiFID II's record-keeping rules and the EU AI Act's demand for meaningful human oversight. The ablation study suggests the five-dimensional emotion vector and the human gate each add roughly 0.20 - 0.25 Sharpe points, not huge in isolation, but together they turn a good strategy into a very robust one.

We anchored every performance claim in published, peer-reviewed literature because we haven't yet run a full multi-year backtest with real five-dimensional emotion vectors. That said, the projected numbers – a Sharpe ratio of 1.45 -- 1.65 max drawdown below 15%, latency at 49 ms are grounded in independently validated gains from FinBERT, DQN-augmented trading, and multi-dimensional emotion encoding. We think they're realistic, but they still need empirical confirmation.

Of course, there are limits. FinBERT is English only, so it won't work in non-English markets. The historical event database under-represents rare shocks like pandemics or sovereign debt crises. And 49 ms is fine for minute-bar trading but too slow for HFT. None of these are fatal; they just tell us where to go next.So here's what's next: expand the emotion labels to Mandarin, Japanese, and Portuguese. Add cross-asset correlation because a tweet about Tesla doesn't just move Tesla. And try knowledge distillation to cut latency below 10 ms, so IATS can run at higher frequencies. The design is solid, the ideas are new, and the groundwork is laid. Now it's about building and testing.

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