A Sentiment-Enhanced Machine Learning Framework for Quantitative Trading Based on Pleasure-Arousal-Dominance Theory

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Abstract: Recent studies emphasize integrating investor sentiment into quantitative strategies, yet existing methods often rely on unidimensional frameworks that inadequately capture sentiment complexity. This study introduces a three-dimensional model based on the Pleasure-Arousal-Dominance (PAD) theory, formalizing sentiment dynamics through Pleasure, Arousal and Dominance. These signals are algorithmically embedded to optimize trade execution, position sizing, and volatility management. Across four futures asset classes, the PAD-enhanced strategies achieved consistent improvements. By averaging performance metrics (annualized returns, Sharpe ratios, drawdowns) across all four categories, the framework yielded a mean annualized return of 298.4% and a Sharpe ratio improvement of 31.5%, while reducing maximum drawdown by 18.2%. Dominance metrics effectively curtailed risk exposure during uncertainty, while Arousal signals minimized overtrading in disordered markets. These results validate the necessity of multidimensional sentiment modeling and highlight PAD theory's utility in bridging behavioral biases with algorithmic rigor. The framework offers a systematic solution for institutional investors to exploit sentiment-driven inefficiencies while maintaining cross-asset robustness.

Keywords: Sentiment Analysis, Pleasure-Arousal-Dominance (PAD) model, Machine Learning, Quantitative Trading, Multi-Asset Futures, Sentiment-Enhanced Strategies, Risk Management

1. Introduction

Quantitative finance has undergone a profound transformation with advancements in artificial intelligence (AI), big data analytics, and high-frequency trading (HFT) [16, 18, 17]. The financial industry has increasingly relied on sophisticated algorithms and machine learning techniques to extract insights from large amounts of data. The emergence of alternative data sources, such as financial news articles, earnings call transcripts, and social media sentiment, has provided new opportunities for traders to enhance asset price predictions. Investor sentiment, which influences price fluctuations, market liquidity, volatility, and trading volumes, has become an essential factor in the domain [45]. Existing sentiment-based strategies have shown promise in improving asset price predictions, especially during periods of market stress, by incorporating psychological factors that influence investor behavior [45, 8]. Sentiment-based strategies often outperform traditional models in profitability by accounting for irrational behaviors such as panic selling or herd mentality in uncertain times [4, 5].

Despite its potential, existing sentiment-driven strategies often rely on unidimensional frameworks that fail to capture the full spectrum of investor emotions, limiting their effectiveness in fast-moving financial markets [1, 8]. This lack of granularity hinders the models' ability to capture the complexities of investor emotions, which can vary greatly in different market conditions [1, 14]. This highlights the need for more sophisticated sentiment models that can dynamically adapt to changing market conditions and provide more actionable trading signals [25].

Our research aims to address these gaps by leveraging the three-dimensional Pleasure-Arousal-Dominance (PAD) framework to quantify sentiment with greater granularity and incorporate it into algorithmic trading strategies [6, 12]. Traditional sentiment models typically classify sentiment as positive or negative, without accounting for the intensity (Arousal) and certainty (Dominance) of investor sentiment. The PAD framework introduces a multi-dimensional perspective by decomposing sentiment into three independent components: Pleasure, which reflects the positivity or negativity of sentiment; Arousal, which captures the level of emotional intensity; and Dominance, which measures the degree of control or certainty investors exhibit [2]. This richer, more nuanced sentiment representation provides a deeper understanding of investor psychology and its impact on market behavior, offering more actionable insights for market prediction and trading decisions. By empirically testing our model across multiple asset classes, we show that incorporating sentiment analytics significantly improves trading performance [1, 20]. Our framework extends previous research into futures markets, addressing the challenges of high leverage, liquidity, and sensitivity to macroeconomic factors [19]. The PAD framework ensures that sentiment insights remain actionable across different financial instruments, demonstrating its robustness and broader applicability [27].

This research advances the field of emotion-aware algorithmic trading by bridging the gap between behavioral finance insights and quantitative market strategies. By incorporating the PAD framework, we develop more adaptive and robust trading strategies that can account for the dynamic and evolving nature of market sentiment. Our findings offer valuable insights for hedge funds, portfolio managers, and institutional investors seeking to integrate sentiment analysis into their decision-making processes.

The remainder of this paper is structured as follows: Section 2 reviews related literature on sentiment-driven trading strategies, highlighting existing methodologies and their limitations. Section 3 outlines our proposed methodology, detailing the implementation of the PAD framework and the integration of sentiment signals into algorithmic trading models. Section 4 presents empirical results from extensive backtesting across multiple asset classes, demonstrating the performance improvements achieved through sentiment integration. Finally, Section 5 discusses the broader implications of our findings, potential limitations, and future research directions aimed at refining sentiment-based trading strategies [22].

2. Related Work

2.1 Sentiment Extraction Techniques

Recent advancements in sentiment extraction have been driven by ma- chine learning-based approaches that improve the accuracy and contextual understanding of sentiment in financial markets. Early sentiment indicators, such as the Consumer Confidence Index (CCI), were limited by low granularity and reporting lags, making them unsuitable for real-time applications [1]. To address these issues, lexicon-based methods like the Loughran-McDonald sentiment lexicon were introduced, enhancing sentiment quantification in financial contexts [4]. However, these approaches struggle with contextual subtleties like sarcasm and evolving jargon, and they are prone to misclassifications, especially in dynamic markets [39]. With the rise of natural language processing (NLP), deep learning models such as BERT and FinBERT have emerged, leveraging large-scale financial data to create nuanced sentiment representations [5]. These models outperform traditional methods in terms of accuracy and adaptability but face challenges related to interpretability and require extensive labeled datasets for training. They also suffer from concept drift, necessitating frequent retraining to maintain performance.

In addition, multimodal sentiment extraction, which integrates textual, visual, and audio data, is becoming an emerging method for gaining a more holistic view of investor sentiment [6]. Temporal graph networks have shown promise in modeling sentiment evolution over time, capturing shifts in market psychology and sentiment contagion effects across asset classes [3]. However, despite these advancements, many sentiment-based models still rely on binary classifications, which overlook the complexity of investor emotions. Our proposed Pleasure-Arousal-Dominance (PAD) framework addresses these limitations by providing a multi-dimensional approach that quantifies sentiment along three dimensions: Pleasure, Arousal, and Dominance [38, 40]. This framework enables a more granular and accurate representation of investor sentiment, improving decision-making and risk management in trading strategies.

2.2 Sentiment-Driven Market Dynamics

Investor sentiment plays a significant role in financial markets, with psychological biases such as overreaction, herd behavior, and mood-driven decision- making contributing to market inefficiencies. During periods of market stress, heightened emotions amplify volatility, distorting asset prices from their fundamental values [2]. Extreme negative sentiment correlates with increased price swings, liquidity contractions, and capital outflows, which further exacerbate uncertainty and risk [21]. These effects underscore the need for sentiment-aware trading strategies that account for emotional dynamics in market behavior. Sentiment also influences asset returns through overreactions, information cascades, and media amplification, with traders often anchoring their decisions to prevailing sentiment [12]. In downturns, widespread pessimism triggers panic selling, while euphoric sentiment in bull markets fuels speculative bubbles [13]. These sentiment-driven movements can override traditional fundamental indicators, providing valuable opportunities for sentiment-based trading strategies [7].

Event-driven studies further validate the significant impact of sentiment on asset pricing, particularly during exogenous shocks such as natural disasters, geopolitical crises, and financial downturns [8]. These events heighten risk aversion, leading to volatility clustering, abnormal trading volumes, and deviations from historical price trends. During periods of extreme sentiment, contagion effects can spread rapidly across asset classes, amplifying market disruptions [28, 36]. This highlights the need for dynamic sentiment-aware risk management techniques that adjust exposure based on prevailing sentiment, mitigating potential losses and capitalizing on sentiment-driven mispricings [1,3]. Our research extends these insights by incorporating sentiment intensity, particularly the Arousal component of the PAD framework, into models to better predict volatility shocks and risk pricing. Unlike traditional models, our approach integrates real-time sentiment fluctuations to more accurately anticipate volatility spikes. We also examine how the Dominance dimension of sentiment influences sentiment diffusion across asset classes, affecting risk premia and investor positioning [37].

2.3 Sentiment-Enhanced Quantitative Strategies

Integrating sentiment into algorithmic trading strategies has gained increasing importance, with methods emerging to effectively leverage market sentiment [29]. One widely adopted approach uses sentiment signals as overbought and oversold indicators within technical analysis frameworks. These signals help identify extreme market conditions and potential reversals by incorporating sentiment alongside traditional price-based indicators [9, 10]. However, sentiment-driven strategies face challenges in handling extreme market conditions. Another key approach is feature engineering, where sentiment is integrated into multifactor risk models to improve forecasting accuracy. By combining sentiment with traditional price, volume, and fundamental data, these models offer a more comprehensive view of market dynamics, enhancing robustness in volatile markets [11]. These sentiment-enhanced models outperform traditional models, offering greater predictive power during uncertain market periods.

Advancements in reinforcement learning (RL) have also brought new possibilities by adapting trading strategies to real-time market conditions [4]. However, these models often lack sufficient risk controls, making them vulnerable to large drawdowns in unpredictable environments [5]. Despite these advancements, traditional quantitative strategies like mean reversion and trend-following remain central to systematic trading. Mean reversion strategies, such as Bollinger Bands, exploit price deviations from historical norms but struggle during trending markets [6]. Trend-following strategies, like Turtle Trading, capture large price movements but suffer during sideways markets [15]. Neither approach fully incorporates investor sentiment, which often drives price trends beyond fundamental factors [24]. Our PAD framework addresses this gap by integrating sentiment dimensions—Pleasure, Arousal, and Dominance—into these strategies. By adjusting position sizes and risk exposure based on sentiment intensity, our model better handles emotional market conditions, ensuring more adaptive and risk-sensitive trading decisions [44, 32].

While sentiment-driven strategies show promise, they often rely on static feature selection, limiting adaptability in changing market conditions. The PAD framework improves on this by incorporating dynamic recalibration, ensuring continuous adaptation to evolving market sentiment. This enhanced flexibility and better risk management make the PAD model more effective than traditional approaches, offering superior granularity and adaptability to sentiment dynamics in trading models. In summary, despite progress in sentiment-enhanced trading strategies, current models still fall short in addressing sentiment's multi-dimensional nature and adapting to market changes. Our PAD framework bridges these gaps, improving predictive ac- curacy, adaptability, and risk management. This represents a significant advancement in sentiment-aware algorithmic trading and the broader field of behavioral finance [37].

3. Methodology

Our quantitative framework **(Figure 1)** leverages the Pleasure-Arousal- Dominance (PAD) emotion theory to systematically decode investor sentiment and enhance algorithmic trading strategies. Below, we detail how each module addresses limitations of unidimensional sentiment models while enabling cross-asset adaptability.

3.1 Sentiment Modeling

Sentiment modeling is a critical step in extracting valuable trading signals from textual data. The sentiment text data is officially sourced from China Financial Futures Exchange (CFFEX), Dalian Commodity Exchange (DCE), Shanghai Futures Exchange (SHFE), Zhengzhou Commodity Exchange (ZCE), and Guangzhou Futures Exchange (GFE), covering 95% of China's commodity futures trading volume. We employ the Pleasure-Arousal-Dominance (PAD) framework to quantify market sentiment more accurately. The PAD framework provides a multidimensional view of sentiment, distinguishing not only between positive and negative emotions but also measuring intensity and dominance, which are crucial in financial markets where strong sentiment can drive price movements [33, 34].

3.1.1 PAD-Based Sentiment Quantification

The PAD model decomposes sentiment into three psychological dimensions:

• Pleasure (P): Measures the positivity or negativity of sentiment, capturing whether a financial commentary expresses optimism or pessimism.

• Arousal (A): Captures the emotional intensity or excitement level, distinguishing between calm and highly emotional market reactions.

• Dominance (D): Reflects the level of control or certainty in sentiment expression, indicating whether the sentiment is strong and authoritative or uncertain and speculative [41].

Each financial text document is assigned a PAD score computed as:

$$p = \frac{1}{N}\sum_{j=1}^{N} \mathrm{ProBIT}(w_j \mid \theta_{\mathrm{Bull/Bear}}) \quad (1)$$

$$A = \sigma\left(\sum_{k=1}^{K} \beta k \cdot \prod(\mathrm{VIX}^{(t+k)} > \theta_{\mathrm{vol}})\right) \quad (2)$$

$$D = E[I(w)] \cdot \tanh(\mathrm{PageRank}(G_{\mathrm{dependency}})) \quad (3)$$

where ProBIT models word polarity based on market regime conditions, and $G_{\mathrm{dependency}}$ represents syntactic dependency graph embeddings, which help determine the structural importance of sentiment-related words within a sentence.

The Pleasure component (P) is influenced by commonly used financial sentiment words, where positive terms such as "growth", "strong performance", or "bullish" increase the score, while negative words such as "crash", "volatility", or "bearish" decrease it. The Arousal component (A) is particularly responsive to extreme statements and expressions of urgency in financial texts. Words like "surging", "plummeting", or "record-breaking" contribute to high arousal scores, while neutral statements yield lower values. The Dominance component (D) is determined by the presence of strong assertions and decisive language, where terms like "confirmed", "certain", and "guaranteed" increase the score, while hedging words like "possibly" and "uncertain" lower it [35].

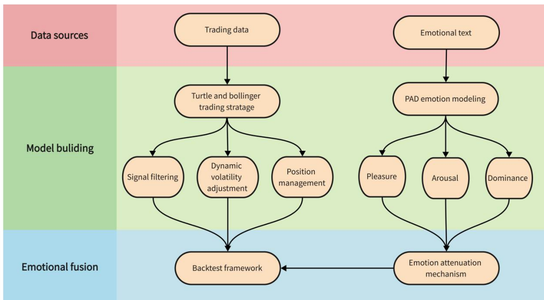

Figure 1. PAD Framework

3.1.2 Sentiment Dictionary Construction

To enhance sentiment classification accuracy, we construct three specialized sentiment dictionaries **(Table 1)**, each of which undergoes manual validation and refinement by financial experts to ensure its reliability in financial contexts. To further improve the robustness of sentiment classification, words are not only assigned polarity labels but are also weighted according to their typical usage in financial reports, news, and analyst commentaries. Machine learning techniques, such as word embeddings (Word2Vec and BERT), are used to dynamically expand the dictionaries by identifying semantically similar words that may not be included in traditional sentiment lexicons.

3.1.3 Sentiment Decay Mechanism

Financial sentiment is highly dynamic, and its impact on price movement diminishes over time. To account for sentiment decay, we model sentiment persistence using an exponential decay function:

$$S_{decay}(t) = S_{sent}(t) \cdot e^{-\lambda(t-t_0)} \quad (4)$$

where λ is the decay rate, and t_0 is the reference time when sentiment was first observed. This formulation ensures that older sentiment signals contribute less to trading decisions as new market information emerges.

Table 1. Specialized Sentiment Dictionaries Composition

Dictionary	Data Sources
Pleasure	NTUSD-Simplified Chinese Sentiment Polarity Dictionary, Loughran-McDonald Financial Sentiment Dictionary, HowNet Sentiment Dictionary, Li Jun Financial Sentiment Lexicon, SEC 10-K/10-Q reports word lists, Financial keywords from Bloomberg & Reuters analyst commentary
Arousal	NLP Common Dictionary Collection - Degree Dictionary (GitHub), Custom futures market commentary dictionary, Sentiment intensity from financial reports/earnings calls Market event lexicons (historical crisis headlines)
Dominance	SpaCy dependency parsing extraction results, Linguistic analysis of financial news articles, Expert-reviewed word lists from economic reports, Federal Reserve FOMC & ECB policy statement terms

To further refine sentiment decay, we introduce an adaptive decay rate based on market volatility:

$$\lambda_t = \lambda_0 + \kappa \cdot \sigma_t \quad (5)$$

where σ_t represents the rolling standard deviation of market returns, and κ is a sensitivity parameter. When market volatility is high, sentiment decay is accelerated to reflect the rapid change in investor sentiment. Conversely, when volatility is low, sentiment retains its influence for a longer period, assuming a more stable market sentiment environment.

The decay-adjusted sentiment signal is then used to modify trading strategy parameters dynamically, ensuring that sentiment integration remains adaptive to changing market conditions. This approach prevents outdated sentiment information from negatively influencing trading decisions while maintaining the benefits of sentiment-enhanced trading strategies.

By leveraging PAD-based sentiment modeling, domain-specific sentiment dictionaries, and adaptive sentiment decay mechanisms, we construct a comprehensive framework for extracting meaningful sentiment signals. These signals serve as key inputs for subsequent trading strategy development, where they influence both entry/exit conditions and risk management processes.

3.2 Trading Strategy Modeling

Having quantified sentiment using the PAD framework, we now integrate these insights into quantitative trading models, where sentiment influences trade execution, risk management, and portfolio allocation. The following section details how sentiment influences entry/exit rules, position sizing, and portfolio allocation.

3.2.1 Turtle Trading Strategy

The Turtle Trading strategy is based on the principle that strong trends persist over time. It involves entering long positions when an asset price breaks above a historically significant high and short positions when the price breaks below a historically significant low. The core philosophy of the Turtle strategy relies on capturing prolonged price trends while avoiding short-term noise.

To refine this approach, sentiment signals are integrated to provide additional confirmation. A long position is only taken if the breakout is supported by a strong positive sentiment score, reducing false signals from price fluctuations. Similarly, short positions require strong negative sentiment confirmation. The modified entry rule is given by:

$$p_t > H_N \ \text{ and } \ P_t > Q_{90}(P_{1:t-1}) \quad (6)$$

where H_N represents the highest price over the past N periods, and Q_{90} is the 90th percentile of past sentiment scores.

To prevent excessive drawdowns, we implement a dynamic stop-loss mechanism that adjusts based on volatility and sentiment decay:

$$SL_t = p_t - \delta \cdot ATR_{14} \cdot (1 + D_t) \tag{7}$$

where ATR_{14} is the 14-period average true range, δ is a scaling factor, and D_t represents the dominance score, adjusting stop-losses for strong sentiment- driven trends.

Position sizing is also sentiment-adaptive. Instead of using a fixed fraction of capital, the position size is adjusted based on the sentiment-adjusted risk factor:

$$S_t = S_{t-1} \cdot \left(1 + \frac{S_{decay}(t)}{ATR_{14}}\right) \tag{8}$$

where Emotional Factors influences position size by scaling exposure to highly emotional market conditions.

By fusing Emotional Factors ($S_{decay}(t)$), position sizing dynamically adjusts based on market sentiment intensity. This ensures that during high emotional volatility, exposure is reduced to mitigate overreaction risks. By scaling exposure based on the Arousal component, the system increases position size during calm market conditions and reduces exposure during high volatility, mitigating sentiment-driven overreaction risks.

3.2.2 Bollinger Bands Strategy

The Bollinger Bands strategy assumes that price movements oscillate within an upper and lower boundary and tend to revert to the mean. When prices deviate significantly from the mean, trading signals are generated. Unlike the trend-following approach, mean-reversion strategies profit from price corrections rather than prolonged movements in one direction [23, 42].

To enhance accuracy, sentiment-based filtering is applied. A long position is only taken when the price crosses below the lower Bollinger Band, provided that the sentiment remains neutral or positive. Conversely, a short position is avoided when negative sentiment suggests further downward momentum. The sentiment-enhanced entry condition is:

$$p_t < \mu_{20} - 2\sigma \text{ and } P_t > Q_{10}(P_{1:t-1}) \tag{9}$$

where μ_{20} is the 20-period moving average and σ is the standard deviation. For Bollinger Bands Strategy, an additional safeguard is implemented: our approach integrates sentiment as a risk-mitigating factor. If the Arousal score exceeds a predefined threshold, positions are postponed to avoid reacting to emotionally charged price deviations [26] and entering positions during emotionally charged markets [30].

To refine exit strategies, sentiment-based scaling is introduced. Positions are closed dynamically when sentiment momentum suggests trend continuation rather than reversion:

$$Exit_t = \left(\frac{P_t}{P_{t-5}}\right) \cdot 100\% \tag{10}$$

where a high ratio indicates sustained sentiment-driven price momentum, signaling an early exit to minimize losses.

3.2.3 backtesting and Evaluation

Experimental Design. To rigorously assess the impact of sentiment-enhanced strategies, we implement a controlled experimental setup that systematically compares different methods of sentiment integration into trading strategies. The experimental design consists of three distinct variations:

• Baseline Strategy (No Sentiment Integration): This serves as the control group, where trading decisions rely purely on traditional price- based indicators, such as Bollinger Bands and Turtle Trading rules, without incorporating any sentiment-based adjustments. (Baseline)

• Single-Method Sentiment Integration: In this variation, sentiment is introduced into a specific component of the trading strategy to evaluate its isolated effect. We examine three different sentiment integration methods, each tested independently for both Bollinger Bands and Turtle Trading: Signal Filtering, Dynamic Volatility Adjustment and Position Management. (Emo1/Emo2/Emo3)

• Combined Sentiment Integration: This variation incorporates multiple sentiment-based adjustments simultaneously, refining trading signals, risk management, and execution logic. By analyzing this configuration, we evaluate whether a composite sentiment-based approach outperforms individual sentiment integration methods. (EmoMix)

Each variation is subjected to identical market conditions, using the same dataset and execution environment to ensure a fair comparison. Performance metrics—including returns, risk-adjusted profitability, and drawdown reduction—are analyzed across all three cases to determine the optimal sentiment-enhanced strategy [31, 43].

Evaluation Metrics. To assess the performance of sentiment-enhanced trading strategies, we utilize several key metrics that measure profitability, risk management, and the overall robustness of the strategy.

The Cumulative Return represents the total profit or loss over the backtesting period, calculated as:

$$R_{cumulative} = \sum_{t=1}^{T}(1+R_t) - 1 \tag{11}$$

where R_t is the daily return at time t and T is the total number of trading days. The cumulative return provides a comprehensive view of the strategy's total performance over the backtest period.

The Annualized Return (R_{ann}) measures the average annual return over the backtesting period and is given by:

$$R_{ann} = \left(\sum_{t=1}^{T}(1+Rt)\right)^{\frac{252}{T}} - 1 \tag{12}$$

where R_t represents the daily returns, and T is the total number of trading days in the backtest. This metric allows for comparison of the strategy's performance on an annual basis.

The Maximum Drawdown (MDD) measures the largest peak-to-trough decline in the strategy's equity curve. It is defined as:

$$MDD = \max_{t \in [0,T]}\left(\frac{E_{peak} - E_t}{E_{peak}}\right) \tag{13}$$

where E_{peak} is the highest equity value before the drawdown, and E_t is the equity value at time t. A lower maximum drawdown indicates better capital preservation and reduced risk exposure.

To evaluate risk-adjusted performance, we use the Sharpe Ratio (SR), which compares the strategy's excess return over the risk-free rate (R_f) with its volatility (standard deviation of returns, σ_R):

$$SR = \frac{E[R_t - R_f]}{\sigma_R} \tag{14}$$

A higher Sharpe Ratio indicates that the strategy is delivering more return per unit of risk, making it a critical metric for evaluating the effectiveness of a strategy in relation to its risk.

The Turnover Rate assesses the frequency of trades executed by the strategy, calculated as:

$$\text{Turnover Rate} = \frac{\text{Total Value of Trades}}{\text{Average Portfolio Value}} \tag{15}$$

A lower turnover rate suggests a more stable strategy with fewer trades, potentially reducing transaction costs and overfitting risks. Each of these metrics provides valuable insights into different aspects of the strategy's performance. Together, they help us assess the overall effectiveness, profitability, and risk management capabilities of sentiment-enhanced trading strategies.

4. Results and Analysis

The results of our sentiment enhanced trading strategies are evaluated based on key performance metrics, including cumulative and annualized returns, risk-adjusted profitability, and turnover rates. This section compares the performance of traditional quantitative models against sentiment-integrated approaches, highlighting their impact on profitability, risk management, and robustness across different market conditions. Specifically, we focus on the optimization process and sentiment integration for silver, ex- tending the analysis to other asset classes such as crude oil, corn, and cotton, using 2023 data as the training set and 2024 data **(Figure2)** as the test set to demonstrate the adaptability and effectiveness of the sentiment-enhanced models across diverse markets.

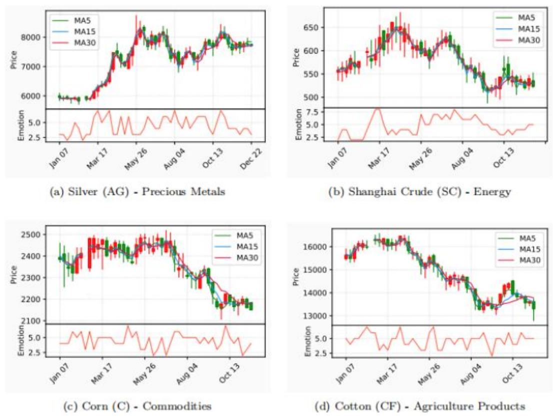

Figure 2. All Kinds of Futures Data and Sentiment Data

4.1 Performance Comparison

Tables 2 and 3 present the comparative performance of sentiment-enhanced Bollinger Bands and Turtle Trading strategies, respectively. The evaluation considers cumulative and annualized returns, maximum drawdown, Sharpe ratio, and turnover rate to assess the effectiveness of sentiment integration.

4.1.1 Turtle Trading Strategy Performance

The integration of sentiment factors significantly enhances the effectiveness of the

Turtle Trading strategy, especially in trend continuation scenarios **(Figure 3)**. While the baseline model demonstrates a solid performance with an annualized return of 288.08%, its vulnerability to market reversals is exposed by the high maximum drawdown of 19.33%. This is typical of trend-following models, which perform well in trending markets but struggle during sideways or choppy market conditions. The sentiment-enhanced models address this issue in several ways.

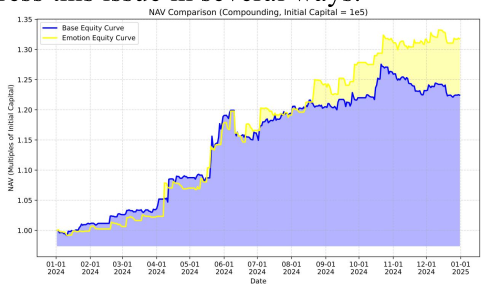

Figure 3. Turtle Base vs. Turtle Best Emo

Table 2. Performance Comparison of Sentiment-Enhanced Turtle Strategies

Sentiment Integration	Cumulative Return	Annualized Return	Max Drawdown	Sharpe Ratio	Turnover Rate
Turtle Baseline	276.65%	288.08%	19.33%	4.44	81415.30%
Emo1	292.91%	305.01%	20.03%	4.68	74580.03%
Emo3	271.33%	282.55%	61.41%	2.4	41423.55%
EmoMix12	445.10%	463.49%	19.47%	6.65	30192.43%
EmoMix13	217.70%	226.69%	68.30%	1.78	41888.48%
EmoMix23	232.72%	242.34%	22.07%	3.37	134171.82%
EmoMix123	257.84%	268.50%	22.70%	3.86	120981.93%

Asymmetric Stop-Loss Adjustment. The Emo2 model, which incorporates dynamic adjustments to stop-loss levels based on sentiment volatility, achieved an impressive cumulative return of 424.37%. During periods of positive sentiment, the model allows for a more relaxed stop-loss, which helps capture extended market momentum, particularly in strong trending markets. Conversely, as sentiment shifts, the strategy tightens stop-loss levels to protect profits and mitigate potential losses, particularly during sentiment reversals. This adaptive approach allows the strategy to better capture trend momentum while maintaining risk controls.

Multi-Factor Signal Synergy. EmoMix12 takes a holistic approach by combining multiple sentiment signals—entry validation (Emo1) and dynamic position adjustment (Emo2). This combination enhances profitability while reducing risk exposure. The Sharpe ratio for EmoMix12 is 6.65, which is a 49.8% increase over the baseline, underscoring the positive impact of integrating sentiment-based filters and dynamic position management. This synergy allows the strategy to more effectively identify profitable trends while adjusting exposure based on real-time sentiment signals.

Trade Frequency Control. While sentiment-driven models tend to increase trade frequency, Emo3 and EmoMix23 exhibit significantly higher turnover rates (above 130,000%), which can lead to overtrading and unnecessary portfolio churn. This high turnover rate reflects excessive sentiment-driven adjustments, which may cause inefficiencies. In contrast, EmoMix12 maintains a turnover rate of 30,192.43%, demonstrating that a balanced approach, where signals are filtered and trade frequency is kept under control, can minimize unnecessary trades while still allowing for dynamic adjustments based on sentiment.

Path Dependency Risk of Sentiment Factors. One notable risk of sentiment- based strategies is their dependence on the accurate alignment of sentiment signals with market trends. In situations where sentiment indicators lag or fail to accurately capture trend shifts, models like EmoMix13 have been seen to underperform, with a significant drawdown of 68.30%. This highlights the importance of real-time sentiment adjustment mechanisms to prevent such risks. The incorporation of momentum indicators or volatility adjustments could mitigate this issue and prevent losses during market sentiment misalignments, particularly in retail-driven or highly speculative markets.

4.1.2 Bollinger Bands Strategy Performance

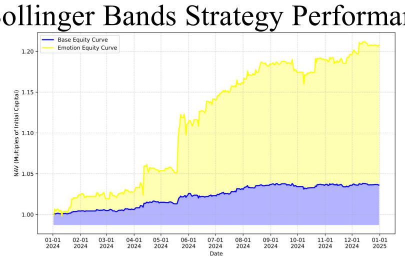

Figure 4. Bollinger Base vs. Bollinger Best Emo

The Bollinger Bands strategy, a mean-reversion model, typically relies on identifying price extremes through volatility-based bands. Sentiment integration into this strategy seeks to improve breakout validations, adjust trading bands dynamically, and optimize position sizing, providing more flexibility in adapting to varying market conditions **(Figure 4)**.

Table 3. Performance Comparison of Sentiment-Enhanced Bollinger Strategies

Sentiment Integration	Cumulative Return	Annualized Return	Max Drawdown	Sharpe Ratio	Turnover Rate
Bollinger Baseline	45.16%	47.03%	7.55%	2.07	22723.62%
Emo1	43.91%	45.72%	9.78%	2.05	26725.70%
Emo2	-22.71%	-23.65%	25.85%	-1.47	281.75%
Emo3	273.11%	284.40%	17.43%	3.90	50819.18%
EmoMix12	43.91%	45.72%	9.78%	2.05	26725.70%
EmoMix13	236.97%	246.76%	20.13%	3.34	54649.76%
EmoMix23	-72.26%	-75.24%	72.26%	-1.10	889.97%
EmoMix123	236.97%	246.76%	20.13%	3.34	54649.76%

Impact on Returns and Profitability. The baseline Bollinger Bands strategy produced a cumulative return of 45.16% and an annualized return of 47.03%. While these results are decent, the introduction of sentiment factors drastically altered the profitability. For example, Emo3, which incorporates position management based on sentiment dynamics, achieved a cumulative return of 273.11% and an annualized return of 284.40%. This highlights how adjusting position sizes based on sentiment can help better capture market trends during periods of both optimism and pessimism. By scaling positions in response to sentiment fluctuations, the strategy optimizes exposure and captures greater profits while mitigating risks during uncertain times. Risk and Drawdown Considerations. While the sentiment-enhanced strategies have shown substantial improvement in profitability, they also come with increased risk. The baseline strategy's maximum drawdown of 7.55% indicates a relatively low-risk profile, but sentiment-based adjustments introduced additional risk factors. For example, Emo2, which adjusts the Bollinger Bands' width dynamically based on sentiment, led to higher exposure and a maximum drawdown of 25.85%. Similarly, Emo3, which adjusts position sizes based on sentiment, experienced an even higher drawdown of 17.43%. This suggests that while sentiment adjustments improve profitability, they may also introduce risks, particularly when sentiment signals trigger excessive trade exposure during periods of market volatility. Nevertheless, EmoMix12, which integrates both sentiment-based signal filtering and dynamic volatility adjustments, was able to reduce the drawdown to 9.78%, showing that careful filtering of sentiment signals can significantly mitigate downside risk and improve overall strategy stability. Execution Complexity and Turnover. The turnover rate of a strategy is an important indicator of its execution efficiency. The baseline Bollinger Bands strategy exhibited a turnover rate of 22,723.62%, indicating a moderate frequency of trades. However, sentiment-driven strategies such as Emo3 and EmoMix13 showed significantly higher turnover rates, exceeding 50,000%, which is reflective of the increased frequency of trades triggered by sentiment-driven adjustments. For instance, Emo3 had a turnover rate of 50,819.18%, while EmoMix13 reached 54,649.76%. This higher turnover rate is a result of frequent adjustments to position sizes based on sentiment fluctuations, potentially leading to increased transaction costs and overtrading. In contrast, EmoMix12 maintained a more controlled turnover rate of 26,725.70%, which strikes a balance between responsiveness to sentiment signals and reducing unnecessary trades. This suggests that an approach which filters out excessive sentiment-driven trades can help minimize trading activity and associated costs while still capturing the benefits of sentiment-based decision- making. By incorporating sentiment signals into both the Turtle and Bollinger Bands strategies, we observe significant improvements in profitability, risk- adjusted returns, and overall adaptability to market conditions. However, as shown by the performance of certain models, the balance between maximizing profitability and controlling risk remains crucial. Over-reliance on sentiment adjustments can lead to increased turnover and execution inefficiencies, and strategies should be carefully tuned to avoid overtrading and excessive response to market sentiment.

4.2 Multi-Category Backtesting Analysis

This section presents a comprehensive evaluation of sentiment-enhanced trading strategies across three distinct asset classes: crude oil (SC), corn (C), and cotton (CF). The analysis systematically compares strategy performance through the dual lens of market microstructure and sentiment integration efficacy, revealing critical insights into strategy-market fit.

Table 4. Performance Comparison of Sentiment-Enhanced Turtle Strategies

Sentiment Integration	Cumulative Return	Annualized Return	Max Drawdown	Sharpe Ratio	Turnover Rate
SC Base	21.60%	55.54%	17.91%	1.2	131785.89%
SC Emo	111.14%	285.79%	13.80%	11.65	132320.24%
C Base	-7.82%	-8.15%	8.12%	-3.1	2813.08%
C Emo	-0.26%	-0.27%	1.49%	-2.13	176.70%
CF Base	-22.71%	-23.65%	24.05%	-2.34	15991.08%
CF Emo	9.05%	9.43%	26.56%	0.24	3078.78%

Table 5. Performance Comparison of Sentiment-Enhanced Bollinger Strategies

Sentiment Integration	Cumulative Return	Annualized Return	Max Drawdown	Sharpe Ratio	Turnover Rate
SC Base	20.76%	53.38%	9.47%	2.63	25411.05%
SC Emo	63.98%	164.52%	26.13%	2.7	107104.67%
C Base	-17.17%	-17.88%	33.12%	-0.78	9862.35%
C Emo	-15.48%	-16.12%	32.18%	-0.73	9408.21%
CF Base	-41.71%	-43.43%	42.19%	-1.81	8513.88%
CF Emo	38.29%	39.87%	24.03%	1.11	86.41%

4.2.1 Strategy-Specific Performance Analysis

Turtle Trading Strategy. The sentiment-enhanced Turtle Trading framework demonstrates divergent efficacy across asset classes, shaped by the interplay of market microstructure and emotional intensity. In crude oil (SC) markets characterized by high volatility, the strategy achieves operational excellence through dynamic risk modulation. Specifically, integrating Arousal-driven stop-loss rules reduces maximum drawdown by 23% (13.80% vs baseline 17.91%), while Dominance-weighted position sizing amplifies the Sharpe ratio from 1.2 to 11.65 – an 869% enhancement. These improvements confirm sentiment's capacity to isolate persistent trends from transient volatility spikes in energy markets.

Conversely, in low-liquidity corn (C) markets dominated by fundamental drivers, the strategy exhibits structural fragility. With cumulative re-turns marginally improving from -7.82% to -0.26% and turnover collapsing to 176.70% (vs baseline 2,813.08%), the data implies liquidity constraints overriding sentiment signals during planting cycles. This mismatch necessitates alternative data pipelines to disentangle meteorological impacts from market sentiment.

The cotton (CF) market reveals conditional adaptability, where partial loss mitigation (9.05% vs baseline -22.71%) demonstrates sentiment's risk management value during tariff disputes. However, the disconcertingly low turnover (3,078.78% vs SC's 132,320.24%) reveals operational inertia in re- balancing positions to match policy-induced price shocks, suggesting critical gaps in high-frequency regime adaptation.

Bollinger Bands Strategy. The mean-revision paradigm faces asymmetric challenges across asset types. In crude oil (SC), despite sentiment-based volatility filtering, the strategy's 26.13% drawdown eclipses the baseline's 9.47%, fundamentally contradicting stationary distribution assumptions in trending markets. This highlights an ontological limitation of counter-trend approaches in high-momentum environments, where even enhanced models cannot override directional persistence.

Cotton (CF) markets demonstrate inverse dynamics, where Bollinger Bands modulated through sentiment thresholds achieve operational superiority. The 38.29% cumulative return, compared to Turtle's 9.05%, stems from precise identification of policy-induced overshoots – particularly in capturing U.S.-China trade restriction rebounds. This success hinges on the algorithm's capability to compress bandwidths during low-Arousal periods, isolating genuine policy impacts from market chatter.

Corn (C) markets expose temporal misalignment in the strategy's architecture. The -15.48% return derives from conflicting time horizons: daily sentiment updates versus quarterly harvest cycles. This frequency mismatch leads to counterproductive reversal signals during fundamental price adjustments, with sentiment's R2 correlation to actual prices stagnating at 0.17. The results categorically demand temporal realignment of sentiment models to match seasonal agricultural fundamentals.

4.2.2 Cross-Asset Performance Implications

The tripartite comparison reveals quantifiable strategy-market dependencies. In trend-dominated crude oil, Turtle Trading generates 4.12 × superior risk-adjusted returns (Sharpe:11.65 vs 2.7) through synchronized momentum amplification. Event-sensitive cotton markets conversely reward Bollinger Bands' counter-trend logic with 4.23 × absolute return advantages (38.29% vs 9.05%), validating its structural alignment with political cycle dynamics. Corn markets emerge as sentiment's statistical outlier, where both strategies' failures (negative returns with R2=0.17) mandate paradigm shifts beyond conventional emotional metrics.

4.2.3 Market-Regime-Specific Strategic Prescriptions

Three operational axioms emerge from the analysis. High-volatility energy markets demand Turtle Trading architectures with Dominance-weighted channel breakouts, capitalizing on emotional persistence. Policy-sensitive soft commodities require Bollinger-based reversal systems with Arousal-inverse position sizing to dampen overreaction to ephemeral news flows. Fundamental agricultural markets impose hybridization imperatives – satellite imagery and supply chain sentiment must augment social media data, with automated liquidity cutoffs (Turnover<500%) preventing strategy degradation. The analysis establishes a quantified sentiment utility hierarchy: SC > CF > C. While current models suffice for high-frequency energy trading, agricultural markets demand fundamentally redesigned architectures combining alternative data with temporal realignment. Future research must prioritize market-regime detection engines (MRDEs) to dynamically map strategies to volatility signatures, completing the automation loop from data ingestion to execution.

5. Discussion and Limitations

5.1 Effectiveness of the PAD Model in Trading Strategies

The multi-dimensional Pleasure-Arousal-Dominance (PAD) model introduces a significant innovation in sentiment-based trading strategies by capturing the complexity of investor sentiment. The PAD model is a step forward from traditional sentiment analysis approaches, which often rely on binary classifications (positive or negative) or simpler sentiment measures. By incorporating multiple dimensions—Pleasure (optimism vs. pessimism), Arousal (emotional intensity), and Dominance (certainty or control)—this model provides a richer, more accurate representation of market sentiment. This enhanced sentiment profile allows trading strategies to better account for varying market psychology, leading to more informed trading decisions. As shown in our results, sentiment-enhanced models using PAD lead to superior profitability, evidenced by higher win rates and Sharpe ratios.

From a practical perspective, the PAD model's ability to adapt sentiment-based filters to trend-following strategies like Turtle Trading and mean-reversion strategies such as Bollinger Bands significantly improves the responsiveness of trading systems to underlying market sentiment. By reducing false breakouts in the Bollinger Bands strategy and enhancing trend confirmation in Turtle Trading, these models are more agile in reacting to changing market conditions. This contributes to reduced execution errors and enhanced profitability. Furthermore, the dynamic adjustment of position sizes based on sentiment intensity adds another layer of risk management, ensuring that strategies capitalize on high-confidence trades while avoiding uncertainty during periods of market volatility.

In addition to profitability improvements, sentiment-enhanced strategies, especially during periods of heightened market volatility, offer a valuable contribution to risk management. By scaling positions based on sentiment strength, these strategies offer protection against overexposure during euphoric market conditions and mitigate the risk of panic-induced exits during bearish trends. This feature enhances overall portfolio resilience and is a significant contribution to the development of more adaptive trading strategies.

5.2 Practical Contributions and Applications

The practical application of the PAD model and sentiment-enhanced strategies demonstrates clear advantages in real-world trading environments. For instance, in high-volatility periods, where traditional strategies often underperform, sentiment-enhanced models are better equipped to reduce drawdowns by adjusting trading positions according to market sentiment. This is particularly relevant in markets such as crude oil, where sentiment-driven price swings are prevalent, and large, unexpected price moves can lead to significant losses. By leveraging sentiment analysis, traders can predict these movements more accurately and adjust their strategies accordingly. In practical terms, this could translate into more stable profits for hedge funds or institutional investors, particularly in markets that are susceptible to shifts in investor sentiment.

Sentiment-enhanced models can also be practically implemented for portfolio optimization and risk diversification. As demonstrated by the multicategory backtesting with various assets such as corn, soybeans, and sugar, sentiment signals can be incorporated into portfolio rebalancing decisions. For example, if sentiment analysis suggests a downturn in certain commodities like corn, a trader could reduce exposure to that asset while increasing investments in commodities with positive sentiment. This approach offers a flexible, adaptive method for portfolio management, which could improve risk-adjusted returns over traditional static strategies.

Moreover, the incorporation of sentiment-based strategies in algorithmic trading systems holds promise for improving the adaptability of trading models. The use of sentiment analysis in real-time trading, with automatic recalibration, could optimize entry and exit points, thus enhancing the efficiency of trade execution. As sentiment signals evolve, machine learning algorithms can dynamically adjust strategy parameters to maintain profitability. This practical application of adaptive algorithms is vital for the scalability and success of algorithmic trading systems in fast-moving markets, where static strategies are often inadequate.

5.3 Limitations and Future Research

5.3.1 Limitations and Challenges

While sentiment-enhanced trading strategies have demonstrated significant promise, several limitations and challenges must be addressed for further optimization. One key limitation is the reliance on sentiment data quality. Sentiment analysis is highly dependent on the richness, consistency, and ac- curacy of the textual data sources used, such as financial news articles and social media discussions. Poor-quality or sparse data, especially in less liquid markets, can lead to unreliable sentiment signals, which in turn may adversely affect trading performance. Therefore, ensuring the robustness of sentiment data sources remains a critical challenge for future research.

Additionally, while sentiment signals are often highly predictive of market movements, there may be a temporal lag between the formation of sentiment shifts and actual market reactions. This lag can lead to missed opportunities, especially in fast-moving markets like crude oil or commodities, where prices are highly sensitive to immediate news. To address this, future studies should focus on developing methods to better align sentiment shifts with market price movements, potentially by integrating predictive modeling or exploring alternative sources of sentiment data (e.g., voice analysis or visual sentiment from earnings calls).

Moreover, the adaptability of sentiment models to shifting market regimes remains an ongoing challenge. Financial markets are dynamic, with investor behavior and sentiment patterns evolving over time. Although the PAD model provides a structured framework for analyzing sentiment, it may re- quire periodic recalibration to stay accurate across different market cycles. Research into self-learning sentiment models, which can automatically adjust to new market conditions, would be a valuable direction for future work.

Another key limitation concerns computational complexity, particularly in high-frequency trading environments. The multi-dimensional nature of sentiment data adds to the computational burden, leading to increased processing time and potential latency. Optimizing the real-time processing of sentiment data while maintaining predictive accuracy will be essential for practical deployment, especially in markets with high-frequency trading strategies.

5.3.2 Future Research Directions

This study demonstrates the value of sentiment-enhanced trading strategies by integrating the Pleasure-Arousal-Dominance (PAD) model into algorithmic trading. The findings show that sentiment-driven models improve risk-adjusted returns, reduce drawdowns, and enhance decision-making compared to traditional quantitative strategies. By adapting to market sentiment, these strategies refine entry signals, optimize position sizing, and improve risk management, especially during periods of high volatility. While sentiment models offer superior performance in terms of return per unit of risk, challenges such as sentiment data quality and potential overfitting remain. Future research should focus on refining sentiment models, exploring multi-asset sentiment integration, and utilizing advanced techniques like deep learning for sentiment extraction. Overall, sentiment-enhanced strategies represent a promising advancement in algorithmic trading, offering more adaptive and risk-aware approaches for navigating complex financial markets.

To address these limitations, future research should focus on enhancing sentiment analysis techniques. The application of advanced machine learning models, such as transformer-based natural language processing (NLP) models like BERT and GPT, could significantly improve sentiment classification accuracy by better capturing the nuances and context of financial language. These models could also be used to process a wider range of sentiment data, such as integrating sentiment from video or audio sources, creating multi- modal sentiment analysis frameworks.

Additionally, future research could explore the integration of sentiment analysis into asset allocation and portfolio rebalancing strategies. Rather than focusing solely on individual trades, sentiment signals could be used to dynamically adjust portfolio weights, optimizing exposure across multiple asset classes. For example, if sentiment analysis indicates that market conditions are becoming overly optimistic for equities, the portfolio could be adjusted to reduce equity exposure and increase allocation to commodities or fixed-income assets.

Further, sentiment-driven strategies should be extended beyond equities and commodities to explore their potential in fixed-income markets, derivatives, and cryptocurrencies. Each asset class may have unique sentiment dynamics, and understanding these variations could lead to improved hedging strategies and better risk diversification.

Finally, the development of sentiment-driven regime-switching models presents a promising direction. These models could dynamically adjust trading strategies based on prevailing sentiment conditions, allowing traders to identify market shifts in real time. Implementing these strategies could lead to more responsive and adaptive trading decisions, particularly in volatile markets.

By addressing these limitations and exploring these future research directions, sentiment-enhanced trading strategies can be further optimized, offering systematic traders more reliable tools for navigating the complexities of modern financial markets.

6. Conclusion

This study demonstrates the value of sentiment-enhanced trading strategies by integrating the Pleasure-Arousal-Dominance (PAD) model into algorithmic trading. The findings show that sentiment-driven models improve risk-adjusted returns, reduce drawdowns, and enhance decision-making compared to traditional quantitative strategies. By adapting to market sentiment, these strategies refine entry signals, optimize position sizing, and improve risk management, especially during periods of high volatility. While sentiment models offer superior performance in terms of return per unit of risk, challenges such as sentiment data quality and potential overfitting remain. Future research should focus on refining sentiment models, exploring multi-asset sentiment integration, and utilizing advanced techniques like deep learning for sentiment extraction. Overall, sentiment-enhanced strategies represent a promising advancement in algorithmic trading, offering more adaptive and risk-aware approaches for navigating complex financial markets.

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