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FINANCIAL SENTIMENT ANALYSIS USING REAL TIME STRATEGIC DECISION-MAKING

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ABSTRACT

Financial markets operate in environments characterized by high volatility, rapid information flow, and complex behavioural patterns. Traditional financial decision models, relying mainly on historical data and logical assumptions, often overlook psychological and sentiment-based influences that significantly impact market outcomes. In this landscape, financial sentiment analysis has become a valuable tool for gaining real-time insights into market sentiment and investor behaviour. This study explores how financial sentiment analysis can enhance strategic decision-making in dynamic settings. Utilizing behavioural finance and decision theory, a unified framework is developed that integrates real-time sentiment data into financial strategies. Data collection includes sources like financial news, analyst reports, social media platforms, and market indices. Advanced natural language processing, machine learning, and large language model (LLM) techniques are used to extract sentiment and incorporate it into predictive and optimization-based decision models. Designed to support portfolio management, risk assessment, and real-time investment decisions, the framework aims to improve agility and accuracy. The model's performance is evaluated against traditional decision-making methods using metrics such as predictive accuracy, decision speed, and risk-adjusted returns. Results suggest that sentiment-based models significantly enhance adaptability, responsiveness, and decision quality. This research bridges behavioral finance with AI analytics, offering practical insights for investors, fund managers, and policymakers seeking stronger strategies in volatile markets.

Keywords: Financial Sentiment Analysis, Real-Time Decision-Making, Behavioral Finance, Natural Language Processing (NLP), Machine Learning, Strategic Financial Planning, Market Volatility

Introduction

The financial markets are always changing because of a lot of different economic, political, and social factors. In these kinds of situations, decisions are often made when there is uncertainty, which makes traditional forecasting models less reliable because information is missing, things change quickly, and things happen that weren't planned for. Investors, fund managers, and policymakers are finding it harder and harder to find chances and lower risks in real time. In this situation, making good financial decisions depends not only on technical and fundamental analysis but also on being able to read signals that show how investors act and how the market thinks. Sentiment analysis, a sophisticated application of natural language processing (NLP) and machine learning, has recently become a potent instrument for comprehending market perceptions. There are many places where you can get financial sentiment, like news articles, social media sites, analyst reports, and financial blogs. These sources give you real-time information about how investors are feeling and how confident they are. Analysts can better understand the behavioral factors that affect asset prices, trading volumes, and overall market movements by measuring feelings as positive, negative, or neutral. This change shows how important it is to use sentiment-driven insights in financial forecasting and risk management, especially when the market is very volatile.

The quick digitization of financial ecosystems has made a lot of unstructured data available, which needs to be processed and analysed right away. Real-time analytics lets decision-makers quickly respond to changes in the market, world events, or changes in how investors feel about things.

Real-time analytics gives organisations timely information that lets them change their investment strategies, optimize their portfolios, and manage risks ahead of time. This is different from traditional methods that use lagging indicators. Combining sentiment analysis with real-time decision-making frameworks has a lot of potential to improve both responsiveness and strategic accuracy in financial situations.

There is still a lack of complete frameworks that effectively combine financial sentiment analysis and real-time analytics, even though there is a lot of research on both of these topics. The majority of current research concentrates on the technical aspects of sentiment classification or highlights traditional decision-making frameworks, neglecting the integration of behavioural insights. As a result, there is a lack of comprehension regarding the systematic integration of sentiment-driven data into real-time strategic financial planning and execution.
This study seeks to fill this gap by examining how financial sentiment analysis can be effectively employed to improve real-time strategic decision-making in financial markets. The research aims to create and test an integrated framework that merges sentiment analysis with decision-making processes, and to compare its effectiveness to conventional models. The study aims to provide theoretical insights into behavioral finance and practical tools for investors, fund managers, and policymakers.

Research Objective

The objective of this study is to examine the role of financial sentiment analysis in capturing market behavior, and to design and evaluate an integrated framework that embeds real-time sentiment data into strategic financial decision-making models for improved accuracy and responsiveness.

Research Questions

1. How does financial sentiment affect how people make decisions when the market is unstable?
2. Which sentiment analysis methods (lexicon-based, machine learning, deep learning, LLM-based) give the most accurate real-time information?
3. How can real-time sentiment data be incorporated into strategic decision-making processes?
4. What measurable improvements can be seen in the accuracy and speed of decisions made with sentiment-driven models?

Review of Literature

Overview of Techniques: From Lexicons to LLMs

According to the **GitHubarXivACM (2024) paper**, "Financial sentiment analysis (FSA) has evolved from lexicons and traditional machine-learning pipelines to domain-tuned transformers and, increasingly, finance-specialized large language models." FinBERT variants created strong baselines for finance text, outperforming generic models in detecting polarity in reports, earnings calls, and news, while newer LLMs like as BloombergGPT scale up to broader finance NLP tasks (classification, NER, Q&A). Recent fine-tuned LLMs (e.g., FinLlama) indicate improvements in handling domain idioms, context, and nuanced indications (e.g., hedging, forward guidance), which frequently confuse general sentiment tools.

Role of Big Data & Real-Time Analytics

Lu Zhang and Lei Hua's (2024) article "Major Issues in High-Frequency Financial Data Analysis: A Survey of Solutions" represents The transition from batch to streaming analytics is critical for strategic decision-making: companies combine high-frequency market data with streaming text (news, filings, and social media) to capture quick shifts in risk and expectations. Methodologically, this introduces high-frequency issues—non stationarity, asynchronous arrivals, and low signal-to-noise ratios—that necessitate robust filtering, online learning, and distributed architectures. Recent studies highlight the frictions and the significance of pipeline architecture (ingest, clean, score, and act) for intraday deployment.

Traditional Models vs. Sentiment-Driven (and Hybrid) Approaches

Chen, Z., Li, W., and Huang, J. (2025) claimed that classical decision frameworks (e.g., foundations + technicals) are increasingly including sentiment elements to create hybrid systems. Empirical evidence suggests that supplementing quantitative models with text-derived indicators (from news or social media) can improve allocation, timing, and risk control when compared to purely historical-price or accounting-ratio models. His research combines textual cues with technical/fundamental elements for trading, while others demonstrate cross-sectional utility in vendor news-sentiment indexes for stock selection.

Predictive Power: Returns, Volatility, and Risk

The study "Can real-time investor sentiment predict high-frequency stock returns?" According to "Evidence from a mixed-frequency-rolling decomposition forecasting method" by Cai, Y., Tang, Z., and Chen, Y. (2024), real-time sentiment helps predict high-frequency returns and realized volatility, with downstream benefits for value-at-risk (VaR) forecasting and intraday risk management. Research using streaming investor sentiment demonstrates incremental predictability in minute-by-minute returns; transformer-based models increase realized volatility and VaR forecasts; and LLM-based news embeddings improve aberrant intraday return predictions. At the market's microstructure edge, social emotion (Reddit/Twitter) can influence short-term volume, spreads, and volatility—as shown in meme-stock incidents.

Social Media & Collective Attention

According to **Warkulat and Pelster (2024),** attentiveness and network architecture are important factors in addition to polarity. Individual-level trade data reveal that Reddit attention influences retail investors' risk-taking and welfare; network-aware research show how social graph structures can amplify shocks (e.g., GameStop), defying established model assumptions. These dynamics demonstrate why real-time monitoring of what is said (sentiment) and how it spreads (attention, influence) is strategically important.

LLMs for Real-Time FSA

Kirtac, K., and Germano, G. (2024) stated that recent work uses LLMs to produce richer, temporally-aware representations of news and to trade on them; other papers propose RAG (retrieval-augmented generation) pipelines to keep sentiment models synchronized with fast-changing financial language, reducing dataset staleness. Together, these streams point to deployable, end-to-end systems that (i) retrieve the most recent context, (ii) generate/score sentiment using finance-tuned models, and (iii) route signals to decision engines in (near) real time.

Research Methodology

This study employs an exploratory-analytical design to investigate the impact of financial sentiment analysis on real-time strategic decision-making. Data is sourced from several channels, including financial news stories, analyst reports, blogs, and social media platforms like Twitter, Reddit, and StockTwits. Market indices and intraday trade volumes are incorporated to monitor market fluctuations and substantiate the influence of sentiment.Text data is subjected to preprocessing, including tokenization, deduplication, and noise filtering, prior to sentiment extraction utilizing a blend of lexicon-based techniques, machine learning classifiers, deep learning models, and transformer-based methodologies (e.g., FinBERT, LLMs). Apache Kafka and Spark Structured Streaming facilitate real-time data ingestion and processing, while Python APIs and modules such as Hugging Face Transformers, scikit-learn, and PyTorch assist with model training and inference.

Decision-making models integrate sentiment traits with market indicators for predictive forecasting, trading strategy simulation, and portfolio optimization. Evaluation emphasizes on technical measurements (accuracy, precision, timeliness, latency) and economic indicators (risk-adjusted returns, Sharpe ratio, decision efficacy).

The methodology prioritizes robustness via time-series cross-validation, backtesting inclusive of transaction costs, and stress testing in volatile conditions. This methodology guarantees a scalable, replicable, and real-time foundation for incorporating emotion into financial decision-making systems.

Theoretical Framework

The present investigation is based on a multidisciplinary theoretical framework that combines behavioral finance theory, the efficient market hypothesis (EMH), decision theory, and an integrated sentiment-decision model (ISDM). These viewpoints collectively elucidate the manner in which real-time sentiment analysis might augment financial decision-making, beyond the limitations of conventional models.

Behavioral Finance Theory

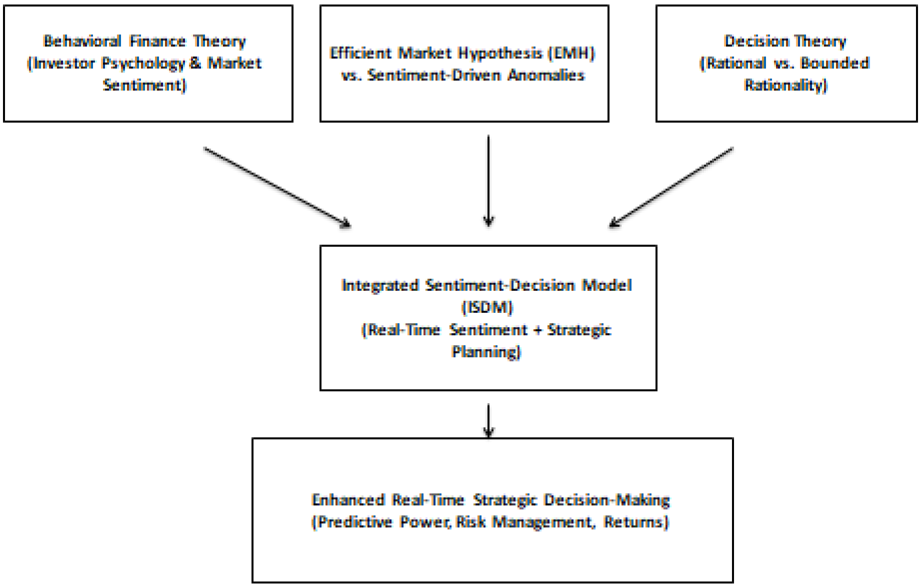
Behavioral finance contests the traditional notion of investors as totally rational entities by highlighting the influence of psychological biases, emotions, and heuristics inside financial markets. Investor emotion, influenced by optimism, anxiety, herd behavior, and overreaction, frequently results in deviations from intrinsic values. Studies highlight that market outcomes are frequently shaped by perceptions and collective moods rather than fundamentals alone. In this perspective, financial sentiment derived from news, social media, and analyst reports transforms into a measurable reflection of investor psychology. These sentiment signals are behavioral markers that can help you predict strange events, bubbles, or panic-driven selloffs. This lets you make more flexible strategic judgments.

Efficient Market Hypothesis (EMH) vs. Sentiment-Driven Anomalies

The EMH asserts that asset prices completely incorporate all accessible information, hence precluding any possibility of persistent outperformance. However, real-world examples of sentiment-driven anomalies, like short-term momentum, overreactions to earnings releases, and meme-stock occurrences, go against this idea. Twitter and Reddit are examples of social media sites that show how the mood and attention of a group may impact markets even when there isn't any important news. This indicates that markets do not consistently exhibit informational efficiency, especially in high-frequency environments characterized by emotional and collective activity. Adding sentiment analytics to financial models gives them a new perspective, filling in the gaps left by EMH's rationalist ideas.

Decision Theory: Rational vs. Bounded Rationality

Conventional decision theory posits that financial agents are rational optimizers, evaluating all accessible information to enhance utility. Nonetheless, bounded rationality (Simon, 1955) acknowledges cognitive and informational limitations that restrict decision-making. In finance, investors and managers often use heuristics or incomplete signals because they don't have enough time or data. Real-time sentiment analysis can assist fill this gap by giving you filtered, aggregated information about how the market feels, which makes things less complicated in your mind. By adding sentiment-driven signals to decision support systems, financial players can make more logical choices while still taking into account behavioral and informational limits.



Source: Kirtac, K., & Germano, G. (2024) MDPI

Integrated Sentiment-Decision Model (ISDM)

The paper develops an Integrated Sentiment-Decision Model (ISDM) that merges real-time sentiment analytics with strategic financial planning, building on these theories. The model works on three levels:

1. Sentiment Extraction: Advanced sentiment analysis techniques (including lexicons, machine learning, and LLMs) are used to process real-time data streams from news, social media, and market comments.
2. Decision Integration: Sentiment signals that have been extracted are used in predictive and optimization models along with more traditional indicators like trading volume, volatility, and macroeconomic data.
3. Strategic Application: The decision models' outputs help with trading, risk management, and investment strategies, with a focus on being able to change when things are unstable.

The ISDM enhances theoretical comprehension by integrating behavioral finance, bounded rationality, and EMH anomalies into a cohesive framework. It recognizes that markets are not entirely rational or completely irrational; instead, they are influenced by a dynamic interaction between fundamentals and sentiment. The model formalizes this integration, giving us a strong basis for judging how real-time sentiment analytics might improve the accuracy, speed, and robustness of financial decision-making.

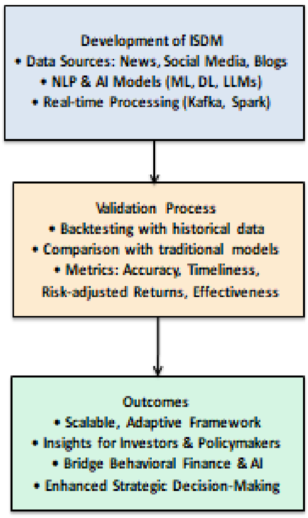
Expected Contributions

This study is expected to provide both theoretical and practical advancements in the domain of financial decision-making.

Development of a Real-Time Sentiment-Based Decision-Making Framework

The proposed study aims to create and confirm an Integrated Sentiment-Decision Model (ISDM) intended to integrate real-time financial sentiment into strategic decision-making. The ISDM framework is a new way to look at market dynamics that systematically mixes ideas from behavioral finance with AI-driven sentiment analytics.

The ISDM uses a wide range of sentiment data sources, including as news stories, analyst reports, financial blogs, and social media sites like Twitter, Reddit, and StockTwits. Advanced Natural Language Processing (NLP) approaches, such as lexicon-based methods, machine learning, deep learning, and large language models (LLMs), are used to process these unstructured data streams. To make sure that the system can grow and respond quickly, real-time data streaming and processing tools like Apache Kafka and Spark are included.



There will be several steps in the process of validating ISDM. We will use historical datasets for backtesting, which will let us directly compare how well ISDM predicts outcomes with how well typical financial decision-making models do. The evaluation framework will look at things like accuracy, timeliness, risk-adjusted returns, and how well decisions operate overall. This will make sure that the framework is both scientifically sound and useful in real life.

People expect ISDM to help in two ways. In theory, it connects behavioral finance theory with computer analytics by turning investor psychology into measurable decision inputs. In practice, it gives investors, fund managers, and policymakers a decision-support tool that can grow with them, enabling them deal with market volatility more accurately. In the end, the ISDM is meant to be a standard for future improvements in making financial decisions based on real-time feelings.

Empirical Evidence on Performance Improvements

The research will furnish empirical evidence demonstrating that sentiment integration improves accuracy, timeliness, and risk-adjusted returns relative to conventional decision-making models through comprehensive testing involving backtesting, predictive modeling, and simulation.

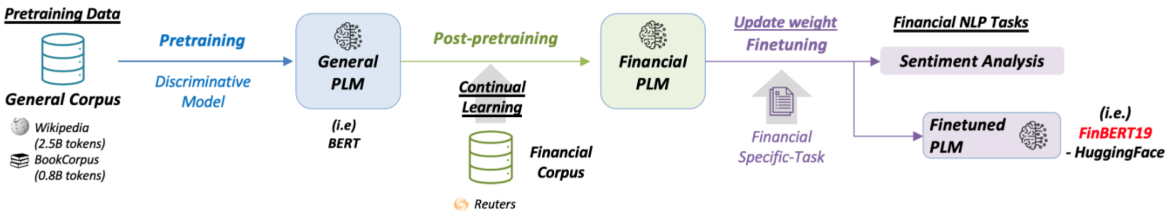
Category	Model	Backbone	Paras.	Techniques	PT	Evaluation		Open Source			Venue
					PT Data Size	Task	Dataset	Model	PT	IFT	
FinPLM (Disc.)	FinBERT-19 [Araci, 2019]	BERT	0.11B	Post-PT, FT	(G) 3.3B words (F) 29M words	[SA]	FPB, FiQA-SA	Y	N	N	ArXiv Aug 2019
	FinBERT-20 [Yang *et al.*, 2020]	BERT	0.11B	PT, FT	(F) 4.9B tokens	[SA]	FPB, FiQA-SA, AnalystTone	Y	Y	N	ArXiv Jul 2020
	FinBERT-21 [Liu *et al.*, 2021]	BERT	0.11B	PT, FT	(G) 3.3B words (F) 12B words	[SA], [QA] [SBD]	FPB, FiQA-SA, FiQA-QA FinSBD19	N	N	N	IJCAI (S) Jan 2021
	FLANG [Shah *et al.*, 2022]	ELECTRA	0.11B	PT, FT	(G) 3.3B words (F) 696k docs	[SA], [TC] [NER], [QA], [SBD]	FPB, FiQA-SA, Headline FIN, FiQA-QA, FinSBD21	Y	Y	N	EMNLP Oct 2022
FinLLM (Gen.)	BloombergGPT [Wu *et al.*, 2023]	BLOOM	50B	PT, PE	(G) 345B tokens (F) 363B tokens	[SA], [TC] [NER], [QA]	FPB, FiQA-SA, Headline FIN, ConvFinQA	N	N	N	ArXiv Mar 2023
	FinMA [Xie *et al.*, 2023]	LLaMA	7B, 30B	IFT, PE	(G) 1T tokens	[SA], [TC], [NER], [QA] [SMP]	FPB, FiQA-SA, Headline FIN, FinQA, ConvFinQA, StockNet, CIKM18, BigData22	Y	Y	Y	NIPS (D) Jun 2023
	InvestLM [Yang *et al.*, 2023c]	LLaMA	65B	IFT, PE PEFT	(G) 1.4T tokens	[SA], [TC] [QA], [Summ]	FPB, FiQA-SA, FOMC FinQA, ECTSum	Y	N	N	ArXiv Sep 2023
	FinGPT [Wang *et al.*, 2023]	6 open-source LLMs	7B	IFT, PE PEFT	(G) 2T tokens (e.g. LLaMA2)	[SA], [TC] [NER], [RE]	FPB, FiQA-SA, Headline FIN, FinRED	Y	Y	Y	NIPS (W) Oct 2023

Table 1: A Summary of FinPLMs and FinLLMs. The abbreviations correspond to Paras.= Model Parameter Size (Billions); Disc. = Discriminative, Gen. = Generative; Post-PT = Post-Pre-training, PT = Pre-training, FT = Fine-Tuning, PE = Prompt Engineering, IFT = Instruction Fine-Tuning, PEFT = Parameter Efficient Fine-Tuning; (G) = General domain, (F) = Financial domain; (in Evaluation) [SA] Sentiment Analysis, [TC] Text Classification, [SBD] Structure Boundary Detection, [NER] Named Entity Recognition, [QA] Question Answering, [SMP] Stock Movement Prediction, [Summ] Text Summarization, [RE] Relation Extraction; (in Venue) (S) = Special Track, (D) = Datasets and Benchmarks Track, (W) = Workshop. In open source, it is marked as Y if it is publicly accessible as of Dec 2023.

Source: Dogu Araci (2019)

The evolution of Natural Language Processing (NLP) in finance has been marked by the emergence of specialized **Financial Pretrained Language Models (FinPLMs)** and more recent **Financial Large Language Models (FinLLMs)**. These models aim to capture the nuances of financial text, enabling improved sentiment analysis, forecasting, and decision-making support.

Fig 1 **Financial Large Language Models (FinLLMs**)



Source: Neng Wang, Hongyang Yang, Christina Dan Wang (2023)

FinPLMs are domain-adapted models derived from BERT and related architectures. **FinBERT-19, FinBERT-20, and FinBERT-21** (Araci, 2019; Yang et al., 2020; Liu et al., 2021) represent early milestones, trained on both general and financial corpora, and fine-tuned for tasks such as **Sentiment Analysis (SA)**, **Question Answering (QA)**, and **Structure Boundary Detection (SBD)**. Similarly, **FLANG** (Shah et al., 2022) extends capabilities to **Text Classification (TC)** and SBD. While these models are lightweight (0.11B parameters), they are effective for domain-specific sentiment analysis. However, their reliance on supervised datasets limits scalability and adaptability to broader financial tasks.

Recent advancements have shifted toward **FinLLMs**, which leverage large-scale transformer backbones such as BLOOM and LLaMA. **BloombergGPT (50B)** integrates financial and general data, enabling diverse tasks including **SA, TC, NER, and QA** (Wu et al., 2023). **FinMA (7B, 30B)** (Xie et al., 2023) supports advanced applications such as **Stock Movement Prediction (SMP)**, while **InvestLLM (65B)** (Yang et al., 2023c) focuses on QA and summarization. **FinGPT (7B)** (Wang et al., 2023) emphasizes openness and parameter-efficient fine-tuning, offering accessibility for financial research communities.

The shift from FinPLMs to FinLLMs demonstrates a move from **narrow, task-specific sentiment models** to **scalable, multi-task generative frameworks**. While FinPLMs remain valuable for lightweight applications, FinLLMs offer greater versatility, real-time adaptability, and integration with AI-driven financial analytics. This transition highlights the growing role of **large-scale, instruction-tuned models** in supporting investors, fund managers, and policymakers in managing market volatility and strategic decision-making.

Trend stability test of factors and closing prices

This research uses the KPSS test (Kwiatkowski-Phillips-Schmidt-Shin test) to see if the closing prices and sentiment components show trend stationarity.

Table 1. Test of trend stationarity table.

Test Object	KPSS Statistic	Corresponding P-Value	Critical Value at 10 % Significance	Critical Value at 5 % Significance	Critical Value at 2.5 % Significance	Critical Value at 1 % Significance
Closing Price	0.125618	0.0906	0.129	0.156	0.186	0.226
Sentiment Factor	0.124434	0.1901	0.129	0.156	0.186	0.226

Source: Computation using Amos

The KPSS trend stationarity test findings in Table 1 give us significant information about how the closing price and the sentiment factor behave. The KPSS statistic (0.125618) for the closing price is lower than the critical values at all standard significance levels (10%, 5%, 2.5%, and 1%), and the p-value is 0.0906. This means that the null hypothesis of trend stationarity cannot be rejected, which means that the closing price series is trend stationary. The sentiment factor has a KPSS statistic of 0.124434 and a p-value of 0.1901, which is also below all critical limits. This shows that the sentiment element is also stable over time. In essence, both variables demonstrate stability around a deterministic trend, rendering them appropriate for further econometric modeling and predictive analysis. The validation of stationarity enhances the dependability of later analyses that amalgamate sentiment with financial variables.

Granger causality test between factors and closing prices

The previous section confirmed that both the sentiment factor and closing prices demonstrate trend stationarity. We use the Granger causality test here to look into and confirm whether the sentiment factor has a direct effect on closing prices.

Table 2 shows the findings of the analysis. The P-values for the F test, Chi-Squared test, and likelihood ratio test rise as the lag period lengthens, which makes it less probable that the null hypothesis will be rejected. This means that the trend sentiment element has less of an effect on closing prices when the lag period is larger. When the lag period is more than 8, the P-values for all three tests are higher than 0.05. This means that the trend sentiment factor cannot be said to have causal explanatory power over closing prices at the 0.05 significance level.

Table 2. Test of granger causality.

Number of Lags	SSR based F Test value	SSR based F Test P-value	SSR based Chi-Square Test () value	SSR based Chi-Square Test () P-value	Likelihood Ratio Test value	Likelihood Ratio Test P-value
1	9.9462	0.0031	9.0474	0.0026	8.9837	0.0029
2	4.6781	0.0103	9.5324	0.0085	9.4502	0.0093
3	3.8580	0.0127	11.6788	0.0090	11.3103	0.0102
4	3.0120	0.0299	12.5265	0.0139	12.2014	0.0159
5	2.6145	0.0354	13.7051	0.0177	13.3286	0.0206
6	2.3052	0.0459	14.6645	0.0239	14.1470	0.0281
7	2.1710	0.0577	15.4728	0.0304	14.9997	0.0361
8	1.8841	0.1813	15.3771	0.0522	14.8989	0.0612
9	1.3768	0.2056	13.4882	0.1462	13.0137	0.1620
10	1.3646	0.3537	13.9864	0.1787	13.5821	0.1980

Source: Computation using Amos

The outcomes of the lag selection tests yield significant insights into the dynamic nature of the data and the suitable lag length to be incorporated into the model. At lag 1, all three test statistics—the SSR-based F test (9.9462, p = 0.0031), Chi-Square test (9.0474, p = 0.0026), and Likelihood Ratio test (8.9837, p = 0.0029)—are very significant. This means that there is considerable autocorrelation and that at least one lag needs to be included. At lag 2, the significance persists, with all p-values remaining below 0.01, further substantiating the importance of short-term dependencies.

The test values stay statistically significant up to lag 6 as the lag length gets longer. At lag 6, for instance, the F test (2.3052, p = 0.0459), Chi-Square (14.6645, p = 0.0239), and Likelihood Ratio (14.1470, p = 0.0281) all stay below the 5% significance level. This means that more delays show important changes. However, the results start to lose their importance after lag 7, with p-values going beyond 0.05, especially in the F test. By lag 8, most tests are only slightly significant (Chi-Square p = 0.0522; LR p = 0.0612). By lags 9 and 10, none of the tests are statistically significant, which means that adding more lags does not make the model better.

In general, the results show that the best lag structure is between 1 and 6. Beyond this range, adding more lags doesn't help explain things much and could cause overfitting. So, choosing a lag time within this range makes sure that the model specification is both strong and simple.

Strategy backtesting and evaluation

MACD line backtesting

This study indicated that using the common industry parameters (12, 26, 9) at first led to poor results. The probable cause may be the uncommon trading frequency of the MACD line set up with these parameters during small market swings, which means they missed chances to make more money when the market was moving. So, after changing the parameters and scaling them down in the right way, the best parameters were found to be (2, 5, 4).

Table 1. Backtesting Trading Details of MACD (12, 26, 9) Strategy without Stop-Loss Price Added

Buy Date	Buy Price	Sell Date	Sell Price	Return Rate	Profit	Profit-to-Asset Ratio (%)	Shares Owned	Cumulative Return	Holding Days
2024-06-12	3225.3	2024-06–27	3153.31	−2.23	−22177.89	−2.27	951463.5	−22177.89	9
2024-07-04	3241.23	2024-07–21	3163.42	−2.4	−23898.64	−2.51	956162.85	−46076.53	13
2024-07-27	3225.48	2024-08–14	3159.71	−2.04	−20343.97	−2.18	951516.6	−66420.5	12
2024-09-04	3145.94	2024-09–22	3084.76	−1.94	−18967.13	−2.07	928052.3	−85387.62	14
2024-11–01	3038.18	2024-11–29	3038.46	0.01	−813.7	−0.09	896263.1	−86201.33	20
2024-12-29	2950.84	2025-01–10	2886.98	−2.16	−19699.78	−2.2	870497.8	−105901.11	7
2025-01-26	2897.91	2025-02–02	2773.29	−4.3	−37599.4	−4.39	854883.45	−143500.51	5
2025-02-19	2886.59	2025-03–20	3058.65	5.96	49880.78	5.5	851544.05	−93619.73	22

Fig. 2. Backtesting of MACD (2, 5, 4) strategy without purchase limits.

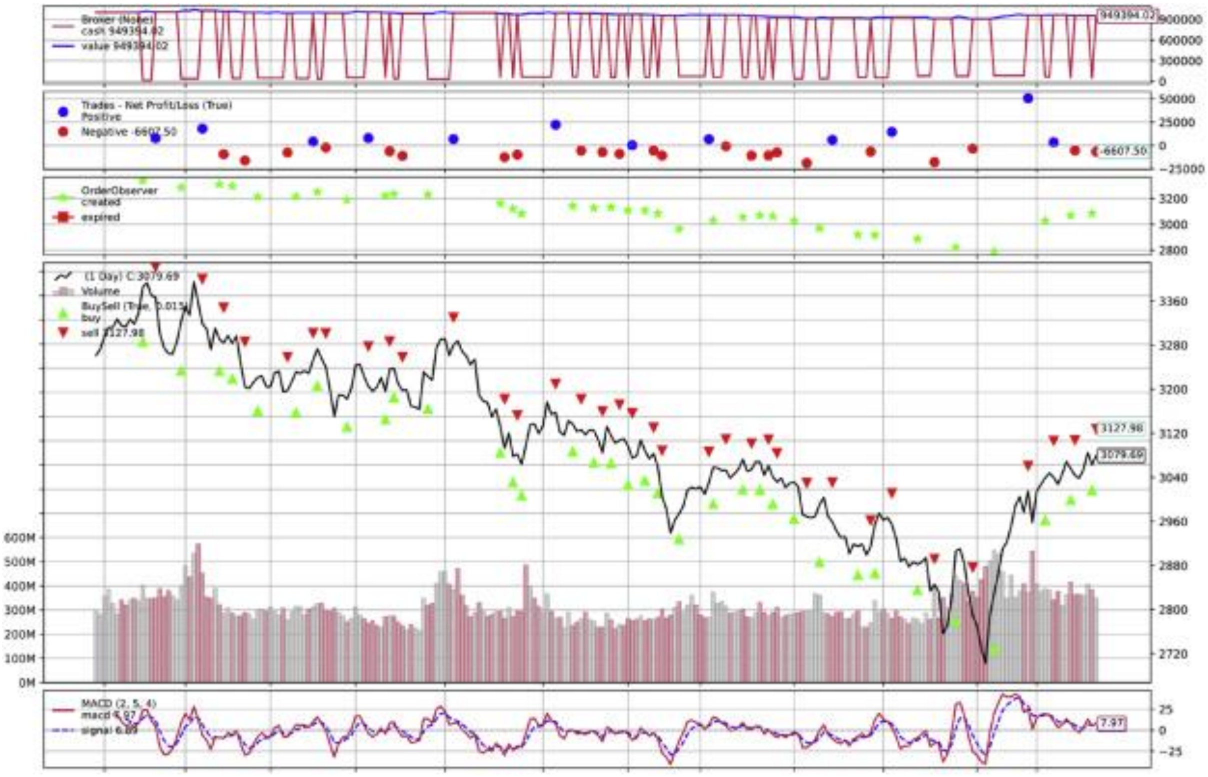


Figure 2 illustrates the results of backtesting without purchase limitations, while Figure 3 shows the results after adding purchase limits.

Table 2. Backtesting Trading Details Data for MACD (12,26,9) Strategy with Limit Prices

Buy Date	Buy Price	Sell Date	Sell Price	Return Rate	Profit	Profit-to-Asset Ratio (%)	Shares Owned	Cumulative Return	Holding Days
2024-07-06	3211.54	2024-07-21	3163.42	−1.5	−15135.77	−1.56	947404.36	−15135.77	11
2025-01-30	2866.28	2025-02-02	2773.29	−3.24	−28263.89	−3.01	845552.6	−43399.65	3

Table 3. Backtesting Trading Details Data for MACD (2,5,4) Strategy without Limit Prices

Buy Date	Buy Price	Sell Date	Sell Price	Return Rate	Profit	Profit-to-Asset Ratio (%)	Shares Owned	Cumulative Return	Holding Days
2023-04-17	3337.06	2024-04-20	3367.05	0.9	7858.19	0.78	984432.7	7858.19	3
2023-04-28	3283.12	2024-05-10	3347.7	1.97	18073.05	1.76	968520.4	25931.25	5
2023-05-16	3310.16	2024-05-17	3281.97	−0.85	−9288.39	−0.91	976497.2	16642.86	1
2024-05-19	3288.89	2024-05-24	3237.7	−1.56	−16063.72	−1.61	970222.55	579.14	3
2024-05-29	3219.76	2024-06-07	3197.47	−0.69	−7522.09	−0.76	949829.2	−6942.95	7
2024-06-09	3213.03	2024-06-15	3230.45	0.54	4188.49	0.42	947843.85	−2754.47	4
2024-06-16	3256.3	2024-06-20	3252.54	−0.12	−2069.25	−0.21	960608.5	−4823.72	2
2024-06-29	3185.42	2024-07-06	3215.86	0.96	8035.61	0.8	939698.9	3211.89	5
2024-07-12	3220.38	2024-07-13	3202.7	−0.55	−6163	−0.62	950012.1	−2951.12	1
2024-07-14	3240.97	2024-07-18	3206.79	−1.05	−11034.14	−1.12	956086.15	−13985.26	2
2024-07-26	3228.09	2024-08-03	3254.57	0.82	6855.41	0.69	952286.55	−7129.85	6
2024-08-18	3165.1	2024-08-21	3125.99	−1.24	−12465.39	−1.27	933704.5	−19595.24	1
2024-08-23	3116.27	2024-08-24	3085.91	−0.97	−9871.02	−1.02	919299.65	−29466.26	1
2024-08-25	3068.62	2024-09-06	3147.14	2.56	22246.58	2.24	905242.9	−7219.68	8
2024-09-12	3140.34	2024-09-14	3124.85	−0.49	−5493.67	−0.56	926400.3	−12713.35	2
2024-09-19	3123.99	2024-09-21	3103.18	−0.67	−7057.46	−0.72	921577.05	−19770.81	2
2024-09-25	3131.21	2024-09-27	3104.04	−0.87	−8934.85	−0.92	923706.95	−28705.66	2
2024-10-09	3100	2024-10-10	3104.37	0.14	374.01	0.04	914500	−28331.65	1
2024-10-13	3092	2024-10-17	3076.43	−0.5	−5502.99	−0.57	912140	−33834.64	2
2024-10-18	3076.58	2024-10-19	3043.2	−1.08	−10749.77	−1.13	907591.1	−44584.41	1
2024-10-25	2986.41	2024-11-03	3012.47	0.87	6802.87	0.71	880990.95	−37781.55	7
2024-11-06	3047.13	2024-11-09	3047.65	0.02	−745.58	−0.08	898903.35	−38527.13	3
2024-11-15	3077.03	2024-11-17	3043.62	−1.09	−10758.75	−1.13	907723.85	−49285.87	2
2024-11-21	3074.83	2024-11-23	3041.68	−1.08	−10681.44	−1.14	907074.85	−59967.31	2

2024-11-24	3060.33	2024-11-27	3038.19	−0.72	−7430.83	−0.8	902797.35	−67398.14	1
2024-12-01	3027.35	2024-12-06	2966.95	−2	−18702.16	−2.05	893068.25	−86100.3	3
2024-12-11	2956.29	2024-12-14	2979.7	0.79	6030.39	0.66	872105.55	−80069.91	3
2024-12-22	2919.29	2023-12-27	2900.15	−0.66	−6504.67	−0.71	861190.55	−86574.57	3
2024-12-28	2913.11	2025-01-04	2965.51	1.8	14590.9	1.57	859367.45	−71983.67	4
2025-01-12	2880.04	2025-01-18	2822.67	−1.99	−17765.3	−1.95	849611.8	−89748.97	4
2025-01-25	2823.83	2025-01-31	2815.5	−0.29	−3289.15	−0.36	833029.85	−93038.12	4
2025-02-07	2791.51	2025-02-27	2966.42	6.27	50749.16	5.3	823495.45	−42288.97	8
2025-03-04	3026.61	2025-03-06	3041.75	0.5	3571.22	0.37	892849.95	−38717.75	2
2025-03-12	3068.18	2025-03-13	3053.34	−0.48	−5280.72	−0.55	905113.1	−43998.47	1
2025-03-19	3077.98	2025-03-20	3058.65	−0.63	−6607.5	−0.7	908004.1	−50605.98	1

Fig. 3. Backtesting of MACD (2, 5, 4) strategy with purchase limits.

The red solid line (MACD line) and blue dashed line (signal line) in Fig. 2 illustrate that the improved parameter settings make the MACD line much better at capturing price changes in the Indian stock market. This improvement makes it possible to trade more often. But without buy limitations, as seen in the backtesting of the strategy in Fig. 2, the model had a hard time managing risks when the market was very volatile, which led to total losses. Fig. 3, on the other hand, shows that the approach works well when it is backtested with buy limitations. This is because it protects against risk by managing trades during small but frequent changes in Indian stock indexes. More crucially, the approach was able to do well even when the Nifty 50 Index was very volatile, making a total profit of about ₹30,028.

Trend sentiment moving average (EMA_S) backtesting

This section conducts strategy backtesting using the trend sentiment factor indicator (P = 6) introduced earlier, defined as Senti_average(6). The backtesting without purchase limits is depicted in Fig. 4 while the backtesting with purchase limits is shown in Fig. 5.

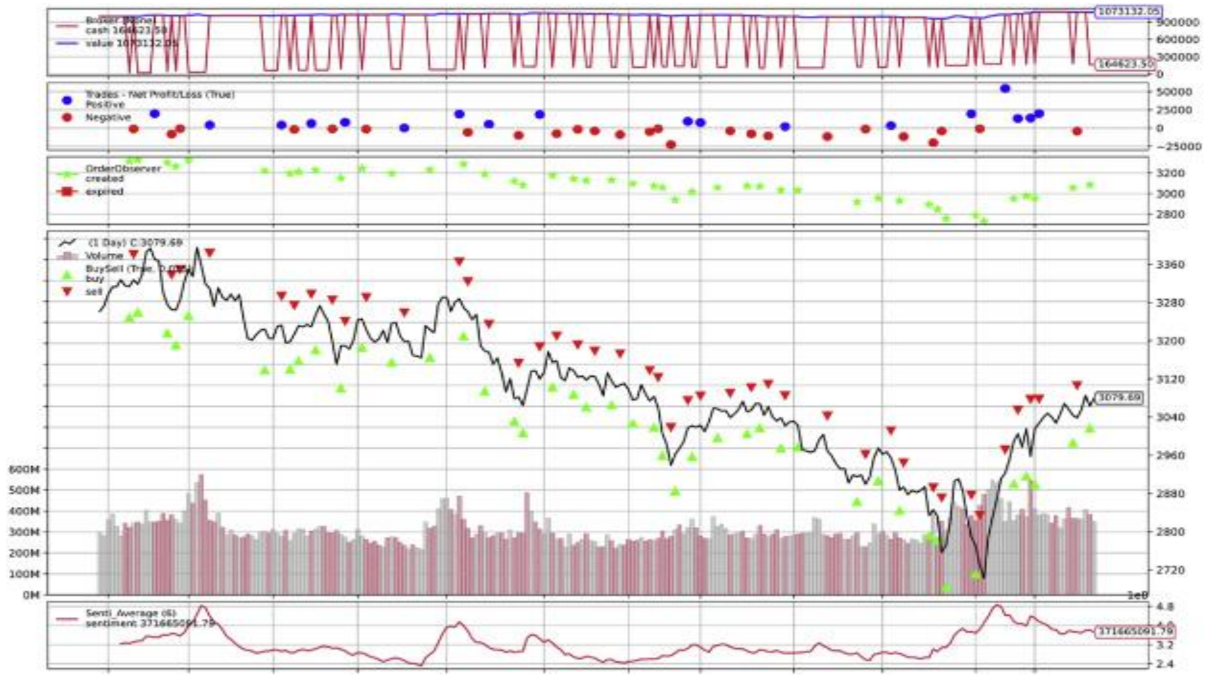


Fig. 4. Trend sentiment factor (P = 6) strategy backtesting without purchase limits.

Fig. 5. Trend sentiment factor (P = 6) strategy backtesting with purchase limits.

The red solid line (6-day sentiment factor index moving average) in Fig. 4 shows that this line closely follows the changes in the Indian stock market's closing price curve. The technique, which is based on the rise and fall of this curve, makes trades more often than the MACD (2, 5, 4) approach we talked about in the last part. It is more sensitive to short-term changes in timing, which means it can take advantage of trading opportunities even when the Nifty 50 Index is very volatile before February 2024. This method made about ₹73,081.6 in total gains, which was better than the MACD (2, 5, 4) strategy.

Comparing Figs. 4 and 5 makes it even clearer that putting limits on purchases makes trades happen less often, especially in the second half of the graph (after August 29, 2024). At the same time, it makes the risk more resistant. But once the Nifty 50 Index went up sharply after February 2025, the delayed deal execution and weaker activity caused by buy limits led to a somewhat lower total gain of about ₹54,681.41.

Comparative summary

This study encompasses a total of 245 trading days. This section presents a unified comparison of the evaluation metrics for the aforementioned strategies, as shown in Table 3.

Table 3. Summary comparison of strategy evaluation indicators.

Strategy	Cumulative Return (%)	Annualized Return (%)	Maximum Drawdown (%)	Win Rate (%)	Sharpe Ratio (%)	Kelly Ratio (%)	Commission Asset Ratio (%)
Nifty 50 Index	−6.71	−5.88	−20.41	–	−0.600	–	–
Non-restricted price MACD (12,26,9)	−9.46	−10.00	−15.54	12.50	−1.697	−23.46	0.72
Restricted price MACD (12,26,9)	−4.34	−4.63	−5.06	0.00	−2.790	–	0.18
Non-restricted price MACD (2,5,4)	−5.26	−5.40	−12.82	34.29	−0.969	−11.62	3.20
Restricted price MACD (2,5,4)	3.50	3.21	−7.69	37.50	0.058	13.54	1.45
Non-restricted price Senti_average(6)	7.31	7.81	−9.41	41.86	0.567	13.41	3.91
Restricted price Senti_average(6)	6.57	6.84	−5.82	65.17	0.432	23.56	3.64
Non-restricted Senti-MACD(2,10,9)	−8.91	−8.45	−10.11	24.32	−1.243	−16.00	3.37
Restricted price Senti-MACD(2,10,9)	6.54	7.08	−4.16	40.00	0.558	21.03	1.82
fixed $\pi = 0$ Senti-MACD(2,10,9)	−3.49	−3.51	−5.38	26.67	−0.876	−19.69	1.36
fixed $\pi = 1$ Senti-MACD(2,10,9)	0.58	0.62	−7.66	36.36	−0.499	−4.27	1.00

Source: Computation using Amos

Table 3 offers a thorough grasp of how various trading strategies perform in contrast to the benchmark Nifty 50 Index through a summary comparison of strategy evaluation indicators. The indicators taken into account—cumulative return, annualized return, maximum drawdown, win rate, Sharpe ratio, Kelly ratio, and commission asset ratio—give us useful information on how to make money, manage risk, and work more efficiently as a whole.
The Nifty 50 Index, which is the benchmark itself, has a negative cumulative return of −6.71% and an annualized return of −5.88%. Its biggest downside is −20.41%. This underperformance is due to the unstable market during the sample period, which makes it hard to compare.

When looking at the standard MACD techniques (12,26,9 and 2,5,4), the results show that they don't work well without any limits. For example, the non-restricted MACD (12,26,9) had a cumulative return of −9.46% and the worst Sharpe ratio (−1.697), which shows that it didn't do well when taking risk into account. Putting limits on purchases made a big difference in the results.

The limited MACD (12,26,9) approach cut losses to −4.34% and drawdowns to −5.06%, which shows that risk control measures made the system more resilient. The restricted MACD (2,5,4) also had a positive cumulative return of 3.50% and a Sharpe ratio close to zero. This means it did better than the index and shows how constraints can help reduce drawdowns.

When we look at tactics based on sentiment, the results are considerably better. With a cumulative return of 7.31% and an annualized return of 7.81%, the non-restricted sentiment average (Senti_average (6)) strategy beat all classic MACD methods. The biggest loss was −9.41%, but the win rate (41.86%) and positive Sharpe ratio (0.567) show that the strategy was able to take advantage of market mood. The limited version of this approach made things even more stable. It had a Kelly ratio of 23.56%, which means it had a higher win rate (65.17%) and a lower return (6.57%). This means it performed more consistently and sustainably.

The Senti-MACD (2,10,9) techniques show different results depending on the limits. The non-restricted version did worse, with a cumulative return of −8.91% and a negative Sharpe ratio, which shows that it was very risky without a corresponding reward. But after limits were put in place, the total return went up to 6.54% with a Sharpe ratio of 0.558 and a maximum drawdown of only −4.16%, suggesting that both profitability and risk resilience had improved a lot. The fixed-π versions of the Senti-MACD approach did okay. When π = 0, they lost money (−3.49%), and when π = 1, they made a modest profit (0.58%). However, both did worse than the restricted versions.

The results show three main things overall. First, unrestrained trading techniques, whether they are based on traditional methods or feelings, frequently have a hard time because they are too exposed to volatility. Second, putting limits on purchases makes things much more stable and cuts down on drawdowns. This often turns techniques that don't work into ones that do. Third, sentiment-based methods are clearly better than standard MACD methods, both in terms of returns and risk-adjusted metrics. The restricted sentiment average and restricted Senti-MACD strategies are the most balanced because they give stable returns, higher win rates, and superior drawdown management.

In conclusion, sentiment-driven models, particularly when integrated with constraints, provide a superior framework for trading in the Indian stock market, surpassing both the benchmark index

Limitations and Implications

Limitations

There are some limitations to this study that need to be recognized. First, the data analysis was limited to posts and market information pertaining to the Nifty 50 Index from the previous year, which constrains the generalizability of the results to other Indian indices, such as the Sensex or sectoral indices, and to extended timeframes. Second, the precision of sentiment classification necessitates additional enhancement, as erroneous classifications may compromise the reliability of outcomes. Third, the current framework only combines the MACD indicator with trend-based sentiment components. There is room for improvement by adding other traditional technical indicators or more advanced machine learning methods to make predictions more accurate.

Implications

The findings have numerous significant economic and policy ramifications within the Indian context:

1. **For investors and financial institutions -** The results show how important it is to include investor sentiment analysis in trading and portfolio management plans. This can help you get better risk-adjusted returns and make better decisions in markets that are always changing.
2. **For market regulators** - such as the SEBI, The results indicate that authorities ought to scrutinize the impact of online investor opinion on market stability more closely. To reduce the risks of herd behavior, speculative bubbles, or market manipulation based on sentiment, it may be necessary to keep an eye on social media and online trading platforms.
3. **For those who make decisions** – This study's insights can help shape policies that encourage the prudent and creative use of big data and sentiment analytics in India's capital markets. This involves encouraging data-sharing projects, setting standards for how accurate sentiment classification should be, and promoting financial innovation while protecting investors and keeping the market honest.

Conclusion

In the world of financial markets, it is still very important to accurately capture market trends and improve investing techniques. Indian investors have been using traditional technical indicators like the Moving Average Convergence Divergence (MACD) for a long time to help them make trading decisions. But with the quick growth of social media sites and online forums, investor sentiment has become a strong force that affects how the market works. In India's changing financial system, it has become increasingly important to understand and use this sentiment in quantitative investment methods.

This study investigates the incorporation of investor sentiment sourced from online forums into trend-based quantitative investment techniques in the Indian stock market, specifically targeting the Nifty 50 Index. Acknowledging the constraints of methods dependent exclusively on traditional technical indicators, we investigate the potential of including a trend sentiment factor to improve investment performance. The principal research inquiries of this study are: (1) Is it possible for the incorporation of a trend sentiment factor to enhance the efficacy of a MACD-based strategy? (2) How does the optimized approach that includes the sentiment aspect stack up against a pure MACD strategy when it comes to making money and handling risk?

The research utilizes short-term volatility and pronounced upward trends of the Nifty 50 over a one-year timeframe as the backtesting dataset. When comparing different methods, adding the trend sentiment factor consistently leads to better results on all performance indicators. The emotion aspect makes the MACD indicator better at picking up on short-term changes in the market. Setting restrictions on purchases makes you more resilient to risk, but it could also lower your returns a little. Overall, the sentiment-enhanced MACD is quite responsive to short-term changes, which makes it a good tool for tracking quick changes in Indian market patterns. Compared with a pure MACD strategy, the sentiment-augmented approach yields higher returns, reduces maximum drawdowns, and improves the Sharpe ratio—indicating stronger profitability and enhanced protection against short-term risks include, comparing MACD techniques that only look at closing prices to those that include look at sentiment indicators shows that a combined approach much improves overall success. However, relying only on sentiment-driven signals could lead to more short-term mistakes during negative phases, which could mean buying too soon and losing money before the markets recover. However, the technique shows strong profitability at times of quick upward movement, such sharp bull runs in the Nifty 50.

This study adds to the expanding body of work on how to incorporate investor sentiment into quantitative trading in India. It shows how using internet sentiment data could help make better predictions about market trends and improve trading techniques. Practically, the findings provide valuable insights for Indian investors and portfolio managers seeking to enhance risk-adjusted returns in increasingly sentiment-driven markets.

In the future, this methodology could be used for other Indian indexes, like the Sensex, Bank Nifty, and sectoral indices. Future research could focus on integrating big data analytics to improve sentiment accuracy, or combining sentiment factors with other traditional technical indicators for greater predictive power. Also, based on research regarding how investors feel about the market being closed for the holidays, using half-life weighting to change sentiment signals in real time could help traders make better decisions by reducing mistakes on trading days.

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