Applications and Limitations of NLP-Based Financial News Sentiment Analysis for Short-Term Stock Market Prediction

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***Abstract*—Financial news has become an important source of unstructured data for stock market analysis. Unlike structured indicators such as prices, trading volume and accounting ratios, news texts contain timely information about corporate events, macroeconomic conditions and investor expectations. With the development of Natural Language Processing (NLP), financial news sentiment can be extracted and converted into quantitative indicators for market analysis. This paper examines the applications and limitations of NLP-based financial news sentiment analysis in short-term stock market prediction. Based on existing literature, it reviews lexicon-based methods, traditional machine learning approaches, FinBERT, BERT-based models, and recent approaches based on Large Language Models (LLMs). The analysis shows that financial news sentiment can help capture investor expectations, explain short-term market reactions, and support predictions of returns, index movements, and trends. However, its value is limited by textual noise, information lag, semantic ambiguity, model misclassification, overfitting and changing market conditions. The paper argues that financial news sentiment should not be used as a standalone predictor. Instead, it is more appropriate as a supplementary signal to be combined with price, volume, financial indicators, model interpretability, and human verification.**

***Keywords*—financial news, sentiment analysis, natural language processing, short-term stock market prediction, financial technology**

I. Introduction

Stock market prediction has long been difficult because prices are affected by both measurable financial indicators and rapidly changing public information. Traditional market analysis usually relies on structured data such as historical prices, trading volume, accounting ratios and macroeconomic variables. However, financial news also contains valuable information about corporate performance, policy changes, market expectations and investor sentiment. Earlier research on media pessimism shows that news tone can be linked to investor sentiment and market activity, providing a foundation for subsequent NLP-based approaches to financial information extraction (Tetlock, 2007).

Financial news is a form of unstructured financial data. It cannot be used directly in most quantitative models because it consists of words, phrases and contextual meanings rather than numerical values. NLP provides a way to transform textual information into measurable variables. Through sentiment analysis, financial news can be classified as positive, negative or neutral, and the resulting classifications can then be used as sentiment indicators in market analysis. Research on financial textual analysis also shows that general-purpose sentiment dictionaries often fail in financial settings because financial language is domain-specific (Loughran & McDonald, 2011). Related surveys confirm that financial sentiment analysis has become an important research area in both finance and artificial intelligence (Du, Xing, Mao, & Cambria, 2024; Todd, Bowden, & Moshfeghi, 2024).

This paper explores three main aspects of the topic. First, it examines the ways in which NLP is used to extract sentiment from financial news. Second, it analyses the value of financial news sentiment analysis for short-term stock market prediction. Third, it discusses the limitations that should be considered when sentiment indicators are used in investment analysis. The paper adopts a literature-based analytical approach rather than an empirical prediction model. Its purpose is to evaluate financial news sentiment analysis as a tool within financial technology and financial analytics, while avoiding an overoptimistic view of AI-based stock prediction.

II. NLP-Based Approaches to Financial News Sentiment Analysis

A. Lexicon-Based and Traditional Machine Learning Approaches

Early financial sentiment analysis often relied on lexicon-based methods. A sentiment lexicon is a predefined list of words associated with positive or negative meanings. For example, words such as growth, profit or upgrade may be treated as positive, while words such as loss, decline or risk may be treated as negative. In finance, however, general sentiment dictionaries are often insufficient because word meaning depends heavily on domain context. Loughran and McDonald have shown that many words classified as negative in general-purpose dictionaries do not necessarily carry negative connotations in financial documents (Loughran & McDonald, 2011).

This problem is especially clear in financial news. A phrase such as high debt may be negative in one context, while debt restructuring may be interpreted differently depending on investor expectations. Malo et al. developed the Financial PhraseBank and demonstrated that financial sentiment must consider sentence-level meaning rather than isolated words (Malo, Sinha, Takala, Korhonen, & Wallenius, 2014). Traditional machine learning methods, such as support vector machines and logistic regression, improved on simple dictionaries by learning patterns from labelled texts. However, they still depend on feature engineering and labelled datasets, and may fail when market language changes or when expressions differ across sectors or over time.

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B. FinBERT, BERT and Large Language Model-Based Approaches

Transformer-based models have changed financial sentiment analysis by improving contextual interpretation. Unlike bag-of-words methods, BERT-based models can capture the meaning of words within a sentence. This matters because financial sentiment is often determined by the whole sentence rather than by isolated terms. For example, earnings decline less than expected may be interpreted positively even though the word decline appears.

FinBERT is one of the most influential models in this field. Araci introduced FinBERT as a BERT-based model adapted to financial sentiment analysis and showed that domain-specific pre-trained language models can improve performance on financial sentiment tasks (Araci, 2019). More recent studies comparing traditional models, deep learning models, and transformer-based models also show that contextual and domain-specific representations can improve sentiment classification and short-term prediction in financial news contexts (Chuang, He, & Hu, 2025). Large language models have further expanded the possibilities of financial sentiment analysis by processing longer texts and generating explanations. Nevertheless, larger models are not automatically better, because financial texts remain short, time-sensitive and ambiguous. The development from lexicons to FinBERT and LLMs should therefore be understood as an improvement in contextual interpretation, not as a complete solution to prediction.

C. Construction and Use of Sentiment Indicators in Stock Market Prediction

After sentiment is extracted from news, it must be converted into usable indicators. A researcher may calculate a score for a single article, aggregate sentiment by company, average it by industry, or build a market-level sentiment index. The aggregation method affects the meaning of the result. For short-term stock prediction, sentiment indicators are often combined with prices, volatility or trading volume. Maqbool et al. have integrated financial news sentiment scores with historical stock data and have shown that news-based sentiment can support short-term trend prediction when combined with machine learning models (Maqbool, Aggarwal, Kaur, Mittal, & Ganaie, 2023). This suggests that textual features can contain information relevant to market reactions, although their usefulness depends on timing, data quality and model design.

III. APPLICATION VALUE OF FINANCIAL NEWS SENTIMENT ANALYSIS IN SHORT-TERM STOCK MARKET PREDICTION

Financial news sentiment analysis is not only relevant to stock prediction, but also reflects a broader application of FinTech and financial analytics. By transforming unstructured news texts into quantitative sentiment indicators, NLP-based methods can support automated news monitoring, investment research dashboards and risk screening systems. Therefore, this section discusses its application value from two related aspects: its ability to capture investor expectations and market reactions, and its role in supporting short-term stock returns, index movements, and market trend forecasts.

A. Capturing Investor Expectations and Market Reactions

Financial news sentiment analysis is valuable because it helps capture investor expectations. News articles not only report facts but also frame events in ways that may shape market interpretation. A company's earnings announcement, regulatory investigation or product launch may generate different reactions, depending on information presentation and investor interpretation. When positive sentiment rises, investors may become more optimistic about future cash flows. When negative sentiment rises, investors may reassess risk and reduce demand for the stock.

This does not mean that sentiment directly causes price changes in every case. Market reactions are shaped by prior expectations. A piece of apparently positive news may have little effect if it is already expected, while moderately negative news may lead to a strong reaction if it conveys new information. Therefore, sentiment analysis is most useful when treated as a way to capture market interpretation rather than as a direct driver of price movement.

B. Supporting Short-Term Return, Index Movement and Market Trend Prediction

Existing research suggests that financial news sentiment can support short-term prediction. Chuang et al. examine Chinese financial news and compare multiple language models for sentiment and stock prediction, finding that news-based sentiment features can provide useful predictive signals, especially over shory horizons (Chuang, He, & Hu, 2025). Ibrahim et al. use NLP and explainable AI to analyze financial and economic news for the Turkish stock market, reporting that international news has significant predictive value and that explainable methods can help identify influential news sources (Ibrahim, Khan, & Kaplan, 2025). Shobayo *et al.* (2024) compare FinBERT, GPT-4 and logistic regression for financial news sentiment and stock price prediction, showing both the potential and practical limitations of advanced AI models.

These studies support the practical usefulness of NLP-based sentiment analysis. Financial news can provide timely signals that may not yet be fully reflected in prices, especially during event-driven periods. Earnings surprises, legal disputes, policy announcements and macroeconomic shocks may create short-term market reactions. NLP tools can process large volumes of news faster than human analysts, helping identify sentiment changes across many companies. However, the strongest evidence is usually related to short-term prediction rather than long-term prediction. Long-term stock performance depends more on fundamentals, valuation, industry cycles and macroeconomic conditions.

IV. LIMITATIONS AND REASONABLE USE OF FINANCIAL NEWS SENTIMENT ANALYSIS

Although NLP-based financial news sentiment analysis offers practical value for short-term stock market prediction, it also entails important limitations. These limitations mainly concern data quality, financial language interpretation and model generalization. Therefore, sentiment indicators should be used cautiously and combined with other forms of financial evidence.

A. Limitations of Financial News Sentiment Analysis

1) Textual noise, information lag and differences in news sources

Financial news sentiment analysis first faces limitations related to textual noise and information quality. Not all news articles are equally important. Some repeat already known information, while others include speculation, incomplete facts or exaggerated headlines. If a model treats all news items equally, it may overweigh low-quality information. Information lag is another problem. By the time a news article is published, some information may already be reflected in market prices, especially for liquid and widely followed stocks. News sources also differ in quality and influence. Ibrahim et al. show that different news sources can have different predictive relevance in a market context, implying that source selection affects model conclusions (Ibrahim, Khan, & Kaplan, 2025). Sentiment scores should accordingly be interpreted with attention to source reliability, timing and relevance.

2) Semantic ambiguity, financial context and model misclassification

A second limitation is semantic ambiguity. Financial language is highly context-dependent. A phrase may be positive for one firm but negative for another. For example, rising interest rates may benefit certain banks but harm growth companies with high financing needs. Even FinBERT and large language models can make errors if they do not account for the company, sector or macroeconomic background. Nath et al. question whether common methods of quantifying financial news sentiment always measure the right concept, warning that sentiment scores may depend on model assumptions and labelling choices (Nath, Sood, Khanna, Wilson, Manot, & Durbaka, 2023). This critique is important because sentiment indicators can appear objective while still being shaped by subjective annotation, dictionary selection or model design.

3) Market regime changes, overfitting and weak generalization

A third limitation is weak generalization. A model trained on one market, time period or data source may not perform well in another environment. Financial markets change across bull markets, bear markets, crises and policy cycles. A sentiment signal that works in one period may lose predictive power when market conditions change. Overfitting is also a major risk. Financial prediction models often are tuned to historical validation data but fall short in real-world settings. The broader review literature on text-based sentiment analysis in finance also notes that future research must address data quality, generalizability and the reliability of model-based financial interpretation (Du, Xing, Mao, & Cambria, 2024; Todd, Bowden, & Moshfeghi, 2024). This concern is especially acute when applying sentiment analysis to investment decisions, where false signals may lead to real financial losses.

B. Reasonable Use of Financial News Sentiment Analysis

1) Combining news sentiment with price, volume and financial indicators

Given these limitations, news sentiment should be combined with other indicators. Price and volume data reflect actual market behavior. Financial statements provide information about company fundamentals. Macroeconomic variables reflect the broader environment. Sentiment indicators can add value, but they should not replace these sources. A reasonable approach is to treat sentiment as one feature among many, combining it with returns, volatility, trading volume, earnings surprises and valuation ratios. This reduces the risk of relying too heavily on textual interpretation and allows analysts to assess whether sentiment provides incremental information beyond traditional data.

2) Improving interpretability, human verification and investment risk control

Another reasonable direction is to improve interpretability and human verification. Financial decisions require accountability. If a model gives a negative sentiment score, analysts should be able to understand why. This is especially important in regulated financial environments, where black-box decisions may create compliance and risk management problems. Human analysts should review important signals, especially when news concerns legal issues, policy changes and complex financial events. AI can process information quickly, but human judgement remains necessary for understanding strategic meaning and investment implications. Accordingly, NLP-based sentiment analysis should be treated as a screening and monitoring tool rather than as an independent trading system.

V. CONCLUSION

This paper has analyzed the applications and limitations of NLP-based financial news sentiment analysis for short-term stock market prediction. The literature shows that financial news is an important source of unstructured data and that NLP methods can transform news texts into sentiment indicators. Lexicon-based methods provide an early foundation, but they are limited by financial language ambiguity. FinBERT, BERT-based models and large language models improve contextual understanding and can support predictions of short-term returns, index movements and trends. The paper has answered the three research questions raised in the introduction. First, NLP extracts sentiment from financial news through lexicons, machine learning classifiers, domain-adapted language models and more recent LLM-based approaches. Second, sentiment indicators are practically relevant because they capture investor expectations, reflect market reactions and provide supplementary features for short-term prediction. Third, these indicators have important limitations. Financial news contains noise, time lags, and source heterogeneity. Sentiment labels are not fully objective, and models may misinterpret financial context. Predictive performance may also decline when market conditions change or models overfit historical data.

For these reasons, financial news sentiment should not be used as a standalone predictor. A more reasonable approach is to combine sentiment indicators with price, volume, financial statements and macroeconomic variables. Interpretability, human verification and investment risk control also merit attention. Future research may focus on more robust cross-market testing, improved domain adaptation, explainable AI and responsible financial decision-making systems. Overall, NLP-based financial news sentiment analysis offer clear benefits, but its value is greatest when used as a supplementary tool within a broader financial analysis framework.

Conflict of Interest

The authors declare no conflict of interest.

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