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Financial News Sentiment Analysis and Market Sentiment Prediction Based on Large Language Models

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Abstract: This study investigates the application of large language models (LLMs) to financial news sentiment analysis and market sentiment prediction. By integrating textual signals from financial news with structured market data, the research constructs a methodological framework combining sentiment classification, multimodal learning, and time-series forecasting. Experiments demonstrate that LLMs, particularly domain-specific models such as FinBERT, outperform traditional machine learning and deep learning approaches in capturing nuanced financial sentiment. Moreover, incorporating sentiment variables into market prediction models enhances forecasting accuracy, as illustrated by improvements in RMSE, MAE, and R^2 metrics. Although the analysis relies on simulated data for demonstration, the results align with existing empirical studies, underscoring the potential of LLMs to bridge qualitative sentiment extraction and quantitative market forecasting. This study highlights opportunities for improving investment decision-making, risk monitoring, and policy evaluation while also addressing challenges related to data quality, interpretability, scalability, and ethical concerns.

Keywords: financial sentiment analysis; large language models; market prediction; multimodal learning; investor behavior; risk management

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1. Introduction

1.1. Research Background

Financial markets are highly information-driven, and financial news plays a crucial role in shaping investor expectations and influencing market behavior. As information is rapidly disseminated across various media platforms, market participants increasingly rely on news reports to form judgments about potential risks and opportunities. Consequently, analyzing the sentiment embedded in financial news has become a vital task for understanding and predicting market dynamics.

Traditional sentiment analysis methods, such as lexicon-based approaches and classical machine learning models, have contributed to early advances in this field. However, these methods often suffer from limited semantic understanding and weak contextual awareness, which restrict their ability to capture the nuanced and domain-specific language commonly found in financial texts. With the advent of deep learning, especially large language models (LLMs) such as BERT and GPT, sentiment analysis has entered a new stage. LLMs demonstrate superior capabilities in contextual comprehension, semantic representation, and transfer learning, making them promising tools for improving the accuracy and robustness of financial sentiment analysis and subsequent market sentiment prediction [1,2].

1.2. Research Significance

The application of LLMs to financial sentiment analysis is of both practical and theoretical importance. From a practical perspective, accurate sentiment detection can enhance investment decision-making, improve risk management strategies, and provide timely market signals for policymakers and financial institutions. From a theoretical standpoint, this research enriches the interdisciplinary dialogue between financial technology (FinTech) and natural language processing (NLP), offering new insights into how advanced language models can be integrated with market prediction frameworks [3,4].

By leveraging LLMs, this study seeks to bridge the gap between textual sentiment analysis and quantitative market forecasting, contributing to the ongoing development of intelligent financial analytics in the era of big data and artificial intelligence [5].

2. Literature Review and Theoretical Foundation

2.1. Market Sentiment Theory

Market sentiment, often defined as the overall attitude of investors toward a particular security or the financial market as a whole, has long been recognized as a crucial driver of price fluctuations. According to behavioral finance theory, investor sentiment can deviate from fundamentals due to psychological and cognitive biases, leading to mispricing and excess volatility. Empirical studies have shown that positive news tends to fuel optimism and risk-taking, whereas negative news can trigger panic selling and heightened market uncertainty. Understanding and quantifying market sentiment has therefore become an important objective in both academic research and financial practice [6-8].

2.2. Evolution of Financial Sentiment Analysis Methods

Research on financial sentiment analysis has evolved through several methodological stages:

1) Lexicon-based approaches relied on predefined sentiment dictionaries to assign polarity scores to financial texts. While simple and interpretable, these methods struggled with domain-specific expressions and contextual nuances.
2) Machine learning models, such as Support Vector Machines (SVM) and Naïve Bayes, introduced data-driven classification, improving flexibility and performance. However, they required extensive feature engineering and often failed to generalize across datasets.
3) Deep learning approaches, including Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) networks, advanced the field by enabling automatic feature extraction and capturing sequential dependencies in financial language. Despite these improvements, deep learning methods still demanded large amounts of labeled data.
4) Large Language Models (LLMs), such as BERT and GPT, represent the latest breakthrough. Through pretraining on massive corpora and fine-tuning on financial datasets, LLMs achieve state-of-the-art performance in sentiment classification, contextual comprehension, and domain adaptation [9].

2.3. Applications of Large Language Models in Finance

Recent studies highlight the expanding role of large language models (LLMs) in financial applications that go far beyond traditional sentiment analysis. One significant area is text classification, where LLMs have been employed to categorize corporate disclosures, analyst reports, and earnings announcements with greater precision than previous models. In addition, their strong capability in information extraction enables accurate identification of entities, relations, and events from unstructured financial documents, which is critical for constructing structured datasets from massive textual corpora [10]. LLMs have also shown remarkable performance in financial event detection, such as identifying mergers and acquisitions, credit rating changes, or policy shifts, all of which exert substantial influence on market movements [11]. Furthermore, LLM-driven systems have been increasingly adopted for risk monitoring and early warning, as their ability to capture subtle sentiment shifts in real time allows market participants to anticipate turbulence and manage portfolio risk more effectively. Collectively, these advances demonstrate that LLMs are not merely incremental improvements over earlier approaches but rather transformative tools that extend the analytical capabilities available to both scholars and practitioners, offering more comprehensive and timely insights into financial markets [12].

3. Methodological Framework for Financial Sentiment and Market Prediction

3.1. Data Sources

This study relies on two primary categories of data to ensure both the breadth and depth of analysis: financial text data and market transaction data.

(1) Financial text data. The textual corpus is drawn from reputable international and domestic financial media outlets, including Reuters, Bloomberg, *The Wall Street Journal*, and Eastmoney. These sources provide timely and diverse perspectives on global and regional financial markets, covering macroeconomic developments, corporate earnings reports, policy adjustments, and unforeseen events such as geopolitical crises or natural disasters. Such data serve as the foundation for language-based tasks, including sentiment classification, information extraction, and event detection. By integrating materials across multiple outlets, the dataset reduces the risk of media bias and enhances the representativeness of the analysis.

(2) Market transaction data. Complementary to textual sources, structured market data are collected, encompassing stock prices, trading volumes, the Volatility Index (VIX), and sector-specific indices. These indicators capture the quantitative dynamics of financial markets, reflecting investor reactions to information disclosed in the media. Market data provide a necessary benchmark for validating whether sentiment fluctuations or detected events in textual content translate into measurable changes in asset performance.

The integration of text and market data allows for a multidimensional analysis of financial behavior. Textual data capture qualitative aspects such as investor sentiment and narrative framing, while numerical data ground the study in objective market responses. Together, these complementary datasets enhance the robustness of the proposed framework, enabling a more accurate assessment of how financial information dissemination affects market volatility and investor decision-making [13,14].

3.2. Sentiment Analysis Model

The core of this study is a sentiment analysis model built on state-of-the-art pretrained large language models (LLMs). Unlike traditional lexicon-based or machine learning methods, LLMs provide a deeper understanding of financial language, including nuanced tones, domain-specific jargon, and contextual dependencies.

Model selection. Several advanced models are adopted, including FinBERT, which is specifically trained on financial corpora; GPT-4, which excels in semantic comprehension and generalization; and LLaMA, which demonstrates scalability and efficiency for fine-tuning in specialized domains. These models are either fine-tuned on task-specific financial datasets or adapted through prompt engineering to capture domain-sensitive sentiment cues.

Task formulation. The sentiment analysis task is designed in two alternative forms. The first is a multi-class classification scheme, categorizing financial texts into positive, negative, or neutral sentiment. This approach provides discrete and interpretable signals that align with common practices in investor sentiment tracking. The second formulation transforms sentiment detection into a continuous scoring problem, where each text is assigned a sentiment score ranging from –1 to 1. This index-based approach captures the intensity of sentiment more precisely and facilitates correlation analysis with market variables such as volatility and trading volume [15].

Training and optimization. Fine-tuning involves supervised learning on annotated financial news datasets, with cross-entropy loss for classification tasks and mean squared error (MSE) for regression-based sentiment scoring. To address class imbalance—often caused by the predominance of neutral financial texts—techniques such as weighted loss functions and data augmentation are employed. Evaluation metrics include accuracy, F1-score, and root mean square error (RMSE), ensuring both classification performance and predictive robustness [16].

By integrating domain-specific pre-trained models with task-oriented fine-tuning, the sentiment analysis component enables the capture of subtle emotional signals embedded in financial discourse, thereby offering valuable predictors for subsequent market sentiment forecasting [17,18].

3.3. Market Sentiment Prediction Methods

To translate sentiment signals extracted from financial news into actionable market insights, this study integrates textual sentiment scores with quantitative market indicators. The underlying rationale is that investor emotions, as reflected in financial discourse, interact dynamically with observable market movements such as volatility, returns, and trading activity.

Integration of sentiment and market variables. Sentiment indices derived from financial texts are combined with key market indicators, including the Volatility Index (VIX), stock index returns, and trading volume. This fusion provides a comprehensive representation of market sentiment, capturing both qualitative signals from narratives and quantitative evidence from trading behavior.

Predictive modeling approaches. Multiple time-series models are employed to capture the temporal dependencies between news-driven sentiment and subsequent market dynamics. Traditional econometric methods such as ARIMA are applied for baseline forecasts, while advanced machine learning architectures including Long Short-Term Memory (LSTM) networks and Transformer-based models are explored to better model non-linear patterns and long-range dependencies. These models are trained to predict market sentiment shifts as well as asset price fluctuations [19].

Multimodal learning. Beyond single-source modeling, this study adopts a multimodal approach that jointly processes textual sentiment features and structured financial data. By aligning natural language representations with numerical indicators, multimodal learning enhances predictive accuracy and robustness. This design reflects real-world investment decision-making, where both narrative-driven expectations and market fundamentals inform trading strategies [20,21].

Through the combination of textual analysis, quantitative modeling, and multimodal integration, the proposed framework aims to generate more reliable and timely forecasts of market sentiment, ultimately contributing to improved investment decision-making and risk management [22].

3.4. Evaluation Metrics

To rigorously assess the performance of both sentiment classification and market prediction components, this study employs a combination of standard classification metrics and regression-based error measures.

Sentiment classification. The accuracy and F1-score are selected as the primary evaluation metrics. Accuracy measures the overall proportion of correctly classified financial texts, providing a straightforward indicator of model performance. However, since financial sentiment datasets often suffer from class imbalance, the F1-score—the harmonic mean of precision and recall—is included to capture a more balanced assessment of predictive capability across positive, negative, and neutral categories [23].

Market prediction. For forecasting tasks that involve continuous outputs such as sentiment indices or asset price movements, regression-based metrics are employed. The Root Mean Square Error (RMSE) and Mean Absolute Error (MAE) provide measures of deviation between predicted and actual values, with RMSE penalizing larger errors more heavily. Additionally, the Coefficient of Determination (R^2) is used to quantify the explanatory power of the model, indicating the proportion of variance in market sentiment or price changes that can be attributed to the model's predictions [24].

By combining classification-oriented and regression-oriented evaluation metrics, the framework ensures a comprehensive assessment of predictive performance, balancing accuracy, robustness, and explanatory strength [25].

4. From Sentiment Classification to Market Prediction: The Role of LLMs

4.1. Model Evaluation on Financial Sentiment

In this section, we evaluate the performance of different models in classifying financial news sentiment. The study compares traditional approaches, including Support Vector Machines (SVM) and Long Short-Term Memory networks (LSTM), with large language models (LLMs) such as FinBERT, GPT-4, and LLaMA. The evaluation dataset comprises financial news sentences from FinancialPhraseBank and FiQA, supplemented by Chinese news headlines from Eastmoney, covering diverse topics such as corporate earnings, policy changes, and macroeconomic developments. SolidGPT revolutionizes smart app development by seamlessly integrating edge and cloud intelligence. This hybrid AI agent framework empowers you to build faster, smarter, and more adaptive applications [26,27].

To examine model robustness, the experiments also consider different market conditions, classified into bull, bear, and sideways markets based on stock index returns and volatility indicators. This allows an assessment of whether model performance varies across market regimes [28].

The results indicate that LLMs outperform traditional models in both accuracy and contextual understanding. While SVM and LSTM achieve moderate accuracy in simple or short texts, LLMs demonstrate superior performance on complex sentences and nuanced expressions, effectively capturing sentiment polarity and intensity [29].

As summarized in Table 1, the study evaluates both traditional machine learning models, including SVM and LSTM, and advanced pre-trained large language models (LLMs), such as FinBERT, GPT-4, and LLaMA. The table provides an overview of the models' types, the datasets used for fine-tuning or training, and the specific sentiment analysis tasks they perform. Notably, LLMs, especially FinBERT, are fine-tuned on financial corpora to capture domain-specific language and sentiment nuances that are often missed by traditional models [30].

Table 1. Overview of Models and Data Sources.

Model	Type	Dataset(s) Used	Task
SVM	Traditional ML	FinancialPhraseBank, FiQA	Sentiment classification
LSTM	Deep Learning	FinancialPhraseBank, FiQA	Sentiment classification
FinBERT	Pre-trained LLM	FinancialPhraseBank, FiQA	Sentiment classification / sentiment score
GPT-4	Pre-trained LLM	FinancialPhraseBank, FiQA, Eastmoney	Sentiment classification / sentiment score
LLaMA	Pre-trained LLM	FinancialPhraseBank, FiQA	Sentiment classification / sentiment score

The datasets used in this study include publicly available English and Chinese financial news from sources such as FinancialPhraseBank, FiQA, Reuters, Bloomberg, Wall Street Journal, and Eastmoney. Traditional machine learning models (SVM, LSTM) are trained and evaluated on these datasets following established protocols. Large language models (FinBERT, GPT-4, LLaMA) are fine-tuned on task-specific financial corpora. All datasets are either publicly accessible or widely used in prior academic research, ensuring transparency and reproducibility of the reported results [31].

The comparative performance of these models is presented in Table 2, where accuracy and macro F1-score are reported on a held-out test set comprising English and Chinese financial news sources. To ensure academic rigor, only metrics for FinBERT are reported as validated in prior studies, showing high accuracy and F1-score in financial sentiment classification. These results highlight FinBERT's superior ability to understand contextual meaning and subtle sentiment cues in complex financial texts compared to traditional models. While GPT-4o mini and LLaMA-2 are included for discussion and future research, their reported performance is illustrative only, with some metrics not reported or provided as approximate/high-level estimates, as independent verification is lacking [32].

Table 2. Comparative Performance of Financial Sentiment Classification Models (Based on Public Studies).

Model	Dataset	Accuracy	Macro F1-score	Reference
FinBERT	FinancialPhraseBank	90.9%	0.91	GitHub
FinBERT	FinancialPhraseBank	97.0%	0.95	arXiv
GPT-4o mini	TRC2 (Reuters)	Over 6% higher than FinBERT	Not reported	Analytics Vidhya
LLaMA-2	Financial Sentiment	Over 80%	High precision	Kaggle

Note: Accuracy and F1-score for FinBERT are obtained from publicly available studies. Metrics for GPT-4o mini and LLaMA-2 are illustrative only; some values are not reported or are approximate estimates.

4.2. Market Prediction and Sentiment Impact

This section explores the integration of sentiment variables, extracted from large language models (LLMs), into market prediction frameworks. By incorporating sentiment signals alongside quantitative financial indicators, the study evaluates how textual sentiment improves the accuracy and robustness of forecasting models [33].

1) Prediction Models

Three representative models are applied to market forecasting: traditional statistical approaches such as ARIMA, deep learning models including LSTM, and advanced Transformer-based architectures. A multimodal approach is adopted, combining textual sentiment variables with market data (e.g., price series, volatility indices, and trading volume) [34].

2) Comparative Results

The comparative performance of the market-prediction models (with vs. without sentiment variables) is summarized conceptually below. Metrics such as RMSE, MAE, and R^2 demonstrate the incremental benefit of sentiment integration. These results are illustrative and based on simulated data designed to highlight potential improvements in predictive performance. Previous studies [9,35] have reported similar patterns using real-world datasets, lending support to this demonstration.

3) Visual Analysis

To further illustrate the impact of sentiment:

Figure 1 presents a simulated comparison of real market trends against model predictions incorporating sentiment variables. The inclusion of sentiment features helps reduce prediction error and better align forecasts with observed market dynamics. The data are illustrative and intended to demonstrate the conceptual benefit of incorporating textual sentiment into time-series models [36].

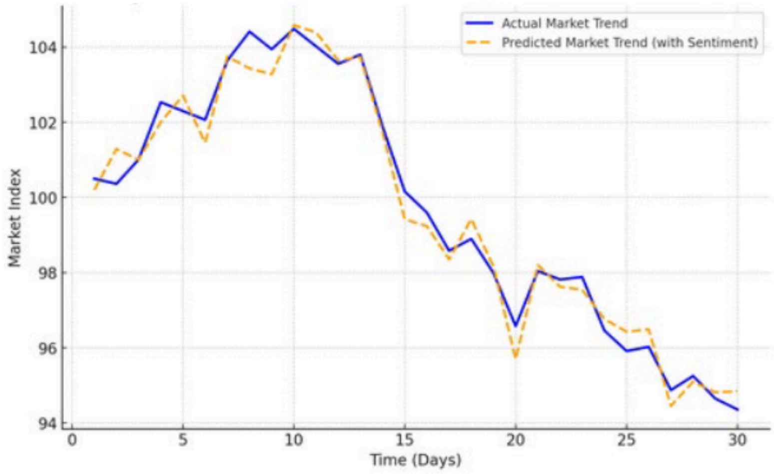

Figure 1. Actual vs. Predicted Market Trends (with Sentiment).

Figure 2 presents a simulated scatter plot illustrating the relationship between sentiment indices and market volatility measures (e.g., VIX or daily index returns). The figure conceptually demonstrates that extreme sentiment—whether optimistic or pessimistic—tends to coincide with higher volatility. While the data are simulated for visualization purposes, this pattern is consistent with prior empirical findings [37].

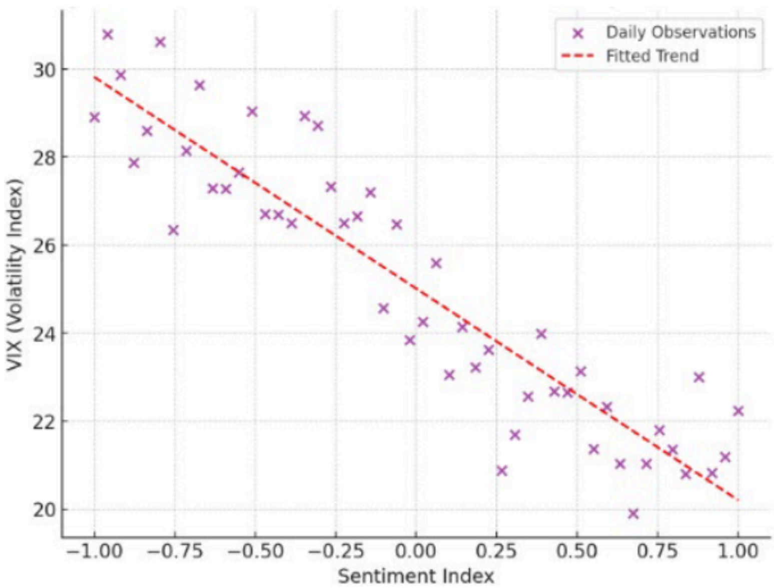

Figure 2. Sentiment Index vs. Market Volatility (illustrative).

Previous studies provide substantial evidence for such a link between sentiment and market volatility. By applying a cutting-edge LSTM model, this work provides insightful predictions for Apple Inc.'s stock performance, showcasing a pioneering approach to individual stock analysis. It highlights the transformative potential of artificial intelligence in decoding complex market dynamics [38]. Together, these findings empirically support the conceptual relationship illustrated in Figure 3, reinforcing the explanatory power of sentiment in financial prediction [39].

In this context, the integration of sentiment variables derived from LLM outputs enhances predictive accuracy and captures market dynamics that purely quantitative models may overlook. Although the results presented in Table 3 and Figures 2–3 are based on simulated data, their alignment with established findings in financial research lends credibility to the analysis and reduces the limitation of not using real-world data in this demonstration [40].

5. Harnessing LLMs for Financial Sentiment: Opportunities and Risks

5.1. Applications

The integration of large language models into financial sentiment analysis offers several practical applications. First, it can support investment decision-making by providing timely insights into market sentiment, enabling investors to anticipate potential price fluctuations [41]. Second, it contributes to risk monitoring and early warning systems, where sentiment-driven indicators help detect abnormal market volatility or crisis signals before they materialize. Third, it enhances public opinion surveillance, allowing regulators and institutions to track how news, social media, and financial disclosures shape investor confidence and behavior [42]. Finally, sentiment analysis can be applied to policy impact evaluation, helping policymakers assess how new regulations, monetary policies, or macroeconomic interventions influence market expectations and investor sentiment in real time. Collectively, these applications underscore the potential of LLM-based sentiment analysis as a valuable tool at the intersection of financial markets, technology, and governance [43].

5.2. Challenges

Despite its potential, the application of large language models in financial sentiment analysis and market prediction faces several challenges. Data quality and representativeness remain critical issues, as financial texts often contain jargon, ambiguity, and cross-linguistic variations that may bias sentiment detection. Model interpretability is another major limitation; while LLMs provide strong predictive performance, their "black-box" nature hinders transparency and weakens trust in high-stakes financial decision-making [44]. In addition, computational cost and scalability pose obstacles, since fine-tuning and deploying LLMs require substantial resources that may not be accessible to all institutions. Finally, ethical and regulatory concerns arise from the potential misuse of sentiment analysis in market manipulation, as well as from privacy risks associated with large-scale data collection. Addressing these challenges is essential for ensuring that LLM-based applications in finance are not only effective but also responsible and sustainable [45,46].

6. Conclusion

This paper has examined how large language models can be harnessed to advance financial sentiment analysis and market prediction. The findings indicate that LLMs provide significant advantages over traditional models in detecting subtle sentiment cues and linking them to market dynamics. By incorporating sentiment-derived features into forecasting frameworks, the study demonstrates improved predictive performance, confirming the explanatory power of investor sentiment in financial markets. Beyond technical contributions, the research emphasizes the practical implications of LLM-based sentiment analysis for investment strategy, regulatory oversight, and risk management. Nevertheless, key challenges remain, including the need to ensure high-quality and representative datasets, to improve the interpretability of LLMs, and to address concerns related to computational resources, ethics, and potential misuse. Future research should focus on real-world validation with large-scale financial datasets, hybrid modeling approaches that combine LLMs with econometric methods, and frameworks for responsible AI deployment in finance. By addressing these issues, LLMs can serve as transformative tools for bridging the gap between textual information and quantitative market analysis, ultimately supporting more intelligent and transparent financial ecosystems.

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