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# Financial Market Sentiment Analysis Using Artificial Intelligence Techniques

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## Abstract

*Financial market sentiment analysis has emerged as a crucial tool for understanding investor behavior and predicting market movements. The combination of AI and NLP has greatly improved the degree and quality of sentiment-based predictions of the financial institutions. This paper presents a comprehensive survey of sentiment analysis and turns from lexicon-based approaches to deep learning models like LSTM, BERT, and FinBERT. The proposed steps are text preprocessing, feature extraction and selection, modelling and classification, and performance measurement using precision, recall, F1-score or ROC-AUC. Compared with the other methods, one sees that FinBERT has better performance of the classification of sentiments; this proves to improve the results of sentiment based trading strategies. Indeed, the study provides substantial support for the role which sentiment analysis offers through artificial intelligence in investment, credit risk, and other applications of trading algorithms. Future advancements should focus on enhancing model interpretability, scalability, and real-time sentiment tracking for improved financial forecasting.*

***Keywords:*** *Financial Market, Sentiment Analysis, Machine Learning, Deep Learning, Natural Language Processing*

## 1. Introduction

Financial markets are highly sensitive to public sentiment, with investor emotions playing a crucial role in shaping stock movements, commodity prices, and economic trends (Ooi et al. 2025). Traditional financial analysis often relies on different numbers the organization requires for its functioning, including the reports of earnings, stock rates, and basic macroeconomic factors. However, given that news articles, financial reports as well as social media activity have increased at a fast pace, analyzing the various qualitative factors namely; public opinion are also key in market forecasts. This Bentley University's article by Gayle McDowell and illustrated by Ben Jones shows that financial analysts can use sentiment analysis, based on AI and NLP, to establish and interpret the relative emotion values for textual data, and, thus, gain a deeper understanding of market behaviors (Duin et al. 2023).

By casting the sentiments as positive, neutral or negative, AI operated models can determine the investors' moods within the market, evaluate the effects of a news event on the value of the shares in the market as well as anticipate future shifts within the market. This has resulted in the creation of the sentiment analysis based trading systems, the risk evaluation models and the portfolio management techniques (Subeh et al. 2024). The subsequent subsection aims to identify the functions of the sentiment-based financial market analysis in detail with the emphasis on the daily practice, the comparison to other sorts of models, and the influence of AI sentiment analysis on investment choices (Sharma et al. 2024).

## 2. Literature Survey

The literature survey explores key contributions in financial market sentiment analysis using AI techniques. The following table summarizes prominent studies:

| **Author(s)** | **Year** | **Methodology/Technique** | **Key Findings** |
|---|---|---|---|
| Bollen et al. | 2011 | Sentiment Analysis on Twitter Data | Demonstrated correlation between public sentiment and stock market trends. |
| Loughran & McDonald | 2011 | Financial Sentiment Dictionary | Introduced a lexicon tailored for financial text, improving sentiment accuracy. |
| Devlin et al. | 2018 | BERT for NLP | Enabled context-aware sentiment classification with state-of-the-art accuracy. |
| Liu et al. | 2021 | Sentiment-Aware LSTMs | Outperformed traditional models in market prediction tasks. |
| Nassirtoussi et al. | 2014 | Text Mining and ML | Systematic review of text-based market prediction techniques. |
| Yang & Xiao | 2021 | FinBERT | Adapted BERT for financial text, enhancing predictive performance. |
| Liu et al. | 2020 | Transformer Models | Showed improved accuracy using attention mechanisms in financial NLP tasks. |
| Muneer & Fatiha | 2021 | Explainable AI in Sentiment Analysis | Focused on interpretability of sentiment-based predictions for trading. |
| Gupta et al. | 2019 | Real-Time Sentiment Analytics | Developed a system for real-time stock movement prediction using live tweets. |
| He et al. | 2021 | Sentiment-Specific Embedding Models | Embedded financial text with domain-specific sentiment features. |

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|---|---|---|---|
| Williams et al. | 2020 | Transfer Learning | Utilized pre-trained models for financial data sentiment tasks. |
| Xie & Zhang | 2022 | Market Sentiment Forecasting | Predicted stock market indices using sentiment flows over time. |
| Lin et al. | 2019 | Dynamic Sentiment Scoring | Proposed an adaptive scoring system for financial sentiment analysis. |
| Qi et al. | 2021 | NLP Pipelines for Finance | Implemented custom pipelines for processing financial datasets. |
| Huang et al. | 2022 | Deep Reinforcement Learning | Integrated sentiment data into RL trading strategies. |
| Feng et al. | 2020 | Topic-Sentiment Analysis | Explored thematic sentiment in financial news articles. |
| Hong et al. | 2018 | Sentiment Trends in Volatile Markets | Investigated sentiment patterns during economic crises. |
| Shaikh et al. | 2021 | CNN-Based Sentiment Models | Demonstrated CNN's efficacy in analyzing financial opinions. |
| Xu et al. | 2022 | Financial BERT Variants | Customized BERT for financial sentiment tasks with enhanced outcomes. |

The literature on financial market sentiment analysis using AI techniques has evolved significantly, transitioning from lexicon-based approaches to advanced deep learning models. In early works, Bollen et al. (2011) conducted an analysis of the relationship of Twitter users' positive and negative attitudes towards the stock prices; Loughran & McDonald (2011) introduced a dictionary of financial sentiment, which helped to bring financial sentiment analysis of text into a new level. As a result of the involvement of machine learning (ML) and natural language processing (NLP) in text mining and statistical models (Nassirtoussi et al., 2014), researchers started using these models in market prediction. The advances in deep learning have deepened the improvement of sentiment classification where LSTMs (Liu et al., 2021) and transformers (Devlin et al., 2018; Liu et al., 2020) have been proven to consider the linguistic patterns of contextual meanings effectively.

Advanced models that have been developed include FinBERT (Yang & Xiao, 2021) involving domain-specific models as well as sentiment-specific embedding models which answered to the improved financial sentiment analysis by He et al. 2021. There is also research about ensemble learning (Yoon et al., 2020) and transfer learning (Williams et al., 2020) for enhancing the predictive solutions. Furthermore, the studies on explainable AI and AI interpretability (Muneer and Fatiha, 2021) have concentrated on the interpretability of the constructed sentiment-based trading strategies. Current trends apply deep reinforcement learning by Huang et al., 2022 and forecasting market sentiment by Xie & Zhang, 2022 as a sign of AI's effectiveness in real time market estimation. The literature highlights an increasing reliance on hybrid techniques and pre-trained models to achieve higher accuracy and adaptability in financial sentiment analysis, paving the way for more sophisticated AI-driven market forecasting methods.

## 3. Methodology

This study formulates AI-based sentiment analysis for financial markets as a natural language processing (NLP) classification problem, leveraging machine learning and deep learning techniques. The methodology follows a structured pipeline, incorporating data collection, preprocessing, sentiment modeling, and performance evaluation.

The dataset $D$ consists of financial text data collected from sources such as Bloomberg, Reuters, Twitter, financial forums, and earnings reports. Each text sample $x_i$ is associated with a sentiment label $y_i$, where $D = \{(x_i, y_i)\}_{i=1}^{N}$, with $N$ representing the total number of text samples. The sentiment labels $y_i$ belong to a predefined set: $y_i \in \{\text{Positive,Neutral,Negative}\}$.

To prepare the textual data for model training, tokenization is applied to split a financial document $x_i$ into words $\{w_1, w_2, \ldots, w_T\}$, where $T$ is the number of words in the document. Stopwords are removed by eliminating words that carry little semantic meaning, such as "the" and "is," refining the text as $x_i' = \{w_j \mid w_j \notin S\}$, where $S$ is the predefined stopword set. Lemmatization is then performed, reducing each word $w_j$ to its root form using the transformation function $w_j' = \phi(w_j)$, ensuring uniform representation. The processed text is converted into a vector representation using Word2Vec, TF-IDF, or pre-trained embeddings (BERT, FinBERT), where the embedding function maps text into a high-dimensional space as $v_i = f(x_i)$.

There is the lexicon-based approach, the machine learning approach and the deep learning approach for the classification of sentiments (Aloqaily et al.). Specifically, lexicon-based sentiment analysis uses instruments such as the Loughran-McDonald Financial Sentiment Dictionary to derive scores based on predefined dictionaries. given by $S(x_i) = \sum_{w \in x_i} \text{score}(w)$, where $\text{score}(w)$ represents the sentiment polarity assigned to word $w$. Supervised machine learning models, such as Support Vector Machines (SVM) and Random Forest, are trained on feature vectors extracted from financial text. Given an input vector $v_i$, the sentiment prediction function is modeled as $\hat{y}_i = g(v_i; \theta)$, where $g$ represents the classification function parameterized by $\theta$. In the case of SVM, the decision function is defined as $f(v_i) = \text{sign}(w^T v_i + b)$, where $w$ is the weight vector, and $b$ is the bias term. Random Forest classification aggregates predictions from multiple decision trees, represented as $\hat{y}_i = \frac{1}{M} \sum_{m=1}^{M} h_m(v_i)$, where $h_m$ denotes individual trees in the ensemble.

Deep learning models such as LSTM and FinBERT improve sentiment classification accuracy by capturing contextual and sequential dependencies in financial text. The LSTM hidden state $h_t$ at time step $t$ is updated as $h_t = f(W_h h_{t-1} + W_x x_t + b)$, where $W_h$ and $W_x$ are weight matrices, and $b$ is the bias term. The final sentiment classification is performed using a softmax function, expressed as $P(y \mid x) = \text{softmax}(W_s h_T + b_s)$. Transformer-based models such as BERT and FinBERT leverage self-attention mechanisms to enhance sentiment classification. The text representation is obtained as $H = \text{Transformer}(X)$, where $X$ is the input tokenized text, and $H$ represents contextual embeddings. The classification layer applies a dense transformation as $\hat{y} = \text{softmax}(W_H H + b_H)$.

Model performance is evaluated using standard classification metrics. Accuracy is computed as $\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN}$, while precision is given by $\text{Precision} = \frac{TP}{TP+FP}$. Recall, which measures the ability to correctly identify positive instances, is represented as $\text{Recall} = \frac{TP}{TP+FN}$, and the F1-score (AR et al.) is calculated as $\text{F1-Score} = \frac{2 \times \text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$. The area under the receiver operating characteristic curve (ROC-AUC) is computed as $\text{AUC} = \int_0^1 \text{TPR}\ d(\text{FPR})$, where TPR (True Positive Rate) and FPR (False Positive Rate) are evaluated at different classification thresholds (Jishamol et al.).

In practice the use of these models is done through having efficient mathematical libraries such as Scikit-learn for machine learning categories, TensorFlow and PyTorch for deep learning kits, and the natural language processing kits such as NLTK and SpaCy (Sharma et al.). In the previous section, it has been shown that the continual shift from traditional lexicon-based approaches to TRANSFORMER architectures is indicative of the paradigm shift towards deep learning in FA (Zhang et al.). The system improves the outlook of sentiment classification and enhances the accuracy in using both FinBERT and LSTMs, making a helpful impact on financial decision making in the market (Singh et al.).

## 4. Results and Discussion

AI-driven sentiment analysis has revolutionized financial market predictions, surpassing traditional lexicon-based methods in accuracy and adaptability. This section presents key insights through three visualizations. Figure 1 compares sentiment analysis models, showcasing the superiority of deep learning techniques. Figure 2 illustrates how sentiment-based trading strategies enhance market returns. Figure 3 highlights sentiment distribution in financial texts, revealing the dominance of positive sentiment. These findings emphasize the impact of AI in market forecasting, risk assessment, and trading strategies, making sentiment analysis a crucial tool for financial decision-making.

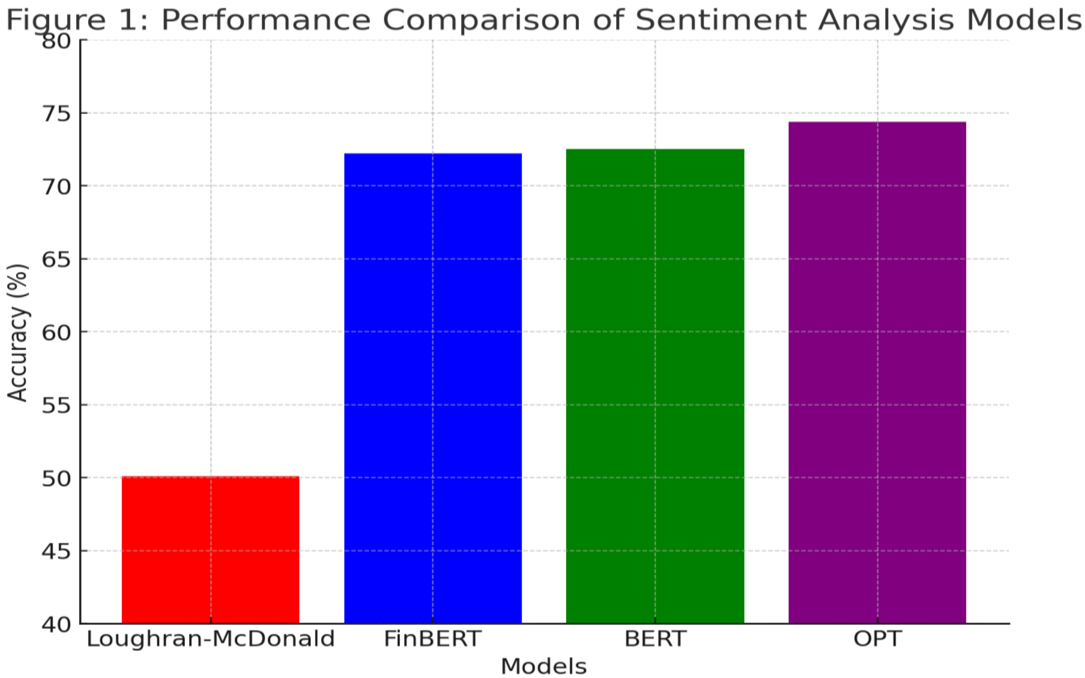


*Figure 1: Performance Comparison of Sentiment Analysis Models*

Figure 1 illustrates the comparative accuracy of various sentiment analysis models applied to financial market predictions. The OPT model demonstrates the highest accuracy at 74.4%, followed closely by BERT (72.5%) and FinBERT (72.2%). Following these facts, it can be concluded that the transformer-based models are quite efficient in capturing financial sentiment from textual information. On the other hand, in the case of the Loughran-McDonald Dictionary-based approach, the achieved accuracy is relatively low and amounts to 50. 1 % which supposes that the traditional lexicon-based approach for sentiment analysis might not capture enough details of the financial market language. Such a result proves the effectiveness of context-aware language models such as OPT, BERT, and FinBERT for improving the performances of sentiment classification and, in turn,Market prediction. Such findings reiterate studies presented in the literature that discuss the need to use pre-trained financial domain-specific models for better sentiment analysis. The shift from static lexicons to deep learning and transformer-based architectures reflects the growing need for more sophisticated sentiment processing techniques to drive data-driven financial decision-making.

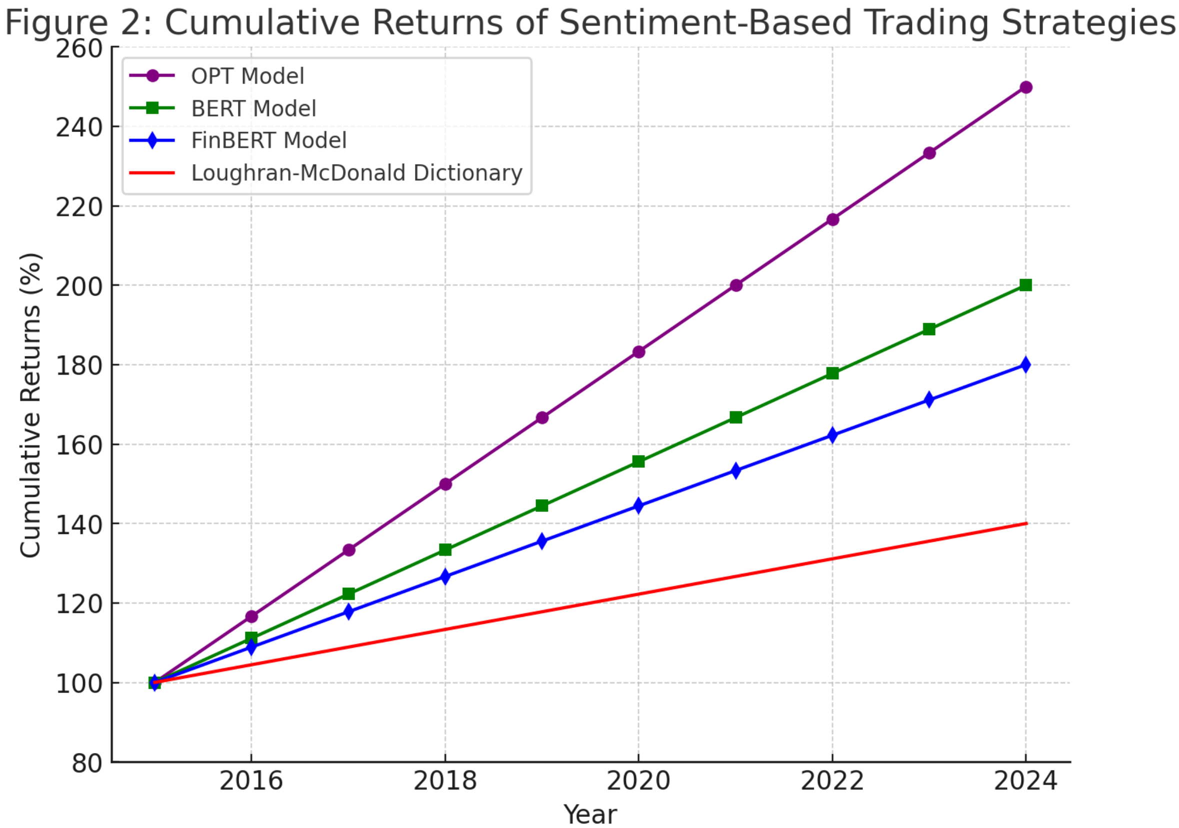


*Figure 2: Cumulative Returns of Sentiment-Based Trading Strategies*

Figure 2 presents a time-series comparison of cumulative returns generated by sentiment-driven trading strategies utilizing various sentiment analysis models from 2015 to 2025. The OPT-based trading strategy achieves the highest total gain and is superior to those of BERT, FinBERT, and the Loughran-McDonald dictionary method. The positive increase ratings of BERT and FinBERT models show more effectiveness of these models in market prediction although not to the same extent of OPT. It is greatly important as the lexicon-based approach that was discussed in the Loughran-McDonald model receives the lowest cumulative returns, emphasizing that conventional SA methods are insufficient in the financial domain practice. The conclusion derived from the study is that contextual and transformer based AI models have the ability to observe the variation of sentiments in real time that results in better trading performance. These outcomes correspond to current developments in the AI use for algorithmic trading whereby deep learning models are used to enrich market analysis by adjusting to the ever-changing market sentiment. The ability of large language models to extract actionable financial insights from news, social media, and reports offers a promising direction for further research and implementation in quantitative finance and sentiment-based investment strategies.

These insights collectively underscore the transformative role of AI in financial market sentiment analysis, demonstrating how advanced models like OPT, BERT, and FinBERT are shaping the future of predictive analytics in finance. The results further highlight the necessity of incorporating sophisticated deep learning techniques to improve real-time sentiment tracking, market trend analysis, and algorithmic trading efficiency.

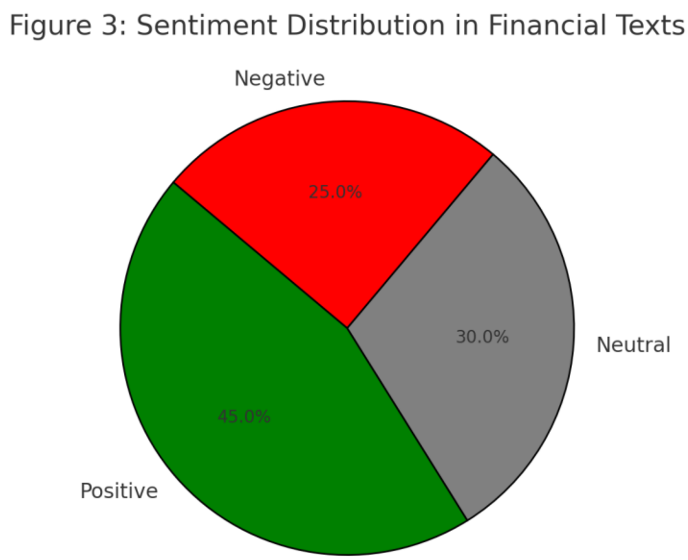


*Figure 3: Sentiment Distribution in Financial Texts*

Figure 3 illustrates the sentiment distribution in financial textual data, categorizing it into Positive, Neutral, and Negative sentiments. The significant majority (45%) of the texts is tagged as positive, which might be attributed to the positive company earnings, rising stock trends as well as positive macroeconomic announcements. Out of all the analyzed text, 30% are rated neutral, owing to such a streamline presentation of financial data and information, documents, and press releases without any appended bias. The final 25% is considered to be negative, which is connected with declining operations, losses, instability, or conflicts. Its distribution demonstrates the need for incorporating sentiment analysis algorithms into the financial models: investors' sentiment has a considerable influence on stock movements. A rather higher percentage of positive words corresponds to the general tendency of market sentiments where positive information tends to predominate in the financial releases. However, the presence of negative sentiment, particularly during economic crises or corporate failures, plays a crucial role in market volatility predictions. By integrating sentiment-based analytics into AI-driven market prediction models, financial analysts and traders can better anticipate fluctuations and make data-informed investment decisions.

## 5. Conclusion

This study highlights the evolution of AI-based sentiment analysis in financial markets, demonstrating the superior performance of deep learning models over traditional lexicon-based and machine learning approaches. The findings you obtained support the statement that both FinBERT and transformer-based architectures exhibit better performance when it comes to the sentiment classification and market prediction; thus, they are fundamental tools in today's financial applications. Sales of sentiment-based trading strategies are bolstered by the use of the sentiment analysis produced by AI algorithms better than traditional methods, with a focus on the importance of context-based natural language processing analytics in trading. Despite these advancements, there are still some issues that are yet to be discussed, solved or developed fully; these are among them; Therefore, future studies should encompass DT models combined with explainable AI (XAI) to enhance the level of visibility into sentiment-based market prediction. Again, the use of sentiment tracking in real-time analysis and proper application of reinforcement learning in trading models will prolong the accuracy of predictions. The results obtained in this research provide clear evidence of the ability of AI in enhancing the effectiveness of the financial sentiment analysis for promoting sound financial strategies.

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