# Predicting Stock Prices Using LLM Analysis of Financial Influencer Content

## Introduction

The intersection of finance and social media has witnessed a significant transformation in recent years. Retail investors, particularly younger generations, are increasingly turning to online platforms and social media influencers for financial guidance, often preferring these sources over traditional financial institutions 1. This shift in information consumption underscores the growing influence of financial influencers (finfluencers) on investment decisions and overall market sentiment 2. Given this evolving landscape, there is a burgeoning interest in leveraging advanced artificial intelligence (AI) techniques, specifically Large Language Models (LLMs), to analyze the content generated by these influencers and potentially predict stock price movements. The sheer volume of textual and multimedia data produced by finfluencers presents a unique opportunity to extract valuable insights into market psychology and future trends.

Large Language Models, a sophisticated subset of AI, have demonstrated remarkable capabilities in understanding and generating human language 4. Trained on massive datasets, these models can perform a wide array of natural language processing (NLP) tasks, making them potential game-changers in various industries, including finance 5. Their ability to analyze vast amounts of text, identify sentiment, and extract relevant information opens up new avenues for understanding and predicting financial market behavior. This report aims to explore the feasibility and methodologies of using LLMs to analyze the content of financial influencers to predict stock prices, addressing the key technical and conceptual considerations for such a project. The objective is to provide a comprehensive overview of the current state of research in this interdisciplinary field, identify challenges and limitations, and offer guidance for potential implementation in a computer science final year project.

This report will first delve into the core concepts and capabilities of LLMs relevant to financial text analysis. It will then examine the landscape of financial influencers, their impact on the market, and the ethical considerations involved. Following this, the report will provide an overview of traditional and modern approaches to stock price prediction, setting the context for how LLMs and sentiment analysis can be integrated. A dedicated section will explore the application of LLMs for sentiment analysis of finfluencer content, highlighting the challenges and existing research in this area. The report will then discuss strategies for integrating influencer sentiment into stock price prediction models, including different machine learning architectures. Finally, it will address the challenges, limitations, and potential biases inherent in this approach, followed by an outline of relevant data sources, tools for implementation, and appropriate evaluation metrics for the prediction model.

## Understanding Large Language Models

Large Language Models represent a significant advancement in the field of artificial intelligence, specifically within the domain of natural language processing. At their core, LLMs are deep learning models that have been trained on exceptionally large datasets of text and code 4. This extensive training enables them to understand, interpret, and generate human-like text for a wide range of tasks. The architecture that underpins most modern LLMs is the transformer network 4. This architecture utilizes a mechanism called self-attention, which allows the model to weigh the importance of different words in an input sequence when processing it 5. This capability is crucial for understanding the context and nuances of language.

The training process for LLMs typically involves two main phases: pre-training and fine-tuning 5. During pre-training, the model is exposed to vast amounts of unlabeled text data, often scraped from the internet, books, and articles. Through unsupervised learning techniques, the LLM learns the statistical relationships between words and phrases, developing a broad understanding of language structure and patterns 5. Following pre-training, the model can be fine-tuned on smaller, task-specific datasets using supervised learning to optimize its performance on particular NLP tasks such as text classification, question answering, or sentiment analysis 5. The sheer scale of the training data and the complexity of the transformer architecture, often involving billions of parameters, are what give LLMs their powerful language processing abilities 7. These models function by taking an input text sequence and predicting the most probable next word in the sequence based on the patterns and knowledge acquired during training 8.

For the purpose of analyzing financial influencer content, several key capabilities of LLMs are particularly relevant. **Sentiment analysis** is a crucial NLP task where LLMs can be used to determine the emotional tone (positive, negative, or neutral) expressed in a piece of text 5. This is vital for understanding the opinions and attitudes of finfluencers towards specific stocks or market trends. LLMs can also perform **text generation**, which might be useful for summarizing lengthy influencer content or generating insights from their discussions 5. **Information extraction** is another important capability, allowing the LLM to identify and extract key pieces of information, such as mentioned stock tickers or specific financial advice, from the influencer's content 5. Furthermore, LLMs have shown an ability to handle nuanced aspects of language like sarcasm and irony, which is particularly important when analyzing informal social media content 16. Their capacity to infer unstated information and synthesize knowledge from diverse sources can also lead to deeper insights from influencer discussions 14.

Several prominent LLMs have emerged as leaders in the field. The **GPT series** (including GPT-3, GPT-4, and ChatGPT) developed by OpenAI are renowned for their general-purpose language understanding and generation capabilities, possessing billions of parameters 7. These models have demonstrated strong performance across a wide range of NLP tasks and are widely accessible through APIs. In the financial domain, **FinGPT** has been specifically developed and shows promising results in financial sentiment analysis and stock movement prediction 17. FinGPT's methodology focuses on incorporating news dissemination patterns and market context to enhance prediction accuracy 18. Other notable LLMs suitable for sentiment analysis include **BERT** and its variants 22. Research has indicated that domain-specific models like FinGPT might outperform general-purpose LLMs in financial forecasting tasks due to their training on relevant financial data 23.

| **Model Name** | **Architecture** | **Approximate Parameter Count** | **Key Strengths in Financial NLP** | **Availability** |
| --- | --- | --- | --- | --- |
| GPT-3 | Transformer | 175 Billion | General language understanding, text generation | API Access |
| ChatGPT | Transformer | Unknown | Conversational AI, broad knowledge | API Access |
| GPT-4 | Transformer | Unknown | Improved reasoning, multimodality | API Access |
| BERT | Transformer | Up to 340 Million | Sentiment analysis, text classification | Open Source, API Access |
| FinGPT | Transformer | Varies | Financial sentiment analysis, stock movement prediction | Open Source |

## The Landscape of Financial Influencers

Financial influencers, or finfluencers, have become a prominent force in the digital age, shaping the way many individuals approach personal finance and investment. These individuals leverage various social media platforms, including Instagram, TikTok, YouTube, and Twitter, to share their insights, opinions, and advice on a wide range of financial topics, from basic budgeting and saving to complex investment strategies and cryptocurrency 1. The finfluencer landscape is diverse, with many specializing in niche areas such as real estate investing, retirement planning, or specific asset classes 1.

The impact of finfluencers on retail investors and market sentiment has grown significantly, particularly among younger demographics 1. Studies indicate that a substantial portion of Gen Z and millennials prefer seeking financial advice from YouTubers and social media influencers over traditional financial advisors, driven by a perception of relatability and trustworthiness 1. This preference highlights the considerable influence these online personalities can wield over their followers' financial decisions. Research has shown that the sentiment and engagement generated by influencers can indeed affect financial markets, driving investor attention and trading dynamics 32. Social media sentiment, more broadly, has been observed to precede or coincide with stock price movements, suggesting that the opinions and recommendations of finfluencers, as part of this broader sentiment, could hold predictive power 33.

Examples of prominent financial influencers illustrate the nature of their content and the scale of their reach. Ryan Scribner, for instance, covers cryptocurrency and wealth-building strategies on YouTube, while George Gammon focuses on macroeconomic and stock market trends 25. Patrick Boyle provides insights into investing in challenging market environments, and Vivian Tu (Your Rich BFF) reacts to current financial news 25. These examples demonstrate the variety of content formats (videos, short posts, live streams) and the diverse range of financial topics covered by finfluencers 25. Categorizing finfluencers by their primary focus (e.g., personal finance, stock investing, cryptocurrency, real estate) and the platforms they use can provide a more structured understanding of this landscape.

However, the rise of finfluencers also brings forth ethical considerations and the potential for misinformation and market manipulation 2. The quality and relevance of content generated by LLMs based on finfluencer data require careful human oversight 11. The possibility of influencers engaging in "pump and dump" schemes or spreading biased information for personal gain poses a significant challenge 2. Social media platforms are susceptible to unverified claims and misinformation, and accurately measuring sentiment while accounting for nuances like sarcasm remains a hurdle for AI 37. Therefore, any project aiming to predict stock prices based on finfluencer content must critically evaluate the reliability of the data and consider the ethical implications of using potentially biased or manipulative information. Regulatory bodies like the SEC are increasingly aware of the potential for market manipulation through social media and are taking steps to address it 36.

## Traditional and Modern Approaches to Stock Price Prediction

Predicting stock prices has long been a challenging endeavor in the field of finance. Both traditional statistical methods and modern machine learning techniques have been employed to forecast future market movements. Traditional approaches often rely on analyzing historical data and identifying patterns or relationships.

**Time series analysis** encompasses a range of statistical techniques used to analyze time-dependent data, such as stock prices. Autoregressive Integrated Moving Average (ARIMA) and Seasonal ARIMA (SARIMA) models are common methods in this category 39. These models aim to identify and extrapolate trends and seasonal patterns from past price data to predict future values 39. While effective for steady and linear data, the stock market's volatility, often influenced by factors like social media sentiment, might require more sophisticated models to capture non-linear dynamics 40.

**Technical analysis** is another widely used approach that focuses on historical price and volume data to identify patterns and predict short-term trading opportunities 42. Technical analysts use various indicators, such as moving averages, Relative Strength Index (RSI), and Bollinger Bands, to assess market trends and potential reversal points 42. LLMs can potentially play a role in technical analysis by automating the generation and interpretation of these indicators 44.

**Fundamental analysis**, in contrast, involves evaluating a company's intrinsic value by examining its financial health, management, and future prospects 42. While crucial for long-term investment decisions, directly incorporating short-term sentiment from finfluencers into fundamental analysis might be less straightforward.

In recent years, **machine learning (ML)** and **deep learning (DL)** techniques have gained prominence in stock price prediction. **Regression models**, such as Linear Regression and Random Forest, can be used to predict continuous output variables like stock prices based on various input features 45. Linear Regression aims to find a linear relationship between the input and output, while Random Forest, an ensemble method, can capture more complex non-linear relationships 46. Notably, research has explored Sentiment-Augmented Random Forest (SARF) models that incorporate sentiment data from LLMs to improve prediction accuracy 47.

**Neural networks**, particularly Recurrent Neural Networks (RNNs) like Long Short-Term Memory (LSTM) networks, have shown significant potential in time series forecasting and stock price prediction 39. LSTMs are designed to learn long-term dependencies in sequential data, making them well-suited for analyzing both stock prices and the evolving sentiment expressed in social media 48. Their ability to capture non-linear and complex relationships is crucial in the dynamic stock market 40. Variations like Bidirectional LSTMs (Bi-LSTMs) can further enhance performance by processing data in both forward and backward directions 52. Hybrid models that combine LLMs with other deep learning architectures like Convolutional Neural Networks (CNNs) and Transformers are also being explored to leverage the strengths of different approaches 44.

## Leveraging LLMs for Sentiment Analysis of Financial Influencer Content

Sentiment analysis plays a pivotal role in understanding the psychology of the market. By gauging the overall opinion and emotional tone expressed in financial content, analysts can gain insights into investor confidence and potential market movements 9. A strong correlation has been observed between stock prices and overall stock sentiment, suggesting that sentiment can act as a leading indicator of price changes 56. News and other forms of financial communication, including influencer content, significantly shape investor perceptions and, consequently, stock behavior 58.

Large Language Models offer advanced capabilities for performing fine-grained sentiment analysis of the content generated by financial influencers across various modalities, including text and potentially transcripts of video or audio content 9. Their ability to understand context, capture nuances in language, and generate human-like text makes them particularly well-suited for analyzing the informal and often complex language used on social media 22. Target-level sentiment analysis, where the sentiment towards specific entities (e.g., a particular stock) is identified, can be crucial for this task 60. Techniques like zero-shot or few-shot learning can be employed with LLMs to perform sentiment analysis even when labeled financial data is limited 61. Implementing sentiment analysis using LLMs typically involves steps such as data preparation, model selection (potentially including fine-tuning on financial datasets or using domain-specific models like FinGPT), sentiment classification, and performance evaluation 17.

Despite their advancements, sentiment analysis using LLMs is not without challenges. Social media content often contains sarcasm, idioms, and domain-specific language that can be difficult for even sophisticated models to interpret correctly 23. The reasoning behind an LLM's sentiment classification is not always transparent, which can make it hard to predict when the model might fail 16. General-purpose LLMs might struggle with the specialized vocabulary used in finance, necessitating fine-tuning or the use of domain-specific models 23. Furthermore, sentiment analysis alone might not be sufficient for accurately predicting stock prices, as market movements are influenced by a multitude of factors 37.

A growing body of research has focused on leveraging LLMs for financial sentiment analysis. Studies have explored the correlation between social media sentiment and stock prices using transformer-based models 64. Various LLM techniques have been investigated for stock market prediction using financial news headlines, and these methodologies can potentially be adapted for analyzing influencer content 63. Models like FinGPT have been specifically designed to enhance sentiment-based stock movement prediction by considering news dissemination and market context 17. This active research area provides a strong foundation for exploring the use of LLMs for analyzing financial influencer content in the context of stock price prediction.

## Integrating Influencer Sentiment into Stock Price Prediction Models

Several strategies can be employed to integrate sentiment scores derived from LLM analysis of financial influencer content into stock price prediction models. A direct approach involves using the sentiment score as an additional input feature alongside historical stock market data to train a time-series prediction model, such as an LSTM network 50. This allows the model to learn the relationship between the sentiment expressed by influencers and subsequent stock price movements.

Another method involves augmenting traditional machine learning models with sentiment features. The Sentiment-Augmented Random Forest (SARF) model, for example, demonstrates how sentiment scores from a financial LLM like FinGPT can be incorporated into a Random Forest model to improve prediction accuracy 47. This approach highlights the potential of combining the nuanced understanding of sentiment provided by LLMs with the robust predictive capabilities of established ML techniques.

LLMs can also be used to generate higher-level features based on sentiment trends or changes in sentiment over time. These features can then be used to enrich the dataset for training a stock prediction model. For instance, an LLM could analyze influencer discussions to identify key market trends or shifts in sentiment towards specific stocks, and these insights could be encoded as features for a Transformer-CNN model 44.

Existing research provides practical examples of how sentiment data from social media, which is analogous to the content produced by finfluencers, can be integrated with stock price data. Projects that merge stock data with sentiment scores from platforms like Twitter offer valuable insights into the data integration process and the potential impact of social media sentiment on prediction models 66. Furthermore, combining sentiment data with traditional financial indicators and macroeconomic data can lead to more comprehensive and potentially more accurate prediction models 50. Systems that integrate sentiment analysis with technical indicators to generate trading signals demonstrate the practical application of combining these different sources of information 17.

The choice of machine learning architecture for integrating sentiment data will depend on various factors, including the structure of the sentiment data and the desired prediction horizon. LSTMs are well-suited for analyzing sequential data, making them a strong candidate for incorporating time-series sentiment data along with stock prices. CNNs might be useful for identifying patterns in sentiment trends or when combined with other data modalities. Hybrid models that leverage the strengths of different architectures could also be explored to potentially achieve better performance. Examining case studies and examples from existing research, such as those involving SARF and LSTM models, can provide valuable guidance for selecting and implementing an appropriate integration strategy.

## Challenges, Limitations, and Potential Biases

Predicting stock prices based on LLM analysis of financial influencer content presents several challenges and limitations. The **data quality and reliability** of influencer content can be variable 11. LLMs trained on or analyzing low-quality or biased content may produce unreliable sentiment analysis and predictions 11. Accurately capturing the true sentiment, especially considering sarcasm and context, remains a hurdle 38. The distribution of sentiment in influencer content might be skewed, and conflicting opinions can make it difficult to derive a clear signal 67.

The **potential for market manipulation** is a significant concern 2. Influencers might intentionally or unintentionally influence stock prices, distorting the relationship between their content and actual market movements. Social media data, including influencer content, often contains **noise and irrelevant information** that can obscure true market signals 44.

LLMs themselves have **limitations** in understanding complex financial contexts and predicting market movements 11. They might struggle with the intricate and rapidly evolving nature of financial markets and the subtle language used in financial discussions 11. The effectiveness of this approach is likely to vary depending on the specific stock, influencer, and market conditions 68. Relying solely on sentiment analysis might not be sufficient, as stock prices are influenced by numerous factors 37.

**Potential biases** inherent in LLMs can also impact the accuracy and fairness of sentiment analysis and predictions 16. LLMs can be biased based on their training data, leading to skewed sentiment analysis or predictions 11. These biases can manifest as preferences for certain viewpoints or products, such as a tendency to favor well-known stocks like Apple and Microsoft, regardless of the actual sentiment expressed by influencers 71. It is important to note that high prediction accuracy does not necessarily mean the model is free from biases 69.

## Data Sources and Tools for Implementation

Implementing a project focused on predicting stock prices using LLM analysis of financial influencer content requires access to several key data sources and tools. **Social media platforms** where financial influencers are active, such as Twitter, Reddit, Instagram, and TikTok, will be primary sources of data 1. These platforms offer **APIs** (Application Programming Interfaces) that allow for programmatic collection of user-generated content 72. Understanding the specific capabilities, limitations, and usage guidelines of each platform's API is crucial for effective data acquisition 72.

In addition to influencer content, **financial news aggregators** and **stock price data providers** offer valuable APIs. Financial news APIs, such as those from NewsAPI.ai, Alpha Vantage, and Tiingo, provide access to real-time and historical financial news, which can provide broader market context 77. Stock market data APIs from providers like Alpha Vantage, Yahoo Finance, and Finnhub offer historical and real-time stock prices, which will serve as the target variable for the prediction model 82.

The recommended programming language for this project is **Python**, due to its extensive ecosystem of libraries for data science, machine learning, and natural language processing 39. Key libraries include **Pandas** and **NumPy** for data manipulation and numerical computation. For interacting with LLMs, the **Transformers** library provides easy access to pre-trained models and tools for fine-tuning. Libraries like **NLTK** or **SpaCy** can be used for text preprocessing tasks such as tokenization and cleaning. Deep learning frameworks such as **TensorFlow** and **PyTorch** will be essential for building and training the stock price prediction models, particularly neural network architectures like LSTMs.

## Evaluation Metrics for the Prediction Model

Selecting appropriate evaluation metrics is crucial for assessing the performance of a stock price prediction model. If the goal is to predict the actual stock price (a regression task), common metrics include **Root Mean Squared Error (RMSE)** and **Mean Absolute Percentage Error (MAPE)** 42. RMSE measures the average magnitude of the errors, giving more weight to larger errors, while MAPE expresses the error as a percentage of the actual value 42. **Mean Absolute Error (MAE)** is another relevant regression metric that measures the average absolute difference between predictions and actual values 54.

If the objective is to predict the direction of stock price movement (up or down, a classification task), metrics such as **accuracy**, **precision**, **recall**, and **F1-score** are more appropriate 43. Accuracy measures the overall correctness of the predictions, while precision and recall focus on the model's ability to correctly identify positive and negative trends. The F1-score provides a balanced measure of precision and recall 43.

For time series forecasting, additional metrics like **Symmetric Mean Absolute Percentage Error (SMAPE)**, **Mean Absolute Scaled Error (MASE)**, and **Weighted Absolute Percentage Error (WAPE)** can be considered 87. These metrics offer different ways of measuring forecast accuracy and are suitable for various scenarios depending on the characteristics of the data and the specific requirements of the project 87.

Model validation and testing are essential to ensure the model generalizes well to unseen data and avoids overfitting. A standard approach is to split the historical data into a **training set** for model development and a separate **test set** for evaluating its performance 90. For time-dependent data like stock prices, using **TimeSeriesSplit** is recommended to prevent lookahead bias 49. **Cross-validation** is another robust technique that involves training and testing the model on multiple different subsets of the data to obtain a more reliable estimate of its performance 90.

| **Metric Name** | **Formula** | **Interpretation** | **Task Type** |
| --- | --- | --- | --- |
| RMSE | n1​∑i=1n​(yi​−y^​i​)2​ | Average magnitude of errors, sensitive to large errors | Regression |
| MAPE | $\frac{1}{n}\sum\_{i=1}^{n}\$ | \frac{y\_i - \hat{y}\_i}{y\_i}\ | \times 100\% |
| MAE | $\frac{1}{n}\sum\_{i=1}^{n}\$ | y\_i - \hat{y}\_i\ |  |
| Accuracy | TP+TN+FP+FNTP+TN​ | Overall correctness of predictions | Classification |
| Precision | TP+FPTP​ | Proportion of correctly predicted positive instances | Classification |
| Recall | TP+FNTP​ | Proportion of actual positive instances correctly predicted | Classification |
| F1-Score | 2×Precision+RecallPrecision×Recall​ | Harmonic mean of precision and recall | Classification |

## Conclusion and Future Directions

This report has explored the potential of using Large Language Models to predict stock prices based on the content generated by financial influencers. The increasing influence of finfluencers on retail investors, particularly younger generations, highlights the relevance of analyzing their content for market insights. LLMs, with their advanced natural language processing capabilities, offer promising tools for extracting sentiment and information from this data. While traditional and modern stock price prediction methods provide a strong foundation, the integration of sentiment derived from finfluencer content through LLMs presents a novel approach that could potentially enhance predictive accuracy by capturing the evolving market psychology.

However, several challenges and limitations must be considered. The quality and reliability of influencer content can vary significantly, and the potential for market manipulation and the presence of noise in social media data are serious concerns. LLMs themselves have limitations in fully understanding complex financial contexts and are prone to various biases that could affect the accuracy and fairness of predictions.

Despite these challenges, the active and growing body of research in this area, including the development of domain-specific LLMs like FinGPT, suggests a promising future for this approach. For a computer science final year project, potential future research directions could include exploring and comparing different LLM architectures for sentiment analysis of finfluencer content, investigating various strategies for integrating sentiment scores into stock prediction models (such as LSTMs or transformer networks), and evaluating the performance of these models on real-world data. Further research could also focus on developing methods for detecting and mitigating biases in LLMs and for identifying and filtering out potentially manipulative content from financial influencers. Evaluating the model's performance in simulated real-time trading scenarios would also be a valuable extension of such a project.

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