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Article

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Bitcoin Price Prediction Based on Social Media Interaction and Sentiment (2022–2025)

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Abstract
A single paragraph of about 200 words maximum. For research articles, abstracts should give a pertinent overview of the work. We strongly encourage authors to use the following style of structured abstracts, but without headings: 1) Background: Place the question addressed in a broad context and highlight the purpose of the study; 2) Methods: Describe briefly the main methods or treatments applied; 3) Results: Summarize the article's main findings; and 4) Conclusions: Indicate the main conclusions or interpretations. The abstract should be an objective representation of the article, it must not contain results which are not presented and substantiated in the main text and should not exaggerate the main conclusions.

Keywords:
keyword 1; keyword 2; keyword 3 (List three to ten pertinent keywords specific to the article; yet reasonably common within the subject discipline.)

1. Introduction

The growing digitalization of financial systems and the decentralization of information flow have positioned cryptocurrencies as one of the most dynamic and unpredictable asset classes of the last decade. Among them, Bitcoin (BTC) remains the most influential in terms of capitalization, market dominance, and public attention. Its price, however, continues to exhibit high volatility driven not only by macroeconomic factors but also by social dynamics and collective sentiment.

In recent years (2022–2025), researchers have increasingly explored the predictive power of social interaction and sentiment analysis to anticipate fluctuations in Bitcoin's price. Social networks such as Twitter, Reddit, and Telegram have become critical sources of behavioral data that reflect investor confidence, fear, and market expectations. These digital traces have proven useful for identifying shifts in market psychology, often preceding significant price movements [1,2,5].

Traditional econometric models (e.g., ARIMA, GARCH, and VAR) have provided valuable insights into volatility and temporal dependencies. Nonetheless, they fall short in capturing the nonlinear and sentiment-driven nature of cryptocurrency markets [8,12]. Consequently, hybrid frameworks that integrate Machine Learning (ML), Deep Learning (DL), and Natural Language Processing (NLP) have gained relevance [6,7,9]. These models—particularly those employing FinBERT, LSTM, and Transformer architectures—enable the extraction of latent sentiment features and their fusion with technical indicators to improve predictive accuracy [10,11].

Despite these advances, several gaps remain. Many studies rely on unaligned or short time frames, lack reproducibility, or ignore the heterogeneity of social influence (e.g., the impact of key opinion leaders). Moreover, the integration of multimodal signals (textual sentiment,

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user activity, and market indicators) remains an open challenge. Addressing these limitations requires a comprehensive and systematic approach capable of modeling the interaction between social emotion and market response.

Therefore, this study aims to analyze and synthesize the evolution of predictive methodologies for Bitcoin prices based on social sentiment and interaction between 2022 and 2025. Through a comparative literature review and methodological analysis, we identify the dominant approaches, highlight the most effective hybrid architectures, and propose a foundation for future experimental validation using real-world datasets.

2. State of the Art

The prediction of Bitcoin prices has evolved from purely econometric approaches to more sophisticated models based on machine learning and natural language processing (NLP). Between 2022 and 2025, research has increasingly emphasized the integration of behavioral and linguistic data-particularly sentiment from social networks-as an explanatory factor of market dynamics.

Of the 77 articles analyzed, approximately 23% explicitly incorporate sentiment analysis or NLP features, while the remainder focus primarily on machine learning (ML), deep learning (DL), or hybrid quantitative methods. This indicates that sentiment-driven approaches are gaining momentum, but still play a secondary role compared to technical models.

2.0.1. Econometric Models

Classical econometric models such as ARIMA, GARCH, and VAR remain relevant for short-term volatility prediction [1] [2]. However, their inability to capture non-linear dependencies or behavioral drivers limits their predictive accuracy in highly speculative markets like cryptocurrencies.

2.0.2. Machine Learning (ML) Approaches

Since 2022, the use of ML algorithms such as Support Vector Machines (SVM), Random Forest, and XGBoost has expanded significantly [3] [4]. These models provide robust adaptability to heterogeneous data and can learn complex relationships, though they depend heavily on feature selection and well-labeled datasets.

2.0.3. Deep Learning (DL) Models

Deep learning methods-especially Long Short-Term Memory (LSTM), Bidirectional LSTM (BiLSTM), and Convolutional Neural Networks (CNN)-achieve superior performance by modeling non-linear temporal dependencies [5][6]. These architectures outperform traditional models but demand large-scale data and high computational resources.

2.0.4. Natural Language Processing (NLP) and Sentiment Analysis

The application of pre-trained language models such as FinBERT, RoBERTa, and VADER has become one of the most prominent research directions. These models correlate social media sentiment with Bitcoin returns and volatility [7][8][9]. The findings suggest that the *source* of the message-such as tweets from influential accounts-may have a stronger impact than the message polarity itself [10].

2.0.5. Hybrid and Multimodal Models

Recent studies employ hybrid or multimodal architectures combining sentiment signals with quantitative market data. Models like CNN–LSTM or FinBERT combined with XGBoost demonstrate improved predictive accuracy [11][12]. Nonetheless, persistent issues remain regarding temporal misalignment between social and market data, as well as the generalization of findings to other cryptocurrencies.

2.0.6. Research Gaps

Despite the methodological advances, several gaps remain:

1. Temporal misalignment between sentiment data and market variables limits causal inference.
2. Deep learning models often lack interpretability.
3. Reproducibility remains low due to heterogeneous datasets and lexicons.
4. Few studies validate across multiple cryptocurrencies, hindering generalization.

Table 1: Comparative Summary of Recent Sentiment-Based Studies (2022–2025)

Ref	Technique(s)	Data Source	Key Findings
	Regression + VADER Sentiment	Twitter posts (2022–2023)	Short-term correlation between sentiment and Bitcoin returns.
	LSTM + FinBERT embeddings	News headlines and tweets	Improves predictive accuracy over statistical baselines.
	VAR + NLP preprocessing	Reddit discussions	Weak long-term relationship between mood and price.
	BiLSTM + Attention mechanism	Twitter (influential accounts)	Volatility impact depends on message source more than polarity.
	Transformer (RoBERTa)	Mixed social media corpus	Robust detection of market optimism and pessimism.
	XGBoost + Sentiment scores	Financial forums	Enhances directional prediction versus linear regression.
	CNN–LSTM hybrid	News and technical indicators	Superior trend classification accuracy.
	ARIMA + Sentiment adjustment	Market data + Google Trends	Improves short-term volatility forecasting.
	Ensemble ML (RF, SVM) + NLP	Twitter and Reddit	Combines behavioral and quantitative signals effectively.
	FinBERT + fine-tuned Transformer	Cryptocurrency tweets	High precision in predicting extreme price movements.

[For] (i) Enjoyment; (ii) Good entertaining films; (iii) Greater understanding of [the] issue portrayed; (iv) Insight into literature and film making; (iv) Discussion on current perspectives in treatment or research on topic; and (v) Opportunity to socialise and catch up with friends. (Female Student, 4165)

3. Results

This section may be divided by subheadings. It should provide a concise and precise description of the experimental results [?], their interpretation as well as the experimental conclusions that can be drawn.

3.1. Subsection

3.1.1. Subsubsection

Bulleted lists look like this:

- First bullet;
- Second bullet;
- Third bullet.

Numbered lists can be added as follows:

1. First item;
2. Second item;
3. Third item.

The text continues here.

3.2. Figures, Tables and Schemes

All figures and tables should be cited in the main text as Figure 1, Table 2, etc.

Figure 1: This is a figure, Schemes follow the same formatting. If there are multiple panels, they should be listed as: (**a**) Description of what is contained in the first panel. (**b**) Description of what is contained in the second panel. Figures should be placed in the main text near to the first time they are cited. A caption on a single line should be centered.

Table 2: This is a table caption. Tables should be placed in the main text near to the first time they are cited.

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Entry 3	Data	Data	Data
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* Tables may have a footer.

4. Discussion

Authors should discuss the results and how they can be interpreted in perspective of previous studies and of the working hypotheses. The findings and their implications should be discussed in the broadest context possible. Future research directions may also be highlighted.

5. Conclusions

This section is not mandatory, but can be added to the manuscript if the discussion is unusually long or complex.

6. List of abbreviations

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7. Notes

8. Funding

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9. Acknowledgments

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10. Data and materials availability statement

The content here.

11. Declarations and conflicts of interest

The content here.

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