Available online at www.HighTechJournal.org

HighTech and Innovation Journal

ISSN: 2723-9535

Vol. 6, No. 4, December, 2025

Investigating the Correlation Between Bitcoin Trading Volume and Technical Indicators Using Data Mining Techniques

Athapol Ruangkanjanases [1], Taqwa Hariguna [2*]

[1] Department of Commerce, Chulalongkorn Business School, Chulalongkorn University, Bangkok, 10330, Thailand.

[2] Department of Information System and Magister Computer Sciences, Universitas Amikom Purwokerto, Purwokerto Utara, 53127, Indonesia.

Received 23 August 2025; Revised 05 November 2025; Accepted 12 November 2025; Published 01 December 2025

Abstract

This study aims to examine the relationship between Bitcoin trading volume and key technical indicators using data-mining techniques to better understand how trading activity influences momentum and volatility in blockchain markets. The methodology involves analyzing a historical dataset of Bitcoin's daily trading records from 2018 to 2023, which includes the Relative Strength Index (RSI), Moving Average Convergence Divergence (MACD), Simple and Exponential Moving Averages (SMA, EMA), and the Average True Range (ATR). Pearson correlation analysis was applied to identify linear associations between trading volume and these technical indicators. The results show significant positive correlations between trading volume and momentum or trend measures such as the 7-day RSI ($r = 0.45$, $p < 0.05$), SMA ($r = 0.38$, $p < 0.05$), EMA ($r = 0.41$, $p < 0.05$), and ATR ($r = 0.48$, $p < 0.05$), indicating that higher participation accompanies stronger market momentum and greater price variability. Conversely, the weak and non-significant correlation with MACD ($r = –0.12$, $p = 0.15$) suggests that volume has limited influence on lagging trend-reversal signals. The novelty of this study lies in integrating volume-based behavior into technical indicator analysis, extending the traditional volume–price–volatility framework to cryptocurrency markets and providing practical insights for momentum-driven trading strategies and volatility-aware risk management.

Keywords: Bitcoin Trading Volume; Technical Indicators; Blockchain Market Dynamics; Data Mining; Cryptocurrency Analysis.

1. Introduction

Blockchain technology has emerged as a transformative innovation in global finance and digital systems, offering a decentralized, transparent, and immutable framework for value exchange and data management. Among its diverse applications, ranging from healthcare to supply chain management, the financial sector has experienced the most profound disruption, primarily through the advent of cryptocurrencies such as Bitcoin [1-3]. Bitcoin, launched in 2009 as the first blockchain-based currency, introduced a peer-to-peer mechanism for transferring value without intermediaries, reducing transaction costs and improving global payment efficiency [4, 5]. Its decentralized structure and verifiable public ledger have established a foundation of trust that traditional financial systems often lack, positioning Bitcoin as both a digital asset and a benchmark for the wider cryptocurrency ecosystem [6]. Beyond its technological innovation, Bitcoin's rise has reshaped modern financial behavior and introduced new dimensions of market dynamics. The cryptocurrency market is characterized by high volatility, speculative sentiment, and rapid information diffusion, making it distinct from conventional asset classes [7]. Understanding these market behaviors—particularly through

* Corresponding author: taqwa@amikompurwokerto.ac.id

http://dx.doi.org/10.28991/HIJ-2025-06-04-015

measurable indicators such as trading volume—is essential for assessing investor activity, liquidity, and overall market stability. Trading volume not only reflects participation levels but also serves as a critical signal of momentum and volatility in digital asset markets [8, 9]. Prior studies have shown that fluctuations in trading activity often coincide with sharp price movements and shifts in market sentiment, underscoring the relevance of volume as both a behavioral and analytical variable [10]. Given Bitcoin's dominance within the broader blockchain economy, analyzing its market activity provides valuable insights into systemic patterns that extend to other cryptocurrencies. Recognizing the centrality of trading volume to these dynamics establishes the foundation for exploring how it interacts with technical indicators—a relationship that remains insufficiently examined in existing research.

Technical analysis (TA) offers a structured approach to capturing market psychology through historical data. Commonly used indicators—such as the Relative Strength Index (RSI) for momentum, Moving Average Convergence Divergence (MACD) for trend shifts, and Simple and Exponential Moving Averages (SMA, EMA) for trend smoothing—translate market sentiment into measurable signals [11-13]. Empirical studies demonstrate their practical relevance: research [14] found that multi-indicator strategies, such as moving-average crossovers, enhance profitability while reducing data-snooping bias; Warmayana [15] confirmed the robustness of RSI across major cryptocurrencies; and Siddique & Wahid [16] showed that combining sentiment data with TA improves prediction accuracy. Similarly, previous studies employed machine-learning and GARCH-based models to analyze indicator performance under various volatility regimes [17-19]. Despite these advances, most studies treat indicators as isolated predictors of price or volatility, neglecting their statistical interaction with trading volume—a gap highlighted by Chowdhury et al. [20].

Existing literature on cryptocurrency forecasting and technical trading strategies has primarily focused on price prediction and volatility modeling while overlooking the interdependence between trading volume and technical indicators. Although indicators such as RSI, MACD, SMA, and EMA effectively capture momentum and trend strength, few studies have examined how trading activity reinforces or contradicts these indicator signals. This omission limits understanding of the behavioral mechanisms underlying market momentum, particularly during high-volatility phases. Furthermore, prior data-driven approaches—ranging from GARCH models to machine-learning algorithms—tend to optimize predictive accuracy rather than exploring underlying statistical relationships among market variables, leaving a methodological gap between traditional technical analysis and modern data-mining techniques. This study aims to fill that gap by applying a data-mining correlation approach to quantitatively examine the relationships between Bitcoin's trading volume and major technical indicators, including RSI, MACD, SMA, EMA, and ATR.

Specifically, it seeks to determine whether trading volume serves as a confirming signal—supporting momentum and trend indicators—or a leading signal that anticipates future price shifts. While prior studies using machine-learning or GARCH models have explored non-linear price prediction, this study identifies linear interdependencies between volume and indicators, providing complementary evidence to those non-linear approaches. The central research question guiding this study is: How does Bitcoin's trading volume statistically interact with key technical indicators, and what do these relationships reveal about market momentum and volatility? The findings of this study are expected to contribute to the cryptocurrency analytics literature in three main ways. First, the study provides empirical evidence of the relationships between trading volume and technical indicators through systematic correlation analysis, extending the theoretical scope of technical analysis. Second, it offers practical insights for traders and algorithmic systems to integrate volume-based validation into decision-making models, improving trading accuracy and risk management. Third, it enhances market transparency by linking trading activity to sentiment-driven volatility, offering implications for liquidity assessment and regulatory monitoring. By bridging data-mining methodologies with classical technical analysis, this research introduces both theoretical novelty and practical value, advancing quantitative understanding of blockchain market dynamics and providing a foundation for future studies involving multi-asset or non-linear modeling frameworks.

2. Literature Review

2.1. Blockchain Market Dynamics

Since its launch in 2009, Bitcoin has established itself as the dominant cryptocurrency, consistently accounting for 35–75% of the total cryptocurrency market capitalization [21]. This dominance positions Bitcoin as a benchmark for digital asset performance, with many altcoins exhibiting price movements that closely mirror its trends. As a result, Bitcoin's trading behavior exerts a cascading influence on the broader blockchain ecosystem, shaping investor sentiment, liquidity, and overall market direction. Bitcoin's dual role as a store of value and medium of exchange reinforces its influence. Studies show that its returns are partly driven by demand like traditional safe-haven assets such as gold [22], strengthening its reputation as "digital gold" and attracting investors seeking inflation hedges or stability during market turbulence [23]. Consequently, shifts in sentiment toward Bitcoin—often amplified by news, social media activity, and collective trading behavior—frequently trigger synchronized price adjustments across cryptocurrencies [24]. This sentiment-driven interdependence underscores Bitcoin's central role in blockchain market dynamics: changes in its trading volume and price volatility often transmit to other digital assets, magnifying collective market responses. Understanding these dynamics provides a necessary foundation for examining how technical indicators and trading volume reflect or reinforce investor sentiment in cryptocurrency markets.

2.2. Relative Strength Index (RSI)

The Relative Strength Index (RSI), introduced by Wilder [25], is a widely used momentum oscillator that measures the speed and magnitude of price changes to identify potential overbought or oversold conditions. Operating on a 0–100 scale, RSI values above 70 typically indicate overbought conditions, while values below 30 suggest oversold levels [11, 26]. These thresholds help traders anticipate market reversals by assessing the strength of recent price movements [27]. Empirical studies show that RSI-based trading strategies can generate significant returns, particularly when combined with complementary indicators such as moving averages or MACD. Research [15] confirmed the robustness of RSI across major cryptocurrencies, while [14] reported that multi-indicator systems using RSI signals improved profitability and reduced false positives. However, researchers note that RSI performance declines in extreme volatility and during speculative bubbles, where sentiment and liquidity dominate price behavior [28-30]. Despite its popularity, few studies have examined how RSI interacts with trading volume, which often amplifies or dampens momentum signals. Understanding whether RSI movements correspond with volume surges can clarify whether RSI reflects intrinsic market strength or is primarily volume-driven—a relationship this study explores through data-mining correlation analysis.

2.3. Moving Averages

Simple Moving Average (SMA) and Exponential Moving Average (EMA) are among the most fundamental indicators used in technical analysis to identify price trends and momentum shifts. Both smooth price data to filter short-term noise, yet they differ in responsiveness: the SMA assigns equal weight to all price observations, while the EMA gives greater weight to recent data, making it more sensitive to rapid price changes [31, 32]. This distinction shapes their applications—SMA is often preferred for long-term trend analysis, whereas EMA is favored in fast-moving markets such as cryptocurrencies, where timely signals are essential [33, 34]. Empirical evidence supports the practical relevance of moving-average–based strategies. Studies show that moving-average crossovers, such as the "golden cross" (short-term average crossing above a long-term one) or "death cross" (the reverse), effectively identify market turning points and confirm price trends [32, 35]. Li et al. [14] found that multi-indicator systems combining SMA or EMA with momentum measures like RSI significantly improved trading accuracy and reduced lag-related errors. However, most studies examine these indicators in isolation from trading volume, overlooking how volume fluctuations might reinforce or weaken moving-average signals. Investigating this relationship through data-mining correlation analysis can clarify whether volume acts as a confirming indicator of trend persistence or as an early signal of potential reversals in cryptocurrency markets.

2.4. Moving Average Convergence Divergence (MACD)

MACD, developed by Gerald Appel in the late 1970s [36], is a hybrid indicator combining momentum and trend-following principles to identify changes in market direction. It measures the difference between short-term and long-term exponential moving averages, typically the 12-day and 26-day EMAs, while a 9-day EMA of the MACD—known as the signal line—is used to generate buy or sell triggers [37]. When the MACD line crosses above the signal line, it indicates bullish momentum; a downward crossover suggests bearish reversal potential. In cryptocurrency markets, the MACD has proven effective in detecting short-term momentum changes and confirming broader trend reversals, though its lagging nature may reduce responsiveness during rapid market swings [38, 39]. Research indicates that combining MACD with complementary indicators enhances prediction accuracy. Li et al. [14] found that integrating MACD signals with RSI and moving averages improved trend identification in volatile markets, while [19] noted that MACD's performance is highly sensitive to data frequency and volatility regimes. Despite its utility, limited research has explored how MACD movements align with trading volume, which could clarify whether momentum shifts reflect genuine trend strength or speculative activity. Examining MACD–volume correlations through data-mining analysis may reveal whether volume serves as a confirming factor or a precursor to MACD signal reversals in cryptocurrency markets.

3. Research Methodology

The research method for this study consists of several steps to ensure a comprehensive and accurate analysis. The flowchart in Figure 1 outlines the detailed steps of the research method.

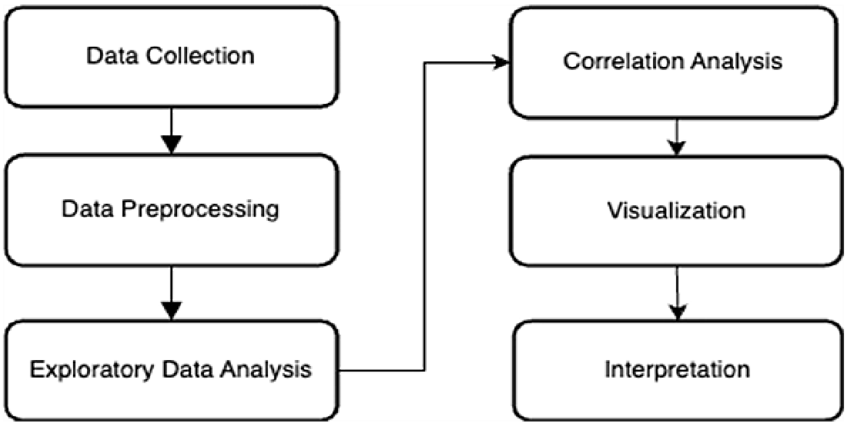

Figure 1. Research Method Flowchart

3.1. Data Collection and Preprocessing

The study utilized a dataset of historical Bitcoin trading data containing various technical indicators relevant for analyzing the correlation between trading volume and market behavior. The dataset covered daily records from January 2018 to December 2023, a period chosen to capture multiple market cycles, including both bullish and bearish phases, ensuring that diverse trading conditions were represented. Key variables included date, open, high, low, close, and trading volume, along with several widely used technical indicators: the Relative Strength Index (RSI) for momentum, Commodity Channel Index (CCI) for cyclical trends, Simple and Exponential Moving Averages (SMA, EMA) for trend smoothing, and Moving Average Convergence Divergence (MACD) for trend-following. Additional indicators—Bollinger Bands, True Range, and Average True Range (ATR)—were incorporated to assess price volatility.

The initial phase involved data cleaning to ensure completeness and accuracy. Missing values were handled using mean imputation, where absent numerical entries were replaced with the respective column means. This method was selected for its simplicity and its ability to preserve the dataset's overall distribution when the proportion of missing data is minimal. While mean imputation may slightly underestimate variance compared to advanced techniques such as regression or multiple imputation, its use here minimized complexity and avoided introducing bias into the correlation estimates. Outliers were identified using the Interquartile Range (IQR) method, which defines data points lying beyond 1.5 times the IQR as anomalous. These extreme values, common in volatile financial data, were reviewed and removed to prevent distortion of statistical results. To ensure comparability across variables with different measurement scales, all numerical features were transformed through standardization, converting each to a mean of zero and a standard deviation of one using the Equation 1.

$$Z = \frac{(X-\mu)}{\sigma} \tag{1}$$

where X represented the original values, μ was the mean, σ was the standard deviation. Standardization was preferred over min–max normalization because it preserves relative variance, enabling more accurate linear correlation analysis. Finally, preprocessing validation included descriptive statistics and visual inspections to confirm data continuity, detect structural breaks, and verify that the dataset reflected typical Bitcoin market behavior. These steps ensured a reliable and unbiased foundation for subsequent exploratory and correlation analyses.

3.2. Exploratory Data Analysis (EDA)

The EDA phase aimed to summarize and visualize the characteristics of Bitcoin's market data and technical indicators, ensuring data readiness for statistical analysis. Descriptive statistics such as mean, median, and standard deviation were calculated for each variable, providing insights into central tendency and dispersion. Bitcoin's trading volume showed a high standard deviation, reflecting the inherent volatility of cryptocurrency markets, while RSI values typically ranged between 30 and 70—consistent with overbought and oversold thresholds used in trading practice. The MACD oscillated around zero, confirming its role in detecting trend reversals, and short-period moving averages (e.g., 10-day EMA) displayed greater sensitivity to price changes than longer-term averages, aligning with their theoretical behavior. Visual analyses complemented the descriptive results. Histograms (Figure 2) illustrated that most technical indicators exhibited near-normal distributions with mild skewness during extreme market conditions. Boxplots (Figure 3) highlighted the presence of outliers, especially in trading volume, True Range, and ATR—typically linked to sudden market reactions to news or macroeconomic shocks. These outliers were not removed at this stage but were considered in later interpretations, as they represented genuine market phenomena rather than data errors.

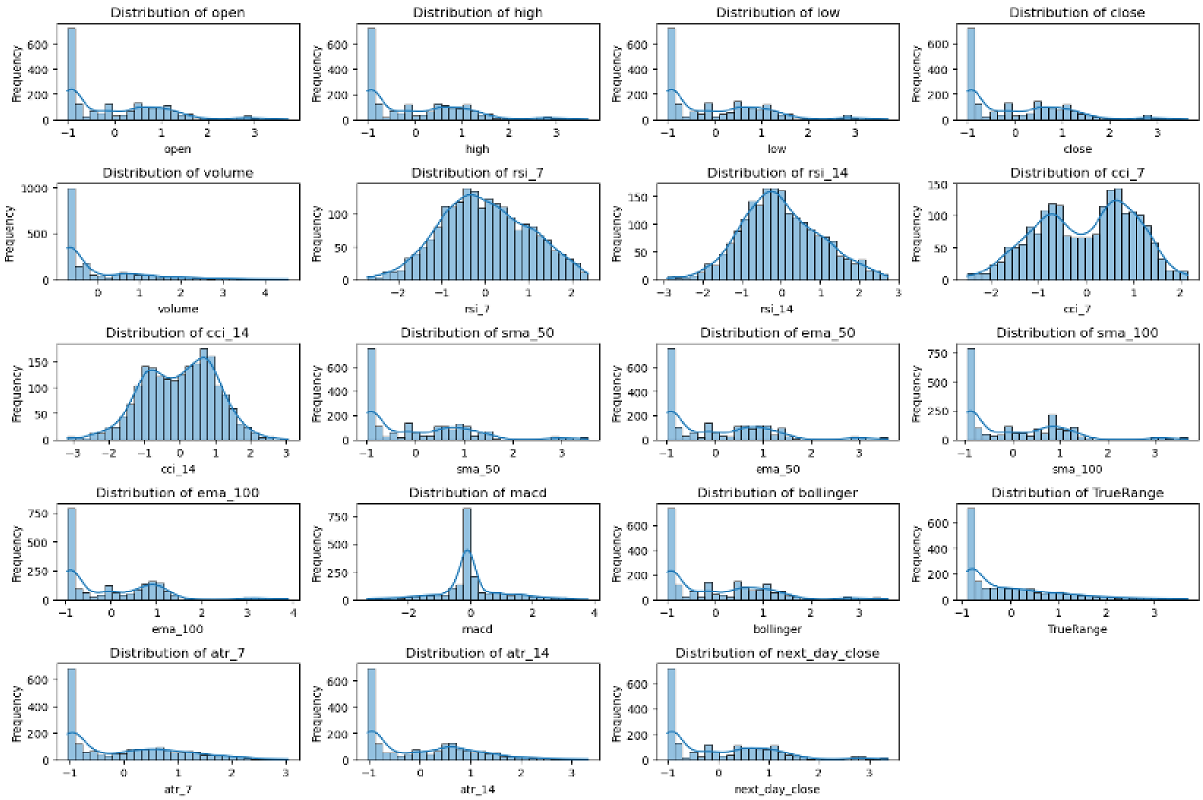

Figure 2. Histograms of Technical Indicator

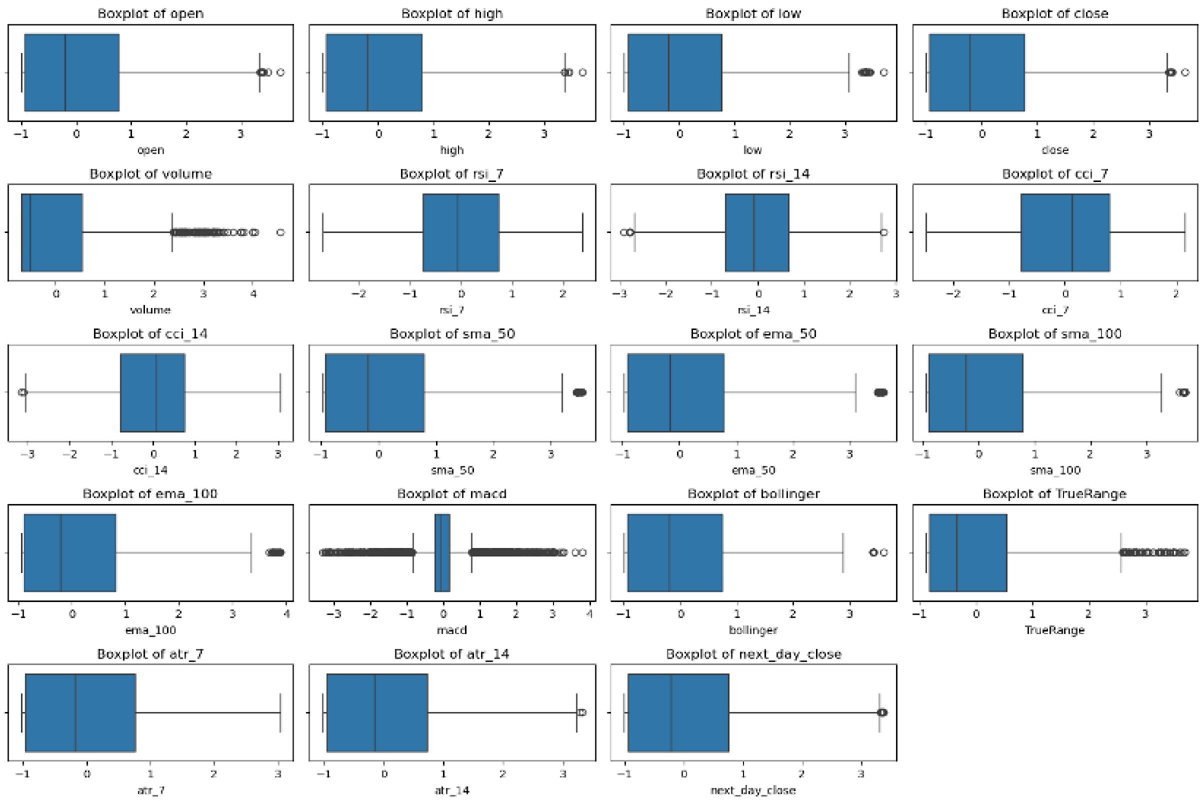

Figure 3. Boxplot of Technical Indicator

3.3. Correlation Analysis

To examine the linear associations between Bitcoin trading volume and key technical indicators, this study employed the Pearson correlation coefficient (r). The coefficient quantifies both the strength and direction of a linear relationship between two continuous variables, expressed as in Equation 2.

$$r = \frac{\sum(X-\bar{X})(Y-\bar{Y})}{\sqrt{\sum(X-\bar{X})^2}\sqrt{\sum(Y-\bar{Y})^2}} \quad (2)$$

where; X and Y represent the two variables under consideration, $\bar{X}$ and $\bar{Y}$ are their respective means, and the numerator captures the covariance between the variables. The Pearson method was selected over non-parametric alternatives such as Spearman's rank correlation because the standardized dataset met assumptions of approximate normality and linearity. Moreover, this study sought to measure direct proportional relationships rather than monotonic trends. Pearson's formulation is well suited for exploring how trading volume covaries with quantitative technical indicators (e.g., RSI, MACD, SMA, EMA, ATR) within a linear analytical framework.

Interpretation of correlation coefficients followed conventional thresholds: values above 0.5 indicated moderate to strong positive association, while those below −0.5 indicated strong inverse relationships. Positive correlations suggested that higher trading volumes coincided with stronger indicator values, consistent with bullish momentum; negative correlations implied that increased trading activity was linked to corrective or bearish phases, as when volume spikes occurred during oversold RSI conditions. To ensure robustness, significance testing was performed for each coefficient using p-values with a 0.05 threshold. The null hypothesis (H_0) stated that no linear relationship existed between trading volume and the given indicator. Correlations with $p < 0.05$ were deemed statistically significant, confirming that the observed relationships were unlikely to occur by chance. Reporting both r and p-values provided a complete picture of the relationships' magnitude and reliability. Significant correlations—such as positive relationships between trading volume and volatility measures (ATR, True Range)—were highlighted as indicators of market participation during volatile periods. Weak or non-significant correlations, particularly with long-term moving averages, suggested independence between trading activity and broader trend measures. This systematic correlation analysis established the statistical foundation for interpreting how volume interacts with technical indicators, advancing empirical understanding of momentum and volatility dynamics in the Bitcoin market.

4. Results and Discussion

4.1. Results of Correlation Analysis

The correlation analysis revealed distinct patterns of association between Bitcoin trading volume and the selected technical indicators. Table 1 summarizes the Pearson coefficients and corresponding p-values, while Figure 4 visualizes these relationships in a correlation heatmap. The coefficients ranged from moderately positive to weakly negative, indicating that some indicators move in tandem with trading activity, whereas others evolve independently.

Table 1. Correlation Coefficients Between Bitcoin Trading Volume and Technical Indicators

Indicator	Correlation with Volume	p-value
RSI (7-day)	0.45	< 0.05
MACD	-0.12	0.15
SMA (50-day)	0.38	< 0.05
EMA (50-day)	0.41	< 0.05
CCI (14-day)	-0.05	0.74
Bollinger Bands	0.32	< 0.05
ATR (14-day)	0.48	< 0.05
True Range	0.30	< 0.05

As shown in Figure 4, several indicators—RSI, SMA, EMA, Bollinger Bands, and ATR—displayed statistically significant positive correlations ($p < 0.05$). The 7-day RSI exhibited the strongest momentum link ($r = 0.45$), implying that surges in trading volume often accompany overbought or oversold phases, when investor sentiment peaks. SMA-50 and EMA-50 correlations ($r = 0.38$ and 0.41) confirm that high-volume periods coincide with trend continuation, reinforcing volume's role as a confirming indicator of price direction. Similarly, Bollinger Bands width and ATR-14 correlations ($r \approx 0.3$–0.5) demonstrate that heavier trading activity typically coincides with wider price ranges and greater volatility.

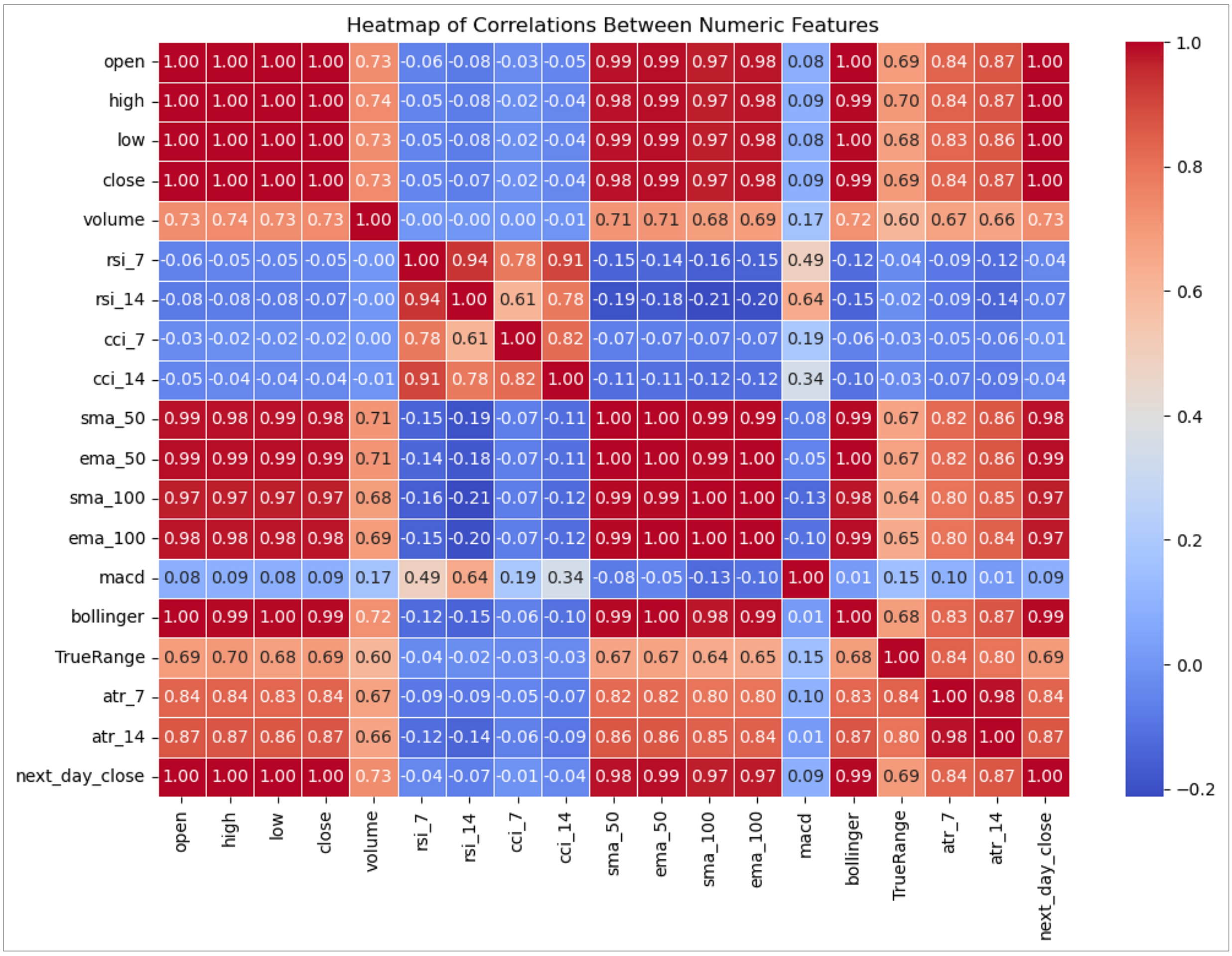

Figure 4. Heatmap of Correlations Between Numeric Features

These relationships are also visible in Figure 5, where spikes in trading volume align with volatile market episodes. By contrast, MACD and CCI showed weak, non-significant associations (r = –0.12 and –0.05). MACD's lagging nature—derived from smoothed exponential averages—means it reacts to price changes after volume has already surged, reducing same-day correlation. CCI, which measures cyclical deviation from a "typical" price, often oscillates without large shifts in participation, explaining its lack of linear linkage. As shown in Figure 6, volume bursts occasionally coincide with MACD crossovers, but this pattern is episodic rather than systematic.

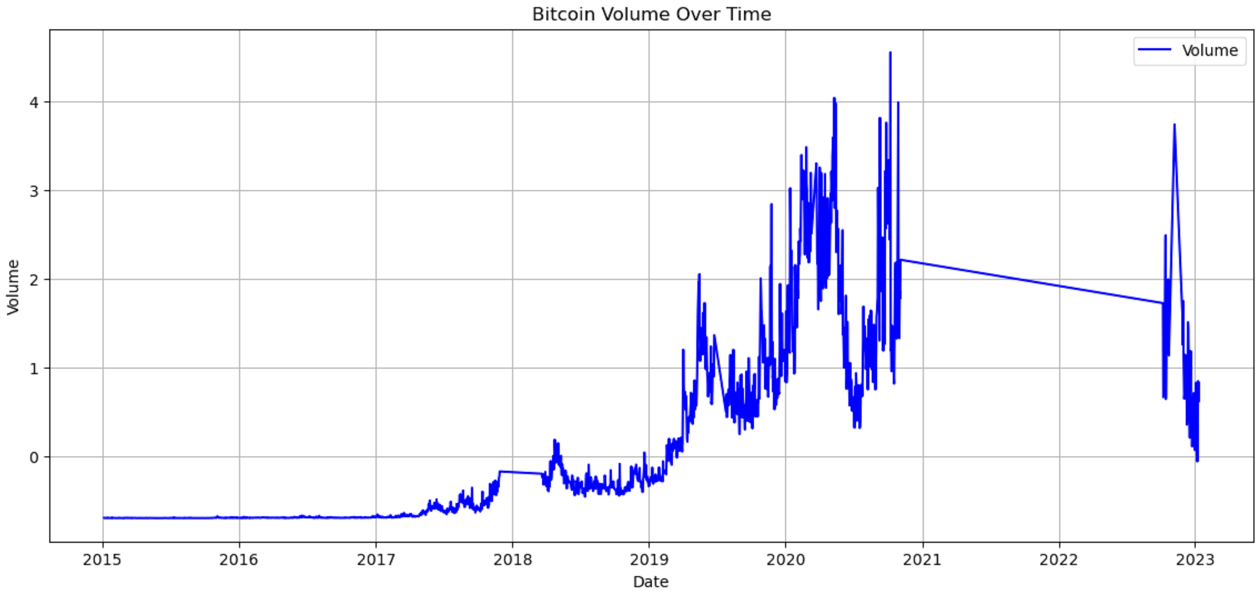

Figure 5. Bitcoin Volume Over Time

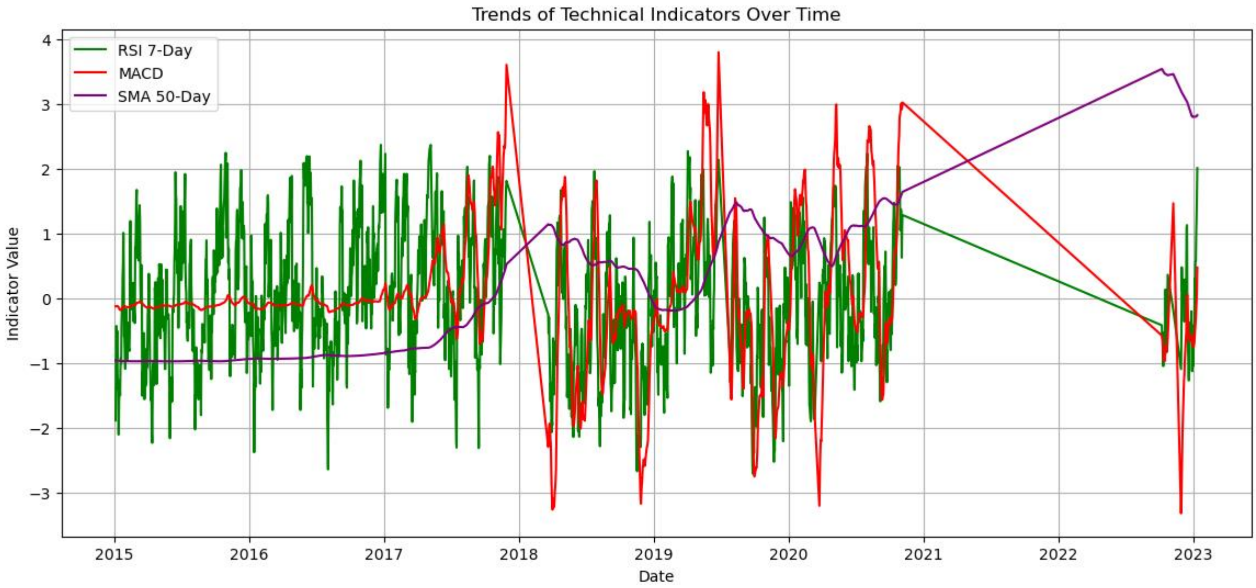

Figure 6. Trends of Technical Indicators Over Time

Overall, these findings highlight two mechanisms: 1) A volume–momentum channel, where participation intensifies alongside short-term trend strength (RSI, SMA, EMA); 2) A volume–volatility channel, where trading activity amplifies price dispersion (ATR, True Range, BB). The mixed outcomes emphasize that volume is a powerful but selective market indicator—strongly confirming momentum and volatility signals, yet less relevant for lagging or mean-reversion measures. This nuanced behavior supports using volume as a complementary input within multi-indicator trading and risk-monitoring frameworks in the Bitcoin market.

4.2. Discussion

The correlation analysis highlights that Bitcoin trading volume exhibits heterogeneous relationships with technical indicators, reflecting the multifaceted dynamics of momentum, volatility, and investor sentiment in cryptocurrency markets. As illustrated in Figures 4–6, indicators responsive to short-term price changes—such as the 7-day RSI, 50-day SMA, and ATR-14—showed significant positive correlations with volume, while lagging or cyclical indicators (MACD, CCI) displayed negligible relationships. These differences underscore that volume interacts most strongly with metrics capturing immediate market participation and risk, whereas smoothed or mean-reverting measures respond more slowly to behavioral shocks. The moderate positive correlation between RSI and volume ($r = 0.45$) suggests that intense trading activity coincides with extremes in market sentiment, consistent with the volume–price relationship theory, where participation surges during overbought or oversold conditions amplify price momentum. This finding supports [15], who confirmed RSI's robustness in volatile crypto environments, and [14], who showed that integrating RSI with additional indicators improves profitability and reduces false positives. Similarly, the significant correlations of SMA-50 and EMA-50 indicate that volume confirms directional persistence, aligning with classical technical analysis and empirical evidence that active participation strengthens existing trends.

The volume–volatility channel is evident in the strong positive relationships between trading volume and volatility indicators (ATR-14 and True Range, $r \approx 0.30$–0.48). As shown in Figure 4, periods of heightened trading volume coincide with expanded price ranges, indicating that information inflow and speculative activity drive simultaneous increases in participation and volatility. This pattern echoes findings by [18, 19], who reported that volume spikes often accompany volatility clustering in cryptocurrency markets. Similarly, the positive correlation with Bollinger Band width reinforces that rising participation reflects widening dispersion, validating the behavioral interpretation of volume as both a signal of investor conviction and a source of market turbulence. By contrast, the weak and non-significant correlations for MACD ($r = –0.12$) and CCI ($r = –0.05$) reveal the selective nature of volume–indicator relationships. The MACD's construction—based on smoothed exponential averages—renders it a lagging indicator, which responds to price changes only after trends are established. Thus, trading volume may spike at or before inflection points, while MACD continues reflecting prior momentum, producing low same-day correlation. Prior work such as [14, 19] found stronger alignment when using lagged or event-window analysis, implying that MACD–volume relationships are time-dependent rather than contemporaneous. Additionally, signal noise in high-frequency trading periods can obscure MACD patterns, as rapid reversals or low-liquidity intervals distort its smoothing function. The CCI's near-zero correlation similarly reflects its mean-reversion design—oscillations around typical price levels that do not necessarily coincide with major shifts in trading participation. These nuances confirm that volume has indicator-specific utility: it reinforces momentum and volatility signals but is less effective for lagging or cyclical oscillators. Overall, two principal behavioral mechanisms emerge 1) A momentum-confirmation channel, where trading volume strengthens short-term price trends captured by RSI, SMA, and EMA; 2) A volatility-amplification channel, where participation surges increase market dispersion, reflected in ATR, True Range, and Bollinger Band width. Both are visible in Figures 5–6, where large volume spikes accompany major directional or volatility shifts. These findings align with information asymmetry theory, suggesting that bursts in trading volume correspond to heterogeneous investor reactions to new information, which heighten both volatility and directional persistence.

The results of this study carry several actionable insights for traders, algorithmic systems, and risk managers. First, momentum confirmation can be improved by integrating volume thresholds into algorithms that utilize RSI or moving-average signals, thereby filtering out low-conviction trades and enhancing precision in high-volatility environments. Second, monitoring the correlation between trading volume and the Average True Range (ATR) can serve as an early warning mechanism for volatility regime changes, enabling traders to tighten stop-loss levels or adjust position sizes proactively. Third, from a portfolio management perspective, sustained uptrends in trading volume that coincide with strong SMA or EMA signals can validate trend-following strategies, while divergences between price trends and volume may indicate potential reversals requiring caution. Finally, for market regulators and exchanges, the observed volume–volatility relationship offers a valuable tool for market surveillance, particularly in detecting speculative bubbles, abnormal trading behavior, or liquidity stress within cryptocurrency markets. Collectively, these implications highlight how understanding volume dynamics can enhance both tactical trading decisions and strategic risk management in blockchain-based financial systems.

The observed relationships are likely phase-dependent. During bullish markets, rising participation tends to magnify price rallies, strengthening volume–momentum correlations; conversely, in bearish or low-liquidity phases, volume may decouple from price indicators as risk aversion dominates. These dynamics mirror findings by Omran et al. [19], who documented regime-specific volume effects in crypto assets. While this study focused on aggregate correlations, future work could extend the analysis using rolling-window or regime-switching models to capture time-varying behavior and assess robustness across market conditions. The results tie back to the theoretical framework of the volume–price–volatility relationship, which posits that volume conveys information about investor expectations and uncertainty. Positive correlations with momentum and volatility indicators validate this link in a blockchain context, showing that volume not only reflects but also amplifies sentiment-driven price movements. However, the heterogeneous results—particularly for MACD and CCI—indicate that this relationship is not uniform, supporting a multi-indicator, data-mining approach where volume complements but does not replace technical signals.

5. Conclusion

This study examined the correlation between Bitcoin trading volume and key technical indicators to uncover how market participation interacts with price momentum and volatility in the blockchain market. The results revealed that trading volume has significant positive associations with the 7-day RSI, 50-day SMA and EMA, and ATR-14, indicating that periods of heightened trading activity correspond to stronger momentum and wider price ranges. These findings confirm that volume functions as a confirming signal for market direction and volatility, validating the behavioral link between participation and price dynamics. Conversely, weak and non-significant correlations for MACD and CCI suggest that volume does not uniformly affect all indicators, particularly those that are lagging or cyclical in nature. Practically, incorporating volume as a complementary variable in momentum-based or volatility-aware trading strategies can enhance timing accuracy and risk control, while the results also caution against relying on volume alone to interpret trend reversals. Overall, the study extends the classical volume–price–volatility framework to cryptocurrency markets, illustrating how participation intensity amplifies both momentum and market turbulence.

Despite these contributions, several limitations should be acknowledged. The analysis relied on a single dataset of historical Bitcoin data and focused on linear correlations, which may not capture the full complexity or regime-specific nature of market behavior. External influences such as macroeconomic factors, sentiment, and liquidity conditions were not explicitly modeled, which could affect the observed relationships. Future research should explore multi-asset and multi-period datasets, applying non-linear, rolling-window, or regime-switching techniques to capture dynamic relationships between volume and indicators across bull and bear markets. Integrating machine learning approaches and sentiment or order-book data could also reveal causal and time-dependent interactions, advancing predictive modeling in blockchain market analytics. Expanding this line of inquiry will help build a more comprehensive understanding of how trading activity, information flow, and behavioral responses jointly shape cryptocurrency price dynamics.

6. Declarations

6.1. Author Contributions

Conceptualization, A.R. and T.H.; methodology, A.R. and T.H.; software, A.R. and T.H.; validation, A.R. and T.H.; formal analysis, A.R. and T.H.; investigation, A.R. and T.H.; resources, A.R. and T.H.; data curation, A.R. and T.H.; writing—original draft preparation, A.R. and T.H.; writing—review and editing, A.R. and T.H.; visualization, A.R. and T.H.; supervision, A.R. and T.H.; project administration, T.H.; funding acquisition, A.R. All authors have read and agreed to the published version of the manuscript.

6.2. Data Availability Statement

The data presented in this study are available on request from the corresponding author.

6.3. Funding

The authors received no financial support for the research, authorship, and/or publication of this article.

6.4. Institutional Review Board Statement

Not applicable.

6.5. Informed Consent Statement

Not applicable.

6.6. Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

7. References

[1] Maidin, S. S. (2025). Analyzing the Evolution of AIGenerated Art Styles Using Time Series Analysis: A Trend Study on NFT Artworks. Journal of Digital Market and Digital Currency, 2(2), 205–229. doi:10.47738/jdmdc.v2i2.32.

[2] Hughes, L., Dwivedi, Y. K., Misra, S. K., Rana, N. P., Raghavan, V., & Akella, V. (2019). Blockchain research, practice and policy: Applications, benefits, limitations, emerging research themes and research agenda. International Journal of Information Management, 49, 114–129. doi:10.1016/j.ijinfomgt.2019.02.005.

[3] Prasetio, A. B., bin Mohd Aboobaider, B., & bin Ahmad, A. (2025). Predicting Customer Conversion in Digital Marketing: Analyzing the Impact of Engagement Metrics Using Logistic Regression, Decision Trees, and Random Forests. Journal of Digital Market and Digital Currency, 2(2), 181-204. doi:10.47738/jdmdc.v2i2.34.

[4] Abbasi, G. A., Tiew, L. Y., Tang, J., Goh, Y. N., & Thurasamy, R. (2021). The adoption of cryptocurrency as a disruptive force: Deep learning-based dual stage structural equation modelling and artificial neural network analysis. PLoS ONE, 16(3 March 2021), 247582. doi:10.1371/journal.pone.0247582.

[5] El Emary, I. M. M. (2024). Classification of Bitcoin Ransomware Transactions Using Random Forest: A Data Mining Approach for Blockchain Security. Journal of Current Research in Blockchain, 2(2), 152–168. doi:10.47738/jcrb.v2i2.33.

[6] Hussain, M. A., Abd Latiff, M. S., Madni, S. H. H., Raja Mohd Rasi, R. Z., & Othman, M. F. I. (2019). Concept of Blockchain Technology. International Journal of Innovative Computing, 9(2). doi:10.11113/ijic.v9n2.238.

[7] Saberi, S., Kouhizadeh, M., Sarkis, J., & Shen, L. (2019). Blockchain technology and its relationships to sustainable supply chain management. International Journal of Production Research, 57(7), 2117–2135. doi:10.1080/00207543.2018.1533261.

[8] Corbet, S., Eraslan, V., Lucey, B., & Sensoy, A. (2019). The effectiveness of technical trading rules in cryptocurrency markets. Finance Research Letters, 31, 32–37. doi:10.1016/j.frl.2019.04.027.

[9] Zhang, W., & Li, Y. (2023). Liquidity risk and expected cryptocurrency returns. International Journal of Finance and Economics, 28(1), 472–492. doi:10.1002/ijfe.2431.

[10] Dewi, D. A. (2025). Analyzing the Impact of Social Media and Influencer Endorsements on Game Revenue using Multiple Linear Regression in the Metaverse. International Journal Research on Metaverse, 2(2), 167–182. doi:10.47738/ijrm.v2i2.29.

[11] Izumi, C. (2024). Analyzing Price Volatility of Hedera Hashgraph Using GARCH Models: A Data Mining Approach. Journal of Current Research in Blockchain, 2(2), 135–151. doi:10.47738/jcrb.v2i2.35.

[12] Saiedi, E., Broström, A., & Ruiz, F. (2021). Global drivers of cryptocurrency infrastructure adoption. Small Business Economics, 57(1), 353–406. doi:10.1007/s11187-019-00309-8.

[13] Turistiati, A. T. (2025). Estimating Player Market Value in Virtual Leagues: A Clustering Approach Using Player Attributes for Metaverse Applications. International Journal Research on Metaverse, 2(2), 154–166. doi:10.47738/ijrm.v2i2.28.

[14] Li, W., Wang, X., Wang, Z., & Yang, M. (2023). Profitability and Data-Snooping Tests of Four Technical Trade Strategies for Cryptocurrency Pair BTC/USDT and ETH/USDT in Cryptocurrency Markets During 2022–2023. Journal of Accounting and Finance, 23(4). doi:10.33423/jaf.v23i4.6453.

[15] Warmayana, I. G. A. K. (2025). Predicting FIFA Ultimate Team Player Market Prices: A Regression-Based Analysis Using XGBoost Algorithms from FIFA 16-21 Dataset. International Journal Research on Metaverse, 2(2), 140–153. doi:10.47738/ijrm.v2i2.25.

[16] Siddique, Q., & Wahid, A. M. (2025). Analyzing Customer Spending Based on Transactional Data Using the Random Forest Algorithm. International Journal for Applied Information Management, 5(2), 111-124. doi:10.47738/ijaim.v5i2.103.

[17] Terentiev, O., Prosiankina-Zharova, T., Savastiyanov, V., Lakhno, V., & Kolmakova, V. (2021). The features of building a portfolio of trading strategies using the SAS OPTMODEL procedure. Computation, 9(7), 77. doi:10.3390/computation9070077.

[18] Bouri, E., Lau, C. K. M., Saeed, T., Wang, S., & Zhao, Y. (2021). On the intraday return curves of Bitcoin: Predictability and trading opportunities. International Review of Financial Analysis, 76. doi:10.1016/j.irfa.2021.101784.

[19] Omran, S. M., El-Behaidy, W. H., & Youssif, A. A. A. (2023). Optimization of Cryptocurrency Algorithmic Trading Strategies Using the Decomposition Approach. Big Data and Cognitive Computing, 7(4), 174. doi:10.3390/bdcc7040174.

[20] Chowdhury, R., Rahman, M. A., Rahman, M. S., & Mahdy, M. R. C. (2020). An approach to predict and forecast the price of constituents and index of cryptocurrency using machine learning. Physica A: Statistical Mechanics and Its Applications, 551. doi:10.1016/j.physa.2020.124569.

[21] Frattini, A., Bianchini, I., Garzonio, A., & Mercuri, L. (2022). Financial Technical Indicator and Algorithmic Trading Strategy Based on Machine Learning and Alternative Data. Risks, 10(12), 225. doi:10.3390/risks10120225.

[22] Balcilar, M., Bouri, E., Gupta, R., & Roubaud, D. (2017). Can volume predict Bitcoin returns and volatility? A quantiles-based approach. Economic Modelling, 64, 74–81. doi:10.1016/j.econmod.2017.03.019.

[23] Hasibuan, M. S. (2025). Market Analysis of NFT Integration in Video Games. Journal of Digital Market and Digital Currency, 2(2), 157–180. doi:10.47738/jdmdc.v2i2.33.

[24] Zhang, Z., Jiang, C., & Lu, M. (2025). Fusion of Sentiment and Market Signals for Bitcoin Forecasting: A SentiStack Network Based on a Stacking LSTM Architecture. Big Data and Cognitive Computing, 9(6), 161. doi:10.3390/bdcc9060161.

[25] Wilder, J. W. (1978). New Concepts in Technical Trading Systems. Trend Research, North Carolina, United States.

[26] Aysan, A. F., Demir, E., Gozgor, G., & Lau, C. K. M. (2019). Effects of the geopolitical risks on Bitcoin returns and volatility. Research in International Business and Finance, 47, 511–518. doi:10.1016/j.ribaf.2018.09.011.

[27] Panigrahi, A. K., Vachhani, K., & Chaudhury, S. K. (2021). Trend identification with the Relative Strength Index (RSI) technical indicator – A conceptual study. Journal of Management Research and Analysis, 8(4), 159–169.

[28] Rosillo, R., Giner, J., Puente, J., & Ponte, B. (2013). Different Stock Market Models Using Support Vector Machines. International Journal of Trade, Economics and Finance, 310–313. doi:10.7763/ijtef.2013.v4.307.

[29] Joshi, D. L. (2022). Use of Moving Average Convergence Divergence for Predicting Price Movements. International Research Journal of MMC, 3(4), 21–25. doi:10.3126/irjmmc.v3i4.48859.

[30] Sarmini, Widiawati, C. R. A., Febrianti, D. R., & Yuliana, D. (2024). Volatility Analysis of Cryptocurrencies using Statistical Approach and GARCH Model a Case Study on Daily Percentage Change. Journal of Applied Data Sciences, 5(3), 838–848. doi:10.47738/jads.v5i3.261.

[31] Jung, H. S., Lee, S. H., Lee, H., & Kim, J. H. (2023). Predicting Bitcoin Trends through Machine Learning Using Sentiment Analysis with Technical Indicators. Computer Systems Science and Engineering, 46(2), 2231-2246. doi:10.32604/csse.2023.034466.

[32] Mazumder, S., Neogy, S., & Das, S. (2023). Simple Moving Average (SMA) Crossover Strategy with Buy Sell Indicator. Asia-Pacific Journal of Management and Technology, 03(04), 26–40. doi:10.46977/apjmt.2023.v03i04.004.

[33] Zatwarnicki, M., Zatwarnicki, K., & Stolarski, P. (2023). Effectiveness of the Relative Strength Index Signals in Timing the Cryptocurrency Market. Sensors, 23(3), 1664. doi:10.3390/s23031664.

[34] Alemerien, K., Al-Ghareeb, A., & Alksasbeh, M. Z. (2024). Sentiment analysis of online reviews: a machine learning based approach with TF-IDF vectorization. Journal of Mobile Multimedia, 20(5), 1089-1116. doi:10.13052/jmm1550-4646.2055.

[35] Vaidya, R. (2020). Accuracy of Moving Average Forecasting for NEPSE. Journal of Nepalese Business Studies, 13(1), 62–76. doi:10.3126/jnbs.v13i1.34706.

[36] Appel, G. (2005). Technical analysis: power tools for active investors. FT Press, Prentice Hall, New Jersey, United States. doi:10.5555/1408581.

[37] Kamalov, F. (2020). Forecasting significant stock price changes using neural networks. Neural Computing and Applications, 32(23), 17655-17667. doi:10.1007/s00521-020-04942-3.

[38] Chong, T., Ng, W.-K., & Liew, V. (2014). Revisiting the Performance of MACD and RSI Oscillators. Journal of Risk and Financial Management, 7(1), 1–12. doi:10.3390/jrfm7010001.

[39] Evelyn, Suryodiningrat, S. P., & Tarigan, M. (2025). K-Means Clustering for Segmenting AI Survey Respondents: Analysis of Information Sources and Impact Perceptions. International Journal for Applied Information Management, 5(1), 58–72. doi:10.47738/ijaim.v5i1.98.