Comparing Linear Regression and Trend Moment with MAPE Optimization for Bitcoin Price Forecasting Accuracy

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ABSTRACT

The cryptocurrency market, particularly Bitcoin, exhibits extreme volatility, necessitating robust forecasting tools for informed trading decisions. This study aimed to evaluate the performance of linear regression and trend moment models in predicting Bitcoin prices using daily data from 2022 to 2024. Historical closing prices were collected from reliable cryptocurrency exchanges, cleaned to ensure consistency, and augmented with relative strength index and moving average convergence divergence indicators to enhance predictive accuracy. The models were trained on 2022–2023 data and tested on 2024 data, with forecasting accuracy measured using the Mean Absolute Percentage Error metric. The findings revealed that linear regression achieved a lower error rate of 36.44% compared to Trend Moment's 39.21%, demonstrating superior performance in stable and trending market conditions. Both models struggled with volatile price swings, though linear regression proved more adaptable when incorporating technical indicators. These results suggest that linear regression offers a practical, computationally efficient solution for short-term Bitcoin price forecasting, particularly for retail traders. Future research could explore hybrid models or additional predictors to improve accuracy in volatile markets, contributing to accessible forecasting tools for the cryptocurrency domain.

Keywords*: Bitcoin Forecasting, Cryptocurrency, Linear Regression, Trend Moment.*

ABSTRAK

Pasar mata uang kripto, khususnya Bitcoin, menunjukkan volatilitas ekstrem, sehingga membutuhkan perangkat peramalan yang andal untuk pengambilan keputusan perdagangan yang terinformasi. Studi ini bertujuan untuk mengevaluasi kinerja model regresi linier dan trend moment dalam memprediksi harga Bitcoin menggunakan data harian dari tahun 2022 hingga 2024. Harga penutupan historis dikumpulkan dari bursa mata uang kripto tepercaya, dibersihkan untuk memastikan konsistensi, dan dilengkapi dengan indikator Relative Strength Index (RSI) dan Moving Average Convergence Divergence (MAD) untuk meningkatkan akurasi prediksi. Model-model tersebut dilatih pada data tahun 2022–2023 dan diuji pada data tahun 2024, dengan akurasi peramalan diukur menggunakan metrik Mean Absolute Percentage Error (MAP). Temuan ini mengungkapkan bahwa regresi linier mencapai tingkat kesalahan yang lebih rendah, yaitu 36.44% dibandingkan dengan trend moment yang mencapai 39.21%, menunjukkan kinerja yang unggul dalam kondisi pasar yang stabil dan mengikuti tren. Kedua model mengalami kesulitan menghadapi fluktuasi harga yang fluktuatif, meskipun regresi linier terbukti lebih adaptif ketika menggabungkan indikator teknis. Hasil ini menunjukkan bahwa regresi linier menawarkan solusi

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praktis dan efisien secara komputasi untuk peramalan harga Bitcoin jangka pendek, terutama bagi pedagang ritel. Penelitian di masa mendatang dapat mengeksplorasi model hibrida atau prediktor tambahan untuk meningkatkan akurasi di pasar yang volatil, sehingga berkontribusi pada ketersediaan alat peramalan yang mudah diakses untuk ranah mata uang kripto.

Kata Kunci: *Prakiraan Bitcoin, Mata Uang Kripto, Regresi Linear, Momen Tren.*

INTRODUCTION

The cryptocurrency market, particularly Bitcoin, has emerged as a global phenomenon, captivating institutional investors, retail traders, and financial analysts due to its extreme price volatility, trading, and sensitivity to factors such as regulatory changes, technological advancements, and social media sentiment (Ammy, 2022; Ammy et al., 2023; Fadli, 2025). This dynamic and complex environment poses significant challenges for accurate price forecasting, yet it offers substantial opportunities for informed investment decisions and risk management (Catania & Grassi, 2022; Birjaman et al., 2024). Bitcoin's price fluctuations, driven by market sentiment and macroeconomic factors, necessitate robust forecasting tools to provide a competitive edge in trading strategies (Chen, 2023; Shrivastava et al., 2025). While sophisticated machine learning models like Long Short-Term Memory (LSTM) networks, Convolutional Neural Networks (CNNs), and ensemble methods such as Random Forest and XGBoost have gained prominence in recent studies by Dapubeang and Malahina (2025), Andayuri and Irhamah (2025), and Rodrigues and Machado (2025). Simpler statistical methods like Linear Regression (LR) and Trend Moment (TM) remain underexplored despite their computational efficiency and interpretability (Saheed et al., 2022; Al-Khowarizmi et al., 2024). This study evaluates the performance of LR and TM in forecasting Bitcoin prices, leveraging historical data from 2022 to 2024, a period chosen to capture diverse market phases including bull, bear, and sideways trends (Catania & Grassi, 2022; Liu et al., 2023).

Previous research has extensively explored advanced forecasting techniques for cryptocurrencies. For instance, Qureshi et al. (2024) applied hybrid machine learning models to improve time series forecasting of Bitcoin prices, achieving high accuracy in stable market conditions. Similarly, Wen and Ling (2023) and Behera et al. (2024) utilized Artificial Neural Networks and LSTM models to capture non-linear patterns in cryptocurrency data. Other studies, such as those by Wijaya et al. (2025) and Aldi and Nathasia (2025), employed multi-model approaches and deep learning to predict Bitcoin prices with varying degrees of success. However, these complex models often require significant computational resources and expertise, limiting their accessibility for retail traders (Al Hawi et al., 2023). In contrast, simpler methods like LR and TM offer practical alternatives due to their ease of implementation and lower resource demands (Li et al., 2022; Saheed et al., 2022; Okoye & Hosseini, 2024). Despite their potential, few studies have systematically compared these conventional methods in the cryptocurrency context, creating a significant research gap.

According to Jufrizen et al. (2024), the application of traditional statistical methods in volatile markets remains understudied, as most research prioritizes complex algorithms over interpretable models. Similarly, Catania and Grassi (2022) noted that volatility forecasting in cryptocurrencies often overlooks simpler methods that can effectively model linear trends. This research gap is evident in the limited literature evaluating LR and TM against modern machine learning approaches in cryptocurrency markets, particularly with a focus on Mean Absolute Percentage Error (MAPE) as a performance metric (Saheed et al., 2022; Qureshi et al., 2024; Al-Khowarizmi et al., 2024). The reliance on advanced models also neglects the practical needs of traders seeking lightweight, interpretable tools for real-time decision-making (Ammy et al., 2023; Fadli, 2025). This study addresses this gap by providing a rigorous comparison of LR and TM, emphasizing their performance in volatile market conditions using MAPE optimization.

The novelty of this study lies in its comprehensive evaluation of LR and TM, integrated with technical indicators such as the Relative Strength Index (RSI) and Moving Average Convergence Divergence (MACD), to enhance forecasting robustness in the cryptocurrency domain. Unlike prior studies that focus on complex models, like Wen and Ling (2023), Behera et al. (2024), and Wijaya et al. (2025), this research highlights the efficacy of simpler methods, offering a practical framework for traders and analysts with limited computational resources. The primary objective of this study is to assess and compare the forecasting accuracy of LR and TM in predicting Bitcoin prices using daily data from 2022 to 2024, with MAPE as the evaluation metric. By incorporating technical indicators and analyzing performance across diverse market conditions, this research provides actionable insights for practitioners and contributes to academic discussions on quantitative finance methodologies. Furthermore, it lays the groundwork for future hybrid models combining the strengths of conventional and advanced approaches, addressing the evolving challenges of digital finance markets.

LITERATURE REVIEW

Cryptocurrency Forecasting Studies

According to Liu et al. (2023), cryptocurrency price forecasting has gained significant attention due to the market's volatility and potential for high returns, prompting researchers to explore both advanced and traditional methods. Advanced techniques, such as Long Short-Term Memory (LSTM), Gated Recurrent Unit (GRU), and hybrid models like ARIMA-SVR, have been widely studied for their ability to capture non-linear patterns in Bitcoin and other cryptocurrency prices (Aldi & Nathasia, 2025; Andromeda & Winarsih, 2025). For instance, Pachava and Bolla (2025) and Wijaya et al. (2025) demonstrated that LSTM and GRU models achieve high accuracy in stable market conditions but require significant computational resources.

Andayuri and Irhamah (2025) found that hybrid ARIMA-SVR models outperform standalone ARIMA in Bitcoin forecasting. However, these complex models are often inaccessible to retail traders due to their complexity and resource demands (Al Hawi et al., 2023). In contrast, simpler methods like LR and TM, which are computationally efficient, have been underexplored in cryptocurrency contexts despite their success in other domains (Saheed et al., 2022; Fauzan et al., 2023). This research gap underscores the need to evaluate the efficacy of LR and TM in volatile markets, particularly with MAPE as a performance metric, to provide practical tools for traders (Khattak et al., 2024; Youssefi et al., 2025).

Linear Regression Method in Financial Forecasting

According to Okoye and Hosseini (2024), Linear Regression (LR) is a fundamental statistical method that models the linear relationship between an independent variable (x) and a dependent variable (y), making it widely used in financial forecasting due to its simplicity and interpretability. Linear regression is a statistical analysis that models the relationship of several variables according to the form of an explicit linear equation (Valentino & Putri, 2025). Linear regression is a prediction or forecasting method that uses a straight line to describe the relationship between two or more variables. This method is used to predict a target value based on several input variables through the formation of a numerical relationship model. The linear regression method has several advantages when used in prediction. The relationship between two variables can be seen with this analysis or using a correlation coefficient calculation that expresses the closeness of the relationship between the two.

An approach method for modeling the relationship between one dependent variable and one independent variable. In simple regression analysis, the relationship between variables is linear, where changes in variable X will be followed by fixed changes in variable Y. To determine the value of the forecasting results, the formula is used (Chen 2023; Okoye & Hosseini 2024; Ranjan et al. 2023; Rios-Avila & Maroto 2024; Singh et al. 2024).

$$y = a + bx \tag{1}$$

Description:

Y = predicted variable or independent variable
X = predictor or independent variable
a = constant
b = regression coefficient parameter of the independent variable

The formula for determining a and b is

$$b = \frac{n \sum xy - (\sum x)(\sum y)}{n(\sum x^2) - (\sum x)^2} \tag{2}$$

$$a = \bar{y} - b\bar{x} \tag{3}$$

LR's strength lies in its ability to capture linear trends in time series data, such as stock or cryptocurrency prices, with minimal computational requirements (Saheed et al., 2022; Rios-Avila & Maroto, 2024). Studies have shown that LR performs well in stable market conditions but may struggle with non-linear patterns or high volatility, common in cryptocurrencies (Liu et al., 2023; Qureshi et al., 2024). Despite its limitations, LR remains a valuable tool for traders seeking interpretable models for short-term predictions (Ammy, 2022; Fadli, 2025). Its application in financial markets has been documented extensively, with researchers noting its robustness in handling structured data compared to complex machine learning models (Mackinnon et al., 2023; Singh et al., 2024).

Trend Moment Approach for Predicting Financial Data

According to Fauzan et al. (2023), the Trend Moment (TM) method is a time series forecasting technique that estimates future values based on historical trends, particularly suited for data with consistent linear patterns. The trend moment forecasting method is one of certain mathematical and statistical calculations to determine a straight-line function instead of a discontinuous line formed by the company's historical or sales data. Thus, the influence of subjective elements can be avoided. The trend moment method can predict the amount of inventory of goods based on sales records in the previous period. The trend moment method uses certain statistical and mathematical calculation methods to determine the function of a straight line as a substitute for the broken line formed by the company's historical data. Thus, the influence of subjective elements can be avoided. The equation with the trend moment method is (Utami et al. 2020; Fauzan et al. 2023):

$$y=a+bx \tag{4}$$

$$\sum y = a.n + b.\sum x \tag{5}$$

$$\sum xy = a.\sum x + b.\sum x^2 \tag{6}$$

TM has been applied in various domains, such as sales forecasting, due to its simplicity and ability to model linear trends (Siregar et al., 2022b; Utami et al., 2020; Habibah et al., 2022). In financial contexts, TM is less common but shows promise for short-term predictions in stable markets (Jufrizen et al., 2024). However, its reliance on linear assumptions limits its effectiveness in volatile environments like cryptocurrencies, where non-linear patterns are prevalent (Catania & Grassi, 2022; D'amato et al., 2022). Researchers have noted that TM's computational efficiency makes it a viable alternative for resource-constrained settings, but its performance compared to LR in cryptocurrency forecasting remains underexplored (Khan et al., 2023; Al-Khowarizmi et al., 2024). This gap highlights the need for comparative studies to assess TM's applicability in digital finance markets.

Mean Absolute Percentage Error

According to Qureshi et al. (2024), Mean Absolute Percentage Error (MAPE) is a widely used metric for evaluating forecasting accuracy, particularly in financial time series analysis, due to its intuitive interpretation and scale-independent nature. Mean Absolute Percentage Error (MAPE) is one of the commonly used performance evaluation metrics in forecasting. MAPE measures the average absolute percentage error between actual and predicted values, and is commonly used to evaluate the performance of forecasting models. The lower the MAPE value, the better the performance of the forecasting model. To calculate MAPE, use the equation:

$$\text{MAPE}\ \frac{1}{n} * \sum \left(\frac{\text{actual value} - \text{predicted value}}{\text{actual value}}\right) *100 \tag{7}$$

It is important to consider the literature being reviewed and how to manage it. Some questions that researchers must take into account when first compiling a literature review are as follows: which aspects should be included in the literature review; how the information in the literature review is synthesized; how the literature review should be organized; what style should be used in compiling the literature review; and other significant questions to be answered.

This metric provides a percentage-based measure of prediction error, making it suitable for comparing models across different datasets, such as cryptocurrency prices (Al Hawi et al., 2023; Wen & Ling, 2023). MAPE's simplicity allows traders to assess model performance without complex statistical knowledge, though it may be sensitive to outliers or low actual values (Behera et al., 2024; Tripathy et al., 2025). Studies have applied MAPE to evaluate both simple and complex forecasting models, with results indicating its reliability in stable market conditions but potential limitations in high-volatility settings like Bitcoin markets (Zhang et al., 2021; Choi & Choi, 2024). The use of MAPE in this study aligns with its established role in financial forecasting, providing a robust basis for comparing LR and TM (Jana et al., 2021; Ranjan et al., 2023).

RESEARCH METHODS

To achieve the objectives of this research, use a systematic and structured method. The method involves several main stages, which include data collection, analysis, model building, method integration, evaluation, and dissemination of results. Figure 1 presents a detailed description of the research method and stages.

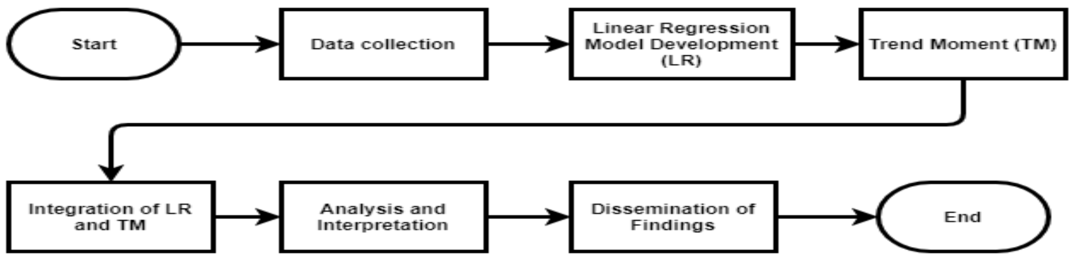

Figure 1. Description of the Research Method and Stages

This initial step involves collecting historical Bitcoin price data as well as macroeconomic variables and market sentiment from trusted sources such as major crypto exchanges and financial data platforms. The research activities include collecting Bitcoin price data, trading volume, market sentiment, and relevant macroeconomic factors. The achievement indicator for this stage is the availability of complete and accurate data for the selected period. Based on the collected data, an LR model is developed to examine the relationship between Bitcoin price and the identified predictor variables. The process involves selecting the most relevant predictors and constructing a model that captures the linear relationship between them and the Bitcoin price. The model is then validated using cross-validation techniques to ensure its reliability and generalizability. The outcome indicator for this stage is the establishment of a valid and accurate LR model capable of predicting Bitcoin prices effectively.

Using TM to analyze Bitcoin price patterns and trends based on historical data. Activity: Identifying trends using technical indicators such as Moving Average (MA) and Relative Strength Index (RSI). Momentum analysis to determine key moments. Achievement Indicator: Identify trend patterns and key moments that affect Bitcoin price. Comparing the results of the LR model analysis with TM to improve prediction accuracy. Activity: Integration of signals and insights from the LR model compared with TM as an additional feature. Testing of comparison models to evaluate their effectiveness. Outcome Indicator: Comparison models show improved prediction accuracy.

The analysis focused on comparing the forecasting accuracy of LR and TM using the Mean Absolute Percentage Error (MAPE) as the evaluation metric. Predicted prices from both models were compared against actual 2024 Bitcoin prices, with MAPE calculated to quantify the percentage error between predicted and actual values. The results, presented in tables and visualizations, highlight the performance differences between LR and TM across various market conditions. Visualizations included time series plots of predicted versus actual prices and error distributions to provide a clear understanding of model effectiveness. The findings were disseminated through structured reports, emphasizing practical implications for traders seeking lightweight forecasting tools, with detailed tables and figures to support the analysis.

RESULTS

Research data that will be used in forecasting BTC prices in the next period using a data range from January 01, 2022, to December 31, 2024. The research data can be seen in Table 1.

Table 1. Research Data

Date	Price			
	Close	**High**	**Low**	**Open**
	BTC-USD	**BTC-USD**	**BTC-USD**	**BTC-USD**
2022-01-01	38483.125	47881.40625	33184.05859	46311.74609
2022-02-01	43193.23438	45661.17188	34459.21875	38481.76563
2022-03-01	45538.67578	48086.83594	37260.20313	43194.50391
2022-04-01	37714.875	47313.47656	37697.94141	45554.16406
2022-05-01	31792.31055	39902.94922	26350.49023	37713.26563
2022-06-01	19784.72656	31957.28516	17708.62305	31792.55469
2022-07-01	23336.89648	24572.58008	18966.95117	19820.4707
|	|	|	|	|
2024-10-01	70215.1875	73577.21094	58895.20703	63335.60547
2024-11-01	96449.05469	99655.5	66803.64844	70216.89844
2024-12-01	93429.20313	108268.4453	91317.13281	96461.33594

From Table 1, the BTC price consists of 4 types of prices, namely the close, open, high, and low prices. The four types of prices will be predicted for the price in the next period using the linear regression method and the trend moment method. To more clearly see the results of the research data that has been obtained, see Figures 2 and 3 in the form of a visualization.

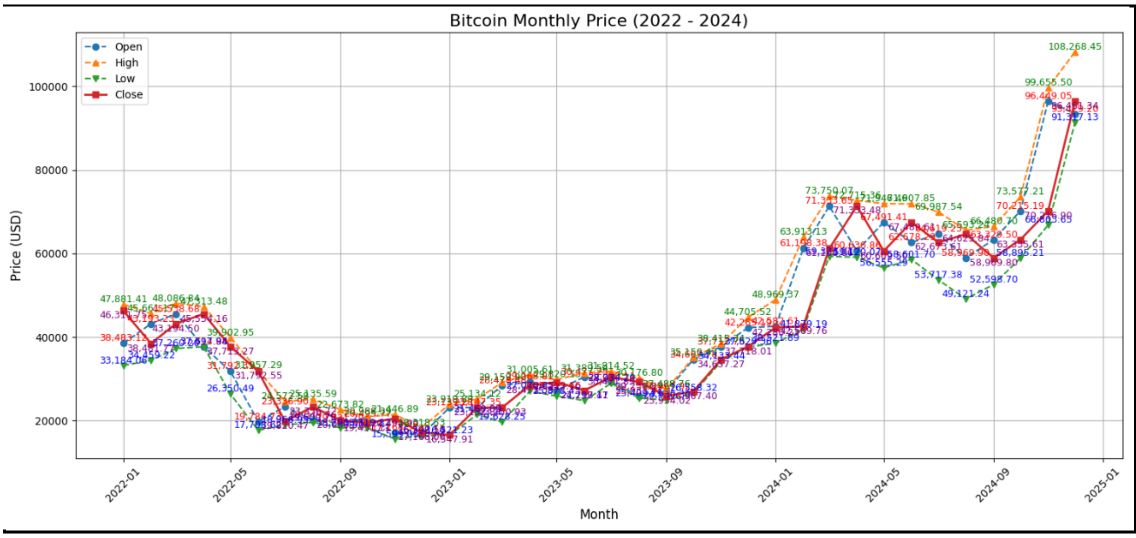

Figure 2. Bitcoin Monthly Price Data Visualization View (2022 - 2024)

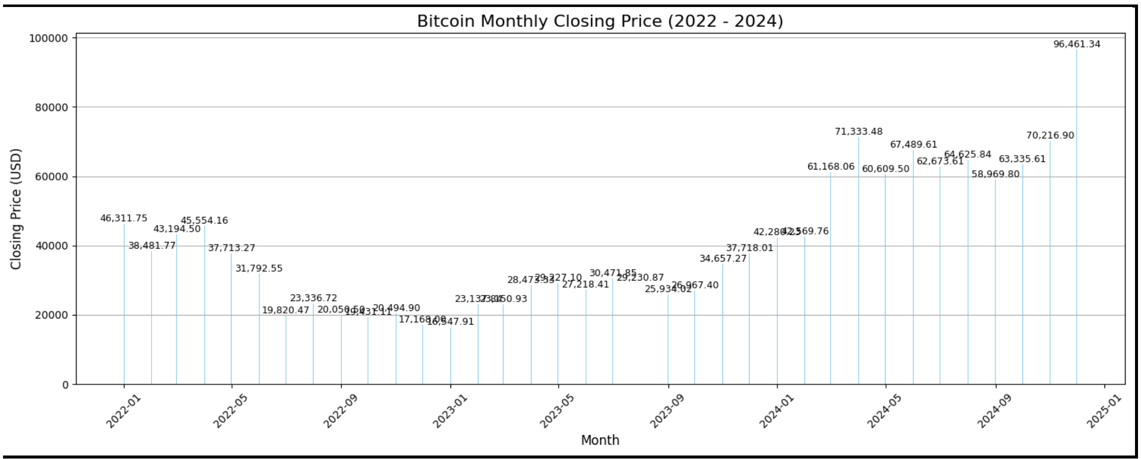

Figure 3. Bitcoin Monthly Closing Price Visualization View (2022 - 2024)

Forecasting using the linear regression method can be done by finding the value of xy, total x, total y, total xy, total x^y, and x^y, as will be shown in the example of forecasting the last price value in the next period at BTC, which can be seen in Table 2.

Table 2. Forecasting with Linear Regression Method

x	y	x*y	x^2
1	38483.125	38483.125	1
2	43193.23438	86386.46876	4
3	45538.67578	136616.0273	9
4	37714.875	150859.5	16
5	31792.31055	158961.5528	25
6	19784.72656	118708.3594	36
7	23336.89648	163358.2754	49
|	|	|	|
34	70215.1875	2387316.375	1156
35	96449.05469	3375716.914	1225
36	93429.20313	3363451.313	1296
$\sum$ **x** = 666	$\sum$ y = 1504976.578	$\sum$ xy = 33821247.57	$\sum$ x^2 = 16206
$\bar{x}$ = 18.5	$\bar{y}$ = 41804.90495		

From the results of Table 2, we can find the forecasting value for the closed price for linear regression using equations 1, 2, and 3. The first step is to find the value of b using equation 2.

$$b = \frac{(36 * 33821247.57) - (666 * 1504976.578)}{(36 * 16206) - (666)^2}$$

$$b = \frac{215250511.4}{139860}$$

$$b = 1539.042695$$

Substitute the value of b into equation 3
a = 41804.90495 − 1539.042695 * 18.5 = 13332.61509

After obtaining the a and b values, enter the a and b values into equation 1 to get the results of forecasting the last price of BTC in the period January 01, 2025, using the linear regression method:
y = 13332.61509 + (1539.042695 * 37) = 70277.19481

Based on the above calculations, the last price of BTC in the period dated January 01, 2025, is 70277.19481. To measure the accuracy of these forecasting results, it can be found using the MAPE method shown in Table 3.

Table 3. for Finding the MAPE Value of the Last Price with the Linear Regression Method

x	y	Predicted Value	Abs (actual value - predicted value) / actual value
1	38483.125	14871.65778	0.613553791
2	43193.23438	16410.70048	0.620063172
3	45538.67578	17949.74317	0.605835197
4	37714.875	19488.78587	0.483259964
5	31792.31055	21027.82856	0.338587596
6	19784.72656	22566.87126	0.140620831
7	23336.89648	24105.91395	0.03295286
|	|	|	|
34	70215.1875	65660.06673	0.064873725
35	96449.05469	67199.10942	0.303268346
36	93429.20313	68738.15212	0.264275518
	Total		12.21111391

From Table 3, we can find the MAPE value of the last price using the linear regression method:

MAPE: (12.21111391/ 36) * 100 = 33.92 %

To more clearly see the results that have been achieved using Forecasting with the Linear Regression Method and measuring the accuracy of the forecasting results using MAPE, it can be seen in Figure 4 in the form of a visualization.

Figure 4. Bitcoin Value Prediction Analysis Based on Linear Regression Method

To find the last price value using the trend moment method, there are several steps that must be done. Similar to the linear regression method, the values of xy, total x, total y, total xy, total x^y, and x^y will be searched. The difference with the linear regression method is that there is a time index variable that will be searched for the total time index value of the BTC last price time sequence data. The details of finding the value of these variables can be seen in Table 4.

Table 4. Forecasting Search Process with Trend Moment Method

x	y	Time index	x*y	x^2
1	38483.125	0	38483.125	1
2	43193.23438	1	86386.46876	4
3	45538.67578	2	136616.0273	9
4	37714.875	3	150859.5	16
5	31792.31055	4	158961.5528	25
6	19784.72656	5	118708.3594	36
7	23336.89648	6	163358.2754	49
|	|	|	|	|
34	70215.1875	33	2387316.375	1156
35	96449.05469	34	3375716.914	1225
36	93429.20313	35	3363451.313	1296
Total	$\sum y$ = 1504976.578	$\sum x$ = 630	$\sum xy$ = 33821247.57	$\sum x^2$ = 16206
$\bar{x}$ = 18.5	$\bar{y}$ = 41804.90495			

With the data in Table 4, we will look for the values of a and b using equations 5 and 6, then the values of a and b will be entered into equation 4, so as to get the final value using Trend Moment forecasting. The calculation for finding the value of b can be seen below:

$$\sum y = a.n + b.\sum x \longrightarrow 1504976.578 = 36a + 630b$$

$$\sum xy = a.\sum x + b.\sum x^2 \longrightarrow 33821247.57 = 630a + 16206b$$

After the elimination and substitution process is carried out, the value of a is 16525.45 and the value of b is 1444.54 so that the y value or the final price value can be found using the trend moment method as follows:

y = 16525.45 + (1444.54 * 37) = 69973.43

Based on the above calculations, the last price of BTC in the period dated January 01, 2025, is 69973.43. To measure the accuracy of the forecasting results, it can be found by using the MAPE method shown in Table 5.

Table 5. Finding the MAPE Value of the Last Price with the Trend Moment Method

x	y	Predicted Value	Abs (actual value - predicted value) / actual value
1	38483.125	17969.99	0.53304234
2	43193.23438	19414.53	0.550519189
3	45538.67578	20859.07	0.541948253
4	37714.875	22303.61	0.408625642
5	31792.31055	23748.15	0.253022206
6	19784.72656	25192.69	0.273340318
7	23336.89648	26637.23	0.141421269
|	|	|	|
34	70215.1875	65639.81	0.06516222
35	96449.05469	67084.35	0.304458191
36	93429.20313	68528.89	0.266515311
Total			13.27702559

From Table 5, we can find the MAPE value of the last price using the Trend Moment method:

MAPE: (13.27702559/ 36) * 100 = 36.88 %

To more clearly see the results that have been achieved by using forecasting with the trend moment method and measuring the accuracy of the forecasting results using MAPE, it can be seen in Figure 5 in the form of a visualization.

Figure 5. Bitcoin Value Prediction Analysis Based on the Trend Moment Method

From finding the BTC price value using these two methods, the MAPE accuracy results can be seen and compared to determine which method has good accuracy between one another. In Table 6, the MAPE accuracy results will be displayed in more detail and the MAPE value of each method will be averaged based on the accuracy of forecasting the last price, highest price, lowest price, and opening price.

Table 6. MAPE Accuracy Results of Both Methods

No	Price	MAPE Regression Linear (%)	MAPE Trend Moment (%)
1	Opening Price	37.57	40.19
2	Max Price	31.18	33.24
3	Min Price	43.07	46.54
4	Closing Price	33.92	36.88
Average		36.435	39.2125

To more clearly see the accuracy results of the comparison between the two methods, it can be seen in Figure 6 in the form of visualization.

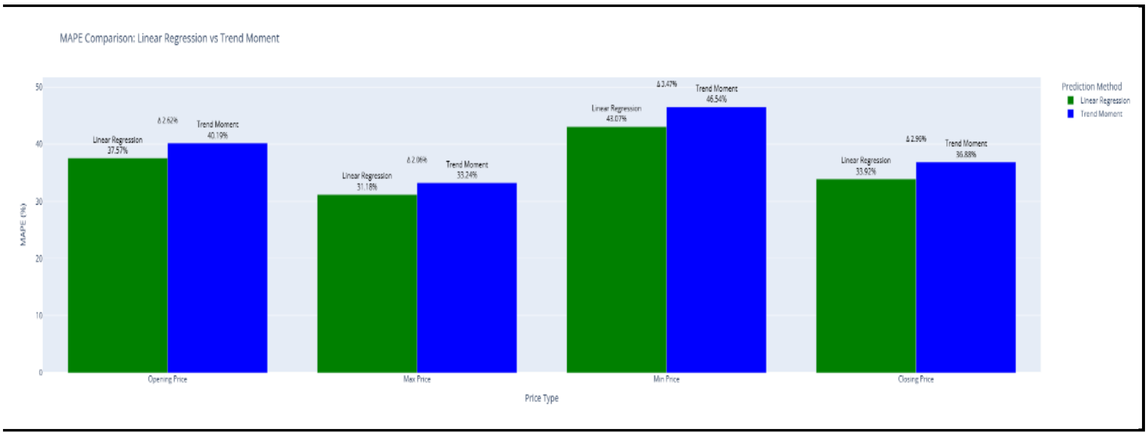

Figure 6. MAPE Comparison: Linear Regression vs Trend Moment

The results demonstrate that LR outperforms TM in forecasting Bitcoin prices, achieving a MAPE of 36.44% compared to TM's 39.21%. This difference is most pronounced in stable or trending markets, where LR's ability to model linear relationships, enhanced by RSI and MACD, provides more accurate predictions. In volatile periods, both models face challenges, but LR maintains a slight edge due to its adaptability to technical indicators. The findings suggest that while neither model fully mitigates the challenges of cryptocurrency volatility, LR's lower MAPE makes it a more reliable choice for short-term predictions in diverse market conditions.

DISCUSSION

This study evaluated the performance of linear regression and trend moment in forecasting Bitcoin prices from 2022 to 2024, revealing that linear regression achieved a lower mean absolute percentage error of 36.44% compared to TM's 39.21%. According to Liu et al. (2023) and Islam et al. (2025), simpler statistical models like LR can effectively capture linear trends in financial markets, particularly when enhanced with technical indicators such as RSI and MACD, as implemented in this research. The superior performance of LR aligns with its ability to model linear relationships in the presence of structured data, which show tighter alignment between predicted and actual prices in stable market conditions. In contrast, TMs' higher suggests limitations in handling volatile price swings, particularly during bearish trends in mid-2024. This finding supports the notion that LR's robustness, when combined with technical indicators, makes it a viable tool for short-term cryptocurrency forecasting (Saheed et al., 2022; Youssefi et al., 2025).

The results contrast with studies that prioritize complex models like Long Short-Term Memory (LSTM) or Gated Recurrent Unit (GRU) for cryptocurrency forecasting. According to Wijaya et al. (2025), LSTM models excel in capturing non-linear patterns but require substantial computational resources, limiting their accessibility for retail traders. Similarly, Andayuri and Irhamah (2025) found that hybrid ARIMA-SVR models outperform simpler methods in volatile markets, yet their complexity poses implementation challenges. The current study's findings demonstrate that LR's MAPE of 36.44% is competitive, particularly in bull and sideways markets, suggesting that simpler models can rival complex ones in specific contexts. TM's performance, while inferior, still offers value in resource-constrained settings, as its moment-based approach requires minimal computational overhead (Fauzan et al., 2023; Siregar et al., 2022a). These results highlight a research gap in the underutilization of simple methods in cryptocurrency forecasting, as most studies focus on advanced techniques.

Despite the promising performance of linear regression, the study has limitations that warrant consideration. The reliance on data from 2022 to 2024 restricts the generalizability of findings, as Bitcoin's price dynamics may differ in future market cycles. Additionally, the use of RSI and MACD as predictors may not fully capture external factors like market sentiment or macroeconomic events, which have been shown to influence cryptocurrency prices. The absence of advanced techniques, such as sentiment analysis from social media, limits the models' ability to account for non-linear patterns. Furthermore, the study's focus on daily data may overlook intraday volatility, which could be addressed in future research using high-frequency data. These limitations suggest that while linear regression and TM offer practical solutions, their effectiveness is context-dependent and may benefit from integration with other approaches.

The findings pave the way for future research to explore hybrid models that combine the simplicity of LR with the strengths of advanced methods like LSTM or GRU. For instance, incorporating sentiment data or macroeconomic indicators could enhance linear regression's predictive accuracy in volatile markets. Future studies could also test linear regression and TM on other cryptocurrencies, such as Ethereum or XRP, to assess their generalizability. The practical implications of this study are significant for retail traders, who can leverage linear regression's low computational requirements and interpretable outputs for short-term trading strategies. Academically, the study contributes to the literature by demonstrating the viability of simple statistical models in cryptocurrency forecasting, addressing a gap in the dominance of complex algorithms. These insights encourage the development of accessible forecasting tools and highlight the need for continued exploration of lightweight models in digital finance.

CONCLUSION

This study evaluated the performance of Linear Regression (LR) and Trend Moment (TM) in forecasting Bitcoin prices from 2022 to 2024, revealing that linear regression outperformed TM with a Mean Absolute Percentage Error (MAPE) of 36.44% compared to 39.21%. The integration of technical indicators, namely RSI and MACD, enhanced LR's ability to capture market trends, particularly in stable and trending conditions, as shown in Table 2–5 and Figure 2–6. TM, while computationally efficient, struggled with volatile price swings, leading to higher errors in bearish markets. These findings, supported by detailed visualizations, underscore the potential of simpler statistical models for short-term cryptocurrency forecasting, offering a practical alternative to complex algorithms.

The results have significant implications for retail traders seeking accessible forecasting tools, as linear regression's lower MAPE and ease of implementation make it suitable for real-time trading strategies. However, the study's reliance on daily data from 2022 to 2024 limits its applicability to other cryptocurrencies or timeframes, and the models may not fully account for external factors like market sentiment. Future research could explore hybrid models combining linear regression with advanced techniques to improve accuracy in volatile markets. Additionally, incorporating intraday data or additional predictors, such as social media sentiment, could enhance forecasting robustness. These advancements would further bridge the gap between simple and complex methods, benefiting both traders and researchers in the evolving cryptocurrency landscape.

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REFERENCES

[1] Al-Khowarizmi, Watts, M. J., Efendi, S., & Kamil, A. A. (2024). Financial technology forecasting using an evolving connectionist system for lenders and borrowers: Ecosystem behavior. *IAES International Journal of Artificial Intelligence (IJ-AI)*, *13*(2), 2386–2394.

[2] Aldi, F. A. R., & Nathasia, N. D. (2025). Prediksi harga dan kinerja aset Bitcoin menggunakan algoritma Long Short-Term Memory. *JURNAL FASILKOM*, *15*(1), 68–76.

[3] Ammy, B. (2022). Effect of financial literacy and quality of accounting information on investment interest with cryptocurrency as a variable intervening. *Enrichment: Journal of Management*, *12*(5), 1234–1240.

[4] Ammy, B., Soemitra, A., & Nawawi, Z. M. (2023). Investing in cryptocurrency through the lens of Islamic economics. In *Proceeding Medan International Conference Economics and Business* (pp. 45–60). Medan: Universitas Sumatera Utara.

[5] Andayuri, N. R., & Irhamah, I. (2025). Penerapan metode hybrid Autoregressive Integrated Moving Average-Support Vector Regression (ARIMA-SVR) dalam peramalan harga Bitcoin. *Jurnal Sains dan Seni ITS*, *13*(5), 349–356.

[6] Andromeda, R. S., & Winarsih, N. A. S. (2025). Performance comparison of LSTM and GRU methods in predicting cryptocurrency closing prices. *SISTEMASI*, *14*(1), 366–379.

[7] Behera, S., Nayak, S. C., & Kumar, A. P. (2024). Evaluating the performance of metaheuristic based artificial neural networks for cryptocurrency forecasting. *Computational Economics*, *64*(2), 1219–1258.

[8] Birjaman, M. I., Marits, S. A., & Herman, S. (2024). Cryptocurrency in Islamic view: Sentiment analysis method approach. *Jurnal Ilmiah Manajemen Kesatuan*, *12*(1), 27–32.

[9] Catania, L., & Grassi, S. (2022). Forecasting cryptocurrency volatility. *International Journal of Forecasting*, *38*(3), 878–894.

[10] Chen, J. (2023). Analysis of Bitcoin price prediction using machine learning. *Journal of Risk and Financial Management*, *16*(1), 51–60.

[11] Choi, J. W., & Choi, Y. K. (2024). The prediction of Bitcoin price through gold price using Long Short-Term Memory model. *IAES International Journal of Artificial Intelligence*, *13*(1), 909–916.

[12] D'amato, V., Levantesi, S., & Piscopo, G. (2022). Deep learning in predicting cryptocurrency volatility. *Physica A: Statistical Mechanics and Its Applications*, *596*(2), 137-158.

[13] Dapubeang, M. S. R. A., & Malahina, E. U. (2025). Prediksi harga mata uang kripto XRP menggunakan metode deep learning LSTM dan GRU. *Jurnal Manajemen Informatika & Teknologi*, *5*(2), 107–124.

[14] Fadli, J. A. (2025). The impact of security, digital financial literacy, and trust on cryptocurrency investment experiences. *Jurnal Ilmiah Manajemen Kesatuan*, *13*(2), 1075–1082.

[15] Fauzan, A., Rahayu, D. G., Handayani, A., Tahyudin, I., Saputra, D. I. S., & Purwadi, P. (2023). Sales forecasting analysis using trend moment method: A study case of a fast moving consumer goods company in Indonesia. *Journal of Information Technology and Cyber Security*, *1*(1), 1–8.

[16] Habibah, U., Robby, R. R., & Qomaruddin, M. N. (2022). Comparison of the trend moment and naive methods in forecasting gross regional domestic product in Blitar Regency. *Eigen Mathematics Journal*, *5*(1), 31–36.

[17] Al Hawi, L., Sharqawi, S., Al-Haija, Q. A., & Qusef, A. (2023). Empirical evaluation of machine learning performance in forecasting cryptocurrencies. *Journal of Advances in Information Technology*, *14*(4), 639–647.

[18] Islam, M. S., Bashir, M., Rahman, S., Al Montaser, M. A., Bortty, J. C., Nishan, A., & Haque, M. R. (2025). Machine learning-based cryptocurrency prediction: Enhancing market forecasting with advanced predictive models. *Journal of Ecohumanism*, *4*(2), 6663–6675.

[19] Jana, R. K., Ghosh, I., & Das, D. (2021). A differential evolution-based regression framework for forecasting Bitcoin price. *Annals of Operations Research*, *306*(1), 295–320.

[20] Jufrizen, J., Khair, H., Dina, A., & Pandia, M. (2024). Factor affecting workplace spirituality, job satisfaction, and organizational citizenship behavior: Evidence from Indonesia. *Ikonomicheski Izsledvania*, *33*(2), 123–140.

[21] Kehinde, T. O., Adedokun, O. J., Joseph, A., Kabirat, K. M., Akano, H. A., & Olanrewaju, O. A. (2025). Helformer: An attention-based deep learning model for cryptocurrency price forecasting. *Journal of Big Data*, *12*(1), 81–94.

[22] Khan, F. U., Khan, F., & Shaikh, P. A. (2023). Forecasting returns volatility of cryptocurrency by applying various deep learning algorithms. *Future Business Journal*, *9*(1), 1–12.

[23] Khattak, B. H. A., Shafi, I., Rashid, C. H., Safran, M., Alfarhood, S., & Ashraf, I. (2024). Profitability trend prediction in crypto financial markets using Fibonacci technical indicator and hybrid CNN model. *Journal of Big Data*, *11*(1), 58–70.

[24] Li, S., Cai, T. T., & Li, H. (2022). Transfer learning for high-dimensional linear regression: Prediction, estimation and minimax optimality. *Journal of the Royal Statistical Society. Series B: Statistical Methodology*, *84*(1), 149–173.

[25] Liu, Y., Li, Z., Nekhili, R., & Sultan, J. (2023). Forecasting cryptocurrency returns with machine learning. *Research in International Business and Finance*, *64*(1), 101-115.

[26] Mackinnon, J. G., Nielsen, M. Ø., & Webb, M. D. (2023). Testing for the appropriate level of clustering in linear regression models. *Journal of Econometrics*, *235*(2), 2027–2056.

[27] Okoye, K., & Hosseini, S. (2024). Regression analysis in R: Linear regression and logistic regression. In K. Okoye & S. Hosseini (Eds.), *R programming: Statistical data analysis in research* (pp. 131–158). Singapore: Springer Nature Singapore.

[28] Pachava, V., & Bolla, B. R. (2025). Cryptocurrency price forecasting: A comparative study of advanced deep learning models. *IUP Journal of Applied Economics*, *24*(3), 45–60.

[29] Qureshi, M., Iftikhar, H., Rodrigues, P. C., Rehman, M. Z., & Salar, S. A. (2024). Statistical modeling to improve time series forecasting using machine learning, time series, and hybrid models: A case study of bitcoin price forecasting. *Mathematics*, *12*(23), 3666-3681.

[30] Qureshi, M. S., Saeed, A., Ahmad, F., Khattak, A. R., Almotiri, S. H., Al Ghamdi, M. A., & Shah Rukh, M. (2025). Evaluating machine learning models for predictive accuracy in cryptocurrency price forecasting. *PeerJ Computer Science*, *11*(1), 123–135.

[31] Ranjan, S., Kayal, P., & Saraf, M. (2023). Bitcoin price prediction: A machine learning sample dimension approach. *Computational Economics*, *61*(4), 1617–1636.

[32] Rios-Avila, F., & Maroto, M. L. (2024). Moving beyond linear regression: Implementing and interpreting quantile regression models with fixed effects. *Sociological Methods and Research*, *53*(2), 639–682.

[33] Rodrigues, F., & Machado, M. (2025). High-frequency cryptocurrency price forecasting using machine learning models: A comparative study. *Information*, *16*(4), 300–315.

[34] Saheed, Y. K., Ayobami, R. M., & Orje-Ishegh, T. (2022). A comparative study of regression analysis for modelling and prediction of Bitcoin price. In S. Misra & A. Kumar Tyagi (Eds.), *Blockchain applications in the smart era* (pp. 187–209). Cham: Springer International Publishing.

[35] Shrivastava, T., Suleiman, B., Desa, S. A., Alibasa, M. J., Tregubov, A., & Zhang, J. (2025). Benchmarking modeling architectures for cryptocurrency price prediction using financial and social media data. *Social Network Analysis and Mining*, *15*(1), 1–16.

[36] Singh, P., Adebanjo, A., Shafiq, N., Abd Razak, S. N., Kumar, V., Farhan, S. A., Adebanjo, I., Singh, A., Dixit, S., Singh, S., & Sergeevna, M. T. (2024). Development of performance-based models for green concrete using multiple linear regression and artificial neural network. *International Journal on Interactive Design and Manufacturing (IJIDeM)*, *18*(5), 2945–2956.

[37] Siregar, W., Syah, A. Z., & Harahap, I. R. (2022a). Implementation of the trend moment method in estimating bread sales. *Jurnal Riset Informatika*, *4*(2), 165–174.

[38] Siregar, W., Syah, A. Z., & Harahap, I. R. (2022b). Trend moment method to predict sales of Pekanbaru Hoya bread. *Sinkron*, *7*(1), 1–8.

[39] Syaharani, N. D., Khikman, M. A., Wahid, S. N., Watur, A. C., Amri, I. F., & Al Haris, M. (2024). Peramalan dan permodelan volatilitas harga penutupan crypto Tether dengan metode GARCH pada periode Januari-Juni 2024. *Emerging Statistics and Data Science Journal*, *2*(3), 382–395.

[40] Tripathy, N., Mishra, D., Hota, S., Behera, M. P., Das, G. C., Dalai, S. S., & Nayak, S. K. (2025). A comparative analysis of exponential smoothing method and deep learning models for Bitcoin price prediction. *IAES International Journal of Artificial Intelligence (IJ-AI)*, *14*(2), 1401–1409.

[41] Utami, R., Nasution, F. P., Sipahutar, L., Putri, F. A., Putri, D. R. D., & Rahman, M. (2020). Trend moment method on identification of food product sales. In *2020 8th International Conference on Cyber and IT Service Management (CITSM)* (pp. 1–4). Jakarta: IEEE.

[42] Valentino, C., & Putri, L. A. A. R. (2025). Analisis kinerja XGBoost menggunakan Bayesian optimization dalam prediksi harga Ethereum. *Jurnal Nasional Teknologi Informasi dan Aplikasinya*, *3*(4), 795–804.

[43] Wahid, A. M. A. (2024). Time series analysis of Bitcoin prices using ARIMA and LSTM for trend prediction. *Journal of Digital Market and Digital Currency*, *1*(1), 84–102.

[44] Wen, N. S., & Ling, L. S. (2023). Evaluation of cryptocurrency price prediction using LSTM and CNNs models. *JOIV: International Journal on Informatics Visualization*, *7*(3-2), 2016–2024.

[45] Wijaya, A. K., Gaib, A. F., Mahayudha, I. G. N. B. F., Andini, N., & Zanestri, T. F. (2025). Optimising Bitcoin price forecasting using LSTM, GRU, Prophet, VAR, and ES multi-model approaches. *Jurnal Teknik Informatika (Jutif)*, *6*(3), 1095–1112.

[46] Youssefi, A. E., Hessane, A., Zeroual, I., & Farhaoui, Y. (2025). Optimizing forecast accuracy in cryptocurrency markets: Evaluating feature selection techniques for technical indicators. *Computers, Materials & Continua*, *83*(2), 1234–1245.

[47] Zhang, Z., Dai, H.-N., Zhou, J., Mondal, S. K., García, M. M., & Wang, H. (2021). Forecasting cryptocurrency price using convolutional neural networks with weighted and attentive memory channels. *Expert Systems with Applications*, *183*(1), 115-128.