The Relationship Between Bitcoin Prices and Ethereum Trading Volume

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Abstract: The paper aimed to investigate the statistical relationship between Bitcoin prices and Ethereum trading volumes, as well as to create a simple predictive model for Ethereum trading volumes based on Bitcoin prices. To perform Spearman's rank correlation analysis and to construct an artificial neural network (ANN) model, daily closing prices of Bitcoin in USD and daily trading volumes of Ethereum were utilized. The timeframe covered by the data starts May 1, 2020 and ends November 22, 2025. In this study, Ethereum volumes were treated as the dependent variable, while Bitcoin prices served as the independent variable. The findings indicate a significant, moderate, positive correlation between Bitcoin prices and Ethereum volumes, and the ANN model successfully predicted Ethereum volumes with a high level of accuracy. These results reinforce existing evidence regarding the relationships among cryptocurrencies. Furthermore, by confirming the efficacy of artificial neural networks (ANN) in predicting trends within the cryptocurrency market, the study also makes a methodological contribution. In addition, the study also offers a simpler modelling approach that highlights the significance of bilateral interactions among major cryptocurrencies through a single-input model. Based on the impressive performance of the ANN model, exchanges, fintech companies, and investment firms could incorporate lightweight machine-learning systems into their forecasting tools to provide real-time analytics with minimal processing requirements.

Keywords: Bitcoin prices, Ethereum trading volume, cryptocurrencies, Spearman's rank correlation, artificial neural networks (ANN)
JEL classification: G10, G12, C45

1. Introduction

The term "cryptocurrency" gained popularity after the publication of Nakamoto's (2008) foundational work. According to Polasik et al. (2015), cryptocurrency (Bitcoin) transactions have risen significantly since 2010. With the increasing popularity of these digital currencies, numerous retailers around the globe are beginning to accept blockchain-powered currencies as a form of payment (Salcedo & Gupta, 2021; Salisu & Ogbonna, 2021).

Digital assets are bought and sold online through a blockchain-based public network, which offers potential rewards but also carries speculative risk (W.R. Martin & Papadimitriou, 2022). Cryptocurrencies are considered a safe-haven asset owing to their low correlation with traditional markets (Klein et al., 2018; Shahzad et al., 2019; Smales, 2022). They are also used for portfolio diversification (Liu et al., 2016; Platanakis & Urquhart, 2019).

Katsiampa (2017) argued that cryptocurrencies are very volatile and related to substantial returns. According to Gil-Alana et al. (2020), investing in cryptocurrency can help diversify portfolios and amplify market gains. Predicting financial markets is a difficult task (Chen et al., 2022).

Granger causality has been utilised for predicting movements in cryptocurrency markets (Tu & Xue, 2019; Canh et al., 2019; Fagarazzi, 2025). Additionally, a multitude of research papers sought to forecast either cryptocurrency values (Indera et al., 2017; Poyser, 2017; Sovbetov, 2018; Jang & Lee, 2017; Fahmi et al., 2018; Lahmiri & Bekios, 2019; Ji et al., 2019; Uras et al., 2020; Pabuçcu et al., 2020), volatility (Walther et al., 2019), returns (Polasik et al., 2015; Abu Bakar & Rosbi, 2017; Liu & Tsyvinski, 2021; Azari, 2019) or direction (Greaves & Au, 2015; Spilak, 2018; Ji et al., 2019).

Several studies have highlighted the interconnectedness of key cryptocurrencies (Aslanidis et al., 2021; Bouri et al., 2021; Elsayed et al., 2022; Kumar et al., 2022; Sila et al., 2024), highlighting the risk spread within the system (Chen et al., 2024). However, there is a lack of research on how Bitcoin prices impact Ethereum trading volume.

This research had two objectives. The first objective was to examine whether there is a statistical relationship between Bitcoin prices and Ethereum trading volumes. The second objective was to develop a simple predictive model for Ethereum trading volumes based on Bitcoin prices. To fulfil the objectives, Spearman's rank correlation analysis and artificial neural network (ANN) were used.

The findings help better understand the relationships between cryptocurrencies, namely between Bitcoin prices and Ethereum trading volume. They show that artificial neural networks (ANNs) can accurately estimate trade volumes, making a methodological addition to quantitative finance research and market modelling. Furthermore, these findings serve as a platform for future research on volatility spillovers, liquidity dynamics and predictive modelling in cryptocurrency markets. For traders and investors, ANN's ability to predict Ethereum's volume based on Bitcoin price fluctuations might help them develop more informed trading strategies. Portfolio managers and fund operators may use this information to manage risk and optimise portfolios that include Bitcoin holdings. Furthermore, regulators and market analysts may use this knowledge to track market trends, assess possible risk transfer between cryptocurrencies and create more effective monitoring or regulatory frameworks.

2. Literature review

While the application of neural networks in analysing time series is still developing, they have proven to be an effective tool for making predictions. As noted by Khashei and Bijari (2010), among 96 studies, conventional methods surpassed neural networks in only 18% of cases, while neural networks either performed adequately or excelled in 72%. This is a key reason for their frequent use in forecasting cryptocurrencies.

ARIMA models for predicting Bitcoin have resulted in significant prediction inaccuracies (Azari, 2019; Abu Bakar & Rosbi, 2017), as they fail to accommodate sudden price fluctuations. McNally (2018) indicates that the prediction errors for ARIMA models in forecasting Bitcoin are notably high, with error rates of 5.45%, 53.47% and 6.87%, suggesting that recurrent neural networks (RNNs) have a superior performance compared to other linear and nonlinear models. ARIMA models can serve as a useful instrument for short-term predictions or during specific periods when the time series behaviour remains relatively stable (Azari, 2019).

Most research studies have utilised neural networks to predict Bitcoin prices or returns. Indera et al. (2017) demonstrate that the Non-Linear Autoregressive with Exogenous Inputs (NARX) model can estimate Bitcoin values using OHLC prices and Moving Average (MA) technical indicators over various time intervals; however, this study lacks a comparison with other models. Another research also assessed multiple models against neural networks. Fahmi et al. (2018) employ internal variables to forecast Bitcoin prices while comparing Linear Regression (LR), neural networks, Bayesian LR and Boosted Decision Tree Regression. The findings indicate that regression models yield more effective predictions. However, they fail to describe the dataset utilised to assess the model or provide a comprehensive explanation of the method.

Jang and Lee (2017) illustrate that Bayesian Neural Networks surpass both linear and nonlinear models in predicting Bitcoin prices and accounting for their significant volatility through internal and external factors. Lahmiri and Bekios (2019) implement Long Short-Term Memory (LSTM) and General Regression Neural Network (GRNN) techniques to forecast the prices of Bitcoin, Digital Cash and Ripple. LSTM demonstrates considerably higher predictive power compared to GRNN.

Uras et al. (2020) forecast the prices of Bitcoin, Litecoin and Ethereum using delayed Open-High-Low-Close (OHLC) prices and volumes, with Simple and Multiple Linear Regression (LR), Feedforward Neural Network (FNN) and LSTM models employed. The best results are achieved by utilising multiple previous prices along with regression models and LSTM, yet neural networks did not perform well. Nevertheless, they only conducted in-sample evaluations because linear regression often shows strong performance in-sample. The model's effectiveness should always be tested out of sample, particularly in regions where neural networks excel.

Ji et al. (2019) investigate deep neural networks (DNN), LSTM, convolutional neural networks, deep residual networks and their combinations with support vector machines (SVM), gated recurrent units (GRU) and linear/logistic regression for predicting Bitcoin prices. The GRU and linear/logistic regression models performed either poorly or comparably with SVM. The findings indicate that LSTM outperforms other models when it comes to predicting Bitcoin prices. DNN excelled over various techniques in forecasting the direction of prices. They used internal variables for predicting Bitcoin values and determined that 20 inputs were sufficient for regression and 50 inputs for classification. However, they employed random sample division instead of sequential sampling, which lacks econometric justification and has an excessive number of inputs.

Dutta et al. (2020) employed an established set of internal and external factors as exogenous and endogenous variables to predict daily Bitcoin values, showing that the GRU model surpasses traditional neural networks and LSTM. Additionally, RNN and LSTM significantly exceed traditional time series models in predicting cryptocurrency prices.

Chen et al. (2020) projected Bitcoin prices at different frequencies (daily and high frequency). LR and Discriminant Analysis (DA) for daily Bitcoin price forecasting with high-dimensional features achieved an accuracy of 66%, outperforming more advanced models. Random Forest, XG-Boost, Quadratic DA, SVM and LSTM had better performance than statistical methods in anticipating Bitcoin prices at 5-minute intervals, achieving an accuracy of 67.2%.

Faghih Mohammadi Jalali and Heidari (2020) employed the first-order grey model (GM (1,1)) for Bitcoin price predictions. GM outperformed RNN and Bayesian neural network (BNN), but did not clarify how the comparisons were drawn using different methodologies.

Studies on predicting cryptocurrency volatility are limited, either relying on high-frequency data (Zhang et al., 2022) or concentrating solely on GARCH-type models (Chu et al., 2017; Walther et al., 2019). Nybo (2021) suggests that neural networks should be applied to forecast the volatility of low-volatility assets, whereas GARCH models are better suited for medium and high-volatility assets.

Šestanović (2021) assesses feed-forward neural networks (FNNs) against logistic regression (LR) for forecasting Bitcoin direction, determining if prices will rise or fall the following trading day. Šestanović (2024) presents an extensive analysis of Bitcoin's price, returns, direction and volatility forecasts. The author evaluated ARIMA and GARCH models alongside neural network (NN) autoregression and Jordan NN concerning their predictive performance, considering both internal and external factors. The comparison of various performance metrics across different time intervals yielded inconclusive results regarding predictions of price, return, or volatility. Results for return and volatility forecasting were consistently observed, irrespective of the model or time period analysed.

Behera et al. (2024) employed three metaheuristic approaches to develop optimal ANNs with minimal control parameters: fireworks algorithm (FWA), chemical reaction optimisation (CRO) and teaching-learning-based optimisation (TLBO) individually. These hybrid models were utilised to simulate and predict the behaviour of four rapidly appreciating cryptocurrencies: Bitcoin, Litecoin, Ethereum and Ripple. Real-time Bitcoin data and hybrid ANNs were used for experiments, applying four performance measures. They analysed the forecasting models' performance and conducted Friedman tests to demonstrate their superiority and statistical relevance. The ANN trained with CRO, TLBO and FWA achieved average ranks of 1, 2 and 2.75, respectively (Behera et al., 2024).

In line with the aforementioned, the following hypothesis was formed:

H1. *Bitcoin prices are significantly related to Ethereum trading volumes.*

3. Methodology

The research adopted a quantitative approach and utilised secondary data. The source of the data was CoinMarketCap. It was reported by Omanović et al. (2020) that cryptocurrency portfolios quickly recovered from April 2020 after underperforming in March 2020. In line with Omanović et al. (2020), the data used covers the period from May 1, 2020, to November 22, 2025. Bitcoin daily closing prices in USD and Ethereum daily trading volume were utilised. The Bitcoin prices served as an independent variable, while Ethereum volumes operated as a dependent variable. The analyses were executed in the programming language R.

Correlation analysis was used for the investigation of the relationship between the Bitcoin price and Ethereum volume. Bitcoin price and Ethereum volume data are non-normally distributed (data contains extreme values, outliers). With the aforementioned, correlation coefficients mustn't be determined from the actual values, but from the ranks of the data. The coefficients Spearman's rho (denoted as r_s) and Kendall's tau were specifically developed for this objective. Kendall's tau extends Spearman's rho. Kendall's tau should be employed when the same rank is repeated too many times in a small dataset. The Bitcoin price and Ethereum trading volume data exhibit almost no tied ranks, meaning that the assumptions requiring the use of Kendall's tau over Spearman's rho are not met.

Neural network analysis is extremely versatile in modelling linear and highly complicated nonlinear relationships, with solid prediction competencies (Leong et al., 2013), outperforming several aspects of other machine-learning models (Kraus et al., 2020). The conventional backpropagation approach was used (Günther & Fritsch, 2012), using the logistic activation function to train each network given by the neuralnet package in R. Since there was only one independent and one dependent variable, 1 node in the hidden layer was logical. To prevent overfitting during the training phase, a 10-fold cross-validation was implemented using a training and testing data set ratio of 90:10 (Chan & Chong, 2012; Liéban-Cabanillas et al., 2017). Other approaches were utilised to evaluate the neural network-based model's superior performance. In particular, linear regression (LR), Random Forest Regression (RFR) and Support Vector Regression (SVR).

4. Results and discussion

The results of Spearman's rank correlation are presented in Table 1.

Table 1. Results of Spearman's rank correlation

p-value	**rho (r_s)**
3.95e-140	0.518

Source: The author (2026)

In line with the interpretation table of Spearman rank-order correlation coefficients by Dancey & Reidy (2007), there is a significant moderate positive relationship between Bitcoin prices and Ethereum volumes. This indicates that the variables tend to move in the same direction. When one increases, the other is likely to increase as well and when one decreases, the other tends to decrease.

The results can be connected with the herding theory, co-movement, spillover effect and limited attention theory. Herding refers to the tendency of individuals to follow the actions of others and replicate group behaviours, instead of making independent decisions based solely on their own private information. The concept of herding originates from Keynes, who examined the reasons behind imitating and aligning with the crowd in uncertain environments (Keynes, 1930).

Bikhchandani & Sharma (2000) wrote about herd behaviour in financial markets. In order for an investor to copy the actions of others, the investor needs to be conscious of and influenced by those actions. Essentially, a person can be considered to be following the crowd if they had proceeded with an investment regardless of other investors' choices, but opted not to invest upon discovering that others have chosen not to invest. Conversely, she engages in herd behaviour when awareness of others investing alters her decision from not investing to going ahead with the investment (Bikhchandani & Sharma, 2000).

Financial markets often exhibit similar trends, highlighting their co-movements. The primary factors accounting for these co-movements among financial markets are economic integration and the characteristics of stock markets (Pretorius, 2002). Bitcoin is the most interconnected cryptocurrency, significantly influencing the spillover risk in the cryptocurrency market (Moratis, 2021).

Limited attention results from the overwhelming amount of information present in our surroundings and the constraints of our ability to process that information. Focus needs to be intentional and demands effort, involving the reallocation of cognitive resources from different tasks (Kahneman, 1973). Individual investors are limited to analysing and evaluating the information that captures their interest the most, which subsequently influences their investment behaviour and results in short-term price discrepancies (Aboody et al., 2010).

A scatter plot with a LOESS trend line is shown in Figure 1.

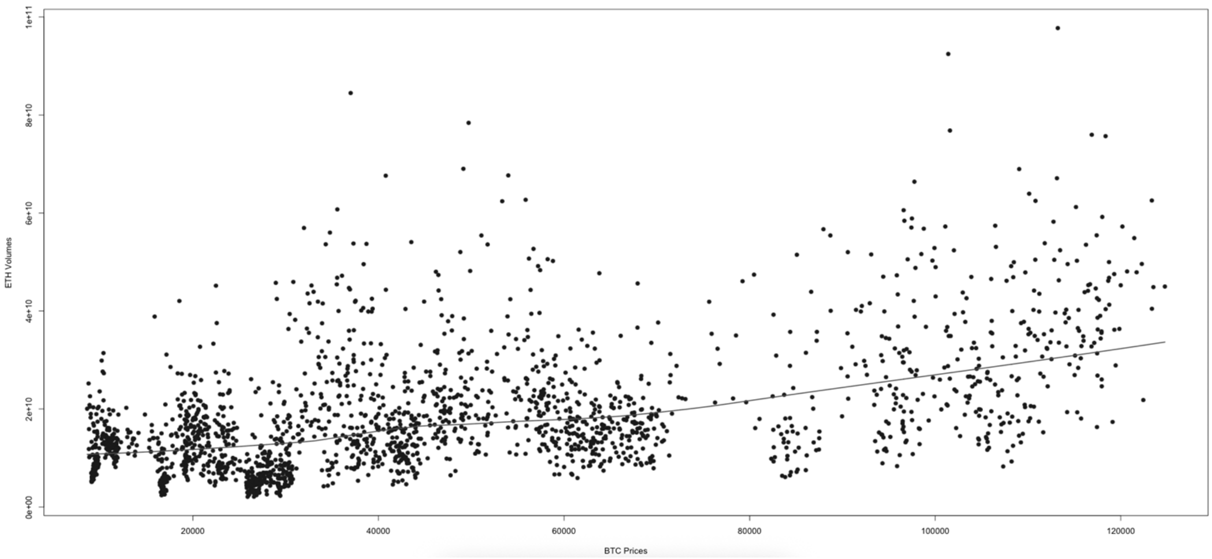

Figure 1. A scatter plot with a LOESS trend line
Source: The author (2026)

Artificial neural network (ANN), linear regression (LR), random forest regression (RFR) and support vector regression (SVR) prediction accuracy (RMSE) are presented in Table 2.

Table 2. Artificial neural network (ANN), linear regression (LR), random forest regression (RFR) and support vector regression (SVR) prediction accuracy (RMSE)

N	**ANN RMSE train**	**ANN RMSE test**	**LR RMSE test**	**RFR RMSE test**	**SVR RMSE test**
1	0.112	0.100	0.100	0.105	0.101
2	0.107	0.141	0.139	0.123	0.142
3	0.111	0.113	0.126	0.101	0.126
4	0.112	0.106	0.107	0.115	0.105
5	0.113	0.095	0.110	0.110	0.109
6	0.112	0.104	0.112	0.108	0.112
7	0.111	0.112	0.109	0.115	0.112
8	0.112	0.102	0.101	0.112	0.095
9	0.112	0.101	0.105	0.121	0.102
10	0.111	0.116	0.111	0.127	0.115
Mean	0.111	0.109	0.112	0.114	0.112
SD	0.002	0.013	0.012	0.008	0.014

Source: The author (2026)

The RMSE values for all methods on both training and test data were satisfactory. The ANN model exhibits the lowest mean RMSE on the test set, indicating superior predictive performance compared to the other methods. Although the ANN shows the best average performance, its standard deviation is relatively moderate, suggesting that while the model performs well overall, its predictive accuracy varies across folds slightly more than in some competing models. Additionally, ANN models are capable of efficiently capturing nonlinear relationships between independent variables and the dependent variable.

The weak form of the Efficient Market Hypothesis (EMH) suggests that all information based on historical prices is incorporated into the current price. Nonetheless, several studies (Urquhart, 2016; Al-Yahyaee et al., 2018; Kristoufek & Vosvrda, 2019) show that the cryptocurrency markets do not operate with complete efficiency. This opens up possibilities for developing and employing predictive models that use past price data to forecast future trends, effectively demonstrated by an artificial neural network (ANN) model.

Cryptocurrency markets act as complex adaptive systems, characterised by extensive interconnections, changing patterns and nonlinear interactions among different variables. As stated in chaos theory and nonlinear dynamics (Peters, 1994), financial markets, especially emerging and less mature ones like the crypto market, do not follow linear trends but are shaped by unpredictable and chaotic fluctuations that are often overlooked in linear models. Artificial Neural Network (ANN) models excel in detecting these intricate patterns and relationships among variables because of their ability to learn from data and represent nonlinear connections.

The first objective was to investigate whether there is a statistical relationship between Bitcoin prices and Ethereum trading volumes. This objective was achieved by utilising Spearman’s rank correlation, which indicated a significant moderate positive correlation between the two variables. This indicates that fluctuations in Bitcoin prices are generally in sync with variations in Ethereum trading volumes, affirming that a substantial relationship exists.

The second objective was to create a straightforward predictive model for Ethereum trading volume based on Bitcoin prices. This objective was also accomplished. Various predictive methods were evaluated and the ANN model produced the lowest mean RMSE on the test set, showcasing the best predictive performance. While the ANN exhibited marginally greater variation between folds than some other models, its overall precision and capacity to identify nonlinear patterns suggest that a reliable predictive model was effectively developed. In line with the aforementioned, the formed hypothesis was accepted.

4.1. Theoretical contributions

The research provides several theoretical advancements to existing literature. Firstly, by showcasing a notable moderate positive relationship between Bitcoin prices and Ethereum trading volumes, the study reinforces the current evidence regarding interconnections among cryptocurrencies. This adds to theories concerning co-movement, spillover effects and herding behaviour, which propose that market participants frequently respond collectively to information or price cues from dominant cryptocurrencies.

Furthermore, the results broaden the perspectives of behavioural finance, especially herding theory and limited attention theory, within the realm of cryptocurrency markets, illustrating that investor actions and constraints in information processing contribute to synchronised market responses. The study also offers methodological contributions by validating the effectiveness of artificial neural networks (ANN) in predicting cryptocurrency market trends.

Despite using a limited set of features, the ANN successfully identified nonlinear patterns, providing additional proof that machine-learning methods can surpass traditional linear approaches in forecasting the dynamics of digital assets. Additionally, by employing a single-input model, the research presents a simplified modelling framework that highlights the significance of bilateral relationships among major cryptocurrencies.

4.2. Practical implications

Several managerial implications arise from these results. Traders and market analysts can take advantage of the insight that Ethereum trading patterns react to movements in Bitcoin prices, allowing Bitcoin to act as an early signal of changes in Ethereum market demand. This understanding facilitates more strategic trading approaches, especially for short-term decisions. Portfolio managers can leverage the established correlation to enhance risk management, as coordinated fluctuations between leading cryptocurrencies could increase liquidity risks during volatile market conditions. The impressive performance of the ANN model indicates that exchanges, fintech companies and investment institutions may incorporate lightweight machine-learning systems into their forecasting tools to enable real-time analytics without heavy computational demands. Furthermore, these findings are beneficial for financial institutions and firms looking into algorithmic trading solutions, showing that even basic ANN frameworks can yield significant predictive insights. From a regulatory perspective, grasping the interconnectedness of cryptocurrencies can assist oversight agencies in pinpointing potential systemic risks that emerge from interrelated market behaviours, particularly in times of increased volatility or speculative spikes.

5. Conclusion

The goals of the study were to investigate if there is a statistical connection between Bitcoin prices and Ethereum trading volumes and to create a straightforward predictive model for Ethereum trading volumes based on Bitcoin prices. Daily closing prices of Bitcoin in USD and daily trading volumes of Ethereum were utilised to perform Spearman’s rank correlation analysis and to build an artificial neural network (ANN) model. The findings indicate a significant, moderate, positive correlation between Bitcoin prices and Ethereum volumes and the ANN model successfully predicted Ethereum's volume with a high level of accuracy. In general, the research demonstrates significant interconnections among leading cryptocurrencies and underscores the usefulness of machine-learning methods for predicting trends in the digital asset market.

This study has several limitations that need to be mentioned. The research design is correlational and predictive, rather than causal, indicating that the analysis cannot ascertain whether fluctuations in Bitcoin prices lead to alterations in Ethereum trading volume. The analysis is based solely on one predictor variable, which streamlines the modelling approach but fails to take into account the wider array of factors that are recognised to impact Ethereum trading activity, including market sentiment, macroeconomic indicators, on-chain metrics and regulatory developments.

Future research could enhance the modelling framework by integrating various explanatory factors, such as measures of investor sentiment, blockchain network activity, macroeconomic indicators, or volatility indices, to refine predictive accuracy and reveal deeper behavioural patterns. Scholars might also utilise more advanced neural network architectures, like LSTM or GRU models, which are particularly effective for time-series forecasting in financial contexts. Conducting comparative analyses across different cryptocurrencies could yield wider insights into cross-market spillovers and lead–lag relationships. In addition, future investigations could examine causal inference methods (for instance, Granger causality, VAR models, or structural modelling) to assess whether fluctuations in Bitcoin prices influence Ethereum trading behaviour. Lastly, analysing the impacts across various market conditions, such as bull markets, crashes, or times of regulatory changes, would help in evaluating the strength and consistency of the identified relationships.

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Odnos između cijene Bitcoina i obujma trgovanja Ethereumom

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Sažetak: Ciljevi rada bili su ispitati postoji li statistička veza između cijena Bitcoina i volumena trgovanja Ethereumom te razviti jednostavan prediktivni model za volumene trgovanja Ethereumom na temelju cijena Bitcoina. Dnevne cijene zatvaranja Bitcoina u USD i dnevni volumeni trgovanja Ethereumom korišteni su za provođenje Spearmanove analize korelacije rangova i za razvoj modela umjetne neuronske mreže (ANN). Vremenski okvir obuhvaćen podacima je od 1. svibnja 2020. do 22. studenog 2025. Volumeni Ethereuma funkcionirali su kao zavisna varijabla, a cijene Bitcoina kao nezavisna varijabla. Rezultati otkrivaju značajnu, umjerenu, pozitivnu vezu između cijena Bitcoina i volumena Ethereuma te da je model ANN učinkovito predvidio volumene Ethereuma s visokim stupnjem točnosti. Rezultati podržavaju sadašnje dokaze o vezama između kriptovaluta. Potvrđujući učinkovitost umjetnih neuronskih mreža (ANN) u predviđanju obrazaca na tržištu kriptovaluta, studija također daje metodološki doprinos. Osim toga, studija nudi jednostavniji pristup modeliranju koji naglašava važnost bilateralnih interakcija među glavnim kriptovalutama korištenjem modela s jednim ulazom. Burze, fintech tvrtke i investicijske institucije mogu integrirati lagane sustave strojnog učenja u svoje alate za predviđanje kako bi ponudile analitiku u stvarnom vremenu bez značajnih zahtjeva za obradom, u skladu s izvrsnim performansama ANN modela.

Ključne riječi: cijene Bitcoina, volumen trgovanja Ethereumom, kriptovalute, Spearmanova korelacija rangova, umjetne neuronske mreže (ANN)
JEL klasifikacija: G10, G12, C45