Date of publication DEC-31, 2024, date of current version DEC-09, 2024.
www.computingonline.net / computing@computingonline.net

Print ISSN 1727-6209
Online ISSN 2312-5381
DOI 10.47839/ijc.23.4.3755

Comparative Research on Cryptocurrency Efficiency: An Objective Analysis of Key Metrics

OLEKSANDR KUZNETSOV[1], OLEKSII SMIRNOV[2], MYKOLA MORMUL[3], YEVGEN KOTUKH[4], VOLODYMYR ZVIERIEV[5]

[1]Department of Theoretical and Applied Sciences, eCampus University, Via Isimbardi 10, 22060, Novedrate (CO), Italy
[2]Department of cyber security and software, Central Ukrainian National Technical University, 8, University Ave, 25006, Kropyvnytskyi, Ukraine
[3]Department of Computer Science and Software Engineering, University of Customs and Finance, av. Volodymira Vernadsky, 2/4, 49000, Dnipro, Ukraine
[4]Technical Sciences, Associate Professor, Professor of the Department of Cybersecurity; National Technical University “Dnipro Polytechnic”; av. Dmytra Yavornytskoho, 19,49005 Dnipro, Ukraine
[5]Department of Software Engineering and Cybersecurity, State University of Trade and Economics, Kyoto, 19, 02156, Kyiv, Ukraine

Corresponding author: Oleksandr Kuznetsov (e-mail: oleksandr.kuznetsov@uniecampus.it).

ABSTRACT Cryptocurrencies have introduced a transformative paradigm in financial technology, challenging traditional financial structures and creating novel transactional frameworks. With the rapid expansion of the cryptocurrency market, the need for objective assessment and comparative analysis of leading digital assets has become increasingly pertinent. This study presents a detailed, data-driven evaluation of five prominent cryptocurrencies: Bitcoin (BTC), Ethereum (ETH), Tether (USDT), USD Coin, and Lido Staked Ether (STETH). Drawing on an extensive dataset sourced from IntoTheBlock, a leading platform for cryptocurrency analytics, we assess these cryptocurrencies based on selected efficiency indicators. Our research methodology encompasses a systematic exploration of financial and network metrics, including market capitalization, volatility, daily active addresses, and transaction statistics. The results provide nuanced insights into the relative performance of these assets, identifying Bitcoin as the most efficient based on the selected criteria. This work emphasizes the significance of empirical, data-centric methodologies, eschewing subjective judgments, to deliver actionable insights for investors, policymakers, and scholars in the domain of decentralized finance.

KEYWORDS Cryptocurrency Efficiency; Comparative Analysis; Blockchain Metrics; Decentralized Finance; Performance Evaluation.

I. INTRODUCTION

MORE recently, in the fast-changing world of FinTech, cryptocurrencies have come to the fore as the so-called disruptive force against traditional systems of finance, changing the paradigm of monetary transactions. Since its inception in 2009 [1], the cryptocurrency market has mushroomed into thousands of digital currencies competing for market dominance or user adoption. In this rapid proliferation, the relative strengths, weaknesses, and market positions of these assets need to be discerned by investors, policymakers, and other stakeholders.

However, in general, the domain of cryptocurrency is marked by volatility, complexity, and volume, which make objective inferences hard to get [2, 3]. The surprising gap in the literature is that, while many of the technical issues, economic consequences, and regulatory complications of cryptocurrencies have been discussed, what is really lacking is any comprehensive data comparison among leading cryptocurrencies by objective performance metrics [4, 5].

The present study fills this gap. Using a rich dataset from IntoTheBlock [6], among the world's top cryptocurrency analytics platforms, we will be making a much-needed systematic examination of the top five cryptocurrencies. In light of this, our objectives are twofold: first, to paint a clear picture of the current positions these cryptocurrencies hold in the market based on selected efficiency indicators; and secondly, to present their comparative analysis in a manner that helps explain the relative strengths and weaknesses of each cryptocurrency.

Concluding, based on the empirical basis of analysis, and following sound research methodologies, this study consequently hopes to proffer a nuanced yet objective approach toward the understanding of the cryptocurrency market landscape. In so doing, we hope to be able to make some useful contributions toward the insights of investors, policymakers who need it for their regulatory functions, and add to the literature on decentralized financial systems [7, 8].

2. STATE OF THE ART

The rapid growth of blockchain technology has facilitated the development of cryptocurrencies and decentralized financial systems. This section critically reviews relevant literature, identifies research gaps, and highlights areas where this study contributes to the field.

Paper [9] examines the security vulnerabilities of Ethereum blockchain-based smart contracts. It provides a systematic review of detection tools, real-life attacks, and preventive mechanisms, emphasizing the critical role of smart contracts that often hold vast amounts of cryptocurrency. However, the study's primary focus is on security, leaving a gap in understanding the broader implications of these vulnerabilities on the decentralized financial ecosystem.

Paper [10] offers a systematic review of blockchain technology, tracing its increasing popularity alongside related technologies like cryptocurrencies. The authors discuss blockchain's unique features, including privacy, security, and decentralization, and its advantages across various domains. Nevertheless, the paper does not delve into the comparative efficiency and effectiveness of cryptocurrencies within the decentralized finance (DeFi) space.

Research [11] investigates the application of blockchain technology in the education sector, particularly regarding data security. It highlights blockchain's enhanced security features and potential to safeguard educational data. However, the study does not address the implications of blockchain technology for the financial sector, including cryptocurrencies and DeFi.

Paper [12] explores blockchain applications in finance, healthcare, and government, emphasizing its decentralization and auditability features. While it provides a broad overview, the paper lacks a detailed comparative analysis of cryptocurrencies and their roles within decentralized financial systems.

Study [13] evaluates the awareness and receptivity of Indian respondents toward a regulated cryptocurrency market, identifying liquidity and security as key factors influencing acceptance. The findings suggest that the Indian public prefers secure and fluid trading markets, such as those offered by cryptocurrencies. Moreover, finance professionals with IT experience exhibit greater receptivity to regulated cryptocurrency markets.

Paper [14] introduces an iterative kappa architecture for collecting and processing data related to cryptocurrency transactions and social media activity, identifying a correlation between Twitter activity and cryptocurrency transactions. The proposed architecture demonstrates flexibility and the capacity to integrate data from multiple sources.

Study [15] reviews investment options in the cryptocurrency market, highlighting the potential for new investors to achieve significant returns compared to traditional strategies. The paper also discusses the risks and rewards associated with various investment models within centralized and decentralized cryptocurrency markets.

Paper [16] examines the sustainability of cryptocurrency adoption in African countries, focusing on blockchain technology's ability to secure financial infrastructures and reduce operational risks. However, it also underscores the challenges and limitations of implementing cryptocurrency solutions in developing nations, particularly in Africa.

While an expanding body of literature explores cryptocurrencies and decentralized financial systems, a significant gap remains in the objective evaluation of cryptocurrency efficiency [17, 18]. Most existing studies rely on subjective expert opinions, which limits their applicability. This study addresses this gap by providing a data-driven analysis of cryptocurrency efficiency, free from subjective influence.

In summary, the current state of research on cryptocurrencies and decentralized financial systems is vast and rapidly evolving. Key developments include understanding the receptivity of specific populations to regulated cryptocurrency markets, designing real-time big data architectures for cryptocurrency transaction analysis, and exploring risks and rewards in centralized and decentralized investment models. The sustainability of cryptocurrency, especially in developing countries, remains an area of active investigation. However, objective evaluations of cryptocurrency efficiency are still lacking, a shortfall this research aims to address.

III. CRITERIA AND INDICATORS FOR CRYPTOCURRENCY EVALUATION

To conduct a comprehensive and objective assessment of cryptocurrency efficiency, we have established a set of criteria and corresponding indicators. These indicators, categorized under financial and network metrics, provide valuable insights into the operational efficiency, market acceptance, and overall health of cryptocurrency networks [19].

A. FINANCIAL INDICATORS

- Market Cap (52-Week High): This efficiency-enhancing metric represents the total value of a cryptocurrency's circulating supply at its 52-week high.
- Market Cap (All-Time High): Another efficiency-enhancing metric, this measures the highest total value of a cryptocurrency's circulating supply since its inception.
- Volatility (30-Day High): As an efficiency-reducing indicator, this metric reflects the highest annualized price volatility observed over the past 30 days.
- Volatility (30-Day Low): Similarly, this efficiency-reducing indicator captures the lowest annualized price volatility over the same period.

B. NETWORK INDICATORS (ADDRESS STATISTICS)

- Daily Active Addresses (7-Day NA Change): An efficiency-enhancing metric that tracks the daily active addresses and their net change over seven days.
- Total Addresses (30-Day Average with Balance): This metric provides the average number of addresses holding a balance over the past 30 days, serving as an efficiency-enhancing indicator.
- Active Address Ratio (30-Day Average): An efficiency-enhancing indicator representing the proportion of active addresses with a balance over a 30-day average.
- Address Birth-Death Ratio (30-Day Average): This efficiency-enhancing metric quantifies the ratio of new addresses to those that have become inactive within a 30-day period.

C. NETWORK INDICATORS (TRANSACTION STATISTICS)

- Number of Transactions (7-Day Average): An efficiency-enhancing metric that represents the average number of transactions conducted over seven days.
- Transaction Volume in USD (7-Day Average): Another efficiency-enhancing indicator, capturing the average USD transaction volume over a seven-day period.
- Average Time Between Transactions (30-Day Average): As an efficiency-reducing metric, this indicates the average interval between transactions over 30 days.

D. OVERVIEW OF SELECTED CRYPTOCURRENCIES

In the rapidly evolving realm of digital finance, cryptocurrencies have become pivotal assets, reshaping monetary transactions and investment paradigms. Given the multitude of cryptocurrencies available, selecting a subset for comparative analysis requires stringent criteria. This study focuses on the top five cryptocurrencies listed on IntoTheBlock [6], a leading platform renowned for its comprehensive cryptocurrency analytics.

IntoTheBlock stands as a key resource in cryptocurrency analytics, leveraging machine learning algorithms to provide granular insights. Its capability to dissect complex datasets makes it invaluable for both novice and seasoned investors. By utilizing IntoTheBlock's extensive array of metrics, users can base their decisions on empirical evidence and robust analysis.

The cryptocurrencies analyzed in this study—Bitcoin (BTC), Ethereum (ETH), Tether (USDT), USD Coin, and Lido Staked Ether (STETH)—are selected based on their prominence and influence within the decentralized finance ecosystem. Their rankings on IntoTheBlock reflect their market significance, adoption rates, and overall impact. Primary data, including efficiency indicators, were sourced directly from IntoTheBlock to ensure consistency and reliability.

- Bitcoin (BTC): Often termed "digital gold," Bitcoin is the first and most recognized cryptocurrency. Launched in 2009, it pioneered the concept of decentralized digital money, operating without a central authority.
- Ethereum (ETH): Introduced in 2015, Ethereum is both a cryptocurrency and a platform for decentralized applications. Its native token, Ether, is used for transaction fees and computational services.
- Tether (USDT): Launched in 2014, Tether is a stablecoin pegged to external reference points such as fiat currencies, reducing volatility.
- USD Coin (USDC): Another stablecoin, USD Coin is pegged to the US dollar and emphasizes transparency, security, and compliance through collaborations with financial institutions and auditors.
- Lido Staked Ether (STETH): This represents staked Ether on the Ethereum 2.0 beacon chain, allowing users to earn staking rewards without locking up their assets.

The subsequent sections provide an in-depth examination of these cryptocurrencies, comparing their performance across the selected indicators to present a comprehensive understanding of their relative standings in the current market.

IV. RESEARCH METHODOLOGY

This research employs a systematic and quantitative methodology to ensure precision and rigor in analysis [20, 21]. The key steps and methods implemented in this study are outlined below:

- Data Collection: Primary data was sourced from IntoTheBlock [6], a leading platform for cryptocurrency analytics. This ensured access to accurate, real-time, and comprehensive datasets for the selected cryptocurrencies.
- Selection of Indicators: A set of efficiency-enhancing and efficiency-reducing indicators was chosen, aligned with the study's objectives. These indicators act as proxies to evaluate the performance, stability, and network activity of each cryptocurrency.
- Normalization: Given the diverse scales and ranges of the selected indicators, data normalization was performed to ensure comparability. This step was critical in mitigating scale biases and standardizing all indicators to a uniform scale.
- Quantitative Analysis: The normalized data was analyzed using statistical tools to derive insights. This involved calculating averages, variances, and other relevant metrics to understand the performance and behavior of each cryptocurrency.
- Comparative Assessment: Based on the derived metrics, the cryptocurrencies were juxtaposed to facilitate a relative evaluation of their strengths, weaknesses, and overall market positions.

By adhering to this structured methodology, this research aims to present an objective, data-driven perspective on the comparative performance of the selected cryptocurrencies. This approach addresses the existing gap in the literature and provides actionable insights for stakeholders within the decentralized finance domain.

V. METHOD FOR ASSESSING THE SPREAD OF SYSTEM INDICATORS

A. GENERAL PROVISIONS

When assessing the efficiency and comparing different technical systems, it is essential to rely solely on objective data and remain uninfluenced by the subjective opinions of experts. In such cases, formalized methods are imperative. One such method is the determination of weight coefficients based on the loss functions of system efficiency [20, 21]. When applying this method, all indicators characterizing the system are presented in quantitative form.

Let there be systems $S^{(1)}, S^{(2)}, \ldots, S^{(K)}$ to be compared. Each of these systems can be characterized by a set of parameters $A = \{\alpha_1, \alpha_2, \ldots, \alpha_n\}$. For each system, any parameter α_i (where $i = \overline{1,n}$ and $\alpha_i \in A$) can take its value, i.e.,

$$\begin{aligned}
S^{(1)} &\to A^{(1)} = \left\{\alpha_1^{(1)}, \alpha_2^{(1)}, \ldots, \alpha_n^{(1)}\right\}; \\
S^{(2)} &\to A^{(2)} = \left\{\alpha_1^{(2)}, \alpha_2^{(2)}, \ldots, \alpha_n^{(2)}\right\}; \\
&\ldots \\
S^{(K)} &\to A^{(K)} = \left\{\alpha_1^{(K)}, \alpha_2^{(K)}, \ldots, \alpha_n^{(K)}\right\}.
\end{aligned} \tag{1}$$

The comparison of systems is carried out by calculating and subsequently comparing partial and system indicators. Partial indicators characterize the system's efficiency from the perspective of performing a specific functional task. The partial indicator for the j -th functional task is given by:

$$\gamma_j^{(k)} = \sum_{i=1}^{F_j} \left(\rho_{ji} \eta_{ji}^{(k)} \right), \tag{2}$$

where:

- ρ_{ji} is the weight coefficient of the significance of the. i .-th parameter within the group of parameters characterizing the j -th functional task;
- $\eta_{ji}^{(k)}$ is the normalized value of the i -th parameter within the group of parameters characterizing the j -th functional task for the k -th system, and
- F_j is the number of parameters included in the j -th group,

$$\sum_{j=1}^{J} F_j = n,$$

where J is the number of parameter groups.

The overall assessment of the k -th system is defined as:

$$\Gamma^{(k)} = \sum_{j=1}^{J} \left(\beta_j \gamma_j^{(k)} \right), \tag{3}$$

where:

- β_j is the weight coefficient of the j -th partial indicator (essentially the j -th functional task);
- $\gamma_j^{(k)}$ is the value of the j -th partial indicator for the k -th system.

It can be observed that β_j does not have an index indicating its belonging to a specific k -th system. This is not an oversight. The fact is that for the systems being compared, only the values of specific indicators differ, while the set (nomenclature) of indicators coincides (otherwise, comparison would be impossible). Therefore, variables such as β_j, l_j and μ_{ji} do not have an index k where μ_{ji} is a logical variable introduced for each i -th parameter of the j -th functional task, indicating the belonging of this parameter to the increasing or decreasing indicators.

B. METHODOLOGY FOR CALCULATING SYSTEM'S PARTIAL INDICATORS

B.1. Parameter Set Decomposition:

The initial parameter set A characterizing the systems under comparison undergoes a thorough analysis. This set is then segmented into groups, each representing distinct functional tasks. Various decomposition methods can be employed for this analysis. The outcome of this analysis is tabulated. The value of the i -th parameter (within the j -th group) for the k -th system is denoted as $\alpha_{ji}^{(k)}$.

B.2. Identification of Enhancing and Reducing Parameters:

Within each parameter group, parameters are categorized as either enhancing or reducing. A parameter α_{ji} is termed 'enhancing' if an increase in its value leads to an overall improvement in system efficiency. For such parameters, the logical variable $\mu_{ji}^{\uparrow}$ is set to one. Conversely, a parameter α_{ji} is termed 'reducing' if a decrease in its value enhances the system's efficiency. For these parameters, $\mu_{ji}^{\uparrow}$ is set to zero. If the i -th parameter from the j -th functional group is enhancing ($\mu_{ji}^{\uparrow} = 1$), the following is calculated:

$$\alpha_{ji\max} = \max_{k=1,K} \alpha_{ji}^{(k)}, \tag{4}$$

where $\alpha_{ji}^{(k)}$ represents the value of the i -th parameter from the j -th functional group for the k -th system, and K is the total number of systems being compared. Similarly, if the i -th parameter from the j -th functional group is reducing ($\mu_{ji}^{\uparrow} = 0$), the following is determined:

$$\alpha_{ji\min} = \min_{k=1,K} \alpha_{ji}^{(k)}. \tag{5}$$

B.3. Determination of Normalized Parameter Values:

As evident from expression (2), to determine the partial indicator, all parameter values must be consolidated. However, direct consolidation isn't feasible since parameters differ in physical significance and dimensionality. The partial indicator γ_i is dimensionless, necessitating parameter normalization. The normalization is executed as:

$$\eta_{ji}^{(k)} = \begin{cases} \dfrac{\alpha_{ji}^{(k)}}{\alpha_{ji\max}}, if \ \mu_{ji}^{\uparrow} = 1; \\ \dfrac{\alpha_{ji\min}}{\alpha_{ji}^{(k)}}, if \ \mu_{ji}^{\uparrow} = 0. \end{cases} \tag{6}$$

B.4. Calculation of Averages for Each Normalized Parameter:

$$\overline{\eta_{ji}} = \frac{1}{K} \sum_{k=1}^{K} \eta_{ji}^{(k)}, \tag{7}$$

where K is the total number of systems under comparison, and F_j is the number of parameters in the j^{th} functional group.

B.5. Determination of Average Deviation for Each Normalized Parameter:

$$\Delta\overline{\eta_{ji}} = \frac{1}{K} \sum_{k=1}^{K} |\eta_{ji}^{(k)} - \overline{\eta_{ji}}|. \tag{8}$$

This metric represents the deviation of system parameter values from the average.

B.6. Calculation of Normalized Deviation Values:

$$d_{ji} = \frac{\Delta\overline{\eta_{ji}}}{\overline{\eta_{ji}}}. \tag{9}$$

B.7. Determination of Normalized Weight Coefficients for Each Parameter Group:

$$\rho_{ji} = \frac{d_{ji}}{\sum_{i=1}^{F_j} d_{ji}} . \qquad (10)$$

The physical significance of the coefficient ρ_{ji} is that its value depends on the spread of parameters. If the parameter values for different systems vary significantly, then this parameter receives the highest weight in system comparison.

B.8. Calculation of Partial Efficiency Indicators:

The value of the partial efficiency indicators $\gamma_j^{(k)}$ for each system across all parameter groups is determined using expression (2).

C. LOSS OF SYSTEM EFFICIENCY FUNCTION

Let's revisit expression (3). To compute the overall system indicator, we need to determine the weight coefficients β_j for each functional task characterized by its set of parameters.

To determine these weight coefficients, we'll make the following assumptions:

- If a chosen set of weight coefficients $\mathrm{B}_T = \beta_1, \beta_2, ..., \beta_j$ maximizes the efficiency estimates for one system k:

$$F^{(k)}(\mathrm{B}_T) = \max_{\mathrm{B}} \Gamma^{(k)}(\mathrm{B}) \qquad (11)$$

- and minimizes the estimates for other systems:

$$\Gamma^{(m)}(\mathrm{B}_T) = \min_{\mathrm{B}} \Gamma^{(m)}(\mathrm{B}) , \; m \neq k , \; m = 1,2,...,K , \qquad (12)$$

then in this case, the system with the maximum is in exceptionally favorable conditions.

The set of coefficients B_T should be such that, based on the generalized efficiency estimate $\Gamma^{(k)}(\mathrm{B}_T)$, the systems are in relatively equal conditions. Or at least, none of them is in a clearly privileged position.

To quantitatively assess the conditions for comparing systems, we use the loss of efficiency function for the k-th system:

$$\theta^{(k)} = 1 - \frac{\Gamma^{(k)}}{\max_{\mathrm{B}} \Gamma^{(k)}} . \qquad (13)$$

Function (13) describes the degree of approximation of the efficiency of the k-th system for a given set B_T to the maximum possible for any B.

By calculating the spread of the loss of efficiency function values, we can explore permissible areas of weight coefficient values based on function (13). For this, for each fixed set of weight coefficient values, we need to find the maximum and minimum values of the loss of efficiency function and construct a function $\rho(B)$ of the form:

$$\rho(B) = \max_{k=1,2,...,K} \theta^{(k)} - \min_{k=1,2,...,K} \theta^{(k)} . \qquad (14)$$

The value $\rho(B)$ characterizes the magnitude of the maximum spread. From expression (14), we can determine the range of weight coefficients where the spread of efficiency losses (or the spread of overall system indicators) does not exceed a certain value or takes a maximum value.

D. METHODOLOGY FOR CALCULATING WEIGHT COEFFICIENTS FOR PARTIAL INDICATORS

Suppose we have J parameter groups. Let's compute the weight coefficients for partial indicators (functional parameter groups), assuming that the values γ_j have already been calculated.

Calculate the weight coefficients for the first group of parameters. For this, β_1 will be changed with a certain step within the limits from 0.1 to 0.9, fulfilling the normalization condition:

$$\sum_{j=1}^{J} \beta_j = 1 . \qquad (15)$$

Using expression (15), we get:

$$\beta_r = \frac{1-\beta_j}{(J-1)} , \; r = 1,2,...,J , \; \forall r \neq j . \qquad (16)$$

For each set B, determine the values of the overall system indicators of all systems according to expression (3).

Calculate the value of $\theta^{(k)}$ using equation (3) and determine the value of $\rho(\mathrm{B}_1)$ using equation (4).

Identify the value of β_1 for which the function $\rho(\beta_1)$ attains its minimum. This particular value of β_1 is adopted as the weight coefficient β_1^*. Similarly, steps (1-5) are executed for $\beta_2, \ldots, \beta_J$.

1. For the final determination of coefficients, normalization is carried out. Since the obtained values $\beta_1, \beta_2, \ldots, \beta_J$ won't satisfy condition (15), we have:

$$\hat{\beta}_j = \frac{\beta_j}{\sum_{r=1}^{J} \beta_r^*} . \qquad (17)$$

2. Computation of Overall System Indicators and System Comparison. The overall system indicators are defined as:

$$\hat{\Gamma}^{(k)} = \sum_{j=1}^{J} \left(\hat{\beta}_j \gamma_j^{(k)} \right) . \qquad (18)$$

3. The best system is considered to be the one for which the value $\hat{\Gamma}^{(k)}$ is maximal:

$$\Gamma_{opt} = \max_{k=1,\ldots,K} \hat{\Gamma}^{(k)} . \qquad (19)$$

In conclusion, the discussed method of evaluating system indicator dispersion provides insights into the significance of parameters of the compared systems. This is achieved by determining weight coefficients based on system efficiency loss functions. The application of this method is particularly relevant when developing or comparing new tools or systems, especially when there aren't enough qualified experts available or when expert surveys are deemed impractical for various reasons.

VI. RESULTS

A. ANALYSIS OF SYSTEM DECOMPOSITION AND PARAMETER SELECTION

Table 1 provides a comprehensive breakdown of the system decomposition and the selection of enhancing (increasing) or decreasing parameters across various groups. The table is structured to offer insights into different cryptocurrencies, namely Bitcoin (BTC), Ethereum (ETH), Tether (USDT), and USD Coin. Each cryptocurrency is evaluated based on various parameters within specific groups.

Key Observations (Table 1):

- Parameter Grouping: The table is segmented into three distinct parameter groups, each containing a varying number of parameters. This hierarchical structure allows for a granular analysis of each cryptocurrency's performance based on specific criteria.
- Enhancing vs. Decreasing Parameters: The column labeled $\mu_{ji}^{\uparrow}$ indicates whether a parameter is enhancing (represented by a value of 1) or decreasing (represented by a value of 0). An enhancing parameter positively impacts the system's performance, while a decreasing parameter has the opposite effect.
- Cryptocurrency Analysis: Each cryptocurrency's performance is evaluated against every parameter within a group. The values represent different metrics, possibly market capitalization, transaction volume, or other relevant indicators, depending on the parameter in question.
- Optimal Values: The last column of the table showcases either the maximum or minimum values, contingent on the nature of the parameter (enhancing or decreasing). For enhancing parameters, the optimal value is the maximum, while for decreasing parameters, it's the minimum.

Specific Insights:

- Bitcoin (BTC) consistently showcases the highest values across most parameters in Group 1, indicating its dominant market position.
- Ethereum (ETH), while trailing Bitcoin in some metrics, outperforms other cryptocurrencies in specific parameters, especially within Group 2.
- Tether (USDT) and USD Coin exhibit similar values across several parameters, suggesting comparable market dynamics or functionalities.
- Optimal Value Analysis: The optimal values column provides a benchmark for comparing the performance of each cryptocurrency. For instance, in Group 1, Parameter 1, Bitcoin reaches the optimal value of 610,730,000,000.00, significantly outperforming other cryptocurrencies.

Table 1. Results of system decomposition and selection of enhancing (reducing) parameters

j	i	$\mu_{ji}^{\uparrow}$	Bitcoin (BTC), $\alpha_{ji}^{(1)}$	Ethereum (ETH), $\alpha_{ji}^{(2)}$	Tether (USDT), $\alpha_{ji}^{(3)}$	USD Coin, $\alpha_{ji}^{(4)}$	USD Coin, $\alpha_{ji}^{(5)}$	$\alpha_{ji\max}$ or $\alpha_{ji\min}$
1	1	1	610,730,000,000.00	253,510,000,000.00	83,900,000,000.00	50,320,000,000.00	50,320,000,000.00	610,730,000,000.00
	2	1	1,280,000,000,000.00	571,670,000,000.00	83,900,000,000.00	56,160,000,000.00	56,160,000,000.00	1,280,000,000,000.00
	3	0	0.3633	0.3644	0.2010	0.1935	0.1935	0.1935
	4	0	0.2809	0.2517	0.0862	0.0557	0.0557	0.0557
2	1	1	+0.6963	-0.1587	+0.0676	+0.0931	+0.0931	0.6963
	2	1	48,220,000	97,930,000	4,140,000	1,720,000	1,720,000	97,930,000
	3	1	0.0205	0.0050	0.0178	0.0134	0.0134	0.0205
	4	1	0.0067	0.0008	0.0027	0.0021	0.0021	0.0111
3	1	1	552,800	1,060,000	98,060	31,960	1,340	1060000
	2	1	18,770,000,000.00	3,440,000,000.00	3,120,000,000.00	4,420,000,000.00	222,140,000.00	18,770,000,000.00
	3	0	600	12	12	12	60	12

Table 2. Intermediate data from the calculation of coefficients of significance of parameters within functional groups

j	i	$\eta_{ji}^{(1)}$	$\eta_{ji}^{(2)}$	$\eta_{ji}^{(3)}$	$\eta_{ji}^{(4)}$	$\eta_{ji}^{(5)}$	$\overline{\eta}_{ji}$	$\Delta\overline{\eta}_{ji}$	d_{ji}	ρ_{ji}
1	1	1.00	0.42	0.14	0.08	0.03	0.33	0.30	0.90	0.31
	2	1.00	0.45	0.07	0.04	0.01	0.31	0.33	1.05	0.36
	3	0.53	0.53	0.96	1.00	0.47	0.70	0.23	0.32	0.11
	4	0.20	0.22	0.65	1.00	0.19	0.45	0.30	0.66	0.23
2	1	1.00	-0.23	0.10	0.13	0.34	0.27	0.32	1.20	0.35
	2	0.49	1.00	0.04	0.02	0.00	0.31	0.35	1.12	0.33
	3	1.00	0.24	0.87	0.65	0.40	0.63	0.25	0.39	0.11
	4	0.60	0.07	0.24	0.19	1.00	0.42	0.30	0.72	0.21
3	1	0.52	1.00	0.09	0.03	0.00	0.33	0.35	1.05	0.41
	2	1.00	0.18	0.17	0.24	0.01	0.32	0.27	0.85	0.33
	3	0.02	1.00	1.00	1.00	0.20	0.64	0.43	0.66	0.26

The data presented in Table 1 offers a multifaceted view of the cryptocurrency market, analyzing various parameters that influence the performance and viability of each digital currency. By understanding these parameters and their optimal values, stakeholders can make informed decisions regarding investment, development, and market positioning. The dominance of Bitcoin in several parameters underscores its established position in the market, while the performance of other cryptocurrencies highlights the dynamic and evolving nature of the digital currency landscape.

B. EXAMINATION OF COEFFICIENT SIGNIFICANCE WITHIN FUNCTIONAL GROUPS

Table 2 offers a meticulous analysis of the normalized parameter values, $\eta_{ji}^{(k)}$, and the subsequent processing of these values. The table is structured to provide insights into the significance of coefficients within functional groups, emphasizing the average arithmetic values, average dispersion values, normalized dispersion values, and normalized weight coefficient values for each parameter group.

Key Observations (Table 2):

- Parameter Grouping: The table is organized into three distinct groups, each containing a set of parameters. This arrangement facilitates a detailed examination of the significance of coefficients within each group.
- Normalized Parameter Values: Columns representing $\eta_{ji}^{(k)}$ provide the normalized values for each parameter. These values are crucial for understanding the relative significance of each parameter within its group.
- Arithmetic Mean: The column labeled $\overline{\eta_{ji}}$ presents the arithmetic mean for each normalized parameter. This average offers a central tendency measure, providing a general sense of the parameter's typical value.
- Average Dispersion: The $\Delta\overline{\eta_{ji}}$ column showcases the average dispersion values for each parameter. Dispersion values indicate the spread or variability of the data, offering insights into the consistency or variability of each parameter.
- Normalized Dispersion and Weight Coefficient Values: The columns d_{ji} and ρ_{ji} represent the normalized dispersion values and the normalized weight coefficient values, respectively. These metrics provide a standardized measure, allowing for a comparative analysis across parameters and groups.

Specific Insights:

- The first group of parameters exhibits a high degree of variability, with Bitcoin consistently showing normalized values close to 1.00 for the first two parameters.
- The second group demonstrates a mix of positive and negative normalized values, suggesting diverse market dynamics or functionalities for the cryptocurrencies under consideration.
- The third group, while having fewer parameters, presents a significant variation in normalized values, especially for Ethereum, which frequently reaches the maximum value of 1.00.

Thus, Table 2 provides a comprehensive analysis of the significance of coefficients within functional groups for various cryptocurrencies. By examining the normalized values and their subsequent processing results, stakeholders can gain a deeper understanding of the relative importance of each parameter. The data underscores the dynamic nature of the cryptocurrency market, with each digital currency exhibiting unique characteristics and trends. The meticulous breakdown of coefficients' significance offers valuable insights for investors, developers, and market analysts, enabling informed decision-making in the ever-evolving digital currency landscape.

C. ANALYSIS OF PARTIAL EFFICIENCY INDICATORS

Table 3 provides a comprehensive view of these efficiency indicators, specifically the partial efficiency indicators, denoted as $\gamma_j^{(k)}$, for each cryptocurrency system across various parameter groups.

Table 3. Calculation of Partial Efficiency Indicators

k / j	**Bitcoin (BTC),** $\gamma_j^{(1)}$	**Ethereum (ETH),** $\gamma_j^{(2)}$	**Tether (USDT),** $\gamma_j^{(3)}$	**USD Coin,** $\gamma_j^{(4)}$	**Lido Staked Ether (STETH),** $\gamma_j^{(5)}$
1	0.77	0.40	0.32	0.38	0.11
2	0.75	0.29	0.20	0.17	0.37
3	0.55	0.73	0.35	0.35	0.06

The table showcases calculated values of partial efficiency indicators for each system across all parameter groups. These indicators provide insights into the performance of each cryptocurrency in relation to specific parameters. A higher value indicates a better performance in that particular parameter group.

For instance, Bitcoin (BTC) exhibits a higher efficiency in parameter group 1 with a value of 0.77, suggesting its dominance in that specific group. On the other hand, Ethereum (ETH) outperforms other cryptocurrencies in parameter group 3 with an efficiency value of 0.73.

It's crucial for stakeholders to understand these nuances as they navigate the complex landscape of cryptocurrencies. Such insights can guide investment decisions, policy-making, and strategic planning in the ever-evolving world of digital currencies.

The Table 4 presents the calculated values for varying weight coefficients, specifically focusing on the optimization of the first weight coefficient, β_1. The goal is to determine the optimal value of β_1 that minimizes the loss function. The table provides a comprehensive view of how the efficiency of different cryptocurrencies changes with varying weight coefficients. The last three columns, representing the maximum, minimum, and the difference of the normalized efficiency values, are crucial in determining the optimal weight coefficient.

Table 5 shifts the focus to the second weight coefficient, β_2. Similar to Table 4, it provides a detailed breakdown of efficiency values for different cryptocurrencies. By analyzing the variations in the efficiency values and the corresponding loss function values, one can deduce the optimal weight for β_2 that would lead to the minimization of the loss function. The consistency in the table's structure allows for a comparative analysis between the effects of varying β_1 and β_2.

The final table in this series, Table 6, is centered around the third weight coefficient, β_3. The structure remains consistent with the previous tables, offering a clear view of how the efficiency of different cryptocurrencies is influenced by varying β_3. The end goal remains the same: to identify the optimal weight that minimizes the loss function. The comparative values in the table provide insights into the relative importance and impact of β_3 in the overall efficiency calculation.

These tables collectively offer a comprehensive view of the loss function's behavior under different weight coefficient scenarios. By systematically varying one coefficient while keeping the others constant, we can isolate the effects of each coefficient on the loss function. Such an approach is crucial in multi-parameter optimization problems, as it allows for a nuanced understanding of each parameter's role. The ultimate aim is to find a combination of these coefficients that would lead to the most efficient cryptocurrency system, as indicated by the minimized loss function.

Table 4. Estimated values for a fixed step

β_1	β_2	β_3	$\Gamma^{(1)}$	$\Gamma^{(2)}$	$\Gamma^{(3)}$	$\Gamma^{(4)}$	$\Gamma^{(5)}$	$\theta^{(1)}$	$\theta^{(2)}$	$\theta^{(3)}$	$\theta^{(4)}$	$\theta^{(5)}$	$\max\limits_{k=1,K} \theta^{(k)}$	$\min\limits_{k=1,K} \theta^{(k)}$	$\rho(B_1)$
0.10	0.45	0.45	0.66	0.50	0.28	0.27	0.20	0.12	0.00	0.11	0.26	0.00	0.26	0.00	0.26
0.20	0.40	0.40	0.67	0.49	0.28	0.28	0.19	0.11	0.02	0.09	0.23	0.05	0.23	0.02	0.20
0.30	0.35	0.35	0.69	0.48	0.29	0.29	0.18	0.09	0.05	0.08	0.19	0.11	0.19	0.05	0.15
0.40	0.30	0.30	0.70	0.46	0.29	0.31	0.17	0.08	0.07	0.07	0.16	0.16	0.16	0.07	0.09
0.50	0.25	0.25	0.71	0.45	0.30	0.32	0.16	0.06	0.09	0.05	0.13	0.21	0.21	0.05	0.16
0.60	0.20	0.20	0.72	0.44	0.30	0.33	0.15	0.05	0.11	0.04	0.10	0.27	0.27	0.04	0.23
0.70	0.15	0.15	0.73	0.43	0.30	0.34	0.14	0.03	0.14	0.03	0.06	0.32	0.32	0.03	0.29
0.80	0.10	0.10	0.74	0.42	0.31	0.35	0.13	0.02	0.16	0.01	0.03	0.37	0.37	0.01	0.36
0.90	0.05	0.05	0.76	0.41	0.31	0.36	0.12	0.00	0.18	0.00	0.00	0.43	0.43	0.00	0.43
$\max\limits_{B} \Gamma^{(i)}$			0.76	0.50	0.31	0.36	0.20						$\min \rho(\beta_1) =$ $\beta_1^* =$		0.09 0.4

Table 5. Estimated values for a fixed step β_2

β_1	β_2	β_3	$\Gamma^{(1)}$	$\Gamma^{(2)}$	$\Gamma^{(3)}$	$\Gamma^{(4)}$	$\Gamma^{(5)}$	$\theta^{(1)}$	$\theta^{(2)}$	$\theta^{(3)}$	$\theta^{(4)}$	$\theta^{(5)}$	$\max\limits_{k=1,K} \theta^{(k)}$	$\min\limits_{k=1,K} \theta^{(k)}$	$\rho(B_1)$
0.45	0.10	0.45	0.67	0.53	0.32	0.34	0.11	0.10	0.00	0.00	0.00	0.68	0.68	0.00	0.68
0.40	0.20	0.40	0.68	0.51	0.31	0.32	0.14	0.09	0.05	0.04	0.06	0.59	0.59	0.04	0.55
0.35	0.30	0.35	0.69	0.48	0.29	0.30	0.17	0.07	0.10	0.08	0.11	0.51	0.51	0.07	0.44
0.30	0.40	0.30	0.70	0.45	0.28	0.28	0.20	0.06	0.15	0.13	0.17	0.42	0.42	0.06	0.36
0.25	0.50	0.25	0.71	0.43	0.27	0.26	0.23	0.05	0.20	0.17	0.23	0.34	0.34	0.05	0.29
0.20	**0.60**	0.20	0.71	0.40	0.25	0.25	0.26	0.04	0.25	0.21	0.29	0.25	0.29	0.04	0.25
0.15	0.70	0.15	0.72	0.37	0.24	0.23	0.29	0.02	0.30	0.25	0.34	0.17	0.34	0.02	0.32
0.10	0.80	0.10	0.73	0.34	0.23	0.21	0.32	0.01	0.36	0.30	0.40	0.08	0.40	0.01	0.39
0.05	0.90	0.05	0.74	0.32	0.21	0.19	0.34	0.00	0.41	0.34	0.46	0.00	0.46	0.00	0.46
$\max\limits_{B} \Gamma^{(i)}$			0.74	0.53	0.32	0.34	0.34						$\min \rho(\beta_2) =$ $\beta_2^* =$		0.25 0.6

Table 6. Estimated values for a fixed step β_3

β_1	β_2	β_3	$\Gamma^{(1)}$	$\Gamma^{(2)}$	$\Gamma^{(3)}$	$\Gamma^{(4)}$	$\Gamma^{(5)}$	$\theta^{(1)}$	$\theta^{(2)}$	$\theta^{(3)}$	$\theta^{(4)}$	$\theta^{(5)}$	$\max\limits_{k=1,K} \theta^{(k)}$		$\rho(B_1)$
0.45	0.45	0.10	0.74	0.38	0.27	0.28	0.22	0.00	0.45	0.22	0.18	0.00	0.45	0.00	0.45
0.40	0.40	0.20	0.72	0.42	0.28	0.29	0.20	0.03	0.39	0.19	0.16	0.08	0.39	0.03	0.36
0.35	0.35	0.30	0.70	0.46	0.29	0.29	0.18	0.06	0.34	0.16	0.14	0.17	0.34	0.06	0.28
0.30	0.30	**0.40**	0.68	0.50	0.30	0.30	0.17	0.08	0.28	0.14	0.11	0.25	0.28	0.08	0.19
0.25	0.25	0.50	0.66	0.54	0.30	0.31	0.15	0.11	0.22	0.11	0.09	0.33	0.33	0.09	0.24
0.20	0.20	0.60	0.63	0.57	0.31	0.32	0.13	0.14	0.17	0.08	0.07	0.41	0.41	0.07	0.35
0.15	0.15	0.70	0.61	0.61	0.32	0.33	0.11	0.17	0.11	0.05	0.05	0.50	0.50	0.05	0.45
0.10	0.10	0.80	0.59	0.65	0.33	0.33	0.09	0.20	0.06	0.03	0.02	0.58	0.58	0.02	0.56
0.05	0.05	0.90	0.57	0.69	0.34	0.34	0.07	0.23	0.00	0.00	0.00	0.66	0.66	0.00	0.66
$\max\limits_{B} \Gamma^{(i)}$			0.74	0.69	0.34	0.34	0.22						$\min \rho(\beta_3) =$ $\beta_3^* =$		0.19 0.4

D. CALCULATION OF SYSTEM-WIDE INDICATORS AND COMPARISON OF SYSTEMS

Figure 1 presents the plots of the functions $\rho(B_i)$. These plots distinctly showcase the minimum values of the loss function.

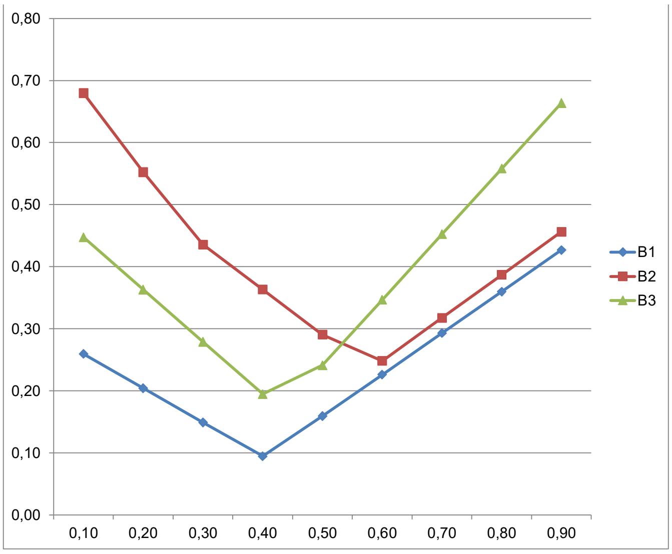


Figure 1. The plots of the functions $\rho(B_i)$

The values which are defined by these minima are given by $\beta_1 = 0.4$, $\beta_2 = 0.6$, and $\beta_3^* = 0.4$. After normalizing these coefficients using equation (17), we obtain:

$$\hat{\beta}_1 = 0.29\,,\ \hat{\beta}_2 = 0.43\,,\ \text{and}\ \hat{\beta}_3 = 0.29\,.$$

Thus, equation (18) can be expressed as:

$$\hat{\Gamma}^{(k)} = 0.29\gamma_1^{(k)} + 0.43\gamma_2^{(k)} + 0.29\gamma_3^{(k)}\,.$$

Substituting the values from Table 3, we derive:

$$\hat{\Gamma}^{(1)} = 0.7\,,\ \hat{\Gamma}^{(2)} = 0.45\,,\ \hat{\Gamma}^{(3)} = 0.28\,,\ \hat{\Gamma}^{(4)} = 0.28\,,\ \hat{\Gamma}^{(5)} = 0.21\,.$$

Consequently, by employing criterion (19), we can determine the most efficient cryptocurrency. Bitcoin (BTC) emerges as the leading cryptocurrency with the highest comprehensive security index.

VII. DISCUSSION

This paper addresses a critical gap in the existing literature by introducing a novel quantitative framework for assessing cryptocurrency efficiency based on objective metrics. Our findings shed light on significant aspects of the current cryptocurrency market and provide valuable insights into the relative efficiency of various digital assets. The following discussion elaborates on these findings and their implications.

A. KEY FINDINGS AND IMPLICATIONS

The identification of Bitcoin (BTC) as the most efficient cryptocurrency, with an efficiency score of $\hat{\Gamma}^{(1)} = 0.7$, aligns with its established market dominance but offers a data-driven validation independent of market sentiment. This result is particularly relevant in the context of recent studies on cryptocurrency market dynamics [22, 23]. Importantly, this efficiency metric encompasses multiple dimensions beyond market capitalization, integrating network activity and transactional performance.

The analysis of Ethereum (ETH), which achieved an efficiency score of $\hat{\Gamma}^{(2)} = 0.45$, reveals intriguing patterns, particularly concerning network indicators. Although Ethereum excels in network activity metrics, such as daily active addresses and transaction volumes, its overall efficiency score indicates that high network activity does not directly translate into broader system efficiency. This nuanced finding adds depth to prior research [24], which has largely emphasized Ethereum's technical capabilities rather than its operational performance.

B. METHODOLOGICAL CONTRIBUTIONS

The proposed methodology for determining weight coefficients using system efficiency loss functions marks a significant advancement in cryptocurrency analysis. This approach offers distinct advantages:

- Objectivity: The exclusion of expert opinions minimizes subjective bias in evaluating cryptocurrency performance.
- Reproducibility: The quantitative nature of this framework ensures consistent application across different time periods and market conditions.
- Adaptability: The framework accommodates evolving parameters as cryptocurrency technologies develop.

The derived normalized weight coefficients ($\hat{\beta}_1 = 0.29$, $\hat{\beta}_2 = 0.43$, and $\hat{\beta}_3 = 0.29$) represent a balanced structure for evaluating cryptocurrency efficiency, providing a solid foundation for future research.

C. PRACTICAL IMPLICATIONS

The findings of this study hold significant practical value for various stakeholders in the cryptocurrency ecosystem:

- For Investors and Market Participants: The efficiency metrics introduced here can complement traditional methods of portfolio optimization and risk assessment. This quantitative framework offers a more objective basis for investment decisions, addressing the sentiment-driven nature of cryptocurrency markets.
- For Developers and Platform Architects: Insights into the relative importance of efficiency parameters can guide technical improvements in cryptocurrency platforms. The strong influence of network indicators underscores the potential for network optimizations to enhance overall system efficiency.
- For Regulators and Policymakers: The quantitative framework provided by this study can aid in developing evidence-based regulatory strategies. By quantifying system efficiency and stability, policymakers can design more informed regulatory interventions.

D. LIMITATIONS AND FUTURE RESEARCH DIRECTIONS

While this study provides valuable insights, certain limitations should be acknowledged:

- Temporal Constraints: The analysis offers a snapshot of a rapidly evolving market. Future studies should adopt longitudinal approaches to explore how efficiency metrics evolve over time.
- Parameter Selection: Despite being comprehensive, the selected parameters are not exhaustive. Future research

could identify and incorporate additional metrics as cryptocurrency technologies advance.

- Market Dynamics: The interplay between efficiency metrics and market behavior, including stability and adoption rates, warrants further investigation.

Future research directions include:

- Expanding the analysis to encompass emerging cryptocurrencies and alternative blockchain architectures.
- Conducting time-series studies to assess the temporal stability of efficiency rankings.
- Investigating correlations between efficiency metrics and market performance during stress events.
- Developing predictive models grounded in efficiency metrics.

E. THEORETICAL IMPLICATIONS

The findings of this study contribute to the broader theoretical understanding of decentralized financial systems. By bridging the gap between technical blockchain analyses [25] and economic evaluations of cryptocurrencies, this work offers a holistic framework for understanding cryptocurrency efficiency.

The demonstrated relationship between network parameters and system efficiency suggests that theoretical models of cryptocurrency systems should prioritize network effects and operational efficiency alongside cryptographic security and consensus mechanisms. This shift in focus could refine the theoretical underpinnings of decentralized financial systems [8].

VIII. CONCLUSION

The rapid evolution of cryptocurrencies and decentralized financial systems has introduced a transformative era of financial innovation. As these systems gain increasing adoption, their impact on the global financial landscape becomes ever more pronounced. This study sought to provide an objective assessment of cryptocurrency efficiency, avoiding the subjective biases often associated with expert evaluations.

The literature review underscored the growing interest in this field, with research ranging from the technical specifics of blockchain technology to the broader socio-economic implications of decentralized finance. Despite this, a critical gap in the objective evaluation of cryptocurrency efficiency was identified and addressed in this research.

The findings of this study highlight Bitcoin (BTC) as the most efficient cryptocurrency based on the established criteria. However, this conclusion should be viewed as a snapshot of the dynamic and rapidly changing digital currency landscape. As the field evolves and more data emerges, it is essential for future research to reassess these conclusions, ensuring their relevance amidst ongoing technological and market developments.

Moreover, while this research provides valuable insights into cryptocurrency efficiency, it emphasizes the importance of considering other critical factors, such as security, regulatory frameworks, and broader market dynamics, when evaluating the overall viability of cryptocurrencies and decentralized financial systems.

As the world stands on the brink of a financial revolution driven by digital currencies and decentralized systems, it is imperative for academia, industry, and policymakers to collaborate effectively [26]. Such a concerted effort will ensure that the potential benefits of these innovations are fully realized while mitigating associated risks, fostering a more inclusive, transparent, and efficient global financial ecosystem.

References

[1] S. Nakamoto, "Bitcoin: A Peer-to-Peer Electronic Cash System," Oct. 2008.

[2] J. Zhang, K. Cai, and J. Wen, "A survey of deep learning applications in cryptocurrency," *iScience*, vol. 27, no. 1, p. 108509, 2024. https://doi.org/10.1016/j.isci.2023.108509.

[3] D. A. Orr, "Cryptocurrency: Its Impact and Forensic Worth," in *Encyclopedia of Forensic Sciences, Third Edition (Third Edition)*, M. M. Houck, Ed., Oxford: Elsevier, 2023, pp. 709–716. https://doi.org/10.1016/B978-0-12-823677-2.00073-8.

[4] K. Xu, J. Zhu, X. Song, and Z. Lu, Eds., "Blockchain Technology and Application," *Proceedings of the Third CCF China Blockchain Conference, CBCC 2020, Jinan, China, December 18-20, 2020, Revised Selected Papers*, vol. 1305. in Communications in Computer and Information Science, vol. 1305. Singapore: Springer, 2021. https://doi.org/10.1007/978-981-33-6478-3.

[5] S.-W. Lee, I. Singh, and M. Mohammadian, Eds., *Blockchain Technology for IoT Applications*. in Blockchain Technologies. Singapore: Springer, 2021. https://doi.org/10.1007/978-981-33-4122-7.

[6] "IntoTheBlock - On-Chain Crypto, DeFi & NFT Analytics." [Online]. Available at: https://app.intotheblock.com/.

[7] A. Aspris, S. Foley, J. Svec, and L. Wang, "Decentralized exchanges: The 'wild west' of cryptocurrency trading," *International Review of Financial Analysis*, vol. 77, p. 101845, 2021. https://doi.org/10.1016/j.irfa.2021.101845.

[8] I. Yousaf, A. Abrar, and L. Yarovaya, "Decentralized and centralized exchanges: Which digital tokens pose a greater contagion risk?," *Journal of International Financial Markets, Institutions and Money*, p. 101881, 2023. https://doi.org/10.1016/j.intfin.2023.101881.

[9] S. S. Kushwaha, S. Joshi, D. Singh, M. Kaur and H.-N. Lee, "Systematic review of security vulnerabilities in ethereum blockchain smart contract," *IEEE Access*, vol. 10, pp. 6605-6621, 2022. https://doi.org/10.1109/ACCESS.2021.3140091.

[10] J. Abou Jaoude and R. George Saade, "Blockchain Applications – Usage in Different Domains," *IEEE Access*, vol. 7, pp. 45360–45381, 2019. https://doi.org/10.1109/ACCESS.2019.2902501.

[11] S. Sudaryono, Q. Aini, N. Lutfiani, F. Hanafi, and U. Rahardja, "Application of blockchain technology for iLearning student assessment," *IJCCS (Indonesian Journal of Computing and Cybernetics Systems)*, vol. 14, no. 2, art. no. 2, 2020. https://doi.org/10.22146/ijccs.53109.

[12] M. Krichen, M. Ammi, A. Mihoub, and M. Almutiq, "Blockchain for modern applications: A survey," *Sensors*, vol. 22, no. 14, art. no. 14, 2022. https://doi.org/10.3390/s22145274.

[13] K. Jindal and A. Chhetri, "Analyzing receptivity of indian respondents for introduction of a regulated cryptocurrency market," *J Stud Res*, vol. 11, no. 2, 2022. https://doi.org/10.47611/jsrhs.v11i2.2315.

[14] A. Barradas, A. Tejeda-Gil, and R.-M. Cantón-Croda, "Real-time big data architecture for processing cryptocurrency and social media data: A clustering approach based on k-means," *Algorithms*, vol. 15, no. 5, art. no. 5, 2022. https://doi.org/10.3390/a15050140.

[15] T. Zatonatska, V. Suslenko, O. Dluhopolskyi, V. Brych, and T. Dluhopolska, "Investment models on centralized and decentralized cryptocurrency markets," *Naukovyi Visnyk Natsionalnoho Hirnychoho Universytetu*, pp. 177–182, 2022. https://doi.org/10.33271/nvngu/2022-1/177.

[16] M. Mbaye, "Sustainability of cryptocurrency in blockchain technology for business development in African countries," *International Journal of Business Ecosystem & Strategy*, vol. 3, no. 4, art. no. 4, 2021. https://doi.org/10.36096/ijbes.v3i4.297.

[17] Z. Lv, J. Wu, D. Chen, and A. J. Gander, "Chapter 3 - Distributed computing to blockchain: Architecture, technology, and applications," *Distributed Computing to Blockchain*, R. Pandey, S. Goundar, and S. Fatima, Eds., Academic Press, 2023, pp. 39–54. https://doi.org/10.1016/B978-0-323-96146-2.00019-X.

[18] D. R. Kiran, "Chapter Six - Wealth and time value of money," *Principles of Economics and Management for Manufacturing Engineering*, D. R. Kiran, Ed., Butterworth-Heinemann, 2022, pp. 53–72. https://doi.org/10.1016/B978-0-323-99862-8.00003-0.

[19] T.-H. Chang and D. Svetinovic, "Data analysis of digital currency networks: Namecoin case study," *Proceedings of the 2016 21st*

International Conference on Engineering of Complex Computer Systems (ICECCS), Nov. 2016, pp. 122–125. https://doi.org/10.1109/ICECCS.2016.023.

[20] O. Kuznetsov, N. Kryvinska, O. Ilchenko, T. Smirnova, and Y. Ulianovska, “Comparative analysis of cryptocurrency trading platforms using the analytic hierarchy process,” in *Proceedings of the 3rd International Workshop on Information Technologies: Theoretical and Applied Problems 2023*, I. Lytvynenko and S. Lupenko, Eds., in CEUR Workshop Proceedings, vol. 3628. Ternopil, Ukraine: CEUR, Nov. 2023, pp. 221–235. Accessed: Sep. 19, 2024. [Online]. Available at: https://ceur-ws.org/Vol-3628/paper16.pdf.

[21] O. Kuznetsov, O. Ilchenko, N. Kryvinska, K. Buravchenko, O. Smirnov, and I. Savchenko, “An empirical assessment of leading blockchain financial services,” *Proceedings of the 2023 IEEE 1st Ukrainian Distributed Ledger Technology Forum (UADLTF)*, Oct. 2023, pp. 1–6. https://doi.org/10.1109/UADLTF61495.2023.10548729.

[22] R. Auer and S. Claessens, *Cryptocurrency Market Reactions to Regulatory News*, Routledge Handbook of FinTech, Routledge, 2021. https://doi.org/10.2139/ssrn.3582324.

[23] A. Brauneis, R. Mestel, R. Riordan, and E. Theissen, “The anatomy of a fee change – evidence from cryptocurrency markets,” *Journal of Empirical Finance*, vol. 67, pp. 152–167, 2022. https://doi.org/10.1016/j.jempfin.2022.03.003.

[24] J. T. George, “Ethereum,” in *Introducing Blockchain Applications: Understand and Develop Blockchain Applications Through Distributed Systems*, J. T. George, Ed., Berkeley, CA: Apress, 2022, pp. 55–106. https://doi.org/10.1007/978-1-4842-7480-4_4.

[25] O. Kuznetsov, A. Rusnak, A. Yezhov, K. Kuznetsova, D. Kanonik, and O. Domin, “Merkle trees in blockchain: A study of collision probability and security implications,” *Internet of Things*, p. 101193, 2024. https://doi.org/10.1016/j.iot.2024.101193.

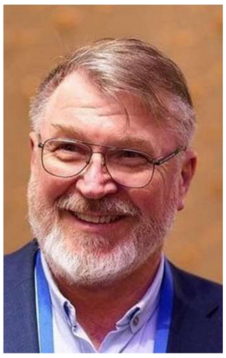
[26] S. Zhang, Y. Wang, E. Luo, Q. Liu, K. Gu, and G. Wang, “A traceable and revocable decentralized multi-authority privacy protection scheme for social metaverse,” *Journal of Systems Architecture*, vol. 140, p. 102899, 2023. https://doi.org/10.1016/j.sysarc.2023.102899.

***OLEKSANDR KUZNETSOV** holds a Doctor of Sciences degree in Engineering and is a Full Professor. He is an Academician at the Academy of Applied Radioelectronics Sciences and the recipient of the Boris Paton National Prize of Ukraine in 2021. Additionally, he serves as a Professor at the Department of Theoretical and Applied Sciences, eCampus University in Italy. His research primarily focuses on applied cryptology and coding theory, blockchain technologies, the Internet of Things (IoT), and the application of AI in cybersecurity.*

***OLEKSII SMIRNOV** Doctor of Engineering, Full Professor, Head of Cybersecurity & Software Academic Department Central Ukrainian National Technical University. His research primarily focuses on cybersecurity & information security, computer science and communication.*

***MYKOLA MORMUL** PhD, associative professor, Teaching disciplines: Higher mathematics, Probability theory and mathematical statistics, Theoretical mechanics, Algebra and geometry, Mathematical analysis, Optimization methods and operations research, Numerical methods. Field of scientific interests: mathematical modeling, optimization methods, statistics and optimization of economic and technical systems.*

***YEVGEN KOTUKH** PhD, Associate Professor, Professor of Cybersecurity Department, Dnipro University of Technology. His research primarily focuses on applied cryptology, coding theory, tokenization technologies, the Internet of Things (IoT), application of AI in cybersecurity, post-quantum cryptography, quantum information science.*



***VOLODYMYR ZVIERIEV** has a candidate's degree in technical sciences and has the scientific title of senior researcher. He is a Valid Member of the Ukrainian Academy of Cyber Security and the Head of the Center for Cyber Intelligence and Security Innovations, Associate Professor of the Department of Software Engineering at the State University of Trade and Economics in Kyiv. His research mainly focuses on applied cryptology, network and system security, and the application of AI in cyber security.*

•••