Journal of Operational and Strategic Analytics
https://www.acadlore.com/journals/JOSA

Interplay of Cryptocurrencies with Financial and Social Media Indicators: An Entropy-Weighted Neural-MADM Approach

Jéfferson Augusto Colombo[1], Tanzina Akhter[2], Peter Wanke[3], Md. Abul Kalam Azad[4], Yong Tan[5*], Seyyed A. Edalatpanah[6], Jorge Antunes[3]

[1] Sao Paulo School of Economics, Fundação Getulio Vargas, 01332-000 São Paulo, Brazil
[2] Department of Business Administration, University of Asia Pacific, 1205 Dhaka, Bangladesh
[3] COPPEAD Graduate Business School, Federal University of Rio de Janeiro, 21941-617 Rio de Janeiro, Brazil
[4] Department of Business and Technology Management, Islamic University of Technology, 1704 Gazipur, Bangladesh
[5] Department of Accounting, Finance and Economics, University of Bradford, BD7 1DP Bradford, UK
[6] Department of Applied Mathematics, Ayandegan Institute of Higher Education, 4681853617 Tonekabon, Iran

[*] Correspondence: Yong Tan (y.tan9@bradford.ac.uk)

Received: 10-07-2023 **Revised:** 11-10-2023 **Accepted:** 11-21-2023

Citation: J. A. Colombo1, T. Akhter, P. Wanke, M. A. K. Azad, Y. Tan, S. A. Edalatpanah, and J. Antunes, "Interplay of cryptocurrencies with financial and social media indicators: An entropy-weighted neural-MADM approach," *J. Oper. Strateg Anal.*, vol. 1, no. 4, pp. 160–172, 2023. https://doi.org/10.56578/josa010402.

Abstract: In the rapidly evolving domain of digital finance, the interplay between cryptocurrencies and external variables such as financial and social media indicators warrants thorough examination. This investigation employs a novel, entropy-weighted Multiple Attribute Decision Making (MADM) model to decipher these intricate relationships. The study's foundation is an expansive dataset, meticulously compiled to encompass a broad spectrum of financial data alongside diverse social media indicators. Central to this analysis is the employment of the Stepwise Weight Assessment Ratio Analysis (SWARA) method, meticulously applied to ascertain the relative importance of various social media indicators. Complementing this, the Complex Proportional Assessment (COPRAS) methodology is adeptly utilized to derive utility functions for each cryptocurrency under scrutiny. The analytical prowess of neural network regressions is harnessed to delineate the influence exerted by a multitude of financial indicators on these utility functions. The findings of this research are pivotal in understanding the dynamics within the cryptocurrency market. Bitcoin and Ripple emerge as pivotal entities, primarily functioning as primary conduits for market shocks. In contrast, Ethereum is identified as a stabilizing force, predominantly absorbing such fluctuations. A nuanced aspect of this study is the differential impact of social media indicators on various cryptocurrencies. Bitcoin and Ethereum display a negative correlation with these indicators, suggesting a complex, possibly inverse relationship with social media dynamics. Conversely, Litecoin, Dogecoin, and Ripple exhibit a positive responsiveness, indicating a heightened susceptibility to social media attention, sentiment, and prevailing uncertainty.

Keywords: Cryptocurrency; Social media; Bitcoin; Ripple; Ethereum; Litecoin; Dogecoin; Multiple Attribute Decision Making

1 Introduction

Cryptocurrency, a concept that revolutionized the financial sector, operates as a virtual currency on a decentralized ledger [1]. Circulating through peer-to-peer networks, it negates the necessity for mediators such as financial or governmental authorities [2]. Originating in 2008, the cryptosystem, pioneered by Satoshi Nakamoto through the Bitcoin project, marked a pivotal shift in the digital financial landscape [3]. Regarded as a digital counterpart of traditional currency [4], its transactional presence in the digital business realm has escalated rapidly [2]. Among various cryptocurrencies, Bitcoin stands out due to its unique features of decentralization, speed, anonymity, and transparency, which distinctly separate it from traditional currencies [1]. The decentralization aspect, in particular, makes Bitcoin's price movements highly sensitive to investors' perceptions rather than institutional regulations [3].

The increasing popularity of cryptocurrencies extends beyond early adopters and enthusiasts, attracting widespread attention. However, recent incidents like the Terra-Luna episode and the 2022 bear market have underscored the complexities in valuing these digital assets, revealing their susceptibility to market sentiment [5]. Hence, elucidating the cause-effect and feedback relationships between cryptocurrencies and social network indicators has become imperative. Yet, the impact of social media indicators on the utility function of cryptocurrencies remains under-explored. This research focuses on eight pivotal social media indicators: BBC Breaking News; (US) Department of State; Donald Trump; Elon Musk; Twitter-based Economic Policy Uncertainty (EPU); Google Trends; Risk Aversion; and United Nations. In the domain of cryptocurrency analysis, the influence of social media and governmental entities is increasingly recognized as pivotal. The BBC, as a prominent UK-based news broadcasting platform, significantly impacts audience reactions, eliciting both positive and negative responses [6]. The United States Department of State, responsible for foreign policy and relations, plays a substantial role in influencing the predictability, returns, and volatility of digital currencies [1]. The tweets of the former US President Donald Trump are considered a notable indicator within the cryptocurrency utility function, reflecting their impact on market dynamics [7]. Similarly, Elon Musk, a globally recognized entrepreneur, wields considerable influence over the decentralized cryptocurrency market through his Twitter activities [8]. This study also incorporates Twitter-based EPU as a tool to gauge economic variability, providing insights into market conditions [1]. Google Trends, which tracks and analyzes user search behavior, is identified as a valuable predictor of Bitcoin returns [5]. Furthermore, this research considers various financial proxies that encapsulate investor risk aversion and economic uncertainty, contributing to the development of a utility-based aversion coefficient [6]. The role of the United Nations is also examined, given its significant presence in the cryptocurrency market and its efforts towards integrating digital currency into global sustainability initiatives [1]. Additionally, this study analyzes data from six major cryptocurrencies: Bitcoin, Ethereum, Dogecoin, Ripple, Litecoin, and Tether, all notable for their market capitalization. A diverse array of financial indicators, including precious metal prices, oil prices, major stock indices, the EUR/USD exchange rate, the VIX, the MSCI ACWI ETF, and Tesla stock prices, are incorporated to comprehensively assess the dynamics of the cryptocurrency market.

Extensive research within behavioral and financial economics has led to the prediction of cryptocurrency price fluctuations and their extrinsic correlation with social media and financial catalysts. In the realm of behavioral economics, it is posited that emotions shape investor sentiments, thereby influencing their decision-making process regarding financial investments [9]. These sentiments, in turn, significantly impact the pricing, return, and volatility of digital assets within the financial market [10]. Such evidence underscores the pivotal role of sentiment in the pricing mechanisms of digital financial assets, including Bitcoin.

A recent advancement in behavioral finance is the utilization of social media platforms to gauge investor sentiment [3]. These platforms offer a plethora of perspectives, opinions, and information, aiding decision-makers in the financial realm [11]. Platforms like Twitter and various chat tools have been identified as primary sources for financial analysts, investors, and regulatory bodies in making key financial decisions [12]. Empirical studies have highlighted the influence of social media on Bitcoin, with particular attention to Twitter's impact on market dynamicsor [4, 7–10]. For instance, Huynh [7] investigated the correlation between sentiments expressed in Donald Trump's tweets and Bitcoin price movements, employing textual analysis to identify spillover effects. Similarly, research has examined Elon Musk's influence on Bitcoin price volatility through his Twitter activities, employing Granger causality to understand the relationship with market returns [8]. Yousaf et al. [4] explored the interconnection between the S&P 500 Twitter sentiment index and various asset classes, revealing that investor sentiments have a pronounced impact during periods of positive or negative sentiment shocks.

However, previous studies have often focused exclusively on individual social media platforms, such as Twitter or stock market sentiment indices, without considering a comprehensive view of all relevant social media platforms. This study aims to fill this gap by examining a wider array of the above eight social media indicators. Furthermore, earlier research did not fully explore diverse financial indicators that could provide insights into both predictive and commodity aspects of the financial market [6].

The structure of this paper is organized into four additional sections. Section 2 presents a detailed literature review, followed by an explanation of the methodology in Section 3. Section 4 delves into the analysis and discussion of results. Finally, conclusions are drawn in Section 5.

2 Literature Review

The allure of cryptocurrency has captivated financial investors, policymakers, and regulatory bodies globally [5], as evidenced by its remarkable 2394% market growth from 2016 to 2017 [2]. Increasingly perceived as a financial safeguard against global economic volatility, cryptocurrencies are being integrated into investment portfolios for their hedging capabilities against traditional financial instruments like gold and the US dollar, as well as against business policy uncertainty and shocks in the Asia Pacific region [1]. Consequently, an upsurge in investment towards this virtual currency is observed [13]. However, the hedging potential of these digital assets is intricately linked to social media and web analytics platforms, such as Twitter and Google Trends. It is posited that cryptocurrency price fluctuations are more influenced by public perceptions than institutional regulations [2]. This observation has spurred behavioral economists and academics to investigate the relationship between cryptocurrency price variations and social media networks [1]. Diverging from existing studies, financial researchers are also exploring the interplay between traditional financial assets and the heterogeneous nature of cryptocurrency assets [6]. This paper synthesizes two prominent strands of the cryptocurrency literature. The first strand investigates the interaction between traditional and alternative financial assets with cryptocurrencies, including their time-varying effects. The second, an emerging research area, examines how media attention and social networks influence cryptocurrency behavior.

In their research, Kumar et al. [14] utilized a Generalized Vector Autoregression (VAR) framework, discovering that indices such as S&P500 and NASDAQ have a more significant influence on cryptocurrencies like Bitcoin and Ethereum, rather than vice versa. Similarly, Ciner et al. [15] employed a LASSO quantile regression approach, finding that US government bond indices and small-cap returns are predictive of the tail behavior of cryptocurrency returns. Elsayed et al. [16] investigated the spillover effect between cryptocurrencies and other assets, identifying that cryptocurrency policy uncertainty significantly impacts return spillovers to other variables, while gold predominantly receives both return and volatility spillovers. Another set of studies, including those by Kumar et al. [14], have examined the interconnectedness between traditional assets and cryptocurrencies in a time-varying manner. They observed a notable increase in connectedness of returns and volatility among these markets following the onset of the COVID-19 pandemic.

While research linking sentiment to cryptocurrencies is burgeoning, it remains underdeveloped. Yousaf et al. [4] noted that the connectedness between the S&P 500 Twitter Sentiment Index and traditional assets (excluding cryptocurrencies) is stronger at the extremes of the return distribution. This finding indicates a pronounced impact of sentiment during extreme positive or negative sentiment shocks. Including cryptocurrencies, Naeem et al. [17] applied the bivariate cross-quantilogram method of Han et al. [18], finding a strong and persistent predictive relationship between happiness sentiment and most cryptocurrency returns. Behavioral economists have increasingly focused on the connection between social media sentiments and investor perceptions and attitudes, recognizing their influence in predicting cryptocurrency prices [3]. Bollen et al. [19], employing neural networks and causality networks, linked social media sentiments to cryptocurrency price forecasting. Wolk [2] explored the relationship between social media platforms and price prediction, using a multi-model approach. However, none of these studies have incorporated an integrated perspective of social media sentiment, encompassing heterogeneous drivers like news headlines, economic variability information, and business policy updates. This study aims to provide a comprehensive view, encompassing a range of social media indices to explore their impact on cryptocurrency market price variations. Alongside social media drivers, this research incorporates a variety of financial indicators, contributing significantly to understanding the speculative price fluctuations of crypto assets from a behavioral finance perspective.

3 Methodology

3.1 Research Sample and Data Collection Procedures

The methodology of this study is predicated on an analysis of secondary datasets, from which seventeen distinct variables were selected, categorized under 'social media indicators' and 'financial indicators' (refer to Table 1).

Table 1. Bitcoin price drivers

Category	List of Variables
Social media indicators	BBC Breaking News, (US) Department of State, United Nations, Donald Trump; Elon Musk, Google Trends, EPU based on Twitter, financial indices for measuring the amount of risks and the prices of risks
Financial indicators	Prices of Gold, Platinum, Palladium, and Silver Prices of oil Brent and WTI the NASDAQ and S&P500 indexes Price of Tesla stock

The influence of the BBC as a social media indicator on Bitcoin price direction is significant, given its standing as a reputable information source in the United Kingdom [6]. The BBC's impact on audience perception is dual-natured: positive when broadcasting hopeful events and negative when focusing on adverse aspects of human nature [10]. The US Department of State's announcements are considered to have a direct influence on Bitcoin price fluctuations. Similarly, the United Nations is acknowledged for its leading role in the digital currency sphere [2]. The tweets of former US President Donald Trump are also analyzed for their impact on cryptocurrency, despite Twitter not being an official channel for policy communication in the US. Trump's tweets are found to correlate directly with Bitcoin's trading volumes, volatility, and returns [7, 20]. Elon Musk's tweets are also considered due to their notable influence on the cryptocurrency market [8]. Parameters such as time, date, username, photos, hashtags, like counts, reply counts, and mentions are used to analyze and visualize Musk's impact on the digital currency world [21].

In the field of cryptocurrency market analysis, Google Trends has emerged as a pivotal tool for predicting investor attitudes and perceptions. This web-based search tool offers extensive data on specific search terms over designated time intervals [2]. It has been observed that a higher frequency of Google searches correlates with increased positive returns in Bitcoin, leading to a surge in trading volume [1]. Furthermore, the concept of EPU has gained prominence in discussions about drivers of Bitcoin returns. An increase in global EPU is found to adversely affect Bitcoin returns [22]. Interestingly, the predictive power of the EPU index on Bitcoin returns exhibits geographical variance. For instance, the EPU index in China is effectively predictive of Bitcoin returns, while the EPU indexes of the United States and Japan do not demonstrate such predictive capacity [1]. In this study, the category of 'Twitter-based EPU' is utilized to gauge economic variability. Additionally, this research integrates a 'risk-aversion index' into its utility function to represent the crypto market's risk perspective. This index comprises financial indices related to risk aversion and economic uncertainty, formulated as a utility-based aversion coefficient [1].

Data pertaining to the query 'Bitcoin' was sourced from Google Trends [2]. This includes the total number of mentions of 'Bitcoin', scaled and compared across various timeframes. Subsequently, the log return of Bitcoin was calculated based on the obtained time series.

To analyze the correlation between influential individuals' Twitter posts and Bitcoin price movements, raw data from the Twitter accounts of Donald Trump and Elon Musk were collected [7, 8]. A textual analysis was conducted to differentiate between positive and negative sentiments, following the approach of Loughran and McDonald [23]. Two proxy variables were developed for positive and negative words:

$$\text{Positivity/negativity} = \frac{\textit{The number of positive / negative words}}{\textit{Total nuber of words}} \times 100 \tag{1}$$

For the financial indicators influencing Bitcoin price fluctuations, this study considers the prices of precious metals (Gold, Platinum, Palladium, Silver), oil (Brent and WTI), stock indices (NASDAQ and S&P500), and Tesla stock prices. These indicators offer alternative investment perspectives due to their predictive and commodity aspects in the crypto market [1]. Data sources include MSCI (ACWI), Yahoo Finance (EUR/USD, Tesla), the NASDAQ Composite (NASDAQ), and SP Global (S&P 500) for financial indicators, and the London Bullion Market Association and Fred Economic Data for Metal and Petroleum data [4].

3.2 Proposed Model

In the domain of MADM, various models have been employed to compute attribute weightings [24, 25], notably including the Entropy Method [24, 26], Information Entropy Weight (IEW) [27], Analytic Hierarchy Process (AHP) or [24, 28, 29], Fuzzy AHP [30, 31], and Rough AHP [32]. Recently, SWARA has been recognized for its efficacy in calculating attribute weights within performance measurement frameworks [33]. Liang and Ding [34] have emphasized the significance of accurately determining these weights, noting the potential for bias due to inherent uncertainties and subjectivity in scaling. Information entropy, conceptualized as a probabilistic measure of uncertainty, plays a pivotal role in this context [35]. It captures the variability in randomness levels across different analysis sub-groups. An attribute's discriminatory power is directly proportional to its information entropy value.

This study utilizes information entropy to establish the initial order of importance for social media indicators in SWARA, facilitating the computation of unbiased weights. These weights are then utilized as inputs in the COPRAS method. Unlike other MADM approaches, COPRAS effectively establishes a utility function for each cryptocurrency [36, 37]. The concept of utility, fundamental in economics and MADM, quantifies latent perceptions or preferences across various criteriaor [38–40]. COPRAS's utility function approach, favored for its simplicity, lacks stringent requirements on latent preference structures beyond the aggregation formula, thus straightforwardly linking social media indicators to partial value functions [41, 42]. This additive aggregation's simplicity renders the approach particularly suitable for subsequent multivariate analysis inputs [43].

3.2.1 SWARA

The following steps outline the SWARA methodology applied in this research [44]:

Step 1: Social media indicators are initially sorted based on their information entropy, from highest to lowest.

Step 2: The first-ranked social media indicator is assigned a null latent preference value. Subsequent social media indicators are assigned preferences relative to the first, based on their pairwise relative importance. This is denoted by S_j, representing the ratio of comparison between a given social media indicator and the one with the highest entropy.

Step 3: Pairwise social-media efficiency K_j is calculated using the formula:

$$K_j = \begin{cases} 1, j = 1 \\ S_j + 1, j > 1 \end{cases} \tag{2}$$

Step 4: Relative weights (q_j) for each social media indicator are computed, based on their sorted pairwise efficiency and importance rank:

$$q_j = \begin{cases} 1 & j = 1 \\ \frac{K_{j-1}}{K_j} & j > 1 \end{cases} \tag{3}$$

Step 5: Final weights are determined as $W_j = \frac{q_j}{\sum_{k=1}^{n} q_k}$, where W_j denotes the weight of each social media indicator j.

3.2.2 COPRAS

The COPRAS method, introduced over two decades ago [37], has been widely explored in various research contexts. It has been combined with SWARA or [45–47], integrated into Fuzzy COPRAS [48], and applied alongside other MCDM methods [49, 50]. This section outlines the application of COPRAS in deriving utility functions for cryptocurrencies based on the social media importance weights identified in the previous section.

Step 1: A decision matrix X is constructed, encompassing m time-series observations and n cryptocurrencies:

$$X = \begin{pmatrix} a_{11} & \dots & a_{1n} \\ \vdots & \ddots & \vdots \\ a_{m1} & \cdots & a_{mn} \end{pmatrix} \quad i = 1, 2, \dots n; j = 1, 2, \dots, m \tag{4}$$

Step 2: The decision matrix X is normalized:

$$\overline{x_{ij}} = \frac{x_{ij}}{\sum_{j=1}^{n} x_{ij}} \tag{5}$$

Resulting in:

$$\bar{X} = \begin{pmatrix} \bar{x}_{11} & \dots & \bar{x}_{1n} \\ \vdots & \ddots & \vdots \\ \bar{x}_{m1} & \dots & \bar{x}_{mn} \end{pmatrix} \tag{6}$$

Step 3: A weighted normalized decision matrix is computed:

$$\widehat{x_{ij}} = \bar{x}_{ij} \times w_{ij}; i = 1, 2, \dots, n; j = 1, 2, \dots, m \tag{7}$$

Thus:

$$\widehat{X} = \begin{pmatrix} \hat{x}_{11} & \dots & \widehat{x}_{1n} \\ \vdots & \ddots & \vdots \\ \hat{x}_{m1} & \dots & \widehat{x}_{mn} \end{pmatrix}; i = 1, 2, \dots, n; j = 1, 2, \dots, m \tag{8}$$

Step 4: The larger, more preferable values, denoted as P_i, are summed:

$$P_i = \sum_{j=1}^{k} \overline{x_{ij}} \tag{9}$$

Step 5: The smaller, more preferable values, denoted as R_i, are summed:

$$R_i = \sum_{j=k+1}^{k} \overline{x_{ij}} \tag{10}$$

The number of cryptocurrencies to be minimized is determined by the difference $m - k$.
Step 6: The minimization of R_i is performed as per Eq. (8):

$$R_{\min} = \min_i R_i; i = 1, 2, \ldots, n \tag{11}$$

Step 7: The relative significance of each cryptocurrency Q_i is calculated:

$$Q_i = P_i + \frac{R_{\min} \sum_{i=1}^{n} R_i}{R_i \sum_{i=1}^{n} \frac{R_{\min}}{R_i}} \tag{12}$$

Step 8: The optimal cryptocurrency i, indicated by K, is identified:

$$K = \max_i Q_i; i = 1, 2, \ldots, n \tag{13}$$

Step 9: Cryptocurrencies are prioritized in descending order.
Step 10: The utility degree N of each subsequent cryptocurrency i is determined:

$$N_i = \frac{Q_i}{Q_{\max}} \times 100\% \tag{14}$$

3.2.3 Transfer entropy

The information flow between two cryptocurrencies, denoted as i and j, is measured by integrating Shannon Entropy [51] and Kullback-Leibler distance [52], assuming a Markov process with k and l levels or factors, respectively [53]. Given the probability distributions $p(i)$ and $p(j)$ for cryptocurrencies i and j, and the joint probability $p(i, j)$, the information flow from cryptocurrency j to i is defined by the following equation [54]:

$$T_{J \to I}(k, l) = \sum_{i,j} p\left(i_{t+1}, i_t^{(k)}, j_t^{(l)}\right) \cdot \log \left(\frac{p\left(i_{t+1} \mid i_t^{(k)}, j_t^{(l)}\right)}{p\left(i_{t+1} \mid i_t^{(k)}\right)} \right) \tag{15}$$

This equation quantifies the deviation from the generalized Markov process $p\left(i_{t+1} \mid i_t^{(k)}\right) = p\left(i_{t+1} \mid i_t^{(k)}, j_t^{(l)}\right)$ at the marginal conditional distribution odds-ratio $\log \left(\frac{p\left(i_{t+1} \mid i_t^{(k)}, j_t^{(l)}\right)}{p\left(i_{t+1} \mid i_t^{(k)}\right)} \right)$.

Analogously, the information flow from i to j is measured, allowing for the determination of causation direction between two cryptocurrencies based on the net information flow. This flow is computed as the difference between flows from i to j and vice versa. The statistical significance of the net information flow between cryptocurrencies is ascertained through bootstrapping the inherent probability distributions for each factor/level in each criterion, enabling repeated execution of this Markov process.

3.2.4 Neural network regression

The response of each cryptocurrency to a set of financial indicators is analyzed using Artificial Neural Networks (ANNs), specifically focusing on Multi-Layer Perceptron (MLP) network architecture, known for its efficacy in forecasting [55]. The ANN regression reveals the non-linear impacts of financial indicators on the variations of each cryptocurrency, while controlling for its latent utility function. The Connection Weight Approach (CWA), as described by Olden et al. [56] and Olden and Jackson [57], is utilized for quantifying the relative importance of each financial indicator on the response levels of each cryptocurrency.

This methodological approach is characterized by two distinctive features. Firstly, it elucidates cause-effect and feedback relationships among cryptocurrencies' utility functions, influenced by the entropy levels of social media indicators. The maximal entropy principle, an established concept in information theory, posits that the most representative probability distribution for a given cryptocurrency's utility function is one with the highest entropy. Secondly, this research diverges from previous studies by investigating the impact of financial indicators on the utility functions of various cryptocurrencies. By computing the information entropy of each social media indicator, the focus is directed towards the most significant criteria for policy making, and their socio-demographic drivers, which are otherwise indeterminable a priori.

4 Results and Discussion

Descriptive statistics for the social media indicators, considered as proxies for the utility function of cryptocurrencies, are presented in Table 2. Drawing on the work of García-Medina and Huynh [1], variables listed in Table 1 are posited as potential influencers of Bitcoin price direction.

Table 2. Descriptive statistics for the social media indicators

Variables	Min	Max	Mean	Median	SD	CV	Skewness	Kurtosis	IE	Signal
BBC Breaking News	-28.55	26.29	0.00	0.05	3.53	5206.64	-0.18	15.46	0.48	pc
Department of State	-33.51	34.97	0.00	0.02	4.06	-3133.82	0.09	8.42	0.45	nc
Donald Trump	-33.93	30.96	0.00	0.01	4.83	37110.38	0.05	5.21	0.58	nc
Elon Musk	-9.39	13.42	0.00	0.02	1.89	536.25	0.07	3.84	0.50	pc
EPU Twitter	-1.64	1.95	0.00	-0.01	0.30	342.83	0.30	3.58	0.51	nc
Google Trends	-1.40	1.23	0.00	-0.01	0.19	104.81	0.26	6.81	0.46	pc
Risk Aversion	-1.18	1.30	0.00	0.00	0.07	945.99	3.75	164.43	0.49	nc
United Nations	-9.48	13.49	0.00	-0.01	3.27	4901.91	0.17	0.27	0.20	pc

Note: pc = positive criterion; nc = negative criterion

The Twitter-based Economic Policy Uncertainty index (EPU-Twitter) is formulated using daily tweet data containing keywords related to economic uncertainty [1]. The 'risk-aversion' category includes financial indices reflecting risk aversion and economic uncertainty, conceptualized as a utility-based risk-aversion coefficient [1]. The influence of news sentiment, particularly from BBC Breaking News, on the cryptocurrency market has been acknowledged in recent studies [58, 59]. RavenPack News Analytics is employed to process real-time news from the BBC [13]. The United Nations is also included, given its significant role in promoting digital currency for achieving financial security and sustainable investment [60].

In the current utility function, BBC Breaking News, Elon Musk, Google Trends, and the United Nations are designated as positive criteria. Positive BBC headlines are seen to boost investor enthusiasm, leading to an immediate increase in Bitcoin returns [11]. Elon Musk's tweets, characterized by a positive tone, have been influential in guiding investor perceptions about Bitcoin trading [8]. Google Trends data reflects an optimistic pursuit of information about crypto assets, correlating positively with Bitcoin returns [2]. The United Nations' efforts to integrate digital currency transactions with sustainability goals are perceived positively by financial investors [60].

Conversely, the Department of State, Donald Trump, EPU Twitter, and risk aversion variables are regarded as negative criteria. Post-2018, cryptocurrency trading platforms have become more sensitive to Donald Trump's negative sentiments, with his tweets acting as a predictive driver for Bitcoin trading dynamics [7]. Increases in EPU Twitter and Risk Aversion are posited to deter demand for cryptocurrencies, thereby reducing their prices.

Figure 1 presents density plots for the social media indicator weights computed using SWARA, based on their respective information entropy distributions. The United Nations, EPU Twitter, and Elon Musk emerge as the most relevant criteria, indicating that cryptocurrency utility functions are largely influenced by perspectives on technological innovation and global socio-economic stability. The least relevant criteria, Risk Aversion, and BBC Breaking News, pertain to daily issues and natural risk aversion related to blockchain technology. However, the closeness of SWARA weights across social media indicators is evident in the overall distribution of the utility function, as depicted in Figure 1. The utility functions exhibit a positive bias, with all COPRAS scores exceeding 0.60 (Figure 2), suggesting the endogenous nature of cryptocurrencies and the potential for obscuring the impacts of other financial indicators as drivers for investment decisions (Table 3).

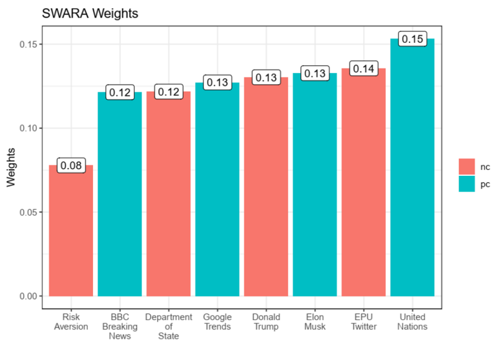

Figure 1. Bar plot for the social media information entropy weights computed using SWARA

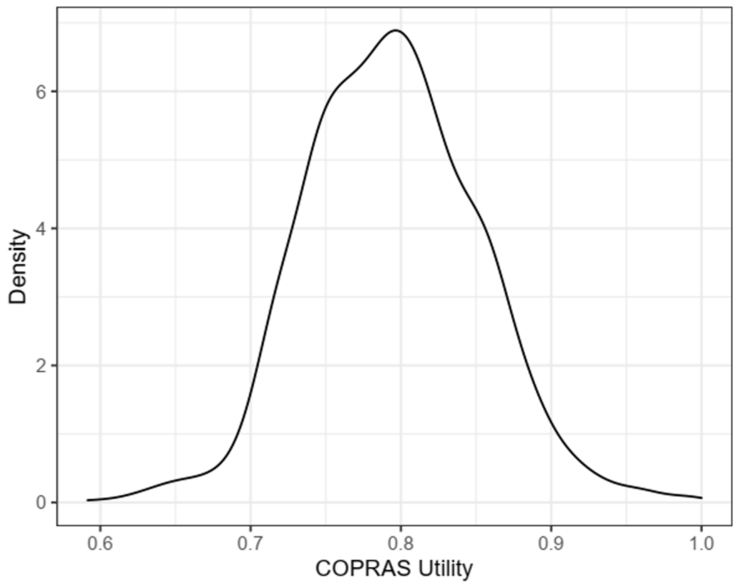

Figure 2. COPRAS utility function results

Table 3. Descriptive statistics for cryptocurrencies and financial indicators

Variables	Type	Min	Max	Mean	Median	SD	CV	Skewness	Kurtosis	IE
Bitcoin	Cryptocurrency	-0.4647	0.2251	0.0025	0.0025	0.0424	16.7035	-0.8916	12.6782	0.4641
Dogecoin	Cryptocurrency	-0.4929	0.6244	0.0026	0.0000	0.0669	25.5714	1.2287	14.9545	0.4275
Ethereum	Cryptocurrency	-0.5507	0.2901	0.0034	0.0016	0.0566	16.7036	-0.3983	9.6467	0.4105
Litecoin	Cryptocurrency	-0.4491	0.5114	0.0025	0.0000	0.0606	24.0914	0.6904	10.4821	0.4164
TETHER	Cryptocurrency	-0.0526	0.0566	0.0000	0.0000	0.0062	1683.1773	0.3249	19.9915	0.4845
Ripple	Cryptocurrency	-0.6163	1.0274	0.0027	-0.0016	0.0753	28.1859	2.2856	36.0601	0.4982
VIX	Financial Index	-0.2998	0.7682	-0.0061	-0.0123	0.0810	-13.2466	1.4136	8.4054	0.4267
ACWI	Financial Index	-0.1190	0.0782	0.0006	0.0011	0.0115	19.6832	-1.1392	20.3782	0.4519
EUR.USD	Financial Index	-0.0206	0.0146	0.0002	0.0003	0.0042	20.1828	0.0335	0.8875	0.4856
NASDAQ	Financial Index	-0.1300	0.0960	0.0008	0.0016	0.0145	18.9881	-0.3594	11.7130	0.4575
S.P.500	Financial Index	-0.1277	0.0897	0.0006	0.0009	0.0125	19.8839	-0.5703	20.4388	0.5584
Tesla	Financial Index	-0.2365	0.1814	0.0017	0.0018	0.0371	22.4521	-0.3723	5.4746	0.4477
Gold	Metal	-0.0586	0.0497	0.0006	0.0010	0.0082	14.8633	-0.6582	5.5414	0.4592
Palladium	Metal	-0.2220	0.1881	0.0015	0.0023	0.0197	12.9791	-0.9180	20.4254	0.3313
Platinum	Metal	-0.1364	0.1009	0.0004	0.0006	0.0145	37.4108	-0.9049	10.6682	0.3818
Silver	Metal	-0.1612	0.0770	0.0005	0.0007	0.0164	35.7171	-1.1281	13.0138	0.4165
DCOILBRENTEU	Petroleum	-0.6437	0.4120	-0.0004	0.0009	0.0374	-98.9822	-3.1391	80.8329	0.4533
DCOILWTICO	Petroleum	-0.2814	0.4258	0.0006	0.0023	0.0358	60.2056	0.7347	38.2336	0.3780

Transfer entropy and neural network results, elucidating cause-effect relationships among cryptocurrencies and financial indicators, are depicted in Figure 3 Additionally, Table 4 details the optimal ANN architecture for each regression, determined after cross-validating the trained models with a randomly selected 20% of the sample. It is observed that Bitcoin and Ripple are pivotal cryptocurrencies, influencing the behavior of other coins such as Tether, Ethereum, Litecoin, and Dogecoin, each representing unique aspects of the cryptocurrency universe.

Economically, the findings underscore Bitcoin's role as a significant information transmitter to other cryptocurrencies (Figure 3). Ripple, in contrast, shows a unique dynamic, where its past values are observed to reduce uncertainty in Bitcoin and influence fluctuations in other cryptocurrencies. Interestingly, Litecoin demonstrates a more independent trajectory, being influenced only by Bitcoin and not acting as a shock transmitter.

The analysis confirms the significant role of Ripple in transmitting shocks within the cryptocurrency market, aligning with the findings of Assaf et al. [61] and Neto [62]. While Assaf et al. [61] reported Ripple's information transmission to Bitcoin and Ethereum, Neto [62] observed Ripple returns influencing attention in Ethereum and Bitcoin, with Litecoin having a limited capacity to transmit shocks. The unique position of Ripple, partly due to Ripple Labs' majority ownership and the SEC lawsuit implications, suggests that Ripple movements convey critical information about the future of cryptocurrency regulation, a crucial aspect of this market. Therefore, these results are congruent with the notion that Ripple movements carry regulatory information, positioning it as a shock transmitter rather than an absorber.

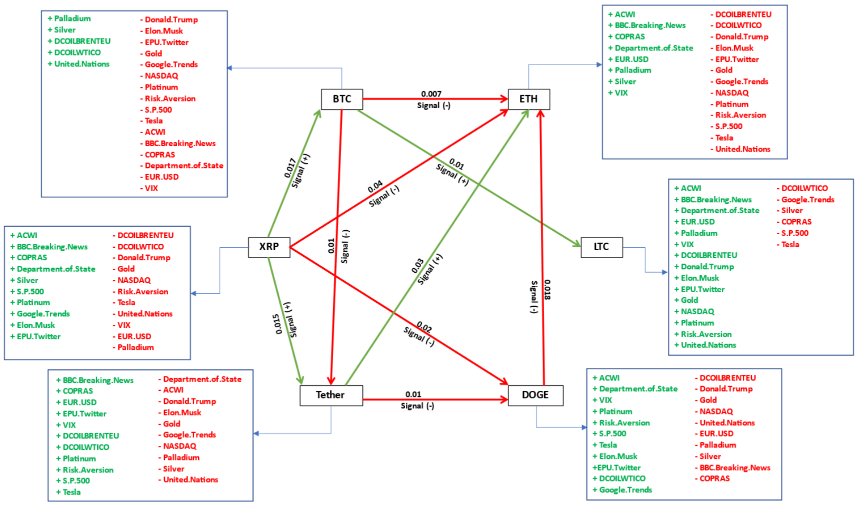

Figure 3. Results for the transfer entropy analysis (arrows among cryptocurrencies: green denotes positive feedback and red negative feedback) and for the ANN regressions for each cryptocurrency (green denotes a positive impact of the financial indicator on the cryptocurrency and red a negative impact)

Note: All results were controlled by COPRAS utility function scores.

Table 4. Best neural network architecture validation

Cryptocurrency	Number of Layers	Neurons per Layer	Dropout	RMSE	MAE
Bitcoin	4	150	0	0.047	0.032
Dogecoin	2	200	0.15	0.054	0.029
Ethereum	2	100	0	0.050	0.029
Litecoin	1	200	0	0.052	0.032
TETHER	4	150	0.6	0.060	0.033
Ripple	4	100	0	0.054	0.027

Validation with 5 folds cross-validation. MAE stands for mean absolute error and RMSE stands for root mean squared error. Dropout is the total amount of regularization in neural networks.

Asymmetries have been observed in the relationship between social media indicators and cryptocurrencies. Bitcoin, Ripple, and Ethereum exhibit different behaviors compared to Tether, Litecoin, and Dogecoin. Risk aversion, typically a negative predictor for the return of risky assets, adversely affects Bitcoin, Ripple, and Ethereum, while positively impacting the other cryptocurrencies. Notably, this positive relationship is anticipated for Tether, a stablecoin, where an increase in risk aversion heightens demand.

Other noteworthy relationships between social media indicators and cryptocurrencies have been identified. The EPU Twitter, while adversely predicting Bitcoin and Ethereum, positively influences Ripple, Tether, Litecoin, and Dogecoin. This suggests that price movements in these cryptocurrencies increase with heightened uncertainty in social media. The sentiments in tweets by Donald Trump and Elon Musk also resonate differently across the crypto market. While Trump's tweets predominantly negatively affect the market (except for Litecoin), Musk's tweets positively influence Dogecoin and Ripple (negatively impacting the remaining cryptocurrencies).

Bitcoin and Ethereum emerge as the most negatively affected cryptocurrencies by social media indicators in the sample. For Bitcoin, seven out of eight relationships are negative, with only the United Nations showing a positive predictive relationship. In contrast, Ethereum exhibits negative associations in six out of eight relationships, with BBC Breaking News and the Department of State as exceptions, showing positive predictive relationships. Conversely, Litecoin, Dogecoin, and Ripple react positively to most social media indicators. Notably, Litecoin and Dogecoin are positively influenced by Twitter sentiment (Elon Musk) and uncertainty (EPU Twitter). In contrast to Litecoin, Dogecoin also responds positively to investor attention (Google Trends), suggesting a strong linkage to social media attention, sentiment, and uncertainty.

5 Conclusions

This study, utilizing a novel neural-MCDM model, has rigorously analyzed the interplay between cryptocurrencies and a spectrum of financial and social media indicators. It is determined that Bitcoin and Ripple, along with Ethereum, function as primary shock transmitters and absorbers, respectively, within the realm of cryptocurrencies. A notable asymmetry is identified in the interactions between social media indicators and various cryptocurrencies. Specifically, Bitcoin and Ethereum are more adversely influenced by social media indicators compared to Tether, Ripple, Litecoin, and Dogecoin. Conversely, Litecoin, Dogecoin, and Ripple exhibit positive responses to social media influences, with Litecoin and Dogecoin being particularly sensitive to Twitter sentiment, including that of Elon Musk, and uncertainty as reflected in the EPU Twitter Index. Furthermore, Dogecoin is observed to react positively to increased investor attention on Google Trends, indicating a strong tie to social media dynamics.

This study contributes significantly to the growing body of literature in behavioral finance that explores the influence of social media platforms on investor sentiment. It extends upon existing research that predominantly focuses on individual social media platforms, offering a more comprehensive view by incorporating an array of platforms including Twitter, various news services, and Google Trends. This integrated approach provides novel insights into the diverse relationships between different social media indicators and cryptocurrencies, each with distinct characteristics. By applying the transfer entropy method, this research elucidates the cause-effect and feedback dynamics among the utility functions of major cryptocurrencies, influenced by the entropy levels of social media indicators. This approach sheds light on the heterogeneous nature of these relationships, enhancing the understanding of how social media indicators differentially impact cryptocurrencies. In doing so, the study offers valuable insights into the complex web of interactions that shape the cryptocurrency market.

Addressing the identified gaps in existing research, this study revisits a secondary dataset comprising a blend of social media and financial indicators. It employs a novel neural-MCDM model, structured in three stages, to derive unbiased utility functions for various cryptocurrencies. This approach, anchored in information entropy, evaluates the latent significance of each social media indicator in the computation of each cryptocurrency's utility function, leveraging the SWARA model for weight computation. Compared to alternative methodologies, information entropy offers reduced bias and enhanced robustness against overlooked assumptions, facilitating a more nuanced interpretation of how distinct cryptocurrencies' utility functions, as determined by COPRAS, are influenced by various social media indicators.

The findings, both anticipated and unanticipated, reveal that Bitcoin and Ripple, along with Ethereum, function as primary shock transmitters and absorbers, respectively, in the cryptocurrency sphere. Notably, the significant role of Ripple, aligning with the research of Assaf et al. [61]and Neto [62], suggests its potential as a conveyer of information regarding future cryptocurrency regulations, particularly in light of Ripple Labs' ongoing legal challenges with the SEC. Bitcoin and Ethereum are observed to be more negatively impacted by social media indicators compared to Litecoin, Dogecoin, and Ripple, which exhibit positive responses to these influences. Despite discernible patterns, the unique characteristics of each cryptocurrency must be considered when assessing their interactions with social media indicators.

The insights garnered from this research are invaluable for policymakers and regulators, enhancing their understanding of the intricate relationship between cryptocurrencies and social media indicators. It is imperative for governmental actions to acknowledge the distinct sensitivities of different cryptocurrencies to social media influences, including attention, sentiment, uncertainty, and posts from government or tech leaders. Such understanding is crucial for navigating the complexities of the digital asset industry, particularly in terms of policy development and regulation. By comprehending the specific channels through which investor sentiment may influence the cryptocurrency market, stakeholders can better anticipate and respond to fluctuations within this dynamic sector.

Author Contributions

Conceptualization, Peter Wanke and Md. Abul Kalam Azad; methodology, Jéfferson Augusto Colombo and Peter Wanke; software, Jéfferson Augusto Colombo and Yong Tan; validation, Yong Tan and S. A. Edalatpanah.; formal analysis, Tanzina Akhter and Peter Wanke; investigation, Md. Abul Kalam Azad and Yong Tan; resources, Jéfferson Augusto Colombo and S. A. Edalatpanah; data curation, Md. Abul Kalam Azad; writing—original draft preparation, Jéfferson Augusto Colombo and Tanzina Akhter; writing— Jéfferson Augusto Colombo, Tanzina Akhter; visualization, Jéfferson Augusto Colombo, Tanzina Akhter.; supervision, Peter Wanke, Md. Abul Kalam Azad, and Yong Tan.

Data Availability

The data supporting our research results may be released upon application to Yong Tan via y.tan9@bradford.ac.uk.

Conflicts of Interest

The authors declare no conflict of interest.

References

[1] A. García-Medina and T. L. D. Huynh, "What drives bitcoin? An approach from continuous local transfer entropy and deep learning classification models," *Entropy*, vol. 23, no. 12, p. 1582, 2021. https://doi.org/10.3390/e23121582

[2] K. Wolk, "Advanced social media sentiment analysis for short-term cryptocurrency price prediction," *Expert Syst.*, vol. 37, no. 2, p. e12493, 2020. https://doi.org/10.1111/exsy.12493

[3] Anamika, M. Chakraborty, and S. Subramaniam, "Does sentiment impact cryptocurrency?" *J. Behav. Finance*, vol. 23, no. 1, pp. 1–17, 2021. https://doi.org/10.1080/15427560.2021.1950723

[4] I. Yousaf, M. Youssef, and J. Goodell, "Quantile connectedness between sentiment and financial markets: Evidence from the S&P 500 twitter sentiment index," *Int. Rev. Financ. Anal.*, vol. 83, p. 102322, 2022. https://doi.org/10.1016/j.irfa.2022.102322

[5] C. Biancotti, "What's next for crypto?" *Bank of Italy Occas. Pap.*, vol. 2, no. 1, 2022. https://doi.org/10.2139/ssrn.4462817

[6] C. Tandon, S. Revankar, and S. S. Parihar, "How can we predict the impact of the social media messages on the value of cryptocurrency? Insights from big data analytics," *Int. J. Inf. Manage. Data Insights*, vol. 1, no. 2, p. 100035, 2021. https://doi.org/10.1016/j.jjimei.2021.100035

[7] T. L. D. Huynh, "Does bitcoin react to trump's tweets?" *J. Behav. Exp. Finance*, vol. 31, p. 100546, 2021. https://doi.org/10.1016/j.jbef.2021.100546

[8] T. L. D. Huynh, "When Elon Musk changes his tone, does bitcoin adjust its tune?" *Comput. Econ.*, vol. 1, no. 1, pp. 1–23, 2022. https://doi.org/10.1007/s10614-021-10230-6

[9] G. Kaplanski and H. Levy, "Sentiment and stock prices: The case of aviation disasters," *J. Financ. Econ.*, vol. 95, no. 2, pp. 174–201, 2010. https://doi.org/10.1016/j.jfineco.2009.10.002

[10] Y. Ahn and D. Kim, "Emotional trading in the cryptocurrency market," *Finance Res. Lett.*, vol. 42, p. 101912, 2021. https://doi.org/10.1016/j.frl.2020.101912

[11] S. Duz Tan and O. Tas, "Social media sentiment in international stock returns and trading activity," *J. Behav. Fin.*, vol. 22, no. 2, pp. 221–234, 2021. https://doi.org/10.1080/15427560.2020.1772261

[12] E. Bouri, R. Demirer, D. Gabauer, and R. Gupta, "Financial market connectedness: The role of investors' happiness," *Fin. Res. Lett.*, vol. 44, p. 102075, 2022. https://doi.org/10.1016/j.frl.2021.102075

[13] L. Rognone, S. Hyde, and S. S. Zhang, "News sentiment in the cryptocurrency market: An empirical comparison with forex," *Int. Rev. Fin. Anal.*, vol. 69, no. 1, p. 101462, 2020. https://doi.org/10.1016/j.irfa.2020.101462

[14] A. Kumar, N. Iqbal, S. K. Mitra, L. Kristoufek, and E. Bouri, "Connectedness among major cryptocurrencies in standard times and during the COVID-19 outbreak," *J. Int. Fin. Mark. Inst. Money*, vol. 77, no. 1, p. 101523, 2022. https://doi.org/10.1016/j.intfin.2022.101523

[15] C. Ciner, B. Lucey, and L. Yarovaya, "Determinants of cryptocurrency returns: A Lasso quantile regression approach," *Fin. Res. Lett.*, vol. 49, no. 8, p. 102990, 2022. https://doi.org/10.1016/j.frl.2022.102990

[16] A. H. Elsayed, G. Gozgor, and L. Yarovaya, "Volatility and return connectedness of cryptocurrency, gold, and uncertainty: Evidence from the cryptocurrency uncertainty indices," *Fin. Res. Lett.*, vol. 47, no. 6, p. 102732, 2022. https://doi.org/10.1016/j.frl.2022.102732

[17] M. A. Naeem, I. Mbarki, and S. J. H. Shahzad, "Predictive role of online investor sentiment for cryptocurrency market: Evidence from happiness and fears," *Int. Rev. Econ. Fin.*, vol. 73, no. 3, pp. 496–514, 2021. https://doi.org/10.1016/j.iref.2021.01.008

[18] H. Han, O. Linton, T. Oka, and Y. J. Whang, "The cross-quantilogram: Measuring quantile dependence and testing directional predictability between time series," *J. Econom.*, vol. 193, no. 1, pp. 251–270, 2016. https://doi.org/10.1016/j.jeconom.2016.03.001

[19] J. Bollen, H. Mao, and X. Zeng, "Twitter mood predicts the stock market," *J. Comput. Sci.*, vol. 2, no. 1, pp. 1–8, 2011. https://doi.org/10.1016/j.jocs.2010.12.007

[20] C. Ajjoub, T. Walker, and Y. Zhao, "Social media posts and stock returns: The Trump factor," *Int. J. Manag. Fin.*, vol. 17, no. 2, pp. 185–213, 2020. https://doi.org/10.1108/IJMF-02-2020-0068

[21] S. J. H. Shahzad, M. Anas, and E. Bouri, "Price explosiveness in cryptocurrencies and Elon Musk's tweets," *Fin. Res. Lett.*, vol. 47, p. 102695, 2022. https://doi.org/10.1016/j.frl.2022.102695

[22] F. Colon, C. Kim, H. Kim, and W. Kim, "The effect of political and economic uncertainty on the cryptocurrency market," *Fin. Res. Lett.*, vol. 39, p. 101621, 2021. https://doi.org/10.1016/j.frl.2020.101621

[23] T. Loughran and B. McDonald, "When is a liability not a liability? Textual analysis, dictionaries, and 10-Ks," *J. Finance*, vol. 66, no. 1, pp. 35–65, 2011. https://doi.org/10.1111/j.1540-6261.2010.01625.x

[24] T. Sheng-Hshiung, T. Gwo-Hshiung, and W. Kuo-Ching, "Evaluating tourist risks from fuzzy perspectives," *Ann. Tour. Res.*, vol. 24, no. 4, pp. 796–812, 1997. https://doi.org/10.1016/S0160-7383(97)00059-5

[25] T. C. Wang and H. D. Lee, "Developing a fuzzy TOPSIS approach based on subjective weights and objective weights," *Expert Syst. Appl.*, vol. 36, no. 5, pp. 8980–8985, 2009. https://doi.org/10.1016/j.eswa.2008.11.035

[26] R. K. Singh and L. Benyoucef, "A fuzzy TOPSIS based approach for e-sourcing," *Eng. Appl. Artif. Intell.*, vol. 24, no. 3, pp. 437–448, 2011. https://doi.org/10.1016/j.engappai.2010.09.006

[27] H. Zhang, C. L. Gu, L. W. Gu, and Y. Zhang, "The evaluation of tourism destination competitiveness by TOPSIS & information entropy–A case in the Yangtze River Delta of China," *Tour. Manag.*, vol. 32, no. 2, pp. 443–451, 2011. https://doi.org/10.1016/j.tourman.2010.02.007

[28] M. Dağdeviren, S. Yavuz, and N. Kılınç, "Weapon selection using the AHP and TOPSIS methods under fuzzy environment," *Expert Syst. Appl.*, vol. 36, no. 4, pp. 8143–8151, 2009. https://doi.org/10.1016/j.eswa.2008.10.016

[29] X. Yu, S. Guo, J. Guo, and X. Huang, "Rank B2C e-commerce websites in e-alliance based on AHP and fuzzy TOPSIS," *Expert Syst. Appl.*, vol. 38, no. 4, pp. 3550–3557, 2011. https://doi.org/10.1016/j.eswa.2010.08.143

[30] J. W. Wang, C. H. Cheng, and K. C. Huang, "Fuzzy hierarchical TOPSIS for supplier selection," *Appl. Soft Comput.*, vol. 9, no. 1, pp. 377–386, 2009. https://doi.org/10.1016/j.asoc.2008.04.014

[31] A. T. Gumus, "Evaluation of hazardous waste transportation firms by using a two step fuzzy-AHP and TOPSIS methodology," *Expert Syst. Appl.*, vol. 36, no. 2, pp. 4067–4074, 2009. https://doi.org/10.1016/j.eswa.2008.03.013

[32] E. K. Aydogan, "Performance measurement model for Turkish aviation firms using the rough-AHP and TOPSIS methods under fuzzy environment," *Expert Syst. Appl.*, vol. 38, no. 4, pp. 3992–3998, 2011. https://doi.org/10.1016/j.eswa.2010.09.060

[33] V. Kersuliene, E. K. Zavadskas, and Z. Turskis, "Selection of rational dispute resolution method by applying new step-wise weight assessment ratio analysis (SWARA)," *J. Bus. Econ. Manag.*, vol. 11, no. 2, pp. 243–258, 2010. https://doi.org/10.3846/jbem.2010.12

[34] G. S. Liang and J. F. Ding, "Fuzzy MCDM based on the concept of α -cut," *J. Multi-Criteria Decis. Anal.*, vol. 12, no. 6, pp. 299–310, 2003. https://doi.org/10.1002/mcda.366

[35] J. Núñez, P. Cincotta, and F. Wachlin, "Information entropy," in *Chaos in Gravitational N-Body Systems*, J. C. Muzzio, S. Ferraz-Mello, and J. Henrard, Eds. Dordrecht: Springer Netherlands, 1996, pp. 43–53. https://doi.org/10.1007/978-94-009-0307-4

[36] A. Kaklauskas, E. K. Zavadskas, S. Raslanas, R. Ginevicius, A. Komka, and P. Malinauskas, "Selection of low-e windows in retrofit of public buildings by applying multiple criteria method COPRAS: A Lithuanian case," *Energy Build.*, vol. 38, no. 5, pp. 454–462, 2006. https://doi.org/10.1016/j.enbuild.2005.08.005

[37] E. K. Zavadskas, A. Kaklauskas, F. Peldschus, and Z. Turskis, "Multi-attribute assessment of road design solutions by using the COPRAS method," *Balt. J. Road Bridge Eng.*, vol. 2, no. 4, pp. 195–203, 2007.

[38] J. S. Dyer, P. C. Fishburn, R. E. Steuer, J. Wallenius, and S. Zionts, "Multiple criteria decision making, multiattribute utility theory: The next ten years," *Manage. Sci.*, vol. 38, no. 5, pp. 645–654, 1992. https://doi.org/10.1287/mnsc.38.5.645

[39] A. Kassem and L. J. Hakim, "Assessing critical success factors (CSFs) for a supplier in a relationship-driven B2B-market," 2016.

[40] M. Rezaeisaray, S. Ebrahimnejad, and K. Khalili-Damghani, "A novel hybrid MCDM approach for outsourcing supplier selection: A case study in pipe and fittings manufacturing," *J. Model. Manag.*, vol. 11, no. 2, pp. 536–559, 2016. https://doi.org/10.1108/JM2-06-2014-0045

[41] S. Gandhi, S. K. Mangla, P. Kumar, and D. Kumar, "Evaluating factors in implementation of successful green supply chain management using DEMATEL: A case study," *Int. Strateg. Manag. Rev.*, vol. 3, no. 1-2, pp. 96–109, 2015. https://doi.org/10.1016/j.ism.2015.05.001

[42] M. Janssen, H. van der Voort, and A. Wahyudi, "Factors influencing big data decision-making quality," *J. Bus. Res.*, vol. 70, no. 1, pp. 338–345, 2017. https://doi.org/10.1016/j.jbusres.2016.08.007

[43] A. T. de Almeida, J. A. de Almeida, A. P. C. S. Costa, and A. T. de Almeida-Filho, "A new method for elicitation of criteria weights in additive models: Flexible and interactive tradeoff," *Eur. J. Oper. Res.*, vol. 250, no. 1, pp. 179–191, 2016. https://doi.org/10.1016/j.ejor.2015.08.058

[44] D. Stanujkic, D. Karabasevic, and E. K. Zavadskas, "A framework for the selection of a packaging design based on the SWARA method," *Eng. Econ.*, vol. 26, no. 2, pp. 181–187, 2015. https://doi.org/10.5755/j01.ee.26.2.8820

[45] S. Hashemkhani Zolfani and M. Bahrami, "Investment prioritizing in high tech industries based on SWARA-COPRAS approach," *Technol. Econ. Dev. Econ.*, vol. 20, no. 3, pp. 534–553, 2014. https://doi.org/10.3846/20294913.2014.881435

[46] J. Nakhaei, S. Lale Arefi, M. Bitarafan, and S. Kildienė, "Evaluation of light supply in the public underground safe spaces by using of COPRAS-SWARA methods," *Int. J. Strateg. Prop. Manag.*, vol. 20, no. 2, pp. 198–206, 2016. https://doi.org/10.3846/1648715X.2015.1132790

[47] A. Valipour, N. Yahaya, N. Md Noor, J. Antuchevičienė, and J. Tamošaitienė, "Hybrid SWARA-COPRAS

method for risk assessment in deep foundation excavation project: An Iranian case study," *J. Civ. Eng. Manag.*, vol. 23, no. 4, pp. 524–532, 2017. https://doi.org/10.3846/13923730.2017.1281842

[48] E. Turanoglu Bekar, M. Cakmakci, and C. Kahraman, "Fuzzy COPRAS method for performance measurement in total productive maintenance: A comparative analysis," *J. Bus. Econ. Manag.*, vol. 17, no. 5, pp. 663–684, 2016. https://doi.org/10.3846/16111699.2016.1202314

[49] M. H. Aghdaie, S. H. Zolfani, and E. K. Zavadskas, "Prioritizing constructing projects of municipalities based on AHP and COPRAS-G: A case study about footbridges in Iran," *Balt. J. Road Bridge Eng.*, vol. 7, no. 2, pp. 145–153, 2012. https://doi.org/10.3846/bjrbe.2012.20

[50] M. M. Fouladgar, A. Yazdani-Chamzini, A. Lashgari, E. K. Zavadskas, and Z. Turskis, "Maintenance strategy selection using AHP and COPRAS under fuzzy environment," *Int. J. Strateg. Prop. Manag.*, vol. 16, no. 1, pp. 85–104, 2012. https://doi.org/10.3846/1648715X.2012.666657

[51] K. Özkan, "Comparing Shannon entropy with Deng entropy and improved Deng entropy for measuring biodiversity when a priori data is not clear," *Forestist*, vol. 68, no. 2, pp. 136–140, 2018. http://doi.org/10.26650/forestist.2018.340634

[52] S. Kullback and R. A. Leibler, "On information and sufficiency," *Ann. Math. Stat.*, vol. 22, no. 1, pp. 79–86, 1951. http://doi.org/10.1214/aoms/1177729694

[53] T. Schreiber, "Measuring information transfer," *Phys. Rev. Lett.*, vol. 85, no. 2, p. 461, 2000. https://doi.org/10.1103/PhysRevLett.85.461

[54] T. Dimpfl and F. J. Peter, "Using transfer entropy to measure information flows between financial markets," *Stud. Nonlinear Dyn. Econom.*, vol. 17, no. 1, pp. 85–102, 2013. https://doi.org/10.1515/snde-2012-0044

[55] J. Mubiru and E. Banda, "Estimation of monthly average daily global solar irradiation using artificial neural networks," *Sol. Energy*, vol. 82, no. 2, pp. 181–187, 2008. https://doi.org/10.1016/j.solener.2007.06.003

[56] J. D. Olden, M. K. Joy, and R. G. Death, "An accurate comparison of methods for quantifying variable importance in artificial neural networks using simulated data," *Ecol. Modell.*, vol. 178, no. 3-4, pp. 389–397, 2004. https://doi.org/10.1016/j.ecolmodel.2004.03.013

[57] J. D. Olden and D. A. Jackson, "Illuminating the "black box": A randomization approach for understanding variable contributions in artificial neural networks," *Ecol. Model.*, vol. 154, no. 1-2, pp. 135–150, 2002. https://doi.org/10.1016/S0304-3800(02)00064-9

[58] S. Cankaya, E. Aykac Alp, and M. Findikci, "News sentiment and cryptocurrency volatility," in *Blockchain Economics and Financial Market Innovation: Financial Innovations in the Digital Age*. Springer, 2019, pp. 115–140. http://doi.org/10.1007/978-3-030-25275-5_7

[59] A. Anamika and S. Subramaniam, "Do news headlines matter in the cryptocurrency market?" *Appl. Econ.*, vol. 2, no. 1, pp. 1–17, 2022. https://doi.org/10.1080/00036846.2022.2061904

[60] C. de Villiers, S. Kuruppu, and D. Dissanayake, "A (new) role for business–Promoting the United Nations' Sustainable Development Goals through the internet-of-things and blockchain technology," *J. Bus. Res.*, vol. 131, no. 1, pp. 598–609, 2021. https://doi.org/10.1016/j.jbusres.2020.11.066

[61] A. Assaf, M. H. Bilgin, and E. Demir, "Using transfer entropy to measure information flows between cryptocurrencies," *Physica A: Stat. Mech. Appl.*, vol. 586, p. 126484, 2022. https://doi.org/10.1016/j.physa.2021.126484

[62] D. Netto, "Revisiting spillovers between investor attention and cryptocurrency markets using noisy independent component analysis and transfer entropy," *J. Econ. Asymmetries*, vol. 26, p. e00269, 2022. https://doi.org/10.1016/j.jeca.2022.e00269