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Reflections of public perception of Russia-Ukraine conflict and Metaverse on the financial outlook of Metaverse coins: Fresh evidence from Reddit sentiment analysis

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ABSTRACT

The present work endeavors to thoroughly examine the dependence of daily closing prices of Metaverse coins on external social media sentiment on Russia's military invasion of Ukraine and the potential benefits of Metaverse technology. We collate the worldwide media chatter on the Ukraine war and uncover the dynamic association with four Metaverse coins by applying wavelet coherence analysis. Subsequently, we systematically estimate the sentiment of discussions on the Reddit community on two topics, namely, the Russia-Ukraine Conflict and Metaverse, to gauge their impact separately on the chosen tokens. Nonlinear association mining and forecasting exercises are carried out to comprehend the predictability of the Metaverse financial assets using the respective sentiment components. The predictive framework utilizes Uniform Manifold Approximation and Projection (UMAP) and Particle Swarm Optimization (PSO)-tuned Extreme Gradient Boosting (XGBR) for feature transformation and fetching forecasts, respectively. Explainable Artificial Intelligence (XAI) methods are utilized to interpret the prediction process for unveiling the feature contributions. The findings suggest that the dependence between the Metaverse coins and media chatter on the Russia-Ukraine war primarily prevails in short and medium-run scales, and the Reddit sentiments on the same and Metaverse can be effectively leveraged for estimating future figures and trends.

1. Introduction

The recent media buzz on extended reality and the growth of blockchain-based solutions in different industrial verticals have necessitated the demand to experience decentralized 3-dimensional immersive reality in the digital spectrum (Far, Rad, & Assar, 2023; Kraus et al., 2023; Yang, 2023). Although the development of the Metaverse technology has been argued to be very nascent, the growth of web 3.0, Augmented Reality (AR), and Virtual Reality (VR) technologies can unleash limitless opportunities for empowering businesses in alternate mixed realities. Facilitating 3D experience via a systematic arrangement of interoperable platforms and sensor instruments unveils abundant strategic implications. Its impact on new products and brand management in the digital realm has slowly garnered traction. Tourism, entertainment, transportation, digital finance, etc. sectors are considered the primary beneficiaries of Metaverse technology in the coming days (Marabelli & Newell, 2023; Park & Lim, 2023; Yoo, Welden, Hewett, & Haenlein, 2023). Social media platforms have seen a tremendous surge in discussing the full potential of Metaverse in shaping and revolutionizing business, governance, and day-to-day life in the upcoming decade. Nevertheless, the platform is yet to be fully developed for end-to-end rollout and enabling complete digital transformation, which has triggered significant chatter on Metaverse at the onset of various events (Aysan, Batten, Gozgor, Khalfaoui, & Nanaeva, 2023; Deng & Matthes, 2023; Liu, Xie, & Wang, 2023). In this context, it is of paramount importance to scrupulously explore the dynamic linkage of the Metaverse financial markets with the floating sentiment on critical issues.

Public perceptions in the form of social media-based uncertainty have been acknowledged to be closely connected with Metaverse financial assets (Aysan et al., 2023; Krittanawong et al., 2023; Qian

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et al., 2022). The said research, nonetheless, is still at a very nascent stage. Profound penetration of public opinion and social media sentiment on conventional financial variables and cryptocurrencies has been acknowledged (Dias, Fernando, & Fernando, 2022; Goodell, Kumar, Rao, & Verma, 2023; Sapkota, 2022; Wang, 2022; Zhang, Li, Li, Zou, & Wu, 2023), wherein distress and unexpected events have been found to exert significant impact. Research by Ghosh, Alfaro-Cortés, Gámez, & García-Rubio, 2023 hinted that media chatter on Russia's military rhetoric against Ukraine shared co-movement with the daily closing prices of three Metaverse coins. The armed conflict has been found to substantially impact global equity markets, agricultural commodities, energy markets, etc., owing to disruptions in the supply chain and geopolitical turmoil. The need to flourish digital technologies in Black Swan events characterized by steep distress and volatility is naturally intensified. Thus, it is critical to evaluate the reflection of social media sentiment on Metaverse financial assets thoroughly to unearth deeper and more meaningful insights. Indirectly, the exploration will test the degree of efficiency of Metaverse coins, which has enormous implications for investors and traders.

Aysan et al. (2023) unveiled the impact of tracking the Twitter-based economic uncertainty index (TEU) in precise monitoring of the Metaverse stock market owing to positive dynamic association. The other emerging crypto assets, NFT, DeFi, etc., sharing a high resemblance with Metaverse financial assets, have been found to share significant nexus with investor sentiment manifested in social media platforms (Ghosh, Alfaro-Cortés, Gámez, & García-Rubio, 2023; Gunay, Goodell, Muhammed, & Kirimhan, 2023). These assets have also been reported to be dynamically connected with conventional financial assets, commodities, and stock markets (Bejaoui, Frikha, Jeribi, & Bariviera, 2023; Ben-Mabrouk, Sassi, Soltane, & Abid, 2024; Wang, 2022). On the other hand, the orthodox financial markets have been proven to be susceptible to the impact of the Russia-Ukraine conflict (Boungou & Yatié, 2022; Tee, Wong, & Hooy, 2023). The volatility from the military conflict has been reported to significantly drive the hedging landscapes (Karkowska & Urjasz, 2023). Hence, it becomes arduous to gauge the penetration of the relevant media chatter on Metaverse assets, which underscores the contribution of the work.

Ante (2023) coined the term "Musk Effect", which explained the exemplified role of tweets of Elon Musk on Bitcoin and Dogecoin returns. Sentiments extracted from the microblogs have been documented to be prudent in predicting stock markets (Nisar & Yeung, 2018; Oliviera, Cortez, & Areal, 2017). Theoretically, it is of paramount importance to evaluate whether the efficient market hypothesis is applicable to emerging Metaverse assets, too. If the chosen assets are found to react immediately to the arrival of new information on relevant topics, it will be challenging to design a robust framework to recognize the inherent pattern for forecasting future figures. Metaverse, being anticipated to revolutionize the digital business space, has yet to be fully adopted. Rollout of the same and the corresponding financial outlook are likely to be influenced by social media discussions and volatile external events as different technological advancements have been found to be reliant on relevant media chatter (Horky, Dubbick, Rhein, & Fidrmuc, 2023; Mnif, Mouakhar, & Jarboui, 2021).

To accomplish the research endeavors, we have chosen Reddit social media platform and RavenPack's media monitor (RavenPack, 2023) to expound on the dependence of four Metaverse coins, namely, Axie Infinity (AXS), Internet Computer (ICP), Decentraland (MANA), and Theta (THETA) on emotion and media chatter on Russia-Ukraine Conflict and the overall prospect of Metaverse. The four coins are chosen based on the higher market capitalization values for the timeline of the investigation. We strive to delve into the sentiment on the Reddit platform on two keywords: Russia-Ukraine Conflict, and Metaverse. The RavenPacks's media tracker is specifically used to evaluate the extent of worldwide media chatter on the military conflict between Russia and Ukraine. Reddit is a pseudo-anonymous social media network that encourages in-depth and thorough analysis of topics of interest. Users can constantly engage in discussions in the absence of any apprehensions and social ramifications. The promotion of content is driven by the voting of the members, which enables thorough elaboration of controversial agendas as well. Its uniqueness in the form of anonymity and provisions for creating subreddit communities provides additional advantages over traditional social media platforms while articulating emerging trends. Hence, the deployment of these data repositories is appropriate. We resort to wavelet coherence and nonlinear association mining tools to uncover the dynamic and complex interplay thoroughly. Subsequently, we build a novel predictive framework combining the UMAP and XGBR models to examine the predictability of the chosen Metaverse coins using the sentiment manifests of the two topics on Reddit. The UMAP methodology is used for better feature transformation, while the PSO algorithm is used for fine-tuning the XGBR model for fetching predictions. The said exercise is necessary to ascertain whether future figures of Metaverse tokens can be forecasted by tracking the social media sentiment on important agendas pertinent to the external environment. Lastly, we invoke dedicated XAI tools to interpret and explain the contribution of the explanatory variables in the predictive process at a granular level, which the PSO-tuned XGBR model is not meant for owing to complex procedural steps.

The contribution of the underlying research is primarily underscored by the endeavor to discover the dynamic interlinkage of the financial outlook of the emerging Metaverse asset on social media echo of the military invasion and technological innovation. Reddit sentiment mining has emerged to be highly prudent in explaining the temporal fluctuations of several orthodox financial market variables. The potency of the same in explaining the dynamics of Chosen Metaverse tokens is of utmost practical relevance in the context of ensuring appropriate market governance. As the empirical research on Metaverse financial assets is relatively scarce, the present research significantly attributes to the cognate literature. The setup to comprehend the impact of the uncertainty and rejoicing of common people linked to the war and the immersive reality on the market outlook of the Metaverse is unique and subjected to thorough scrutiny by robust research methodologies. Basically, the emphasis of the current endeavor is to understand the nexus of financial manifests of the digital realm on the digital sentiment of turbulent and breakthrough events, which generally affect the performance of the orthodox equity markets. The research findings will also delve into the market efficiency patterns of the Metaverse assets. From the perspective of the methodological front, the integration of applied predictive modeling and XAI for decoding the predictability of the chosen coins applying two sets of sentiment indicators suitably position and justifies the contribution of research framework as the emergence of XAI for financial data modeling has recently garnered steep attention.

The remaining segment of the manuscript is arranged as follows. We highlight the pertinent literature to properly articulate the motivation and contributions of the current study in section 2. Then, the utilized tools of the research methodology are illustrated in section 3. Afterward, we outline the detailed information of data sources and key empirical characteristics of the variables in section 4. The detailed results and findings of the research are then discussed in section 5. Finally, the paper is concluded in section 6, briefly mentioning the implications, current scope, and research plans for the future.

2. Literature review

Classical financial markets have previously been found to be profoundly interlinked with investor sentiment and reflection of the turbulent external environment attached to conventional social media (Ante, 2023; Klaus & Koser, 2021; Yousaf, Youssef, & Goodell, 2022). Campaigns, tweets of presidential candidates, and reactions of influential business leaders set the tone of investors, eventually driving the stock markets (Guo, Jiao, & Xu, 2021; Marinč, Massoud, Ichev, & Valentinčič, 2021; Nishimura & Sun, 2021). The adversarial effects of geopolitical rhetoric, invasion, armed conflicts, etc., on stock markets have also been acknowledged in literature (Buigut & Kapar, 2020; Hoque & Zaidi, 2020; Kumari, Kumar, & Pandey, 2023). Therefore, it becomes imperative to expound on the relevant sentiment on Metaverse assets owing to the connectedness of emerging markets and crypto assets. In this section, we briefly discuss the trend of recent literature on the impact of social media sentiment on the financial market and empirical characteristics of Metaverse coins to justify the rationale of the present study.

2.1. Sentiment analysis for financial market modeling

Sentiment analysis on Reddit and other platforms has recently experienced a profound surge in explaining the behavioral patterns of the financial variables (Gric, Bajzík, & Bandura, 2023; Isakin & Pu, 2023; Telli & Chen, 2021; Todorovska et al., 2023, Yu, Liang, Liu, & Wang, 2023). We briefly outline the trend of the allied literature to better understand the scope of contribution. Huynh, Audet, Alabi, and Tian (2021) used sentiment analysis focused on a subreddit forum of people interested in Wall Street news. They used a trust filter to eliminate potential non-reliable stock-related discussions on Reddit. Their regression model with Reddit and financial features predicts short-term and long-term adjusted closing stock prices. Considering Reddit sentiment analysis, the trust filter, the sliding window mechanism, and financial features improve the prediction of stock prices in the experiments. Jung and Jeong (2021) compiled internet memes in Reddit space to represent the societal mood and assessed its impact on the US stock market. It was revealed that large-cap US stock indices were more interlinked with the societal mood than the small-cap stock indices. Biswas, Ghosh, Roy, Bose, and Soni (2023) used news headlines from Reddit social media. The stock prices of the Bombay Stock Exchange are obtained from Yahoo Finance. Reddit headlines are labeled as positive, negative, and neutral using five classification models. That information, along with historical data on price movements, is used secondly to predict stock prices. Cruz, Kinyua, and Mutigwe (2023) managed 87 variables, including technical indicators, fundamental indicators, and two variables, collecting sentiment scores to predict stock prices and identify market manipulators. A negative correlation is found between fundamental stock market indicators and its price. A significant positive relationship is observed between sentiment characteristics and stock price. Parra-Moyano, Partida, and Gessl (2023) developed a random forest model that uses, among others, features from a sentiment analysis regarding cryptocurrencies on Twitter, Google Trends, and Reddit. Their results show that these variables help to capture the behavior of cryptocurrency investors and contribute to improving the model's ability to anticipate trend changes in this market. Costola, Hinz, Nofer, and Pelizzon (2023) analyzed the sentiment of articles published on three platforms (MarketWatch.com, Reuters.com, and NYtimes.com) during the first six months of 2020. They find a statistically significant (positive) relationship between COVID-19 sentiments and the S&P 500 index. However, Rajendiran and Priyadarsini (2023) reviewed the problems of stock market prediction. They conclude that Twitter Sentiment Analysis does not achieve higher performance on the stock prediction.

2.2. Metaverse financial assets modeling

Despite the growing attention of researchers in modeling the dynamics of non-fungible tokens (NFT) and decentralized finance (Chowdhury, Abdullah, Alam, Abedin, & Shi, 2023; Ghosh, Alfaro-Cortés, Gámez, & García-Rubio, 2023; Yousaf, Jareño, & Martínez-Serna, 2023), exploring the financial outlook of Metaverse is yet to reach a sizeable segment. The utility and potential of Metaverse to usher in revolutions in the different business spectrums, nonetheless, have garnered strong traction (Sestino & D'Angelo, 2023; Wan, Zhang, Yuan, & Chai, 2023). Here, we highlight a summary of a handful of the latest research made to unearth the financial perspectives of Metaverse markets. Aysan et al. (2023) employed the wavelet local multiplication correlation method to study the dynamic relationship between the Twitter uncertainty index and Metaverse stocks in the presence of crude oil and gold volatility. Results revealed that economic uncertainty shared a positive bond with the financial markets of Metaverse. Bai, Zhang, and Xue (2023) resorted to Dynamic Stochastic General Equilibrium (DSGE) models to understand the effects of inflations, shocks, monetary policy changes, etc., on the Metaverse economy. The study by Ghosh, Alfaro-Cortés, Gámez, & García-Rubio (2023) implies a long-run synergy between media chatter on travel uncertainty and Russia's military aggression and Metaverse tokens. The insights are drawn based on findings of wavelet-based methodologies, applied predictive analysis, and dynamic time series clustering technique. The findings of Lee, Ho, and Xie (2023) emphasized the positive effects of branded NFT (BNFT) purchase intentions and engagement on expanding the Metaverse economy. Vidal-Tomás (2023) argued that Metaverse commerce is highly susceptible to risk owing to considerably steep dependence on cryptocurrency markets.

The study of previous literature clearly indicates the significance of social media sentiment in sharing close bonds with various financial variables. Tracking Reddit sentiment can be extremely useful in estimating the future movements of the financial markets of heterogeneous assets. On the other hand, it is imminent that, being new entrants in the financial market, uncovering the dependence and predictability of Metaverse coins is of utmost importance. Nevertheless, research on the financial outlook of Metaverse is relatively low, which suitably positions the endeavor of the current study. We strive to contribute to the cognate literature by critically analyzing the impact of media chatter and public sentiment in the Reddit community on the daily closing prices of four Metaverse coins.

3. Research methodology

Here, we thoroughly elucidate the process and research tools used to accomplish the objectives. The sentiment extraction process is initially summarized, preceded by the other components.

3.1. Reddit sentiment mining

To conduct the sentiment analysis of social networks, we used the Reddit.com website, a news aggregator where users can make comments. To do so, we first use *"RedditExtractoR"* (Rivera, 2023), a R package (R Core Team, 2023), which allows us to search for news items that include a certain keyword. We filter out posts with less than five comments to avoid possible unreliable posts in line with Huynh et al. (2021). Next, we go through all the comments available for every news item, perform the sentiment analysis, and save it with the date on which each comment was made and the up-votes (score) that the comment had. For the sentiment analysis, we use the *"syuzhet"* package (Jockers, 2015) also from R, which calls the NRC sentiment dictionary to calculate the presence of ten different emotions (Anger, Anticipation, Disgust, Fear, Joy, Sadness, Surprise, Trust, Negative, Positive) and their corresponding valence in a text file. Finally, we aggregate this information by date so that if there are several comments on the same day, we assign the sum of their scores to that day and keep the information of how many comments correspond to that day. The said procedure results in the decomposition of the overall sentiments in 12 dimensions: Comments, Score, Anger, Anticipation, Disgust, Fear, Joy, Sadness, Surprise, Trust, Negative, and Positive. These manifests represent the overall emotion and expectations of social media on the chosen topics. The expectation of uncertain events and resultant anxiety, speculation, and rejoicing for wellness in the future can be effectively gauged by tracking the 12-dimensional vector. The Positive and Negative components account for the polarity of the sentiment.

3.2. Wavelet coherence analysis

The wavelet coherence (Torrence & Compo, 1998) in a bivariate framework is highly effective in modeling the dynamic interaction of two-time series in continuous time and frequency intervals. Fundamentally inspired by the continuous wavelet transform (CWT) framework, wavelet coherence attempts to measure the magnitude of interrelationship and identify the regions of high co-movement. We use the methodology to comprehend the interdependence of the Metaverse coins with the chosen variables in the time-frequency domain.

If $p(t)$ is a time series, then its CWT is expressed as follows:

$$\omega_p(\tau,\epsilon) = \int_{-\infty}^{+\infty} p(t)\widetilde{\varphi}^*_{\tau,\mathscr{E}}(t)dt; \tau,\epsilon \in R, \epsilon \neq 0 \tag{1}$$

where τ represents the location parameter, ϵ represents the scaling factor for determining the wavelet length, $\widetilde{\varphi}^*_{\tau,\epsilon}(t)$ represents the complex conjugate of $\widetilde{\varphi}_{\tau,\epsilon}(t)$ (with)

$$\widetilde{\varphi}_{\tau,\epsilon}(t) = \frac{1}{\sqrt{|\epsilon|}}\varphi\left(\frac{t-\tau}{\epsilon}\right) \tag{2}$$

as the mother wavelet. We use the Morlet wavelet to facilitate a good trade-off between time and frequency localization. The cross wavelet transformation of two-time series, $p(t)$ and $q(t)$, can be expressed as follows:

$$\omega_{pq}(\tau,\epsilon) = \omega_p(\tau,\epsilon)\omega^*_q(\tau,\epsilon) \tag{3}$$

Where ω^*_q denotes the complex conjugate of ω_q.

The wavelet coherence, $R_{pq}(\tau,\epsilon)$, to gauge the dynamic interplay is estimated as:

$$R_{pq}(\tau,\epsilon) = \frac{\left|\wp\left(|\omega_{pq}(\tau,\epsilon)|\right)\right|}{\sqrt{\wp\left(|\omega_{pp}(\tau,\epsilon)|\right)\wp\left(|\omega_{qq}(\tau,\epsilon)|\right)}} \tag{4}$$

Where $\wp$ denotes the smoothing operator, $\omega_{pq}(\tau,\epsilon)$ shows the area of co-movement between $p(t)$ and $q(t)$. The value of $R_{pq}(\tau,\epsilon)$ lies between 0 and 1, with $R_{pq}(\tau,\epsilon)=1$ implying maximum coherence, and $R_{pq}(\tau,\epsilon) = 0$ suggesting no coherence. The wavelet coherence phase difference is important to decode the behavioral pattern of the association and the lead-lag orientation is computed as follows (Torrence & Webster, 1999):

$$\theta_{pq}(\tau,\epsilon) = tan^{-1}\left(\frac{\Im\left(s^{-1}\omega_{pq}(\tau,\epsilon)\right)}{\Re\left(s^{-1}\omega_{pq}(\tau,\epsilon)\right)}\right) \tag{5}$$

Where the imaginary and real parts of power spectrum are represented by $\Im$ and $\Re$.

We utilize the wavelet coherence analysis to decode the dynamic dependence between the closing prices of Metaverse coins and worldwide media chatter on the Russia-Ukraine war, which subsequently set the path for introspecting the effects of Reddit sentiment.

3.3. Nonlinear association mining

For evaluating the association between the chosen coins and the Reddit sentiment indicators, the current work relies upon two maximal information-based nonparametric exploration (MINE) tools, namely, maximal information coefficient (MIC) and generalized mean information coefficient (GMIC) as defined below.

3.3.1. Maximal information coefficient (MIC)

Developed by Reshef et al. (2011), the MIC aims to expound on the dynamic bivariate linear or nonlinear interplay. Akin to the classical coefficient of determination (R2), MIC can detect and gauge the nonlinear nexus between two variables by virtue of additional competence. It is a member of the MINE statistics family, a set of statistical tools equipped to ascertain dynamic association. The values of the MIC metric range between 0 and 1. The MIC figure close to 0 implies no association, while values close to 1 indicate a strong nexus.

3.3.2. Generalized mean information coefficient (GMIC)

Conceptualized and developed by Luedtke and Tran (2013), GMIC is an extension of the MIC metric by eliminating a few shortcomings of the latter to detect relationships in the presence of noisy data. Likewise, the MIC metric, GMIC, ranges from 0 to 1, wherein values close to 0 suggest low dependence, and values near 1 indicate high association. The inclusive use of GMIC and MIC statistics is sufficient to discover the interplay manifested in functional and non-functional forms generated by the superimposition of orthodox functional forms and complex nonlinear patterns.

3.4. Predictive modeling

The forecasting framework comprises three dedicated methods. The UMAP procedure is invoked to obtain an optimized representation of the raw extracted sentiment dimensions, which can facilitate better training for recognizing the inherent pattern to fetch predictions. The XGBR method is used to predict the future figures of the four Metaverse coins on the basis of extracted sentiment components of two topics, while the PSO algorithm assists in auto-tuning the process parameters of the XGBR.

3.4.1. Uniform manifold approximation and projection (UMAP)

UMAP is a manifold learning procedure that precisely utilizes the utility of Riemannian geometry and algebraic topology for feature transformation and optimal data compression (McInnes, Healy, & Melville, 2018). A fuzzy topological layout of high-dimensional data samples characterizes the manifold. The determination of the embedding manifold is governed by a systematic fuzzy topological setup of improved dimensional projection from the original observations. UMAP strives to reorient the input data samples onto a high dimensional weighted graph, where the edges reflect the likelihood of connection of two vertices.

UMAP invokes exponential distribution to estimate the degree of resemblance between the high dimensional data points as:

$$s_{i/j} = exp\left(-\frac{d(x_i,x_j)-\rho_i}{\sigma_i}\right) \tag{6}$$

Where $d(x_i,x_j)$ denotes the distance between points *i* and *j*; ρ refers to the distance between the *i-th* data point and its first nearest neighbor.

UMAP specifies the high dimensional probability as:

$$s_{ij} = s_{i/j} + s_{j/i} - s_{i/j}s_{j/i} \tag{7}$$

As the topological graph represents a likelihood graph, the number of nearest neighbors (k) is an important parameter and is estimated as:

$$k = 2^{\sum_i s_{ij}} \tag{8}$$

After the successful achievement of the high-dimensional topology, UMAP aims to result in an optimized dimensional representational analog of the same. The similarity metric used in this structure is akin to t-distribution:

$$t_{ij} = \left(1 + a(y_i - y_j)^{2b}\right)^{-1} \tag{9}$$

With $a \approx 1.93$ and $b \approx 0.79$ as default UMAP parameters.

In general, binary cross-entropy is used as a loss function, which is computed as

$$CE(U,V) = \sum_i\sum_j\left[s_{ij}log\left(\frac{s_{ij}}{t_{ij}}\right) + (1-p_{ij})log\left(\frac{1-s_{ij}}{1-t_{ij}}\right)\right] \tag{10}$$

U and *V* refer to the likelihood of resemblance in high-dimensional and transformed dimensional space.

The stochastic gradient descent (SGD) algorithm is utilized in UMAP for quicker convergence. In this work, the number of neighbors has been chosen as 5 for capturing the local information. We do not use UMAP for dimension reduction. Rather, it is used to generate an optimized representation of the raw explanatory variables to train the PSO-tuned XGBR framework for predictive analysis. The UMAP procedure transforms raw sentiment indicators of respective explanatory variables into an optimized representation. The transformed indicators of the Russia-Ukraine conflict and Metaverse are used separately to predict the closing prices of AXS, ICP, MANA, and THETA.

3.4.2. Particle swarm optimization (PSO)

Invented by Kennedy and Eberhart (1995), PSO is a nature-inspired metaheuristic search algorithm that has been highly regarded for resolving NP-Hard problems (Tsao, Delicia, & Vu, 2022). It is a population-based search algorithm that enables candidate solutions in a population to constantly interact in the quest to traverse the search space intelligently. The interaction property distinguishes PSO from the evolutionary algorithm-based search algorithm family to obtain near-optimal solutions at a reasonable computational expense. Unlike the evolutionary computing-based search algorithms, PSO enables candidate solutions in the population to engage while traversing the search trajectory to move toward the near-optimal solution. The current work leverages the PSO algorithm for process parameter tuning of the XGBR model for predicting closing prices of Metaverse coins using two different sets of explanatory features manifested in the form of sentiment indicators.

The PSO encompasses a set of particles, where individual particles inside a group, passages indiscriminately, and said movement is constantly influenced by the adjoining position. The dynamic positions of each particle are updated by the accumulating self and assimilated knowledge. The respective positions of the underlying particles are iteratively updated on the basis of the present position, the optimal position achieved by any particle, and the optimal position occupied by the neighboring particles till the pre-defined termination condition is satisfied. The strength of the positions of the constituent particle is determined by a fitness function for estimating the velocity. They are calculated as follows:

$$V_i^{t+1} = \omega V_i^t + m_1 n_1 \left(p_{best,i}^t - Y_i^t\right) + m_2 n_2 \left(g_{best,i}^t - Y_i^t\right) \tag{11}$$

$$Y_i^{t+1} = Y_i^t + V_i^{t+1} \tag{12}$$

Where, velocity components of particle i in iterations t and $t+1$ are marked by V_i^t and V_i^{t+1}, respectively; the positions counterparts in iterations t and $t+1$ are denoted by Y_i^t and Y_i^{t+1}; the optimal position of the particle and the entire population at step t is denoted by $p_{best,i}^t$ and $p_{best,i}^t$; ω, m_1, and m_2 represent cognitive, social effects, and inertia parameters; n_1 and n_2 refer to two random parameters that reside in the range *[0,1]*. As stated, the PSO is utilized for parameter tuning of XGBR to model the predictive dependence of Metaverse coins on Reddit sentiment. The entire implementation is conducted using the *"pspso"* package.

3.4.3. Extreme gradient boosting regression (XGBR)

XGBR (Chen & Guestrin, 2016) is an ensemble machine-learning algorithm famous for complex pattern-mining tasks. It has been reported to result in superior performance for applied predictive modeling problems in the family of tree-based ML algorithms. The XGBR mimics the principles of boosting tree models. It adopts a second-order Taylor series on the loss function and resorts to several methods to avoid overfitting. Therefore, it is more generalizable and exhibits immunity to multi-collinearity. From the theoretical point of view, the XGBR model employs a number (D) of classical regression trees (CART) sequentially. The errors in the prediction of the previous tree facilitate the training of the subsequent trees, and thereby, the new subsequent model reduces the errors made by the previously trained tree and then makes the prediction. Mathematically, the XGBR estimates the predictions $(\hat{y}_i)$ (as)

$$\hat{y}_i = F(X_i) = \sum_{d=1}^{D} f_d(X_i), f_d \in F, i = 1, \dots, n \tag{13}$$

In eq. 7, the function space of the CART models is characterized by F, and f_d refers to the independent CART model denoted as q, which is the set of rules of an independent CART model that assigns each data observation i into one tree leaf. The calibration process performs the classification of n observations in such a manner that, given the covariates (X), each leaf is associated with a score belonging to the proportion of observations, which are classified into the corresponding group for the set of X_i. This score is marked as $w_{q(X)}$. We consider q as a function $q : \mathbb{R}^p \rightarrow T$, where T points to the total count of leaves of a tree. To obtain the final predictions, the scores of the leaves are aggregated as shown in eq. 13, where $F = \{f(X) = w_{q(X)}\}$, with $q : \mathbb{R}^p \rightarrow T$, and $w \in \mathbb{R}^T$. By reweighing model parameters, gradient boosting methods fit D models in total d iterations $(d = 1, \dots, D)$. Reweighting improves overall performance by imposing penalization. We use the PSO search algorithm to fine-tune three process parameters of XGBR, number of base learners, learning rate, and maximum depth utilizing the *"pspso"* package in the Python environment.

3.4.4. Performance evaluation

Let (Y_t) denotes the observed series and $(\hat{Y}_t)$ denote the estimated series. For predictive efficiency, we use four measures: Nash-Sutcliffe Efficiency (NSE), Theil Index (TI), Index of Agreement (IA), and Directional Predictive Accuracy (DA), which are defined below.

$$NSE = 1 - \frac{\sum_{t=1}^{N} \{Y_t - \hat{Y}_t\}^2}{\sum_{t=1}^{N} \{Y_t - \overline{Y}\}^2}. \tag{14}$$

$$TI = \frac{\left[\frac{1}{N}\sum_{t=1}^{N} (Y_t - \hat{Y}_t)^2\right]^{1/2}}{\left[\frac{1}{N}\sum_{t=1}^{N} (\hat{Y}_t)^2\right]^{1/2} + \left[\frac{1}{N}\sum_{t=1}^{N} (Y_t)^2\right]^{1/2}} \tag{15}$$

$$IA = 1 - \frac{\sum_{t=1}^{N} (Y_t - \hat{Y}_t)^2}{\sum_{t=1}^{N} \{|\hat{Y}_t - \overline{Y}| + |Y_t - \overline{Y}|\}^2} \tag{16}$$

$$DA = \begin{cases} 1, if\ (Y_{t+1} - Y_t)(\hat{Y}_{t+1} - Y_t) \geq 0 \\ 0, Otherwise \end{cases} \tag{17}$$

A predictive modeling approach will be highly efficient if the *NSE, IA, and DA* assume values close to 1 while the *TI* value is close to 0.

3.5. Model interpretation

Though the key objective of the study is to assess whether the chosen Metaverse assets can be predicted based on the floating sentiment in the Reddit engine, it is meaningful to gauge which dimensions of sentiment exert significant influence globally and locally. The insights will be useful for strategic interventions and practical implications. The integrated predictive framework of UMAP and PSO-tuned XGBR is meant for drawing precise forecasts at the expense of model explanation owing to the black box operational procedures. To resolve the same, the XAI tools are utilized to uncover the dependence between target and explanatory variables locally and globally. We utilize the Shapley additive explanations (SHAP) values for ascertaining feature contribution globally and local interpretable model-agnostic explanations (LIME) for assessing the influence of explanatory constructs at the local level. Recently, uncovering complex predictive models through the lens of XAI methodology has seen profound traction (Ghosh, Datta Chaudhuri, Alfaro-Cortés, Gámez, & García, 2022; Kim et al., 2023; Nimmy, Hussain, Chakrabortty, Hussain, & Saberi, 2023). The explanation is specified as follows:

$$g(z^{'}) = \theta_0 + \sum_{j=1}^{M} \theta_j z_j^{'} \tag{18}$$

Here $z^{'} \in \{0,1\}^M$, M refers to the number of features. The value of θ_i is estimated by invoking eq. 14.

$$\theta_i = \sum_{S \subseteq D\{i\}} \frac{|S|!(d-|S|-1)!}{d!} [v(S \cup \{i\}) - v(S)] \tag{19}$$

Where θ_i represents the predictive influence of the *i-th* feature, D denotes the feature set having cardinality d, S is the subset of D with feature i, and *v(D)* represents obtained predictions applying the *i-th* feature.

SHAP caters to several model explainers for achieving interpretation. The current work has relied upon the TreeSHAP tool to assess the relative significance of explanatory features used for drawing predictions. On the other hand, developed by Ribeiro, Singh, & Guestrin (2016), LIME aims to interpret machine learning models locally. It constructs new datasets by inducing random perturbation on the outcome of the prediction model and subsequently explaining the interaction between the dependent and predictor variables using a relatively better explainable machine learning model.

4. Data and variables

Daily closing prices of AXS, ICP, MANA, and THETA from January 2, 2022, to May 21, 2023, have been compiled from the portal of https://www.investing.com/. The timeline of our study is chosen in accordance with the onset of the Russia-Ukraine war. The daily media buzz on the said conflict is collated from RavenPack's media tracker, and the sentiment reflections on the Russia-Ukraine Conflict and Metaverse are curated from the Reddit community as discussed for the same duration. Fig. 1 exhibits the evolution of the daily closing price of the selected Metaverse tokens.

The descriptive statistics and outcome of critical statistical tests to characterize the empirical properties of the Metaverse tokens are outlined in Table 1.

It can be noticed that the chosen Metaverse Coins do not follow the normal distribution, as apparent from the significant Shapiro-Wilk and Anderson-Darling test statistics. The appearance of steep nonlinear movements in the temporal dynamics of the chosen assets is also evident from the output of Terasvirta's NN test. Finally, the underlying series display long memory dependence patterns as the estimated Hurst exponent values of the respective coins are significantly >0.5, suggesting that during the chosen turmoil regime, Metaverse financial markets do not entirely follow the efficient market hypothesis. Therefore, incorporating social media sentiment on pertinent aspects linked to the external environment systematically can be effective in delving into the predictability of the same.

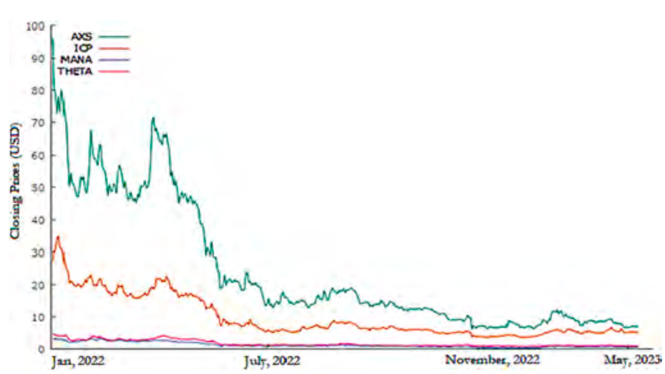

Fig. 1. Temporal Evolutionary Patterns of the Metaverse Coins.

Table 1
Statistical Properties of the Metaverse Coins.

Series	AXS	ICP	MANA	THETA
Minimum	5.980	3.500	0.293	0.721
Maximum	96.410	36.080	3.461	4.941
Mean	22.668	9.436	1.144	1.642
Median	13.175	6.120	0.773	1.169
Std. Dev.	20.610	6.966	0.844	1.009
Skewness	1.430	1.653	1.228	1.383
Kurtosis	0.887	1.995	0.062	0.586
SW Test	0.745***	0.731***	0.779***	0.740
AD Test	54.579***	56.435***	48.411***	58.887***
Terasvirta's NN Test	1734.8***	1206***	1454.1***	1453.6***
Hurst Exponent	0.853***	0.851***	0.855***	0.856***

*** Significant at 1% significance level, #Not significant.

The Figs. 2 and 3 exhibit the box plots of the different sentiment indicators of two keywords, 'Russia-Ukraine Conflict' and 'Metaverse' in Reddit platform. The respective boxplots indicate the presence of skewed distribution in the pattern of explanatory variables.

In a nutshell, the empirical properties of the variables under consideration clearly rationalize the utilization of the nonparametric research methodologies capable of modeling nonlinear temporal dynamics.

5. Results and discussions

We sequentially analyze the major findings of the present research in this section to reflect upon the nexus of media buzz and social media sentiment on the financial outlook of the considered Metaverse coins.

5.1. Findings of dynamic dependence

Figs. 4–7 exhibit the dynamic dependence between the closing prices of the selected Metaverse coins and the prevailing media chatter of the Russia-Ukraine conflict worldwide. The arrows in the wavelet coherence plot account for the lead/lag phase dependence. Arrows pointing to the right indicate in-phase co-movement, while the left orientation implies anti-phase relation. Arrows directed to the right-down or left-up suggest that the first-time series variable leads, whilst right-up or left-down alignment vouches for the lead role of the second-time series.

The wavelet coherence plot reveals that moderate to strong association prevailed mostly in short and medium-run scales. The association is not uniform throughout the timeline. The direction of the arrows suggests an anti-phase relationship, which implies higher media chatter on the military conflict destabilizes the market prospect of AXS. Lower media chatter hints at an improved financial outlook for AXS.

The wavelet coherence between ICP and the media chatter indicator implies a comparatively lower dynamic association than the previous pair. The moderate interplay between the variables can be seen to be primarily confined to short to medium-run scales. Sporadic presence of high correlation can be detected in a handful of pockets lying throughout the timeline of the investigation. Nevertheless, the direction of the association appears to be in phase in nature, as apparent from the domination of right-oriented arrows.

The above wavelet coherence assessment indicates a relatively stronger nexus between MANA and the chosen indicators than the previous pairs. Substantially higher association has emerged in short and medium-run scales from the last quarter of 2022 to May 2023. Even in long-run movements, high association throughout the investigation time horizon can be detected. Anti-phase coherence patterns outshine the in-phase orientation. Therefore, an inference can be drawn that the armed conflict indirectly spurs the daily closing prices of MANA, which resembles the findings of Ghosh, Alfaro-Cortés, Gámez, & García-Rubio (2023).

The final coherence plot implies the existence of moderate and strong

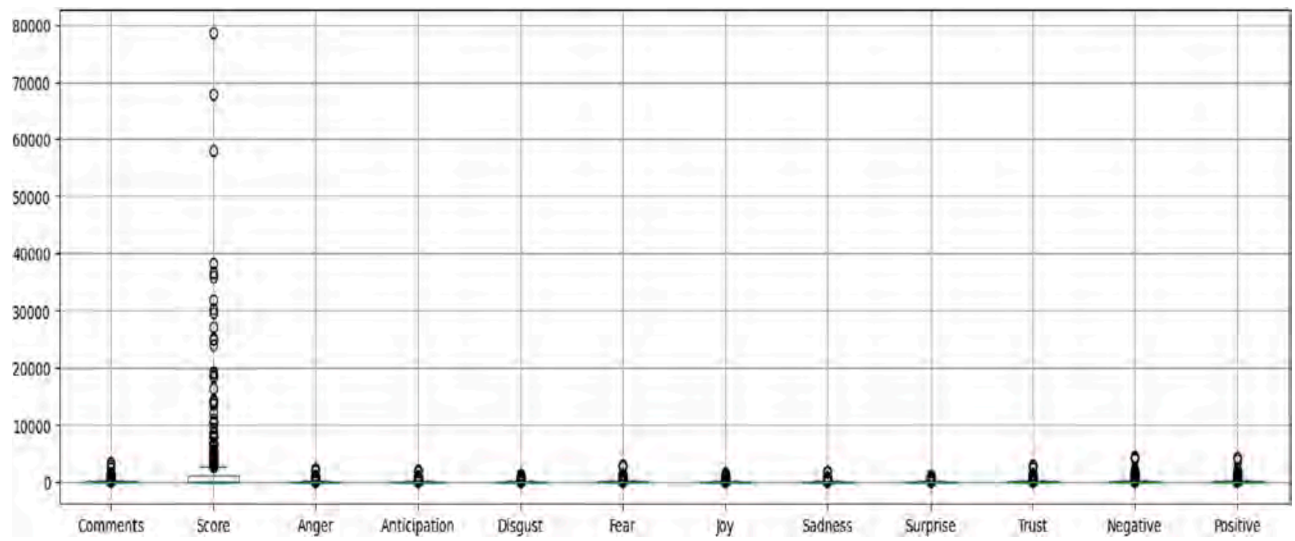

Fig. 2. Box Plot of Sentiment Indicators of ‘Russia-Ukraine Conflict’ Term in Reddit.

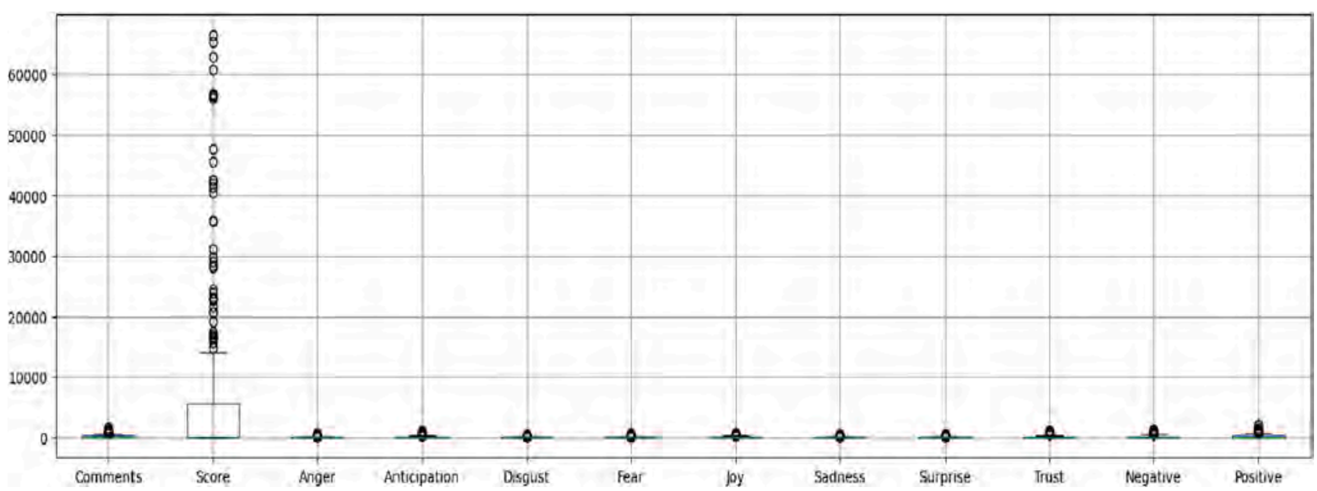

Fig. 3. Box Plot of Sentiment Indicators of ‘Metaverse’ Term in Reddit.

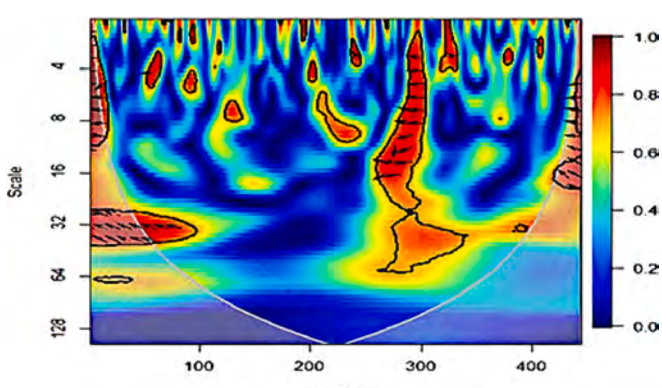

Fig. 4. Wavelet Coherence for AXS and Russia-Ukraine Conflict Media Chatter.

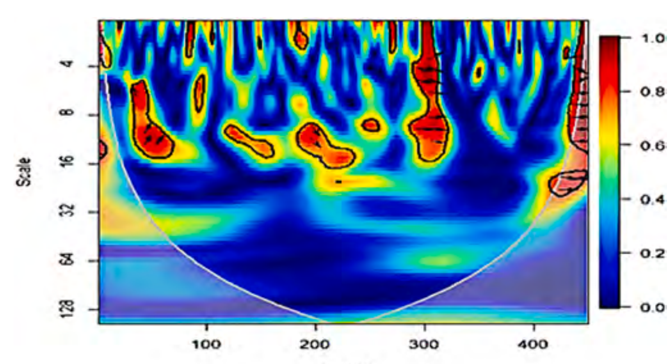

Fig. 5. Wavelet Coherence for ICP and Russia-Ukraine Conflict Media Chatter.

association in short to medium-run granules between THETA and the media chatter. The association intensifies in the later stages of the research period. The absence of interplay, in the long run, is imminent. The coherence appears to be in phase in nature.

Overall, the wavelet coherence analyses indicate that the closing prices of the chosen Metaverse tokens exhibit short and medium-run co-movements with the RavenPack Media tracker, reflecting the chatter pertinent to the Russia-Ukraine conflict worldwide. Barring ASX, the remaining three coins transpire to be positively linked with the media chatter. As discussions of military conflict emerge to be prudent in the dynamic association, it will be interesting to evaluate the impact of the

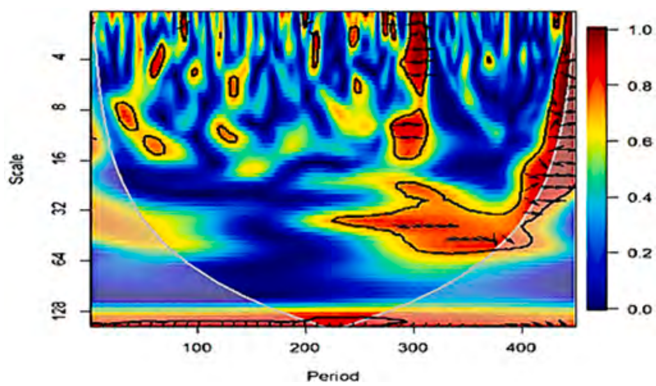

Fig. 6. Wavelet Coherence for MANA and Russia-Ukraine Media Chatter.

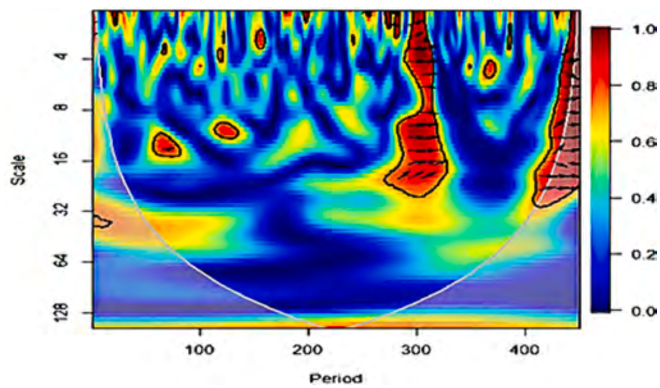

Fig. 7. Wavelet Coherence for THETA and Russia-Ukraine Conflict Media Chatter.

prevailing sentiment on the Metaverse topic itself. Thus, a deeper introspection to gauge the impact of social media sentiment on the daily closing prices of Metaverse coins is justified.

5.2. Findings of nonlinear association mining

As the output of wavelet coherence analysis suggests the presence of a short and medium-run association between the daily closing prices of the assets and media chatter on the Russia-Ukraine war, the investigation to ascertain the influence of public opinion in the Reddit community is important. The choice of inclusion of the sentiment quotient of Metaverse itself, barring the Russia-Ukraine conflict, is meaningful to perceive the emotion around the adoption and applications of the same in driving the financial outlook. Tables 2 and 3 narrate the values of estimated MIC and GMIC figures of respective sentiment dimensions to determine the strength.

The MIC and GMIC figures are not substantially high for the estimated sentiment indicators across the chosen Metaverse coins. ICP shares a relatively higher dependence with the Comments dimension of the Russia-Ukraine conflict than the other Metaverse tokens, as manifested by the MIC and GMIC values. Overall, ICP shares a marginally higher nexus with the respective components than the remaining three coins. The association metric figures rationalize the deployment of feature transformation by UMAP to better train the XGBR model for fetching predictions.

Likewise, the association mining outcome for sentiment indicators pertinent to the Russia-Ukraine conflict, dependence between the dimensions of the Metaverse term and four tokens appear to be similar. The association of MANA and respective sentiment dimensions transpires to be marginally higher than the others. The Surprise aspect shares the maximum interlinkage with the closing prices of MANA, as manifested by the MIC and GMIC metrics, respectively. Nevertheless, the systematic transformation of raw sentiment indicators by the UMAP methodology can effectively carry out predictive modeling.

5.3. Findings of the predictive modeling

We initially transform the raw feature set using the UMAP methodology to obtain an optimized representation of the respective sentiment indicators. Then, the aggregate data of the selected Metaverse coins is partitioned into training (80%) and test (20%) segments in a forward-looking orientation, which has been reported as a benchmark strategy to gauge the accuracy in financial time series prediction (Ghosh, Datta Chaudhuri, Alfaro-Cortés, Gámez, & García, 2022; Jana, Ghosh, & Das, 2021). The forecasting exercises have been conducted incorporating two different sets of sentiment indicators concentrated across two topics. The results of the same, manifested by the four performance indicators on the aggregate dataset, are enunciated in Table 4.

The output of the applied predictive modeling suggests that the closing prices of Metaverse coins can be predicted with a reasonable degree of accuracy by applying the sets of sentiment indicators pertinent to two distinct categories. The values of NSE and IA have surpassed 0.85 for the Russia-Ukraine Conflict sentiment-based prediction, while the values of TI are also low. The DA figures are >0.85, implying the extent of precision in trend direction estimation. On the other hand, the scores of the deployed performance metrics are relatively a tad inferior for the Metaverse sentiment-based prediction process. Thus, the resultant insights suggest that the predictability of the chosen Metaverse coins improves in the presence of the Russia-Ukraine conflict-linked sentiment indicators than the Metaverse term-linked scores. In terms of the Russia-Ukraine Conflict term-linked sentiment dimensions, AXS emerges to be relatively more predictable, and THETA is the least predictable. MANA and ICP appear the highest and least predictable for the other category. The said insights are helpful for traders to track appropriate sentiment

Table 2
The MIC and GMIC Figures for Sentiment Indicators of the Russia-Ukraine Conflict.

Components	AXS		ICP		MANA		THETA	
	MIC	GMIC	MIC	GMIC	MIC	GMIC	MIC	GMIC
Comments	0.2106	0.1187	0.2710	0.1593	0.2337	0.1417	0.2107	0.1381
Score	0.1819	0.1107	0.2547	0.1537	0.1955	0.1249	0.2148	0.1377
Anger	0.2207	0.1260	0.2649	0.1444	0.2207	0.1264	0.2156	0.1193
Anticipation	0.2249	0.1353	0.2635	0.1490	0.2160	0.1293	0.2089	0.1165
Disgust	0.2200	0.1261	0.2682	0.1539	0.2186	0.1270	0.2285	0.1545
Fear	0.2207	0.1265	0.2649	0.1488	0.2207	0.1274	0.2156	0.1301
Joy	0.2231	0.1310	0.2625	0.1495	0.2214	0.1298	0.2105	0.1224
Sadness	0.2134	0.1205	0.2549	0.1408	0.2207	0.1285	0.2108	0.1214
Surprise	0.2264	0.1361	0.2665	0.1565	0.2319	0.1371	0.2024	0.1144
Trust	0.2253	0.1364	0.2581	0.1483	0.2179	0.1294	0.2060	0.1311
Negative	0.2231	0.1310	0.2638	0.1525	0.2214	0.1307	0.2129	0.1346
Positive	0.2250	0.1287	0.2612	0.1497	0.2214	0.1300	0.2132	0.1299

Table 3
The MIC and GMIC Figures for Sentiment Indicators of Metaverse.

Components	AXS		ICP		MANA		THETA	
	MIC	GMIC	MIC	GMIC	MIC	GMIC	MIC	GMIC
Comments	0.2107	0.1375	0.2372	0.1532	0.2457	0.1607	0.2192	0.1394
Score	0.2401	0.1554	0.2219	0.1540	0.2223	0.1454	0.2346	0.1482
Anger	0.2283	0.1492	0.2486	0.1622	0.2625	0.1764	0.2453	0.1615
Anticipation	0.2241	0.1454	0.2516	0.1702	0.2576	0.1727	0.2419	0.1567
Disgust	0.2252	0.1491	0.2233	0.1533	0.2545	0.1668	0.2297	0.1513
Fear	0.2252	0.1541	0.2577	0.1771	0.2635	0.1744	0.2397	0.1615
Joy	0.2182	0.1444	0.2477	0.1612	0.2443	0.1615	0.2289	0.1502
Sadness	0.2090	0.1393	0.2245	0.1495	0.2555	0.1643	0.2320	0.1502
Surprise	0.2237	0.1462	0.2438	0.1601	0.2642	0.1772	0.2366	0.1530
Trust	0.2258	0.1496	0.2384	0.1600	0.2552	0.1706	0.2426	0.1621
Negative	0.2218	0.1493	0.2424	0.1601	0.2564	0.1685	0.2392	0.1597
Positive	0.2173	0.1437	0.2542	0.1648	0.2516	0.1683	0.2338	0.1535

Table 4
Summarization of the Predictive Performance.

	NSE	TI	IA	DA
Russia-Ukraine Conflict Sentiment				
AXS	0.8673	0.2069	0.8759	0.8600
ICP	0.8588	0.2272	0.8671	0.8550
MANA	0.8624	0.2143	0.8705	0.8600
THETA	0.8569	0.2309	0.8643	0.8501
Metaverse Sentiment				
AXS	0.8334	0.2678	0.8398	0.8313
ICP	0.8247	0.2804	0.8306	0.8273
MANA	0.8356	0.2615	0.8411	0.8313
THETA	0.8321	0.2539	0.8375	0.8273

while investing in a particular asset. Despite low MIC and GMIC figures, substantially better predictive performance strongly justifies the effectiveness of feature transformation by UMAP beforehand.

5.4. Findings of the model interpretation

Although the results of predictive modeling duly establish the relevance of close monitoring of social media discussions to accurately estimate the future trends of the Metaverse tokens, negligible insights on the detailed nature of the predictive influence of respective constructs can be inferred. Two XAI methodologies, SHAP and LIME, are utilized to uncover the global and local level contributions of the said indicators. Figs. 8 and 9 depict the global contribution of Russia-Ukraine and Metaverse sentiment indicators in predicting the AXS.

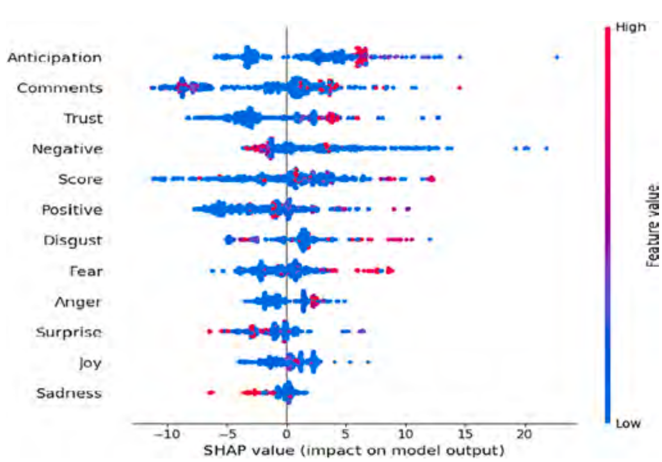

Fig. 8. The SHAP Outcome of Russia-Ukraine Conflict Sentiment for AXS Prediction.

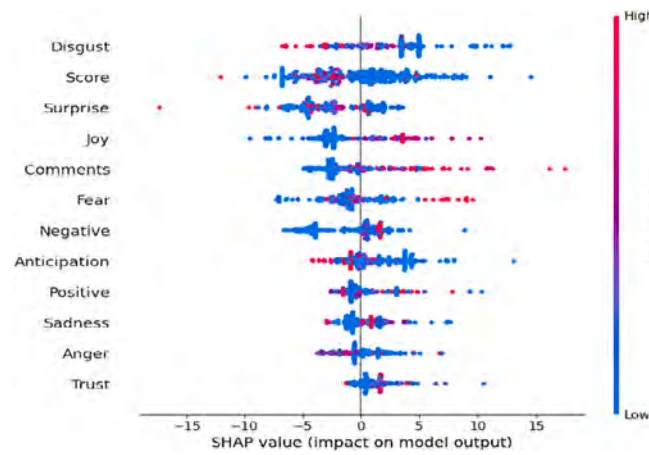

Fig. 9. The SHAP Outcome of Metaverse Sentiment for AXS Prediction.

It can be noticed that Anticipation, Comments, and Trust occupy the top 3 important feature spots. Their impact on AXS oscillates from a negative to a positive direction. Predominantly, the lower values of these features exert significant predictive influence. On the other hand, the Surprise, Joy, and Sadness components appear to be at least three significant features while explaining the AXS daily price movements. In general, when the figures of the dimensions linked to the Russia-Ukraine Conflict sentiment on the Reddit platform are low, its impact on the temporal dynamics of AXS intensifies. On the contrary, as the values increase, i.e., discussions and uncertainty on Russia's military invasion of Ukraine skyrocket, the effects of the same on Metaverse's financial outlook are marginalized.

Interesting insights linked to the global feature contribution of sentiment indicators associated with the Metaverse term are unearthed. The top three important spots are occupied by the Disgust, Score, and Surprise components, respectively, while Sadness, Anger, and Trust resemble the least three critical explanatory features. The direction of influence oscillates from negative to positive end. The lower values of the underlying features dominate the prediction process, similar to the contribution patterns of the Russia-Ukraine sentiment indicators.

The SHAP plots for the remaining Metaverse coins are available on request. Similar findings have been observed for these assets also. Hence, it can be concluded that the financial outlook of Metaverse is affected by Reddit sentiments to a certain extent, beyond which the predictive influence is gradually marginalized. Therefore, improving the predictive accuracy supremely, i.e., attaining forecasts with NSE, IA, and DA values over 0.95, will require the incorporation of other macroeconomic and technical indicators in the prediction process. Table 5 enlists the global feature ranking as evident from the SHAP-based introspection.

Table 5
The Overall Feature Ranking Based On Global Contribution.

Components	Russia-Ukraine Conflict-Linked Sentiment Indicators				Metaverse-Linked Sentiment Indicators				Average Ranking of the respective Indicators	
	AXS	ICP	MANA	THETA	AXS	ICP	MANA	THETA	Russia-Ukraine Conflict	Metaverse
Comments	2	2	2	1	5	1	5	6	1.75	4.25
Score	5	6	6	2	2	4	3	3	4.75	3
Anger	9	11	11	10	11	11	12	10	10.25	11
Anticipation	1	4	3	5	8	8	9	9	3.25	8.5
Disgust	7	1	8	7	1	2	4	5	5.75	3
Fear	8	10	5	6	6	7	2	2	7.25	4.25
Joy	11	9	9	11	4	5	1	1	10	2.75
Sadness	12	12	12	12	10	9	11	8	12	9.5
Surprise	10	8	10	9	3	3	7	7	9.25	5
Trust	3	5	7	4	12	10	10	12	4.75	11
Negative	4	7	1	3	7	6	8	4	3.75	6.25
Positive	6	3	4	8	9	12	6	11	5.25	9.5

In a nutshell, the above ranking infers that the expectation for turnaround and adversarial effects of the Russia-Ukraine Conflict significantly induce predictive prowess on the temporal movements of the chosen Metaverse coins. As expected, Joy and Surprise reflections tend to induce relatively less predictive impact. On the flip side, the Joy and Surprise quotient of the inception and growth of Metaverse in the form of unveiling high expectations on Reddit experience a strong influence on the selected target variables. The Sadness and Anger dimensions share comparatively low predictive influences. We also present the average ranking of the respective indicators by aggregating the ranks across the four Metaverse coins for the two keywords. Inference can, therefore, be drawn that the positive traction toward the Metaverse, being perceived as a game changer in the growing space of digital transformation, outweighs optimism of diplomatic resolution of the Russia-Ukraine Conflict on the Reddit platform while explaining the variation of Metaverse financial assets. We now introspect the local-level contributions of the respective features using LIME plots. Figs. 10 and 11 depict the outcome of LIME analysis for AXS predictions as samples.

The local scale feature contribution analysis suggests the existence of varying degrees of predictive prowess spread across the features. The ranking of features for explaining the variation in the randomly selected sample is not similar to that of the SHAP-based global feature ranking. Several dimensions of the Russia-Ukraine Conflict exert a negative effect on the closing price of AXS on the chosen sample.

The local contribution patterns of Metaverse topic-related sentiment manifests imply that it is equally important to closely track all 12 indicators for estimating precise prediction at a local level, as the feature ranking for the randomly selected data sample is not the same as that of the global counterpart. The presence of both positive and negative predictive influence is amply apparent. Similar findings have been observed for the other three Metaverse coins. Detailed results are available on request.

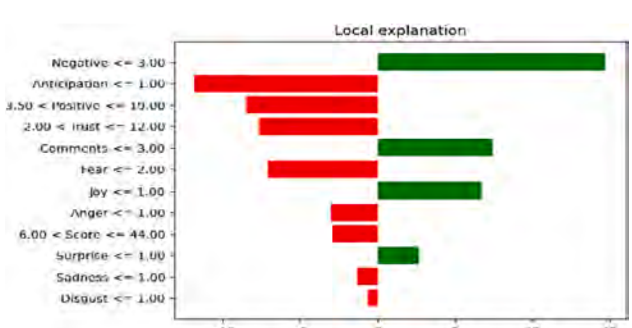

Fig. 10. The LIME Plot of Russia-Ukraine Conflict Sentiment for AXS Prediction.

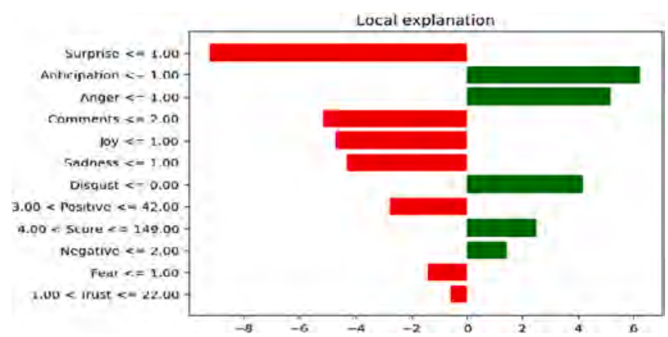

Fig. 11. The LIME Plot of Russia-Ukraine Conflict Sentiment for AXS Prediction.

6. Concluding remarks

The current research strives to systematically analyze the impact of social media sentiment and chatter of critical issues on Metaverse financial assets. The deliberations and sentiments on various agendas in the Reddit platform have been previously reported to exert predictive influence on conventional financial markets and crypto assets (Bowden & Gemayel, 2023; Reichenbach & Walther, 2023). The findings of the research clearly indicate the utility of the same platform in closely tracking the prospects of Metaverse coins. Thus, the Metaverse financial assets are not completely different from the orthodox financial variables in terms of sensitivity toward external sentiment. The impact of the public sentiment of the Russia-Ukraine Conflict on AXS, ICP, MANA, and THETA in the form of predictive prowess resembles the claim of Ghosh, Alfaro-Cortés, Gámez, & García-Rubio (2023). Public perception of the Metaverse itself has been proven to be closely interlinked with the assets. The nature of influence suggests that the confidence of the investors in the turmoil does not completely alienate investment decision-making. The methodological novelty of the current work in the form of a combination of UMAP, PSO-tuned XGBR, and XAI has emerged to be profoundly useful and effective in drawing deeper insights.

Worldwide media buzz on the Russia-Ukraine war has been found to be primarily interconnected with the daily closing prices of AXS, ICP, and THETA in short and medium-run durations. The MANA transpires to share long-run co-movement with the said media chatter, though. Precise monitoring of RavenPack's media chatter can be leveraged for risk mitigation. The overall differences in the dependence structure and the subsequent non-uniform feature ranking, as indicated by XAI methodology for the chosen Metaverse coins, suggest the presence of heterogeneous market outlook and capitalization. Hence, the degree of inefficiency of the underlying coins varies, which resembles conventional financial assets. The said aspects of Metaverse financial markets can, therefore, be leveraged for reaping diversification benefits in dynamic time horizons. The predictive exercises clearly reveal the inefficient structure of the chosen Metaverse coins. Relatively better predictability using Russia-Ukraine Conflict linked sentiment indicators over the Metaverse counterparts shows a stronger impact of turbulent external environment over the innovation in digital immersive reality in shaping market outlook. The SHAP and LIME-based interpretation of the prediction process implies that relative rankings of the sentiment dimensions of respective topics are not uniform, stressing the need to track all dimensions carefully to predict future figures of the Metaverse tokens accurately. The negative emotions of the Russia-Ukraine Conflict sentiment in the Reddit community are more profound in explaining the variations of the chosen assets. At the same time, the amazement over the potential benefits and advantages of Metaverse exerts substantial effects.

The scope of the underlying research is confined to the analysis of user sentiment on two topics in Reddit communities. It is important to examine the predictive dependence of Metaverse financial variables on a wider range of topics to holistically establish the efficacy of sentiment mining in the predictive modeling of emerging and unconventional financial assets. We have strictly restricted our exploration to four metaverse coins selected based on the market capitalization criterion. It will be interesting to compare and contrast the impact of Reddit sentiment on NFT and DeFi coins in the future as well. The present study reports the predictive performance of both sets of sentiment indicators separately and aims to draw insights accordingly. It will be interesting to document the change performance of different sets of sentiment indicators used together on an extended data set. The effectiveness of critical macroeconomic variables and technical indicators in conjunction with the Reddit sentiment to further augment the precision of the prediction, i.e., to account for the unexplained part of the daily dynamics of the Metaverse coins, can be explored, too.

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Data availability

The authors do not have permission to share data.

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