On Using Twitter to Understand the Stablecoin Terra Collapse

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ABSTRACT

Stablecoins have emerged as a solution to the legal status and volatile exchange rate issues surrounding cryptocurrencies like Bitcoin. Terra is a blockchain protocol that enables the creation of stablecoins pegged to fiat currencies, including UST and KRT, which have gained popularity for their use in DeFi applications. However, in May 2022, TerraUSD (UST) lost its peg to the USD, collapsing to a value of 0.091 USD due to a massive withdrawal of UST from the Anchor Protocol, leading to a sharp drop in price. In this paper we analyze people's opinions and thoughts about the topic using Twitter data and we propose a method to identify the accounts that acted as opinion leaders. We observed an increase in negativity in the month leading up to the collapse and identified the United States as the most prolific country in terms of tweets; we identified opinion leaders accounts and we showed that the number of followers is not an important metric to identify opinion leaders. The failure of the Terra project highlights the intrinsic fragility of algorithmic stablecoins, which can fail due to sudden fluctuations in demand and supply, and their potential for success and stability remains uncertain.

CCS CONCEPTS

• **Information systems**; • **Applied computing** → **Computers in other domains**; • **Social and professional topics**;

KEYWORDS

StableCoin, Cryptocurrency, Opinion Leader, Twitter conversations

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1 INTRODUCTION

Blockchain technologies have sparked interest in the digital economy, and the features they offer, mainly anonymity and transparency have garnered attention [23]. However, debates continue regarding its legal status and volatile exchange rates, hindering wider adoption as a medium of exchange [3]. One particular challenge is on developing a stable cryptocurrency that offers stability, wider adoption, lower transaction fees, increased financial inclusion, and reduced risk [21].

A cryptocurrency that is free from volatile exchange rates could have several potential benefits, including stability (i.e., limited fluctuations in value), wider adoption (i.e., more appealing to mainstream users and businesses), lower transaction fees (i.e., require less hedging against exchange rate risks), increased financial inclusion (i.e., financial transactions more accessible and affordable for people in regions with volatile local currencies or limited access to traditional banking services), reduced risk (i.e., less risk of losing money due to sudden shifts in exchange rates) [2].

Stablecoins are a type of cryptocurrency that aims to maintain a stable value relative to another asset, such as a fiat currency or commodity, in order to avoid the volatility that is common in many other cryptocurrencies [4]. Stablecoins use algorithms to ensure their value remains pegged to an underlying asset. They offer fast and secure transactions and a stable option for storing and transferring value, making them popular for payment, storing value, and accessing decentralized finance. Various types of stablecoins exist but they all aim to provide stability and reliability, making them a crucial part of the cryptocurrency ecosystem [5, 18].

Terra is a blockchain protocol that enables the creation of stablecoins pegged to fiat currencies. Its algorithmic bank mechanism adjusts the supply of stablecoins based on changes in demand, maintaining their stability. Terra stablecoins, such as UST and KRT, have gained popularity for their use in DeFi applications, payment, and storage of value. Terra also has its own cryptocurrency, LUNA, which is used as collateral to borrow stablecoins. Terra's DeFi applications include Anchor, TerraSwap, and Anchor, which offer lending, decentralized exchange, and savings platforms. Terra's unique approach to stablecoins and its integration into DeFi applications could have significant implications for the future of finance as blockchain technology continues to evolve.

This study investigates an important theme known globally as the Collapse of the stablecoin Terra [6]. The importance of this topic is related to the fact that Terra wasn't just a project to create a cryptocurrency but it was a complex system of projects composed of Non-Fungible Token (NFT) collections, Decentralized Finance (DeFi) platforms, and Web applications. In May 2022, TerraUSD (UST), one of the largest stablecoins, lost its peg to the USD, collapsing to a value of 0.091 USD. The collapse was caused by a massive withdrawal of UST from the Anchor Protocol, leading to a sharp drop in price. Traders tried to take advantage of arbitrage opportunities, exacerbating the decline and causing a "bank run" or "death spiral." The Terra team announced a more efficient mechanism to burn UST, but the collapse had already damaged community trust. The failure of the Terra project highlights the intrinsic fragility of

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Figure 1: USTC Trend from April to June 2022; source: Coin Market Cap .

algorithmic stablecoins, which can fail due to sudden fluctuations in demand and supply, and their potential for success and stability remains uncertain.

Our investigation starts from an assumption based on what was said by the co-founder of the Terra project, in one of his public declarations, Do Kwon, who stated that 95% of companies entering the cryptocurrency market were going to die. What he said was related to the fact that, actually, watching companies die is a pleasant entertainment and this is also connected with one of the assumptions of the collapse of Terra based on some sort of attack. Our idea is to use Twitter as a passive sensor to measure people's opinions and thoughts about the topic during 2021 and 2022, with a particular attention on the months of the collapse (i.e., April, May and June 2022). In particular, we perform a sentiment analysis, a geo-graphical analysis and an analysis to identify who are the opinion leaders of this specific topic.

Using a dataset of 330,000 tweets from 61,979 different accounts on the topic, we observed an increase in negativity in the month leading up to the collapse. The United States was the most prolific country in terms of tweets, followed by Great Britain and Italy, but the analysis also revealed an interest from accounts based in Mexico. The investigation into opinion leaders showed that there is no correlation between the number of followers and interactions with posted tweets, nor is there a correlation between the number of tweets and the number of interactions with posted tweets. However, by using some basic Twitter metrics, we were able to identify a few accounts that acted as opinion leaders as they were very effective at engaging people.

The remainder of the paper is organized as follows. In Section 2 we review studies in the field of stablecoin and social media; Section 3 shows the idea of this study, whereas Section 4 shows the experimental setting and the obtained results. Discussion, limitation and future work are presented in Section 5 and Conclusions are drawn in Section 6

2 RELATED WORK

To gain insight into the perception of stablecoins in the general public, researchers have turned to analyzing social media conversations, as these platforms are important sources of information and sentiment for investors and traders. In the following, we briefly review some of the most recent approaches.

Oikonomopoulos et al. [17] proposes a model for predicting cryptocurrency prices using sentiment analysis of news and social media data. Machine learning algorithms analyze over 3 million articles and posts related to Bitcoin and Ethereum to derive sentiment scores. The study finds that sentiment analysis of news and social media can be a valuable tool for short-term predictions of cryptocurrency prices, providing traders with valuable insights into market trends and sentiment.

Tandon et al. [19] proposes a framework that combines sentiment analysis, network analysis, and machine learning to predict the impact of social media messages on cryptocurrency value. It finds that social media sentiment and network centrality metrics are significant predictors of cryptocurrency value, and the framework can help investors and traders make more informed decisions.

Kolonin et al. [14] proposes a practical approach for analyzing diverse time-series data, including financial metrics and sentiment analysis from social media news streams, using lagged Pearson correlation for causal analysis in predicting financial markets. It provides an algorithmic framework for data acquisition and analysis, with experimental results showing the ability to discriminate causal connections between different types of market data. The paper concludes with a discussion of present issues and future directions for this work.

Abraham et al. [1] found that tweet volume, rather than sentiment, is a predictor of price direction. By utilizing a linear model that takes tweets and Google Trends data as input, the direction of price changes can be accurately predicted. This approach can provide a purchasing and selling advantage to cryptocurrency users or traders, enabling better-informed decisions related to Bitcoin and Ethereum.

Kraaijeveld and *De Smedt* [15] examines the predictive power of Twitter sentiment for the nine largest cryptocurrencies. It finds that sentiment analysis has predictive power for the returns of Bitcoin, Bitcoin Cash, Litecoin, EOS, and TRON. The study also develops a heuristic approach to discover the presence of cryptocurrency-related Twitter bots, making it the first to explore their presence in the context of multiple cryptocurrencies.

Arti et al. [13] focus on predicting the two-hour price of Bitcoin and Litecoin using a multi-linear regression model. It aims to address the inefficiencies of previous methods that fail to consider the differences between real currencies and cryptocurrencies and utilize social factors increasingly used for online transactions worldwide.

Wu et al. [22] examines the effects of economic policy uncertainty (EPU) on the returns of four cryptocurrencies (Bitcoin, Ethereum, Litecoin, and Ripple) using two new measures of EPU based on Twitter data. The study finds a significant causality between the Twitter-based EPU measures and the BTC/USD exchange rate from October 2016 to July 2017, as well as for Ethereum and Ripple during specific periods. The findings are robust to different measures of Twitter-based EPU and different econometric techniques.

Valencia et al. [20] propose using sentiment analysis and machine learning techniques to predict the price movement of the Bitcoin, Ethereum, Ripple, and Litecoin cryptocurrency markets. The study compares the performance of neural networks, support vector machines, and random forest models using Twitter and market data as input features. The results show that it is possible to predict cryptocurrency markets using machine learning and sentiment analysis, with neural networks outperforming other models.

Abubakr et al. [16] examines the predictive ability of Twitter Happiness Sentiment for six major cryptocurrencies using daily data from August 7, 2015, to December 31, 2019. The study finds a significant nonlinear relationship between Twitter Happiness Sentiment and cryptocurrencies, which is further enhanced by using the quantile-on-quantile (QQ) analysis. The study concludes that high and low sentiment predicts returns of five cryptocurrencies, with statistically and economically significant findings.

3 OUR PROPOSAL

The aim of this study is to analyze a dataset of Twitter conversations to understand if there were any indications of the collapse and how people reacted to it. Additionally, we aim to identify the location of these conversations and the individuals who influenced public opinion. By analyzing the behavior and content of Twitter users, we can identify opinion leaders and understand their impact on the public. This way, we would like to gain insights into the public's response to the collapse and better understand the role of social media in shaping public opinion.

3.1 Sentiment Analysis

Sentiment analysis is a field of natural language processing that identifies and extracts subjective information from text data. The goal of sentiment analysis is to determine the emotional tone behind a series of words. When applied to Twitter, it can help identify the sentiment expressed in tweets and quantify it as positive, negative, or neutral [11, 12]. This technique can be useful in various applications, such as predicting stock prices [7], analyzing the cultural heritage scenario [10], monitoring society health [9], and tracking public opinion on specific topics [8]. By analyzing the sentiment of tweets, it becomes possible to understand the emotional response of individuals and groups to various events, such as the collapse of the Terra stablecoin.

3.2 Geolocalization

Geotagged tweets are tweets that have location information attached to them, allowing them to be mapped and analyzed based on their geographical origin. The importance of geotagged tweets lies in the fact that they provide valuable insights into regional trends, preferences, and opinions. For example, geotagged tweets can be used to identify hotspots of activity for specific events or products, such as concerts or restaurants. They can also be used to track the spread of diseases or natural disasters, and to monitor public sentiment on political issues at the regional level. Geotagged tweets are especially valuable for businesses and organizations that operate in specific regions or markets, as they can help them tailor their strategies and offerings to local needs and preferences. Overall, geotagged tweets provide a rich source of data that can be used to gain insights into the behavior and opinions of people in specific geographic locations.

3.3 Opinion Leader

One initial hypothesis to find opinion leaders within Twitter conversations is to look at who has the most followers, assuming that those with the most followers are also the opinion leaders. This type of analysis is very easy, but there are several drawbacks to using follower count as the sole measure of opinion leadership. While it's true that individuals with a large number of followers may have a significant impact on their audience, there are other factors to consider as well. For example, some users may have a smaller but more engaged following, with a higher level of interaction and influence on their audience. Additionally, follower counts can be subject to manipulation through tactics such as buying followers or using bots, which can inflate the number without necessarily reflecting the actual level of influence.

Furthermore, it's important to consider the context and topic of discussion when determining opinion leadership. A user who is highly influential in one area may not necessarily be influential in another. Additionally, opinion leadership can be subjective and dependent on factors such as the credibility of the source, the relevance of the content, and the trustworthiness of the information being shared. Therefore, other factors should be taken into consideration when looking for opinion leaders within conversations.

4 EXPERIMENTAL ANALYSIS

To address the research questions, we consider a dataset of Twitter conversations related to the Terra collapse. Using the Twitter API, we browse for tweets posted between January 2021 and December 2022, which have one or more of the following hashtags and/or keywords: #Blockchain, #UST, #TerraUSD, #crypto, #cryptocurrency, #CryptocurrencyMarket, #wluna, #CryptoNews, stablecoin, Terra, cryptomarket, TerraUSD, and Terra. This resulted in a dataset of 330,419 tweets, written by 61,970 different accounts.

4.1 Sentiment Analysis

The sentiment analysis is done using the well-known textblob library, which allows you to calculate the polarity of each tweet. The polarity provides information about the sentiment of the analyzed tweet which resulted: positive (47%), negative (7%), and neutral (46%).

Figure 2 shows the results of the sentiment analysis when applied to the tweets posted in the critical period (April 2022 - June 2022). The negative tweets were almost every time less than the others. In the half of May 2022, there was an increase in negative tweets because of the collapse of Terra and positive tweets after this date gradually decreased. Clearly enough, this can be explained by the fact that investors in cryptocurrencies were concerned about the future of their investments and expressed their dissatisfaction or disappointment through negative tweets. Also in the last week of April 2022 there was an increase in the amount of negative tweets, maybe because of a series of sell-offs on the crypto markets after the end of April, which then led to the collapse of LUNA and UST. For example, Starting from the 24 of April the UST almost always fell below the threshold of 1$. On May 8, the real collapse was triggered, culminating in Black Wednesday of May 11 when the entire Terra ecosystem literally started to implode. In fact, as it possible to see from the chart, on May 12th 2022 there was an

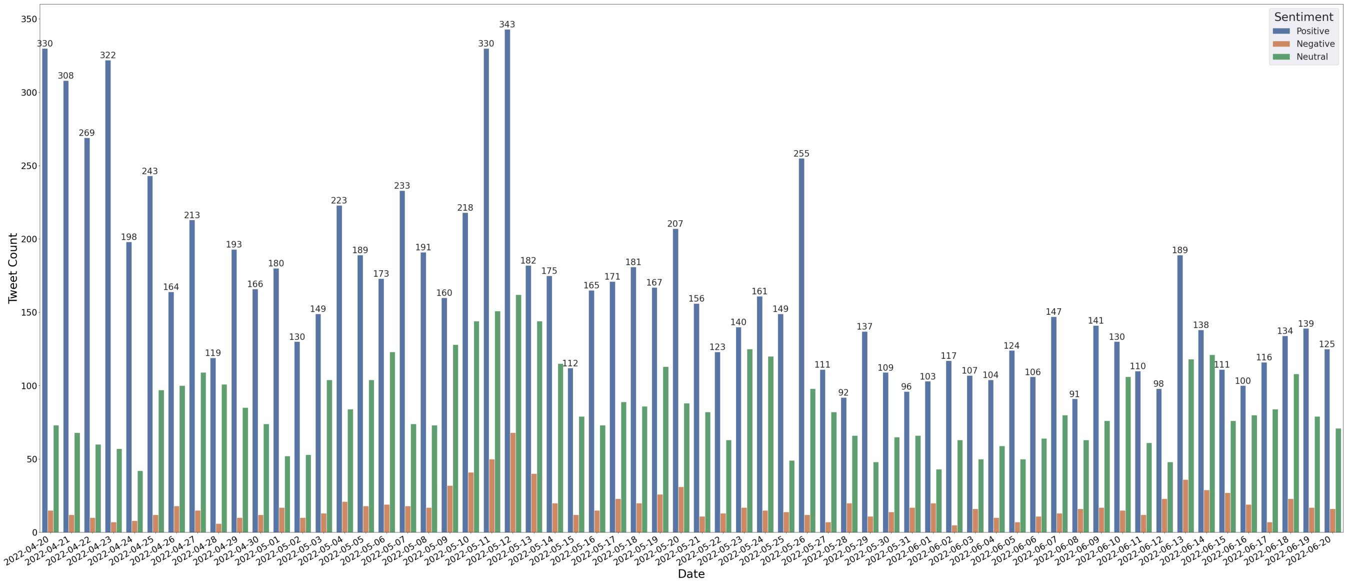

Figure 2: Sentiment Analysis during the critical period (April 2022-June 2022).

exploit of positive tweets. This means that there was an excitement related to the collapse of the crypto, something that surely caused surprise and curiosity. But not only, in many cases there was as well a certain level of happiness or irony associated with it. This may be attributed to the fact that witnessing the downfall of companies can sometimes be viewed as a form of entertainment. Some messages had a positive tone, as they were advertisements designed to attract new followers and suggested that following their profile could help avoid similar problems in the future. These messages aimed to present new opportunities to the audience. Meanwhile, other messages expressed satisfaction or relief at not having invested in cryptocurrency, with statements such as, "*the risks were always there, and I'm glad I didn't take that risky bait*".

Furthermore, the number of neutral tweets also increased, although the increment was not as significant as the other sentiment classes. This indicates that the collapse of Terra stablecoin caused a certain level of polarization in the sentiment towards the cryptocurrency market, with some expressing positive views and others expressing negative ones. To sum up, while the total number of negative tweets was lower than the positive ones, the ratio of increase in negative tweets was higher compared to the other sentiment classes.

4.2 Geo-spatial Analysis

Initially, only the information relating to the state from which the tweet was published was considered, obtaining the count of tweets from a specific country for the entire time frame available to us (February 2021 - December 2023). The amount of tweets was mainly in United States, United Kingdom, and Italy in 2021 and 2022. United States, as we could imagine, were the most present locations in every year. At first sight, it might seem surprising that South of Korea is not listed among the top locations, where the creators of Terra used to live. This is explained by the fact that only few

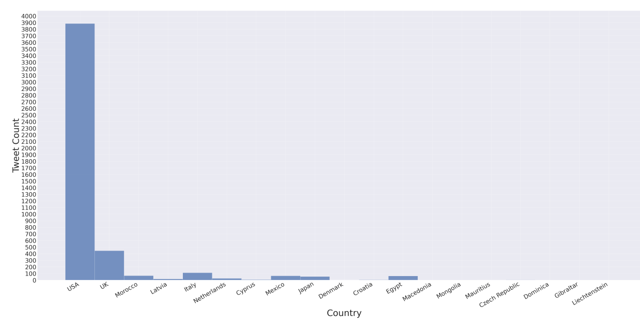

Figure 3: Geo Tweet

percent of people in South Korea use Twitter. Mexico is one of the countries with the largest amount of tweets. This was expected, considered that at the time Latin America was the seventh-biggest crypto market.

Figure 3 shows that people from United States was the one who posted. As the second country, United Kindom showed an interest in posting tweets about this topic in the first two phase (before and during the collapse), with a decrease in the last period. Whereas, Italy had an important and constant role in tweets count. Last but not least Morocco had only 100 tweets less than Italy.

4.3 Opinion leader Identification

The simplest way to identify opinion leaders is by assuming that they are the accounts with the most followers. However, this approach is flawed because followers alone cannot accurately identify opinion leaders for two main reasons: (i) content algorithms on social media platforms now prioritize discovery, which allows smaller creators to achieve greater reach and influence, and (ii) the number of followers can be inflated by fake accounts and bots, making it an

Table 1: Top 15 Opinion leader accounts according to the number of followers. Details are obscured for privacy reasons.

user	fol.wers	n_post	like	retweet	reply	quote
CN***	61082k	2	158	46	54	8
Ma***	34853k	1	7261	1359	468	445
WS***	20468k	2	48	26	8	6
aa***	19647k	2	180	18	14	4
Fo***	18704k	5	561	198	181	94
nd***	17697k	7	10267	1669	711	487
FA***	17230k	1	10083	679	231	114
AB***	13245k	2	123	26	33	6
uf***	11092k	1	1000	157	51	14
Ti***	10323k	2	49	8	2	2
bi***	10157k	6	23633	6525	14949	1409
bu***	9150k	2	661	185	238	253
mc***	8893k	1	4	0	2	0
ht***	8698k	2	30	9	26	8
cz***	8132k	24	244653	39912	29017	4896

Table 2: Correlation among the different metric features that characterize Twitter accounts.

	fol.wers	n_post	like	retweet	quote	reply
fol.wers	1.000	0.005	0.048	0.034	0.025	0.049
n_post	0.005	1.000	0.094	0.090	0.067	0.094
like	0.048	0.094	1.000	0.980	0.849	0.916
retweet	0.034	0.090	0.980	1.000	0.854	0.898
quote	0.025	0.067	0.849	0.854	1.000	0.881
reply	0.049	0.094	0.916	0.898	0.881	1.000

unreliable metric. Table 1 shows the top 15 accounts in our dataset based on the number of followers.

This has made 'followers' a non-relevant metric to identify opinion leader. For instance, the top account (more than 61 million of followers) posted two tweets and received only 158 likes, 8 quote, 54 replies and only 46 accounts retweeted at least one of its two tweets. This account is far from being considered an opinion leader of the topic.

In support of the argument that opinion leaders and followers have nothing to do with each other, Table 2 shows the correlation among the metric features that characterize an account within Twitter. The first important result is the correlation between the number of followers and the interactions with the posted tweet: while it is often assumed that a larger number of followers on social media platforms like Twitter would result in more interactions with posted tweets, this is not necessarily the case. In fact, many users with a smaller following may see more engagement on their tweets than those with larger followings. This is because the quality and relevance of the content being posted is often a more important factor in driving engagement than the number of followers alone.

The second important result is the strong correlation between likes, retweets, replies, and quotes. Likes are a simple way for users to show that they enjoyed or appreciated a tweet, while retweets allow users to share the tweet with their own followers, amplifying its reach. Replies and quotes, on the other hand, allow users to engage in a conversation around a tweet, either by responding directly to the original tweet or by adding their own commentary to it. These different forms of engagement can reinforce each other, with a tweet that receives a lot of likes often also receiving a lot of retweets and replies, and vice versa. This can contribute to the overall virality and impact of a tweet, as it gains traction and spreads across the platform.

Table 3: Opinion leader detection (2021-22) with 2-means to map accounts into 2 classes: top and ordinary accounts. Details are obscured for privacy reasons.

u.name	fol.wers	n_post	like	retweet	reply	quote
Cr*** (T)	1530k	526	6218k	5780k	1945k	3204k
Ai*** (T)	1456k	500	3080k	3083k	534k	514k
ai*** (T)	1564k	472	4230k	4099k	698k	622k

To determine who the opinion leaders are, we used parameters that measure the degree of interaction with a tweet: likes, retweets, replies, and quotes. We calculated these parameters for each individual tweet, and then we calculated how many likes, retweets, replies, and quotes each account received during the analyzed period. We analyzed two different periods: the whole dataset period (2021 and 2022) and the critical collapse period (Apr-Jun 2022).

For each period, we use k-means, an unsupervised learning technique to group these accounts based on their similarity. K-means is a popular clustering algorithm used in unsupervised machine learning to partition a given dataset into k clusters based on the similarity of their features. It has several advantages, including its simplicity, scalability, and efficiency on large datasets. The algorithm works by iteratively assigning data points to the nearest cluster centroid and updating the centroids based on the mean of the data points assigned to the cluster. The process continues until the centroids no longer move significantly, or a maximum number of iterations is reached.

The k-means algorithm requires to specify the number of clusters (k) beforehand, which can be determined through techniques such as the elbow method or silhouette analysis. In this paper, we consider the Silhouette score, a metric that measures how well each data point fits into its assigned cluster compared to other clusters.

By applying the silhouette algorithm to our dataset, we obtained very similar scores for k that ranges from 2 to 4 (whole period) and k=2,3 (critical period).

Table 3 shows the data obtained with k=2, when applied to the whole period. The majority of the accounts (i.e., 61967) are grouped together in one cluster with a centroid close to zero, while only three accounts belong to the second cluster with a centroid that is far from zero. The accounts in the first group cannot be considered opinion leaders since their posts did not stimulate interaction from other users, whereas the accounts in the second group can be defined as opinion leaders.

Table 4 displays the data obtained from a k-means analysis with k=3, when applied to the whole period. In this case, we have three

Table 4: Opinion leader detection (2021-22) with 3-means to map accounts into 3 classes: top, regular, and ordinary accounts. Details are obscured for privacy reasons.

u.name	f.wers	n_post	like	retweet	reply	quote
Cr*** (T)	1530k	526	6218k	5780k	1945k	3204k
Ai*** (R)	1456k	500	3080k	3083k	534k	514k
ai*** (R)	1564k	472	4230k	4099k	698k	622k

Table 5: Opinion leader detection (2021-22) with 4-means to map accounts into 4 classes: top, regular, weak, and ordinary accounts. Details are obscured for privacy reasons.

u.name	f.wers	n_post	like	retweet	reply	quote
Cr** (T)	1530k	526	6218k	5780k	1945k	3204k
Ai** (R)	1456k	500	3080k	3083k	534k	514k
ai** (R)	1564k	472	4230k	4099k	698k	622k
Vo** (W)	374	4096	1001	1332	227	74
We** (W)	402	3513	23k	94	1862	28
Wo** (W)	258	2637	8468	54	1248	6
Of** (W)	243	2568	499	12k	514	26
Wh** (W)	5919	2485	474	13k	546	26
In** (W)	88	2203	2552	274	1288	369
uR** (W)	1021	1612	4599	24	878	14
Ra** (W)	3546	1558	1803	254	240	20
As** (W)	3513	1491	2071	60	176	61
fr** (W)	930	1403	4396	581	1808	195
Mb** (W)	925	1147	941	274	125	7
is** (W)	1254	1146	404	120	62	75
ns** (W)	388	1122	26	3	48	1
al** (W)	37	1122	313	152	18	2
si** (W)	55	1089	1336	88	178	146

distinct classes: top opinion leaders, opinion leaders, and ordinary accounts. In the first cluster (the one very close to zero), there are 61967 accounts that can be defined as ordinary accounts. In the second cluster, there are two accounts that can be identified as opinion leaders. In the third cluster (the one farthest from zero), there is one account that can be defined as a top opinion leader.

Table 5 displays the results of k-means analysis with k=4, when applied to the whole period. With k=4, we have four distinct classes: top opinion leaders, opinion leaders, almost-opinion leaders, and ordinary accounts. In the first group (ordinary), there are 61952 accounts. In the second group (weak opinion leaders), there are 15 accounts. In the third group (opinion leaders), there are 2 accounts. Finally, in the fourth group (top opinion leaders), there is only one account.

During the critical period, a single top opinion leader emerges in the case of k=2, while seven emerge in the case of k=3. However, in the latter case, only one account is of a higher category (the same one that emerged with k=2), and the others can be defined as lower-class opinion leaders (in this case, regular). As can be observed, posting a high number of tweets does not guarantee becoming an opinion leader, just as having a large number of followers does not guarantee a high number of interactions.

5 DISCUSSION, LIMITATION AND FUTURE WORK

The results of the k-means algorithm unequivocally show that during 2021-2022 there are three accounts that stand out from the dataset, regardless of whether the clusters are two, three, or four. The account `Cr***` is the one that stands out the most and should therefore be considered a top opinion leader for the conversations within the dataset. Two other accounts (`Ai***` and `ai***`) also stand out and should be considered opinion leaders, albeit at a slightly lower level than the first. While the top three accounts appear to perform very well, the results in Table 5 are also interesting. Accounts with a very limited number of followers (e.g., 37, 44, or 88) were able to stand out as weak opinion leaders. This is further evidence that the number of followers is not a metric to be used for identifying opinion leaders, whereas unsupervised learning methods might be helpful.

A similar reasoning can be made for the analysis of the critical period, where only one account clearly emerges as the opinion leader.

Certainly, it all depends on the features. In this paper, we used the metrics provided by Twitter to measure the degree of interaction between users, and the results have been satisfactory. However, we are working on identifying composite or derived metrics that allow for a more refined identification of opinion leaders. For example, in our current study, all interactions are considered to be of equal importance, but there are studies that assign different weights to individual interactions. Assigning different weights to individual interactions can help identify opinion leaders by taking into account the quality, relevance, and impact of each interaction. For example, a retweet may be considered more valuable than a simple like, as it indicates that the user found the content worth sharing with their own followers. Similarly, a reply or quote may be given more weight if it sparks a conversation or debate, as this shows that the user is actively engaging with the content and promoting further discussion. By assigning different weights to these interactions, we can create a more nuanced and accurate measure of influence and identify opinion leaders who may have a more subtle but significant impact on their audience. This approach can also help to address the limitations of using follower count as a measure of influence, as it takes into account the actual engagement and impact of the user's content rather than just the size of their audience.

With respect to sentiment analysis, there are limitations that are peculiar of the Twitter platform: (i) tweets often have limited context, which can make it difficult to accurately interpret the sentiment expressed; (ii) users often use sarcasm, irony, or humor in their tweets, which can be difficult for sentiment analysis tools to detect and accurately interpret; (iii) tweets might contain irrelevant or spammy content, which can affect the accuracy of sentiment analysis results.

6 CONCLUSIONS

The study used Twitter as a passive sensor to measure people's opinions and thoughts about the collapse of the Terra stablecoin project

Table 6: Opinion leader detection (Apr-Jun 2022) with 3-means to map accounts into 3 classes: top, regular, weak, and ordinary accounts. Details are obscured for privacy reasons.

u.name	f.wers	n_post	like	retweet	reply	quote
Cr** (T)	1530k	69	600k	556k	189k	377k
Wa** (R)	1708k	78	301k	54k	38k	8k
Ai** (R)	1456k	60	307k	309k	63k	58k
ai** (R)	1564k	43	256k	252k	42k	35k
LB** (R)	438k	40	45k	35k	84k	24k
ku** (R)	2375k	24	50k	19k	94k	4k
Ai** (R)	1564k	13	126k	114k	31k	56k

Table 7: Opinion leader detection (Apr-Jun 2022) with 2-means to map accounts into 2 classes: top, regular, weak, and ordinary accounts. Details are obscured for privacy reasons.

u.name	f.wers	n_post	like	retweet	reply	quote
Cr** (T)	1530k	69	600k	556k	189k	377k

during 2021 and 2022, with a focus on the months of the collapse (i.e., April, May, and June 2022). A sentiment analysis, geographical analysis, and analysis to identify opinion leaders were performed on a dataset of 330,000 tweets from 61,979 different accounts. The results showed an increase in negativity in the month leading up to the collapse, with the United States being the most prolific country in terms of tweets, followed by Great Britain and Italy, and an interest from accounts based in Mexico. The investigation into opinion leaders revealed that there was no correlation between the number of followers and interactions with posted tweets, nor was there a correlation between the number of tweets and the number of interactions with posted tweets. However, using basic Twitter metrics, a few accounts were identified as opinion leaders as they were very effective at engaging people.

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