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Araştırma Makalesi - Research Article

A Text Mining Analysis on Misinformation Regarding the COVID-19 Pandemic

COVID-19 Pandemisi ile İlgili Yanlış Bilgiler Üzerine Bir Metin Madenciliği Analizi

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ABSTRACT

Since the outset of COVID-19 pandemic, a massive amount of information has been generated about the pandemic, where a great deal of it contains less verifiable information disseminated especially via social media. A video propagating various conspiracy theories about the pandemic, called plandemic, was launched, and people started to share posts addressing this issue with this hashtag thereafter. For this research, we collected thousands of tweets using this hashtag, and then combined this collection with a collection of tweets with a similar hashtag #scamdemic to build a study group. Also, we collected tweets that convey more general thoughts about the pandemic, which served as a control group. We showed that the web sources provided in the tweets in the study group tend to be much less credible. Furthermore, we performed two sentiment analysis using Hedonometer and VADER. Hedonometer showed that the average happiness level in tweets spreading misinformation about COVID -19 is almost the same as in regular COVID -19 tweets. However, VADER showed that the tweets spreading the misinformation have significantly more negative sentiment. This could be related to the fact that the VADER also takes into account non-lexical items, such as emoticons and capital letters.

Keywords- Text Mining, Sentiment Analysis, SARS-CoV-2, COVID-19 Pandemic, Twitter Analysis

ÖZ

COVID-19 pandemisinin başından beri pandemi ile ilgili çok büyük miktarda veri üretilmiştir ve bunun önemli bir kısmı genellikle sosyal medya tarafından yayılmış doğrulanmamış veridir. Pandemi ile ilgili birçok komplo teorisinin propagandasını yapan "plandemic" adlı bir video yayımlanması ardından, insanlar pandemi ile ilgili yanlış bilgileri bu etikete sahip tweetler atarak paylaşmıştır. Bu çalışmada, bu etiket ve buna benzer bir etiket olan "scamdemic" yardımıyla binlerce tweet toplanarak bir çalışma grubu oluşturulmuştur. Ayrıca pandemi ile ilgili daha genel bilgiler içeren tweetler toplanarak bir kontrol grubu oluşturulmuştur. Çalışma grubundaki tweetlerde verilen internet kaynaklarının çok daha az güvenilir olduğu gösterilmiştir. İlaveten, Hedonometer ve VADER kullanılarak iki duygu analizi gerçekleştirilmiştir. Hedonometer göstermiştir ki, sahte haber yayan tweetler önemli derecede daha fazla negatif duyguya sahiptir. Bu, VADER'in emoji ya da büyük harfler gibi sözcüksel olmayan yapıları da dikkate alması gerçeği ile ilişkilendirilebilir.

Anahtar Kelimeler- Metin Madenciliği, Duygu Analizi, SARS-CoV-2, COVID-19 Pandemisi, Twitter Analizi

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I. INTRODUCTION

Since the early 2020, the new type of coronavirus SARS-CoV-2, hereafter referred to as COVID -19, has infected millions of people around the world, and more than half a million people have died from COVID -19 [1]. Billions of people around the world have been locked down, and most countries took strict measures to prevent the spread of the virus and to flatten the curve. As of March 2020, the whole world has come to know a new kind of eccentric lifestyle which is mainly based on physical distance, wearing masks and taking strict hygiene measures. These precautions have led people to communicate with each other in unconventional ways. Chat applications, such as WhatsApp and Telegram became an integral part of our daily routine, and social media platforms such as Twitter, Facebook, and YouTube played a more important role than ever in communicating ideas/opinions and even sourcing news during the COVID -19 outbreak [2].

COVID-19 pandemic is one of the most significant problems facing humanity in the new millennium. It is therefore inevitable that such a major problem cannot be considered without its conspiracy theories and myths, which influence public opinion about the virus and thus seriously endanger public health [3]. In this study, we are concerned with misinformation about COVID -19. However, before we get to the details of our research, we provide an illustration below that explains what is meant by the term conspiracy theory.

Figure 1. The seven traits of conspiratorial thinking [4].

The study in [3] summarizes the conspiracy theories regarding COVID -19 performing a Twitter analysis. The authors grouped the tweets containing conspiracy theories about COVID -19 into five main themes: Flu, heat, home remedies, the origin of the virus, and vaccine development. Among them, the most common is the one about the origin of the infection, followed by tweets comparing COVID -19 to the regular flu. To debunk and combat the myths surrounding COVID -19 , the World Health Organization (WHO) recently launched a website called Mythbusters where the myths and urban legends based on the latest clinical research (https://www.who.int/emergencies/diseases/novel-coronavirus-2019/advice-for-public/myth-busters). In fact, the WHO regularly updates the webpage as new myths and lies emerge.

As an aside, there is a subtle difference between misinformation and disinformation. While both refer to false/inaccurate content, in the case of disinformation, there is an explicit intent to spread the misleading content; thus, it is deceptive. In the case of misinformation, the intent is absent, so it is unintentional. Throughout the paper, we will speak of misinformation when referring to the misleading information.

As mentioned earlier, during the pandemic COVID -19 news and opinions usually spread through social media due to social distancing and lockdown. This is also true for misinformation. For example, a tweet claiming that wearing a face mask could cause lung cancer can receive thousands of retweets within minutes (https://www.bbc.com/news/technology-52903680). Worse, scientific misinformation has also been spread via social media. Especially at the onset of the COVID -19 pandemic, the medical community spread inaccurate and even contradictory information about COVID -19 [5]. For example, on January 14, 2020, a fantastic tweet was posted by the WHO shown in Figure 2. Therefore, avoiding misinformation on the internet is as important as providing the needed medical equipment [6].

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Figure 2. A misleading tweet posted on January 14, 2020 by the WHO.

In this paper, we are concerned with identifying general patterns of misinformation in the tweets about the COVID -19. Ultimately, we want to help raise public awareness of misleading information about the virus spreading in social media. To this end, we conducted a comparative study to understand how different tweets containing misinformation about COVID -19 are. The primary challenge was to collect a large number of tweets that are certain to contain misinformation about the virus. This is because misinformation about COVID -19 comes in many different forms, as it is mainly created by regular users rather than bots. Therefore, it is challenging not only for machines but also for humans to recognize them [7]. Nevertheless, we used two hashtags in this study: #plandemic and #scamdemic to label a tweet as including misinformation about the pandemic. In the sequel, we explain what these hashtags promote and how they came about.

Plandamic is a conspiracy theory video of length 26 minutes posted by Judy A. Mikovits, a former virology researcher, on various social media platforms on May 4, 2020. The video contains a plethora of conspiracy theories about COVID -19, from the dangers of wearing face masks to the use of hydroxychloroquine to treat the virus. It's main claim; however, is that a vaccine against COVID -19 will commit genocide against the world's elderly. Within a couple of days, the video went viral, reaching over 8 million views. This was echoed on social media as well. Thousands of tweets propagating various conspiracy theories about COVID -19 were posted with the hashtag #plandemic [8].

Like #plandemic, the hashtag #scamdemic has also been widely used to disseminate conspiracy theories about COVID -19 via Twitter. Although it is known that scamdemic is a combination of scam and pandemic, it remains mysterious how it came to be. Nevertheless, it has been used continuously since its first use in late March 2020. In Figure 3, you can see the number of tweets posted daily. Finally, we note that one might expect to see a similar hashtag #infodemic in this study, which is generally used for the same purposes. However, we intentionally omitted #infodemic because we found that a good rate of tweets with this hashtag contains more credible information compared to the other two hashtags, as this term was coined by the WHO.

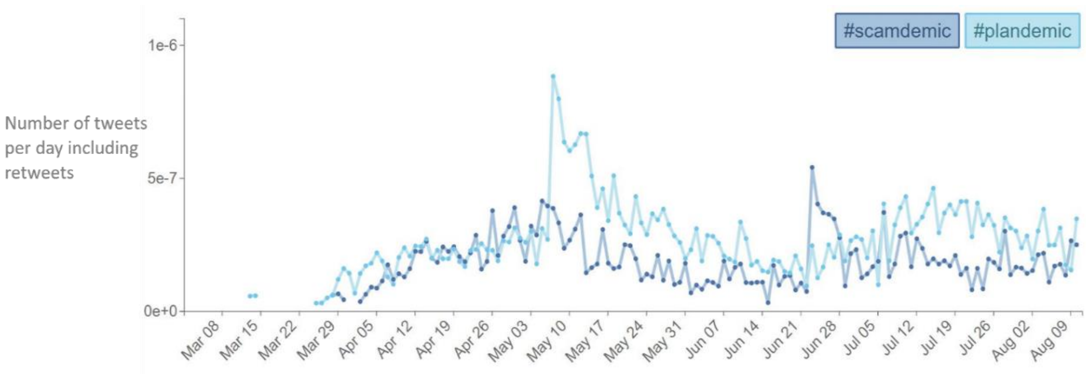

Figure 3. Number of tweets with hashtags #scamdemic and #plandemic posted daily (including retweets)

We collected tweets with the hashtags #plandemic and #scamdemic to create a dataset of tweets containing misinformation about COVID -19. We also created another large dataset where we randomly selected tweets with the hashtag # COVID -19 to allow a comparison between these two types of tweets. With these two datasets, we aimed to answer the following two research questions:

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- Is an external source given in a tweet containing misinformation about the COVID-19 pandemic is less credible than the one given in a more regular COVID-19 tweet?
- Is there a sentimental difference that can be discerned between the two types of tweets on COVID -19?

We conducted two analyses, one for each question. First, to test the credibility of the external sources provided in the tweets, we made use of the URL addresses (including tiny URLs) provided in the tweets.Assuming that a web source is reliable if the corresponding web address has the domain suffix "gov" or "org", we classified the sources as secure or not. Second, we performed two sentiment analysis: Hedonometer and VADER. More specifically, we calculated the average happiness scores of tweets in both datasets using Hedonometer. We also calculated the average negativity, average positivity, and average neutrality of the tweets using the VADER sentiment analysis, which takes into account not only words but also other types of lexicons, such as punctuation and emoticon [19].

Text mining techniques have long been used to extract meaningful and interesting information from unstructured text on social media [9-13]. From investigating consumer attitudes to detecting pandemic outbreaks, the use of text mining in social media is widespread. For these uses, sentiment analysis, a text mining field for detecting opinions in unstructured texts, plays an important role [11]. A recent sentiment analysis of Twitter data aimed to gauge public opinion on mask wearing, social distancing, and the impact of the pandemic on public mental health [12]. As far as the method of sentiment analysis of unstructured text is concerned, the lexicon-based methods, which leverage pre-established lexicons of words, are the state of the art [9,10]. Also, supervised methods using word N-grams, Part-of-Speech, or other features extracted from tweets are used. For example, the study in [13], a convolutional algorithm is used to train a deep neural network extracting the features from Twitter texts using word N-grams. The study showed remarkable performance in classifying tweets according to their sentiment. However, this study can be criticized because, like other supervised methods, it requires a large amount of labeled training data.

The paper is organized as follows. In the subsequent section, we provide an overview of prominent studies analyzing tweets containing misinformation about the pandemic. We then provide insight into our dataset using tf-idf scores and clouds of the most frequent words in them. We continue the paper by presenting our findings based on URL analysis and sentiment analysis. Finally, we summarize the present paper summarizing the results of our study and suggest an important future research direction.

II. LITERATURE REVIEW

On February 15, 2020, at the Munich Security Conference, Dr. Tedros Adhanom Ghebreyesus, Director General of the World Health Organization, expresses his concerns regarding the COVID -19 related fake news as:

… But we're not just fighting an epidemic; we're fighting an infodemic. Fake news spreads faster and more easily than this virus, and is just as dangerous. That's why we're also working with search and media companies like Facebook, Google, Pinterest, Tencent, Twitter, TikTok, YouTube and others to counter the spread of rumours and misinformation. (World Health Organization, 2020)

As mentioned in the introduction and motivated by the quote above, social media has been polluted by a wealth of misinformation about COVID -19. This is likely to lead people taking irrational actions that may ultimately lead to public health problems. Such misinformation can be found on almost all social media though; it is mainly centered on Twitter, as being one of the most widely used platforms for disseminating news [14]. As a result, the analysis of misinformation about COVID -19 in tweets has recently received increasing attention, leading to several studies with impressive results. In the following, we present an overview of these studies.

Singh et. al identified common myths about COVID -19 by analyzing tweets from mid-January to mid-March 2020 [3]. The authors grouped tweets about COVID -19 misinformation into five main themes: Flu, Heat, Home Remedies, Origin of the Virus, and Vaccine Development. Among them, the most common mention is the origin of the virus, followed by tweets comparing COVID -19 to the regular flu. Regarding the type of misinformation/myths in COVID -19 tweets, Sharma et. al categorized the tweets with malicious information into four types: unreliable, conspiracy, clickbait, and political, using a dataset of tweets collected between March 1 and March 30, 2020 [15]. The authors made this categorization based on the reliability of the external links provided in the tweets, where the reliability is assessed by some fact-checking websites. Allowing a single tweet can belong to more than one category, they found that the misinformation is mainly spread through unreliable sources that contain false and misleading news.

Kouzy et. al aimed to identify Twitter accounts that spread misinformation and/or unverifiable information pertaining to COVID-19 [16]. To this end, the authors collected 260 tweets posted on February 27, 2020 ensuring the incorrect content they have. They found that the vast majority of tweets on COVID-19 misinformation are generated by informal personal/group accounts other than journalists, public health accounts, and business/government accounts. In fact, these individual accounts are mostly unverified Twitter accounts with a relatively fewer number of followers. These findings are in line with those reported in [7], where it is stated that accounts followed by a large number of users, such as celebrities and other prominent public figures, produce only a tiny amount of misleading information on COVID-19 spreading in the social media. Furthermore, the same study concluded that AI-based tools have no contribution to propagating misinformation about COVID-19; thus the malicious tweets are authored by humans, which in turn makes them hard to distinguish as being not fabricated.

When it comes to understanding people's motivation to share misinformation about the virus, the study in [17] presents some remarkable results from an online survey that recruited over 1700 adults who are active Twitter or Facebook users in the US. During the survey, participants were shown 15 true and 15 false news stories about COVID -19 in random order. They were first asked their opinion on whether the news they were shown was true or not (to the best of their knowledge), and then whether they would share that news on their social media. The results showed that people with lower intellectual abilities, who usually rely on their intuition, are unable to distinguish between true and false content and are therefore more likely to spread fake information. They even get distracted by social media itself and share fake news simply because they are inattentive and not because of their partisan/fanatical thoughts.

In terms of location identification, the United States, Canada, and the United Kingdom were found to be the three countries hosting the most users posting tweets with fake information on COVID -19, considering all English-speaking countries [18]. This can be attributed to the large population size of these three countries. However, considering the number of users normalized by dividing the total number of users in each country, we find that this type of tweets originates from the United States, Canada and the United Kingdom. Another interesting finding reported in [18] is that tweets with less credible information about COVID -19 tend to stay in the country where they were created, which also means that each country creates its own fake news about COVID -19.

With regard to the use of text mining techniques for COVID -19 related tweets, there are a number of high quality studies in the literature. Of these, an interesting study analyzed around 4 thousand tweets using the search terms “loneliness” and “COVID-19” to see how loneliness is discussed in social media during the pandemic [19]. For this study, an unsupervised text mining technique Topic Modeling [10] was used to identify key topics in the tweets. As a result, 33 topics were identified, which were then they were clustered into three key clusters using Hierarchical Clustering. The themes in the first cluster describe the impact of loneliness on the community during the pandemic, such as death, work, home, and hope. The themes in the second cluster, on the other hand, describe the effects of social distancing on loneliness, such as isolation, lockdown, love, and friend. Finally, the third cluster includes themes that affect people's mental health, such as depression, anxiety, fear, and crisis.

An interesting study presented in [12] conducted a sentiment analysis for Twitter data and found that people are generally positive about wearing masks, but when it comes to lockdown and vaccine, public opinion is much more negative. Different from COVID -19, a remarkable text mining study in [20] considered tweets about the terrorist group ISIS, to compare the views of the West and the East on ISIS. The study showed that people use the same words when describing the terror group and are all against ISIS regardless of where they live and wish for a more peaceful life. For a detailed review on using text mining for social media, please refer to [21].

Finally, not all studies are concerned with identifying a general pattern about COVID -19 misinformation in social media; some of them focus only on one aspect of it. For instance, [16] looks at Twitter conversations with the hashtag #FilmYourHospital. The misinformation associated with this hashtag is that COVID -19 is just a hoax and hospitals are empty. It also asks people to film their local hospitals to provide evidence for this claim. The study in [22] clarifies that this misinformation is being spread by conservative politicians and political activists. This finding contradicts previous findings that the main source of misinformation on COVID -19 is regular users. Ahmed et. al analyze another misinformation circulating on Twitter, which attributes the spread of COVID -19 to the proliferation of 5G networks. The analysis revealed that a large proportion of users spreading the mentioned conspiracy theory are regular users. Finally, the research in [24] analyzed tweets containing misinformation about the possible role of spinal manipulative therapy (SMT) and COVID -19. Specifically, these tweets claim that SMT boosts immunity and therefore may be effective in combating COVID -19. The study concluded that tweets attempting to refute this misinformation are three times more common than those that do spread it.

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III. MATERIALS AND METHODS

A. Data Collection

We created two datasets, one for the study group and one for the control group. In creating the study group, we used the two hashtags #plandemic and #scamdemic as key indicators of the spread of misinformation about the COVID -19 epidemic. Admittedly, one could use other hashtags for the same purpose and thus enrich one's study group. This poses a limitation to our study. On the other hand, we used the hashtag #Covid19 when forming the control group. Again, there are many hashtags available to address the pandemic in general, such as #coronavirus, #2019nCoV, #wuhanvirus, or #CoronavirusOutbreak. We disregarded all these hashtags to make the study group and the control group comparable in terms of size. Also, we ensured that a tweet in the control group did not contain #plandemic or #scamdemic to ensure diversity. Nevertheless, we cannot guarantee the purity of the control group in that there is no tweet in the group that spreads misinformation about the pandemic, as there is no de facto standard in the literature to detect misinformation.

For both datasets, we collected tweets using Twitter Streaming API from June 13, 2020 to July 4, 2020 (for three weeks). We excluded tweets that only contain hashtags or have less than three retweets. This left us with over 45 thousand tweets for the study group, and over 110 thousands of tweets for the control group. See Table 1 for the distribution of the tweets over the hashtags of interest.

Table 1. Number of tweets in the study and in the control group by hashtag.

	Study		**Control**
# scamdemic	18,992	# Covid19	113,733
# plandemic	26,074		
Total	47,242		113,733

B. Getting to Know the Datasets

To gain some insight into the datasets, below we provide a table of the words that occur most frequently, given their tf-idf values. We note again that the study group consists of tweets with the hashtag #plandemic or #scamdemic. In addition, we unified the words representing the coronavirus, such as Covid, the virus, Covid19, #2019nCoV, Covid20, etc., as "Covid19".

In creating the table below, we considered each tweet as a single sentence and the collection of tweets, i.e., the dataset (study or control) as a whole text. Thus, a tf-idf score for a word k is calculated as:

$$\frac{\#\, times\ k\ appears\ in\ all\ tweets}{total\ \#\, words\ in\ all\ tweets} \times \log\left(\frac{\#\, tweets}{\#\, tweets\ containing\ k}\right) \tag{1}$$

Here # stands for the phrase "number of". Using the formulation above, we calculated the tf-idf scores of the unique words in both datasets. Table 2shows the words with the highest tf-idf scores.

To visually represent both datasets, we also provide a word cloud for the study and for the control group, as shown inFigure 4. We note that in doing so, we excluded the hashtags: COVID19, plandemic, and scamdemic, so that they do dominate the word clouds.

IV. RESULTS AND DISCUSSIONS

A. URL Addresses Analysis

Many Twitter users attach an URL addresses (web addresses) to their tweets to substantiate their claims Accordingly, in our case, about a quarter of the tweets contain URL addresses, considering all tweets from the study group and the control group.

We used the percentage of URL addresses in the tweets with the domain suffix *gov* or *org* to estimate the reliability of the external sources cited in the tweets. We assumed that a web address with the suffix "gov" or "org" could be considered a reliable source, with one minor exception. That is, a nonprofit fact-checking organization

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called NewsGuard recently published a red list of websites that spread misinformation about the coronavirus (https://www.newsguardtech.com/coronavirus-misinformation-tracking-center/). the list includes 447 websites, nine of which have the domain suffix "gov" or "org" and whose content is in English. These are the followings: ChildrensHealthDefense.org, GNews.org, OrganicConsumers.org, The Healthy American. org, The Vaccine Reaction.org, WestonAPrice.org, VaccineHolocaust.org, Off-Guardian.org and UKColumn.org.

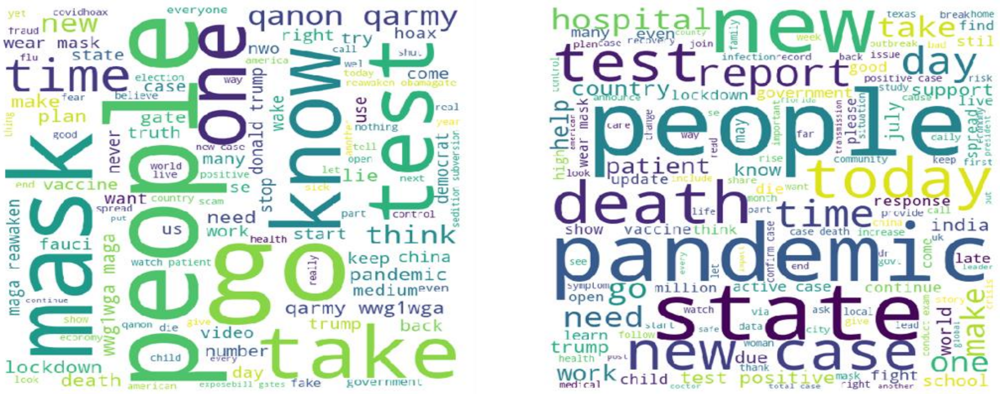

Figure 4. Word clouds for the study group (left) and for the control group (right).

Table 2. The most prevalent words based on the tf-idf scores in both datasets

	Study	Control
1	COVID19 (0.503)	Death (.0226)
2	Mask (.0292)	Pandemic (.0182)
3	QAnon (.02)	Health (.018)
4	Qarmy (.02)	State (.0171)
5	U.S. (.0194)	Vaccine (.0145)
6	Wwg1wga (.0187)	Patient (.0145)
7	Hoax (.0174)	Lockdown (.0138)
8	China (.0164)	Infection (.0133)
9	Lockdown (.0159)	Positive (.0122)
10	Medium (.0143)	Fight (.0121)

We considered the above websites as unreliable sources and therefore omitted them from our analysis. Moreover, for the tweets containing tiny URL addresses such as bit.ly or ow.ly, we used a Python package urllib to retrieve the full name of the web addresses. Using regular expressions, we extracted the full URL addresses in the tweets. Finally, we also disregarded the URL addresses that stem from retweets (i.e., those from the twitter.com domain).

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Table 3. The percentages of the credible URLs in the datasets.

	Study	Control
# Tweets containing URLs	6,437	31,465
# Tweets containing URLs with org/gov suffices	410 (6.36%)	4,455 (14.15%)

Table 3 suggests that only about 6% of the URL addresses given in the tweets with misinformation about the pandemic COVID -19 refer to reliable sources. In contrast, this percentage is about 14% (more than double) for the control group. To determine whether the observed difference is significant, we performed a chi-square test in which the null hypothesis states that there is no relationship between the type of tweet (either misleading or neutral) and the type of web source it contains (either credible or less credible). We found that the test statistic $\chi^2$is equal to 289.08 with df=1, and the corresponding p-value is much smaller than .001. Therefore, we reject the null hypothesis and conclude that there appears to be an association between the type of information in a tweet posted about the pandemic COVID-19 and the credibility of the web source therein.

B. Sentiment Analysis

We wanted to find out if there is a difference between tweets containing misinformation about the COVID -19 pandemic and the other tweets about the pandemic in terms of sentiment. To this end, we conducted two analyses. The first focuses on calculating the average happiness score of the words in the tweets we are interested in. The second analysis, on the other hand, is the state-of-the-art sentiment analysis developed exclusively for social media, known as VADER (Valence Aware Dictionary and sEntiment Reasoner) [9].

1) *Happiness Analysis*: Hedonometer is a tool designed to measure happiness expressed in texts (http://hedonometer.org) [25]. More specifically, Hedonometer assigns a happiness score to over 10,000 unique words, with scores ranging from 1 (least happy) to 9 (most happy), indicating how much happiness is in a word. These scores are based on the average of fifty crowd workers' ratings on Amazon's Mechanical Turk service. The crowd workers rated the words independently in two ways: 1) independently of each other 2) independently of any context. Hedonometer is thus a context-free measure of happiness, which in turn allows Hedonometer to be used in a variety of applications. We also note that win selecting words to be considered for Hedonometer, the developers examined a very large corpus of texts from various domains, such as tweets, Google Books, Wikipedia and so on. For a more detailed explanation of Hedonometer, please refer to [25].

Hedonometer has long been successfully used for sentiment analysis of tweets from various domains. Cody et. al. used Hedonometer on tweets about climate change collected between September 2008 and July 2014 [26]. They found that the average happiness of tweets that contained the phrase "climate change" was generally lower than the happiness of the control group over the 6-year period. Another prominent study published in the journal Nature revealed that travelers generally prefer positive food-related words to negative words, thus happiness increases with distance from the location, relying on the average happiness scores of geolocated tweets estimated using Hedonometer [27]. A recent study using Hedonometerona large corpus of tweets found that sentiment in tweets increases sharply during a visit to a park, while it decreases substantially when users enters an indoor environment [28].

We calculated the average happiness score of the tweets in the study and the control group. To calculate the average happiness score of a tweet, we took the words in the Hedonometer, summed their happiness scores, and then divided by the total number of words in that tweet. Finally, we averaged all the scores assigned to the tweets for both groups. As shown in Table 4, the mean happiness score for the group of misleading tweets is 5.36 with a standard deviation of 0.55; for the group of tweets generally posted on COVID -19, it is 5.52 with a standard deviation of 0.48. We also performed the t-test to see if the observed difference between the mean happiness scores is significant. However, it resulted in a high p-value ($p > .05$).

Table 4. Mean happiness scores of the tweets in the study group and in the control group.

	Study	Control
Mean Happiness Score	5.36 ($\sigma = 0.55$)	5.52 ($\sigma = 0.48$)

Since the average happiness score is quite similar in the study group and the control group, we claim that people tend to use neutral words when spreading misinformation about the pandemic COVID -19 via social media. It is uncommon to encounter offensive words or words that can be perceived as negative when spreading misleading texts about the pandemic. This complicates the problem of detecting misinformation about the pandemic on social media.

2) *VADER(Valence Aware Dictionary and sEntiment Reasoner) Analysis*: when calculating the average happiness scores of the tweets, we standardized the texts. That is, we removed all punctuation (including emojis), acronyms, and letter repetitions (for example, happyyy became happy), and converted all uppercase letters to lowercase. However, it is obvious that punctuation marks, emojis, and repeated letters may also convey special meanings that can be leveraged to capture the true sentiment of a sentence.

The sentiment analyzer VADER is a rule-based sentiment analysis tool which is used evaluate the sentiment in social media [9]. In doing so, VADER takes into account different types of lexicons (punctuation, emoticons, etc.), unlike Hedonometer analysis. Also, VADER outputs not only positivity score, but also scores for negativity and neutrality. Moreover, VADER outputs a compound score that is obtained by normalizing the sum of the valence scores of the individual words in the lexicon and can be used alone to quantify the overall sentiment in the text. To illustrate what VADER outputs, we provide Table 5 that shows three examples with different sentiments along with scores for positivity, negativity, neutrality and composite.

Table 5. VADER outputs for three examples.

Sentence	Negativity	Neutrality	Positivity	Compound
I will fail my exam tomorrow.	0.467	0.533	0	-0.542
Oh, what a nice weather!	0	0.436	0.564	0.475
First, read the instructions.	0	1	0	0

The first sentence above has a negative sentiment, since the speaker of the sentence is afraid of failing his exam; therefore, VADER assigns a high negativity score for that sentence. For the second sentence, on the other hand, VADER generates the highest sentiment score for positivity, as the speaker expresses his positive thoughts about the weather intensely. Finally, the third sentence does not contain any thoughts of the speaker, it just tells him what to do, which in turn causes VADER to output the highest score for neutrality.

VADER maps lexical features such as words, punctuation and capitalizations, to sentiment scores. When determining which feature to assign to which score, VADER relies on a dictionary created by Amazon Mechanical Turk crowd worker ratings, as in the case of Hedonometer. More specifically, for each feature crowd workers give a rating between -4 and 4for positive, negative, and neutral sentiments. VADER then averages the ratings so that each rating is in between -1 and representing strong disagree and strong agree, respectively. We also note that VADER pays special attention to the word "but" for the following reason. The word "but" connects two sentences with opposite sentiments, where the latter has usually more dominant sentiment. Therefore, once VADER detects the "but", it decreases the sentiment scores of the words before the "but" to 50% of their values, whereas increases those after the "but" to 150% of their values.

To date, VADER has found several notable applications in social media analysis, particularly Twitter analysis. Pano and Kashef analyzed over 4 million tweets with Bitcoin prices and concluded that VADER scores correlate with Bitcoin prices, so VADER scores can be used to forecast these prices [29]. A more comprehensive study using VADER for Twitter analysis was conducted by Bhaumik and Yadav considering tweets from different groups of people, such as graduate students, doctors, comedians, etc. This study showed that graduate students' tweets contain the most negative sentiments, whereas tweets posted by comedians have the highest level of positivity. Interestingly, politicians tend to post neutral tweets [30]. In [31], VADER was utilized for understanding

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US mental health during the COVID -19 pandemic. Concretely, a public dataset that consists of all COVID -19 related tweets was analyzed, and found that a large portion of these tweets conveyed positive feelings, which may be used to support the claim that people in the US are optimistic about the pandemic [31]. Finally, a recent study in [32] analyzed 427 tweets with misleading content from and performed the VADER sentiment analysis. The results suggest that tweets propagating fake news have a more negative tone and stronger sentiment polarities than tweets with verifiable news.

Table 6. Mean sentiment scores computed by the VADER for study group and for the control group.

	Study	**Control**
Negativity	$0.12\ (\sigma = 0.11)$	$0.06(\sigma = 0.08)$
Neutrality	$0.81\ (\sigma = 0.13)$	$0.85\ (\sigma = 0.11)$
Positivity	$0.06\ (\sigma = 0.09)$	$0.07(\sigma = 0.08)$
Compound	$-0.09\ (\sigma = 0.28)$	$0.02\ (\sigma = 0.26)$

Table 6 shows the four sentiment scores for the study group and for the control group. At first glance, it may seem that the tweets of the study group convey more negative thoughts than those of the control group, given the corresponding negativity scores. In practice, this could mean that a tweet containing misinformation about the pandemic COVID -19 tends to be more negative. Indeed, in [9] it is suggested that a compound score of less than -0.05 indicates negative sentiment. In our case, since it is less than -0.05 for the study group, this supports the claim that a tweet spreading misleading information about the pandemic sounds negative. At this point, one may think that this result is in contrast to the earlier result that there is no actual difference between the words in malicious tweets and regular tweets about the COVID -19 in terms of happiness score. Roughly speaking, negative sentiment is usually conveyed by capital letters and emoticons in tweets that propagate misleading information, so a sentiment analysis that only reflects the content of words could be effective in this sense.

We also performed the t-test for all sentiment categories and found that the observed difference between the mean sentiment scores is significant ($p < 0.01$) for all categories: Negativity, Neutrality, Positivity, and Compound.

V. CONCLUDING REMARKS

About four million people have died from the virus COVID -19 and millions more have been affected worldwide to date. Since the most important point to avoid the pandemic is to maintain social distance, people are using social media more than ever to communicate with each other and keep up with news. However, this also raises the question of being vulnerable to misinformation about the COVID -19 pandemic on social media. Worse, there is a consensus that distinguishing misinformation spread on social media is a non-trivial task for both humans and machines. In this study, we have attempted to understand the characteristics of such misinformation by means of a Twitter analysis.

We collected two types of tweets: Tweets with the hashtag #plandemic or #scamdemic and tweets with the hashtag #Covid19. Tweets from the former group began to spread after a former medical researcher posted a video called Plandemic, which spread various conspiracy theories about the pandemic. Since then, thousands of tweets have been posted under these hashtags aimed at spreading misleading information about the pandemic. We used these tweets to form the study group. The tweets of on the latter group address more general thoughts about the pandemic and served as the control group.

First, we sought to assess the reliability of the external sources provided in the tweets, including misinformation about the pandemic. For this purpose, we considered the URL address included in the tweets. Basically, we assumed that a website is credible if its corresponding URL address ends with the domain suffix "org" or "gov". From this perspective, we considered a tweet as reliable if it refers a website whose URL address contains "org" or "gov". We analyzed the URL addresses (including tiny URLs) in the study group and in the control group and found that only 6% of the web sources given in the tweets spreading misinformation about the pandemic is credible, while this rate is 14% for regular pandemic tweets. Moreover, we found this difference significant using the chi-square test. Second, we conducted two sentiment analyses to identify sentimental characteristics of the tweets. In the first analysis, we employed a hedonometer to estimate the average happiness score of the tweets in both groups. There seems to be no significant difference in this manner between the tweets of the different groups. That is, there is no clear indication that a tweet disseminating misleading information about the pandemic COVID -19 contains negative words or hate speech.

Nevertheless, the second sentiment analysis based on the VADER method revealed that the tweets of the study group, i.e., the tweets spreading misinformation about the pandemic, contains slightly more negative sentiments. This could be because the negativity in the misleading tweets about the pandemic is expressed not only by the words themselves, but also by capital letters, punctuation, and emoticons, which can be reflected by the VADER method. Last but not least, this study can be extended in various directions, for example, analyzing the sarcastic features of tweets about the pandemic can be considered as a good future work.

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