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Impact of COVID-19 on Societal Behavior via Twitter Analytics

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Original Article

Abstract

The outbreak of the COVID-19 pandemic has caused a notable challenge to the well-being of people all around the globe. In such times, it is of foremost importance to analyze the information posted by people on social media. In this study, a Twitter-based dataset related to COVID-19 has been analyzed, and the effect of the pandemic on societal behavior has been revealed. Tweets have been hydrated and pre-processed using the NLTK toolkit to find the most frequently posted COVID- related words. This research can help identify the social response of people to the Pandemic, realizing *what* people are majorly concerned about and extracting knowledge about the daily trend of sentiments around the world. It has been concluded from our analysis that rather than the expected negative trend in the use of COVID-19 terms on a daily basis, more positive figurative language has been used in the posted tweets.

Resumen

Impacto del COVID-19 en el Comportamiento Social a través de *Twitter Analytics*. El brote de la pandemia de COVID-19 ha provocado un desafío notable para el bienestar de las personas en todo el mundo. Por lo tanto, es extremadamente importante analizar la información que las personas publican en las redes sociales. Se analizó una base de datos de Twitter relacionada con el COVID-19 y se identificó el efecto de la pandemia en el comportamiento social. Los tweets se han procesado previamente utilizando bibliotecas NLTK para encontrar las palabras relacionadas con COVID publicadas con más frecuencia. Esta investigación puede ayudar a identificar la respuesta social de las personas a la pandemia, reconocer qué es lo que más preocupa y obtener información sobre la tendencia diaria en el sentimiento en todo el mundo. Se ha concluido que en lugar de la tendencia negativa esperada en el uso diario de términos COVID19, se ha utilizado un lenguaje figurativo más positivo en los tuits publicados.

Tabla de Contenido

Keywords:
COVID-19, coronavirus, twitter, societal behavior analysis

Palabras clave:
COVID19, coronavirus, twitter, análisis del comportamiento social

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Introduction

Homo sapiens are one of the most intricate species on earth, as they are social and have the knowledge to express their sentiments, intentions, and thoughts using different ways like body language, words, gestures, and social media. The advancement in Internet Technology has resulted in an increased dependency of people over social media platforms like Twitter, which has been significantly high during the COVID-19 pandemic. Twitter is one such social media platform that is widely used by people all around the globe. It helps users to post and interact with messages known as “tweets”.

Significance and impact of social media during the COVID-19 pandemic

When any widespread outbreak takes place, its impact occurs sooner or later in tangible and intangible ways and affects various factors such as health, environment, economy, and even politics.

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Social networking platforms are being used throughout the world for spreading various measures about awareness, prevention, and protection from the COVID-19 pandemic. Nowadays, one can observe that social media is flooding with such kind of messages. However, the adverse side of the COVID-19 pandemic is that this has impacted their mental and societal behavior. This can also be seen in their social media messages shared by them from time to time.

Why Twitter?

Twitter has been one of the platforms for millions of people to express their emotions regarding different issues. It is one of the popular micro blogging social media platform using which people share their information on many topics like voyeurism, event planning, high-level control (Liu, Cheung, & Lee, 2010), etc. It has also been previously used for the exchange of thoughts and information during any calamity (Fu et al., 2016). During the past few months, the whole world has faced COVID-19 as a serious threat, and to prevent its spread, most of the countries had adopted the lockdown policy. This not only severely affects human health, but also the economy, education, sports, etc. During the lockdown phase, people have used Twitter extensively to express their ideas, emotions, and other information. Presently, people including celebrities are connected via twitter, so the leading health-related organisations like the Centres for Disease Control and Prevention (CDC) (Tanne et al., 2020) and the World Health Organisation (WHO) (Cucinotta & Vanelli, 2020) regularly update guidelines related to the pandemic in the form of tweets.

In this paper, we have performed social media data analytics on a Twitter–based dataset related to COVID-19 and have checked its social response based on the use of COVID-19 terms. The use of 'Hashtag' in the shared tweets provides an effective way of analysing and categorizing them more quickly. The proposed mechanism performs the societal behaviour analysis on various tweets shared with hashtags and keywords related to the COVID-19 pandemic. The main essence of this work is to analyze the sentiments based on a daily basis by observing emotions and feelings from the various tweets shared by people during the pandemic.

The structure of the remaining paper is presented as follows. Section 2 presents recent studies on social media for COVID-19 with critical analysis. Section 3 describes the methodology of the proposed framework. Section 4 presents the results gained from experiments using the proposed framework. Section 5 discusses what has been inferred from this study. Finally, Section 6 concludes the paper with its limitations.

Related Studies on Social Behavioural Response to COVID-19

In a short period, many research studies have been carried out that focuses on the different perspectives of COVID-19 like detection of COVID-19, the effect of temperature, behavioural analysis, and the impact of COVID-19 on business, etc. (Hiremath, Kowshik, Manjunath, & Shettar, 2020; Panwar et al., 2020; Panwar, Gupta, Siddiqui, Morales-Menendez, & Singh, 2020; Siddiqui et al., 2020). Bhat et al., (2020) have performed the sentiment analysis on tweets to observe the sentiments of people for two popular hashtags i.e., #COVID-19 with 92646 tweets hashtags, and #Coronavirus with 85513 tweets hashtags respectively. It is found that #COVID-19 consisted of about 51.97% positive, and 34.05% neutral sentiments, whereas, #Coronavirus consisted of about 41.27% neutral followed by 40.91% positive sentiments. The study considers only two hashtags related to the pandemic, but the rest of them are not analysed (Barkur, Vibha, & Kamath, 2020) have analyzed near about 24000 tweets in the Indian region with hashtags #IndiaLockdown and #IndiafightsCorona. These tweets show the opinions and concerns that Indians probably had after the lockdown, such as anger about why the lockdown was not imposed earlier, worry about how daily wage workers would survive in this condition of lockdown, etc. This paper does not address other similar hashtags. We argue that the claimed result says ¨lock-down is positive and India has succeeded in controlling the corona virus spread to a great extent¨, however, presently, India has 1697054 active cases ("India Coronavirus", n.d.) and comes under the list of top 3 affected countries.

The effect on the mental health status of people due to this lock-down has been discussed by Li, Wang, Xue, Zhao, and Zhu (2020), to see the psychological patterns in China using the active data of 'Weibo' users. Their study reveals that linguistic expression includes an increase in health and family, while a decrease in friends and leisure. They have also laid out some suggestions for clinical practitioners and policymakers based on the analysis from their work. However, this data is only limited to 'Weibo' users that majorly consist of the young population. The COVID-19 tweets are analyzed using the Latent Dirichlet allocation (LDA) algorithm for segregating them into clusters and obtained relevant topics of discussion. Mean sentiment was found negative for two topics – death and increased racism, however, found positive for the remaining topics (Abd-Alrazaq, Alhuwail, Househ, Hamdi, & Shah, 2020). The results show that people are using #pandemic, #death, #quarantine, #hope, #staysafe, #fight, and #masks in their tweets and expressing their emotions (Dubey, 2020). However, the analysis shows a positive trend that means people are still hopeful to overcome from the pandemic. Kleinberg, van der Vegt, and Mozes (2020) analyze and measure the people's tweets and it is found that longer text was more helpful in being insightful about worries of people, whereas, shorter Tweet –- sized text was mostly used to spread notions on unanimity (Van Bavel et al., 2020) reviewed the different perspectives during COVID-19 such as fake news propagation, conspiracy theories, and social inequality.

The findings from this study of social media on COVID-19 reveal that the trends of sentiments expressed by people on social media platforms during the pandemic are still evolving. This study will contribute to analyzing large-scale Twitter-based data during the outbreak of COVID-19.

Methodology

A proposed framework has been presented that performs an analysis of the Societal Behavior on the Twitter data set. This framework is shown in Figure 1. It has a two-fold procedure of analyzing the tweets and their respective sentiment scores.

In part (a) of the framework, the sentiment scores that are present in the large-scale dataset are analyzed. These sentiment scores have been calculated by the author of the dataset with his live sentiment analysis model which uses Text blob's sentiment function. This streaming API, sending around 30-40 tweets per second, processes many tweets in English language containing keywords related to COVID-19 to calculate the sentiment scores. In our study, we have categorized these scores into Positive, Negative, and Neutral using the Counter Function of the Collections library in Python, to understand the overall sentiment trends during COVID-19.

In part (b) of the framework, we have analyzed random 372401 tweets by extracting them using Hydrator tool to gain insight about the most frequent used COVID-19 terms to predict the societal behaviour. The extracted knowledge has been represented in the form of graphs and wordcloud for a clearer understanding.

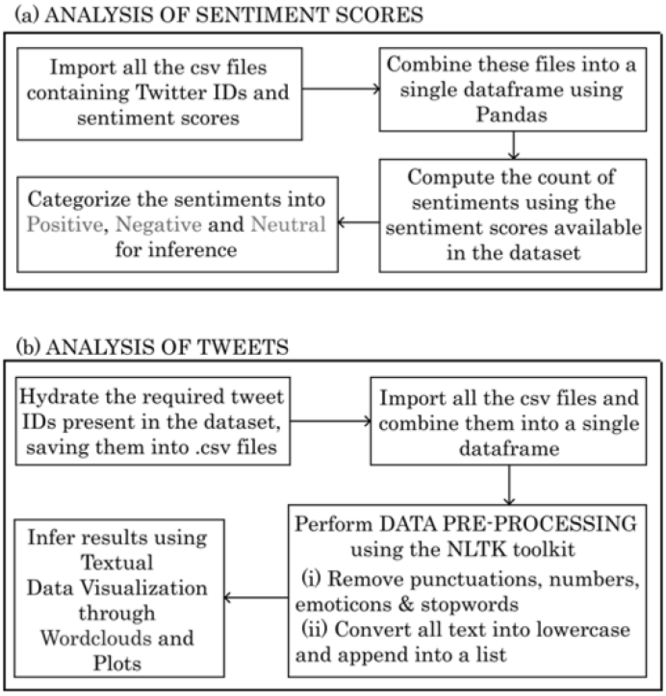

Figure 1: Framework for analysis of Societal Behavior during COVID-19.

Data Source Collection and Description

The primary data set used is the Coronavirus (COVID-19) Tweets Dataset (Lamsal, 2020). This dataset includes CSV files that contain IDs and sentiment scores of the tweets related to the COVID-19 pandemic, which have been collected by a live project of the author (Lamsal, 2021). For the calculation of the sentiment scores, the author of the dataset has implemented TextBlob's Sentiment Analysis module that computes the sentiment polarity as a continuous value and not as a category. Before this calculation of the sentiment scores is done using the tweets, they are pre-processed in which extra spaces, paragraph breaks, URLs, mention symbols and hash symbols are cleaned. The sentiment scores that are obtained from this analysis fall in the range of [-1, +1]. This model selects tweets in English related to COVID-19 from the real-time feed of Twitter by using 54 different keywords that are commonly used while referencing the pandemic. Some keywords used are “covid”, “pandemic”, “lockdown”, “social distancing”, etc. In our study, data from 1st July 2020 – 20th July 2020 were taken. This dataset contains a total of 78392204 tweet IDs with their corresponding calculated sentiment scores. According to the content redistribution policy of Twitter, it is not permitted to share the text contained in tweets. Thus, we have used Hydrator (*DocNow/hydrator*, 2020), which is a free open source software used to extract detailed information using the Tweet IDs. Since the large-scale dataset contains a huge number of tweets, we have hydrated random 372401 tweets and analyzed them.

Data Pre-processing

Before analysis, pre-processing of the data is a crucial step to filter out the required information. This can be done using various libraries available in Python. Herein, ‘Pandas’ is used to read the data available in the .CSV file into a data frame. The Hydrator application created by the *Documenting the Now* project is used to reconstitute Twitter datasets using the Twitter identifiers. After the extraction using the Hydrator application, only the required attribute *“text”* is filtered out from the files. This raw text used in the tweets is pre-processed using the built-in RegEx package, known as *‘re’*, and the Natural Language Toolkit (NLTK). NLTK is a collection of libraries and programs used for the Natural Language Processing (NLP) for English using Python Programming Language.

The following steps have been performed for further cleaning of data with the help of the NLTK toolkit and the Regular Expression (RegEx) package of Python.

- Combined the data into a single data frame using the *‘Pandas’* library of Python.
- Removed all punctuation and numbers from the column ‘text’ of the data frame and only the alphabets have been retained. This text is further converted into lowercase. This has been done using the RegEx package of Python.
- Removed all emoticons from the text to reduce noise.
- Removed unnecessary URL’s from the text that hinders the accuracy of analyzing the text.
- Removed stop-words with the help of the NLTK corpus. The NLTK module contains a list of *stopwords*, which are the words that do not add much meaning to the sentence and are removed for an improved analysis.
- Lemmatized the words using the WordNetLemmatizer() function from the nltk.stem package using Python.

After cleaning the data, all the words present in the ‘text’ attribute of the data frame are inserted into a list. Thus, we can obtain a list of words containing pre-processed text from 372401 tweets in the data set. This is how a list of words containing text from tweets looks like after creation: List = [‘I’m’, ‘old’, ‘enough’, ‘to’, ‘remember’, ‘when’, ‘coronavirus’, ‘was’, ‘just’…].

Table 1 depicts the tweets containing text before pre-processing and text after pre-processing with their corresponding sentiment as per the sentiment score. We have categorized the tweets using his calculated sentiment scores such that tweets are categorized as negative if the sentiment score lies between [-1, 0), as neutral if the sentiment score if 0, and as positive if the sentiment score lies between (0, +1].

Results

The effect of COVID-19 can be seen on the well-being of people as well as in their behavior. People have been facing fear and confusion, which has been impacting their mental health and producing behavioral changes. We have performed a societal behavioral analysis based on frequently used COVID-19 terms in figurative language. Typically, while posting tweets, the user makes use of several hashtags to attract the attention of readers on a topic. Though there are several tweets about COVID-19, we have only focused on the ten most frequently used keywords related to coronavirus that can be seen highlighted in Figure 2. The word cloud of these ten words has also been depicted in Figure 3.

These have been computed using the Counter module of the Collections Library in Python. The *‘most_common()’* method of the Counter module is used to compute the most frequently used COVID-19 terms by providing the numerical value of the required terms as an input parameter to the function. The chart plotted in Figure 2 shows that out of the 372401 hydrated tweets used for societal behavioral analysis, words such as *‘COVID’* and *‘Coronavirus’* appeared the greatest number of times in tweets which are 141628 and 44159 in number, respectively. Other words, like *‘pandemic’, ‘cases’, ‘positive’, ‘lockdown’* etc. have also been significantly used in these tweets. Table 2 presents the count of these most frequently used keywords.

Table 1.

Text Before and After pre-processing

SNo.	Text *Before* Pre-processing	Text *After* Pre-processing	Sentiment
1	RT@urstrulyMahesh: Twoweeksoflockdownandwehavebeengoingstrong. Hugelyappreciatetheunitedeffortsofourgovernments👏👏👏	twoweekslockdowngoingstronghugelyappreciateunitedeffortsgovernments	Positive
2	#digitaltransformation tools thathelpedQuixy setup virtual workspacewhereemployeescanworkfrom home with zero impacton business operations. https://t.co/uRfweM5VfY	digitaltransformation tools helped quixy setup virtual workspace employees work home zero impact business operations	Positive
3	RT @ajbends: We'relosingthefightto COVID. Everybodyisjobless. OurPresidentis a fascist. Nazis are in ourstreets.	losingfightcovideverybodyjoblesspresidentfascist nazis streets	Negative
4	RT @DaniOliver: Hey, so, I got #Covid19 in March. I've been sick for over 3 months w/ severe respiratory, cardiovascular & neurological symptoms	heygotcovidmarchsickmonths w severerespiratorycardiovascular neurologicalsymptoms	Negative
5	COVID-19 outbreak in Thailand has ended!\n\nThe country has reported zero local transmission of COVID-19 for 48 consecutive days	covid outbreak thailand ended country reported zero local transmission covid consecutive days	Neutral
6	RT @INCIndia: Shri @RahulGandhi interactswithIndian nurses fromaroundtheglobeonthe COVID-19 pandemic. Tune in tomorrow a10AM	rahulgandhiinteractsindian nurses aroundglobecovidpandemic tune tomorrow	Neutral

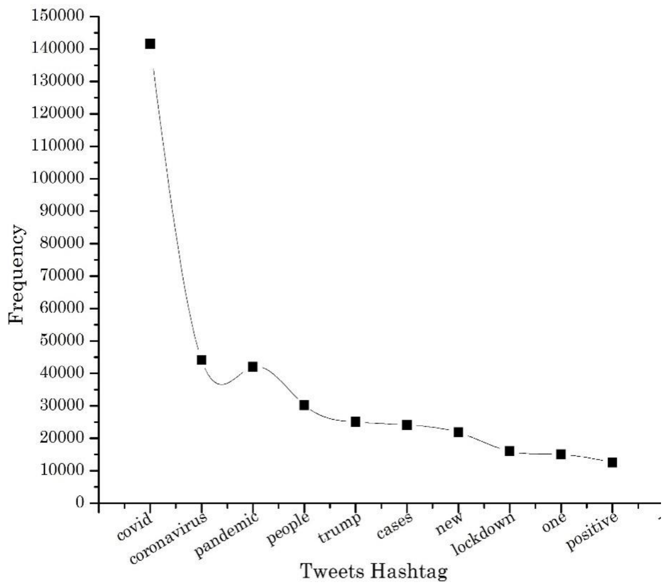

Figure 2. Chart showing the frequency of the top ten COVID-19 term used in Tweets with their respective frequencies

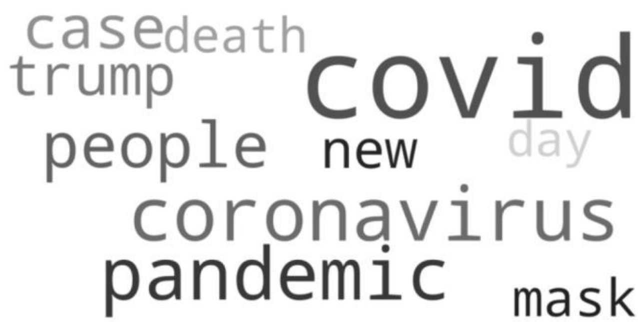

Figure 3: Wordcloud of 10 most frequently tweeted words

A word-cloud (or a tag cloud) is a visual representation of text data, which is typically used to depict keywords, in our case, COVID-19 terms used in Twitter Analytics. They help in extracting the most pertinent parts of the textual data. To visualize these word clouds, Matplotlib is used. Matplotlib is a comprehensive library for creating interactive visualizations using Python. Thus, for a lucid understanding of the use of COVID-19 terms in figurative language by people, a word cloud of 50 most frequently tweeted terms has been plotted in Figure 4.

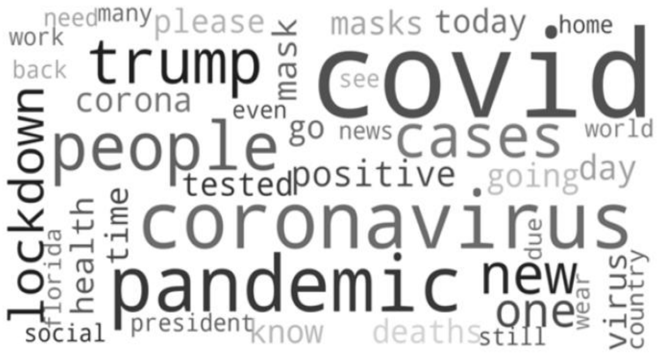

Figure 4. Wordcloud of 50 most frequently tweeted words

In any wordcloud, the size and boldness of the word reflects how frequently it has been used in all the analyzed tweets. The word *'covid'* has the largest size and is the boldest, reflecting its significance. Other words like *'people', 'deaths', 'mask', 'health'* have also been significantly used by people while posting tweets. It can also be observed that since the largest users of Twitter belong to the United States, words like *'trump'* and *'florida'* have also been used by people in context to COVID-19. Thus the use of COVID-19 terms as figurative language can be seen in the plotted wordcloud.

Table 2.
Top ten most frequently used keywords.

S.No.	Word	Frequency
1	COVID	141628
2	Coronavirus	44159
3	Pandemic	42029
4	People	30276
5	Trump	25041
6	Cases	24085
7	New	21811
8	Lockdown	16044
9	One	15026
10	Positive	12587

For the purpose of *Twitter Analytics,* the daily trend in the sentiment of tweets has been analyzed. This helps us to closely observe the societal behavior in the COVID-19 pandemic on a daily basis, for a period of 20 consecutive days. The average sentiment score of all the tweets from a single day can be seen depicted in Figure 5. It can be seen that the trend of the average sentiment score was the highest on 3rd July 2020, while the minimum was on 6th July 2020. The overall trend first increased till 3rd July 2020 and then significantly dropped. An increase in the trend is observed from 7th July 2020 to 14th July 2020, with a subsequent drop and rise. Thus, this trend in the average score did not constantly increase or decrease for a long period.

Table 3.
Average Sentiment score by date.

Date	Average Sentiment Score
July 1, 2020	0.04883
July 2, 2020	0.05156
July 3, 2020	0.078475
July 4, 2020	0.0472
July 5, 2020	0.031504
July 6, 2020	0.020581
July 7, 2020	0.040447
July 8, 2020	0.040851
July 9, 2020	0.038665
July 10, 2020	0.044398
July 11, 2020	0.052422
July 12, 2020	0.056849
July 13, 2020	0.063482
July 14, 2020	0.062721
July 15, 2020	0.043645
July 16, 2020	0.029014
July 17, 2020	0.043425
July 18, 2020	0.062256
July 19, 2020	0.046152
July 20, 2020	0.049634

Table 4.
Categorization based on sentiment scores

Negative	Sentiment score < 0
Positive	Sentiment score > 0
Neutral	Sentiment score = 0

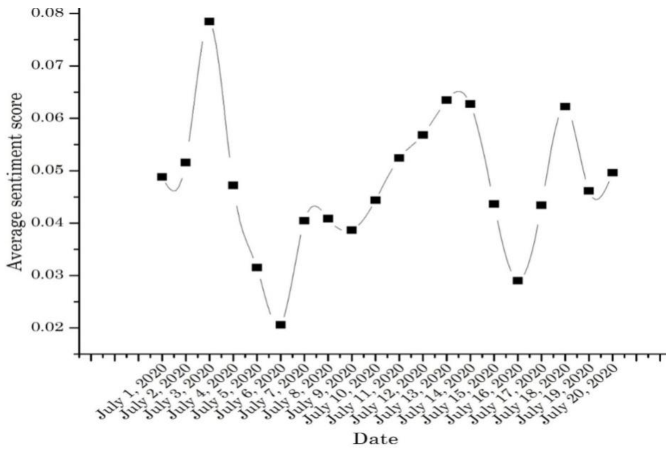

Figure 5: Line Plot of Daily Average Sentiment Scores for 20 days

The corresponding Table 3 lists these daily average sentiment scores that have been plotted in Figure 5. To further analyse the sentiment scores of the available tweets, we have categorized all the tweets into Positive, Negative and Neutral using their sentiment scores according to the classification presented in Table 4. Thus, a tweet is labeled Negative if its sentiment score is less than zero, Positive if it is greater than zero, and Neutral if it is equal to zero.

To draw a comparison between the Positive, Negative and Neutral sentiments drawn from the tweets collected on each day, Figure 6 has been plotted for a better insight. The exact count of the number of positive, negative, and neutral tweets corresponding to the above plot (Figure 6) has been done using the Counter function of Python, as presented in Table 5. Out of 78392204 total tweets posted in 20 days. Despite the prevalent fear and panic sue to the pandemic; people have remained calm and optimistic. The following proportion: 40.6% positive, 24.0% negative and 35.4% neutral sentiments, has been calculated.

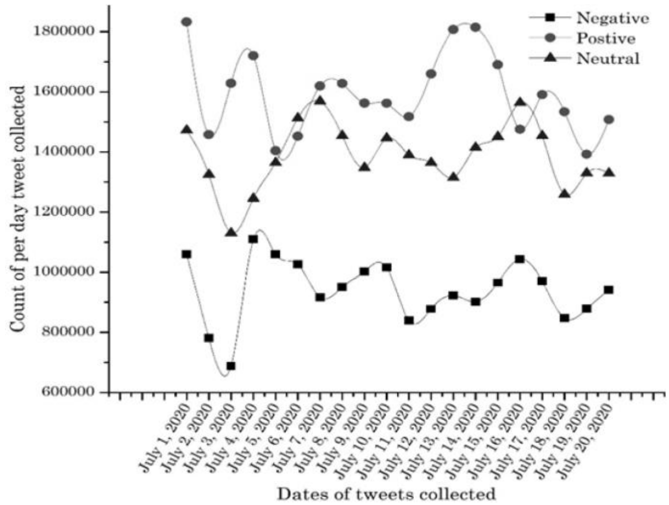

Figure 6: Daily Comparison of the number of positive, negative and neutral tweets posted from 1st July 2020 to 20th July 2020

Table 5.
Daily count of positive, negative, and neutral sentiments

Date	Negative	Positive	Neutral
July 1, 2020	1060265	1832679	1472227
July 2, 2020	781388	1457712	1324559
July 3, 2020	687485	1628580	1130035
July 4, 2020	1110173	1720400	1245603
July 5, 2020	1059470	1404111	1364323
July 6, 2020	1026634	1452597	1512650
July 7, 2020	916266	1619456	1568523
July 8, 2020	950730	1627876	1454339
July 9, 2020	1002547	1562400	1347613
July 10, 2020	1015901	1562171	1446155
July 11, 2020	839353	1517393	1389570
July 12, 2020	877958	1659861	1364574
July 13, 2020	923018	1807735	1314688
July 14, 2020	901446	1814584	1414696
July 15, 2020	965421	1690434	1450793
July 16, 2020	1043857	1475557	1564159
July 17, 2020	969862	1590466	1453995
July 18, 2020	847164	1533694	1258762
July 19, 2020	878379	1392403	1329622
July 20, 2020	940859	1507841	1329207

Despite these ill impacts, many people have managed to look at the brighter side. However, this Twitter-based study cannot be considered as a benchmark study. The reason behind this is that even today, millions of people in developing countries like India, Nepal, and Bangladesh do not know about the usage of Twitter. The ground reality is very different as a large proportion of the population is unaware of social media, particularly in underdeveloped and developing countries. It will not be wrong to say that they are the real victims of this pandemic. They are dependent on daily work for their necessities. Therefore, in the world of Twitter, we can sense the optimism regarding the situation but if we keep in mind the people who do not have social media accounts, the results could be highly misleading.

Impact of COVID-19 on the Society

Positive impact. Across the globe, people have several concerns related to the pandemic. From our analysis, 40.6% of the tweets posted by people contain the usage of positive COVID-19 terms. Even though these people are not comfortable with this pandemic, they have tried to tweet positively about the situation. The main positive impacts are:

- Improved hygiene and reduction in other infectious diseases: Due to the COVID-19 pandemic, it has become mandatory for everyone to follow measures of personal hygiene, keep their surroundings clean, and implement other necessary precautionary measures. In general, this practice has reduced the increase of infectious diseases (Roshan, Feroz, Rafique, & Virani, 2020).
- Work-from-Home Culture: Previously, it was believed that efficient work could be done only in-person from offices. Now, the pandemic has evolved this belief and has enabled us to continue working from home by adapting to the changing environment. This has also been reflected in an extracted tweet: *"#digitaltransformation tools that helped Quixy setup virtual workspace where employees can work from home with zero impact on business operations. https://t.co/uRfweM5VfY"*. Doctors, scientists, and public health officers believe that the pandemic also provides a unique path through which we can now see a positive impact on health due to changes in human behaviour (Kraemer et al., 2020).
- Reduction of Sexually Transmitted Infections (STI): Miguel Duarte Botas Alpalhão has said during his lecture at the University of Lisbon, that a decline in sexually transmitted infections is expected during the lockdown (Alpalhão & Filipe, 2020). Except for hospitals and pharmacies, lockdown protocols are strictly followed in all the places.
- Protective measures by the Governmental Bodies: To prevent the spread of the infection, government and other non-government organizations have implemented various measures for the protection of citizens. The united efforts of the government have been appreciated by people and are also being reflected in the tweets extracted by us: "*Two weeks of lockdown and we have been going strong. Hugely appreciate the united efforts of our governments".* Additionally, proper testing measures and quarantine policies have been imposed by the government for the safety and protection of everyone.
- Improvement in the air-quality index: The pandemic has had a positive effect on the weather, and the air quality has improved dramatically around the globe. NASA reports the aerosol (soot and sulphate) concentration has gone down drastically over North India and other countries, thus bringing clear skies after decades (Ravilious, 2020).

Negative impact. In a state of a global emergency, people are restricting social gatherings and are staying in their homes in most countries. Despite several positive impacts as discussed above, there is a significant use of negative terms in context to COVID-19 as well. In this analysis, it is found that 24% of the tweets posted by people contain negative terminology because of factors like fear, anxiety, boredom, loneliness, and depression due to being in a state of self-isolation. The typical negative impact of the pandemic that have been noticed globally are listed as follows:

- Circulation of Inaccurate Information: A lot of fake news and theories have proliferated since the outbreak of the pandemic (Apuke & Omar, 2021). False information and claims that are posted on social networking sites like Twitter are misleading. Rumors and disinformation spread as fast as the infection. Some theories like the spread of COVID-19 due to 5G technology in various countries have been popular. Another incident involved people consuming chlorine to kill the virus in their bodies (van der Linden, Roozenbeek, & Compton, 2020). To stop the spread of fake news that makes the condition worse, the United Nations has been working to spread only accurate information and tackle the spread of misinformation (Department of Global Communications, 2020).
- The emergence of misinformation has also led to racism against Chinese citizens all around the world. On January 24, 2020, misinformation that COVID-19 infected Chinese passengers were present at the Kansai International Airport, caused discrimination against the Chinese in Japan with the "#ChineseDon'tComeToJapan" hashtag being trending on Twitter for a long time

(Shimizu, 2020). This led to widespread discrimination against the Chinese, even Toronto and parts of USA (Rich, 2020). The spread of misinformation has led to disturbance in communal harmony.

- Loss of lives*:* Many people have lost their lives during the COVID-19 pandemic. It has also resulted in poverty, domestic violence and financial crises. Developing countries like India and Nepal have recorded the highest number of suicide cases ("875 people commit suicide", 2020). In India over 298 suicides have been reported, out of which 109 were due to financial distress, 55 due to fear of infection and 33 due to withdrawal (Arinda, Patel, & Gaikwad, 2020). Similarly, in Nepal until 27th June 2020, 1647 people have committed suicide during the period of lock-down (IANS, 2020). Patients with existing critical health issues and those who have become victim to sudden medical conditions like heart attacks and brain haemorrhage cannot get timely treatment due to the lack of mobility.
- Impact on Health*:* Lockdown and its extended period have significantly changed the existing lifestyle pattern. Due to less physical exertion because of staying at home, the eating habits of people have changed which as well can impact their health. These changes may be concerned with our physical and mental health. The continuous stay at home and lack of physical activities with immense anxiety and depression have led to an increase in Body Mass Index (BMI) (Pietrobelli et al., 2020; Siddiqui, Morales-Menendez, & Ahmad, 2020). Other people who have been infected by COVID-19 have also significantly posted tweets displaying negative emotions. One such tweet extracted by us is: *"Hey, so, I got #Covid19 in March. I've been sick for over 3 months w/ severe respiratory, cardiovascular & neurological symptoms".*
- Impact on the Global Economy: In addition to health, the most unfavourable impact of this lockdown is its serious effect on the economy worldwide. After the World War-II, the world is experiencing the most difficult phase of economic crisis (Sohrabi et al., 2020). In the USA, approximately 3.8 million people have become unemployed (Eisma, Boelen, & Lenferink, 2020). People have been constantly worrying about their financial status. Temporary unemployment has also increased the level of stress. During the COVID-19 crisis, 15.7 million Mexicans have faced unemployment ("15.7 million Mexicans ", 2020).
- Bereavement in the relationship: A fear of loss of employment puts people in an anxious state as reflected in an extracted tweet: "*We're losing the fight to COVID. Everybody is jobless. Our President is a fascist. Nazis are in our streets*". Hence, anger and frustration are common emotions in such scenarios. There is an increase in domestic violence cases which lessens the bonding in families. An increase in domestic violence has also been observed globally during the lockdown (Mohan, 2020). In South Africa, 87000 divorce cases were registered in the first eight days of lockdown (Hall & Tucker, 2020). Likewise, in London, the domestic abuse calls to London police have risen by a tenth during the lockdown (Grieson, 2020).
- Increase in Sedentary Lifestyle due to COVID-19: Due to the confinement of people in their houses in this pandemic, physical inactivity has led to increases in the sedentary lifestyle of people. In an Italian survey, change in the eating habits and lifestyle during COVID-19 has been observed (Di Renzo et al., 2020). Mental health is also affected by increased odds of stress, anxiety, and lessened well-being.

Neutral impact. During this pandemic, both positive and negative terms have been used by people in their tweets. However, from our analysis, a proportion of 35.4% of the tweets contain words that have a sentiment score of zero, reflecting that they are neutral. Some countries like Myanmar, Tajikistan, Yemen, Taiwan had adopted stringent measures and policies to prevent the spread of the virus, and have almost NIL cases at present. Turkmenistan in Central Asia has not recorded any case of COVID-19 due to the strict measures of the Turkmen government (Banka, 2020). Another tweet extracted by us: *"COVID-19 outbreak in Thailand has ended!\n\nThe country has reported zero local transmission of COVID-19 for 48 consecutive days"*, states that the spread of COVID-19 has paused in Thailand, and has been classified as Neutral. Further, the people who had been working remotely and had adopted ways of online learning, have also been less impacted by the pandemic since online learning has taken over the Internet at a fast rate. Various podcasts, webinars and interaction are being conducted online, reflecting a negligible impact, as shown in another extracted tweet that has been assigned a sentiment score of zero: *"RT @INCIndia: Shri @RahulGandhi interacts with Indian nurses from around the globe on the COVID-19 pandemic. Tune in tomorrow at 10AM"*

Inference Drawn

A lot of research has been done on analyzing the sentiments of people through Twitter. Exploring the sentiments and emotions of people regarding a particular issue, and extracting meaning has become significant via social media mining. Analysis of sentiments is used to gain an understanding of the opinion and determine the emotional tone behind the used words in figurative language. After knowing the trend of sentiments in our analysis, we can see that people have mixed opinions about the situation but have remained optimistic using words that depict positive emotions.

This research work done is on a large – scale dataset which gets updated every day. The trend of sentiment scores and the most frequently used words can help to analyze and implement strategies for the benefit of the people. Since millions of people post tweets about the pandemic each day, it is difficult to analyze the sentiment of each tweet, but such Twitter analysis can give us a fair idea about the perspective of people by looking at the use of COVID-19 terms.

Conclusion

Societal behavioral analysis of humans in response to the COVID 19 pandemic is a serious concern that needs to be addressed. The sentiments of tweets posted by people are segregated into three categories i.e. positive, negative and neutral based on the sentiment scores as shown in Figure 6. While the sentiment scores help us to obtain an idea of the sentiments of the society on a daily basis, more detailed information about the kind of words used in the tweets can be obtained by extracting the tweets using the tool Hydrator.

The main limitation of the work is the information contained in the dataset. Only tweets in English are selected and sentiment scores present in the dataset are calculated using TextBlob on raw text. Very few tweets are geo-tagged, which hinders the scope of focusing where the people posting these tweets belong. It is also known that the majority of Twitter users are from countries like USA, UK, Japan, and so on. Twitter is not widely used by developing countries and thus a fair judgment about the sentiments of people all around the world cannot be made by international bodies to take decisions. Since it is known that the pandemic has caused distress and damage to people all around the world, our analysis show that a larger proportion of tweets contain words with positive sentiment, which is opposite of what is expected.

This study shows that the pandemic has evoked a range of emotions in people, the responses to which have mostly been positive, despite the prevailing panic. However, this does not provide any concrete conclusive opinion about the rising fear among people, and when the present conditions will revert to those before COVID-19.

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