Post-COVID Psychological Impact on Social Media Users: A Study on Twitter Users

Md Rasel MIA*, Ahmed Imran KABIR, Abdullah Al FAHAD
School of Business and Economics, United International University, Bangladesh
mraselmia@outlook.com, ahmedimran@bus.uiu.ac.bd, aaf5623@gmail.com

In China, healthcare specialists discovered a new and unknown virus around the end of December 2019. Later, it was recognized as Coronavirus; the virus rapidly spread over the globe. Lockdowns, and social isolation were the primary measures taken by every nation's government to control of the virus. In February 2022, the World Health Organization (WHO) announced that fast immunization reduces Coronavirus infection rates by 21 percent. After the COVID-19 epidemic, the researchers anticipated that another pandemic, mental health, would spread over the world. In fact, the psychological influence on the general population during and after the COVID-19 outbreak has grown vulnerable. The purpose of this work was to do a sentiment analysis on Twitter data using the Python programming language in order to determine the psychological influence of Twitter users in the post-COVID era.

Keywords: *COVID-19, Post COVID, Mental Health, Psychological Impact, Sentiment Analysis, Natural Language Processing, Automated text analysis, NLP, Social Media Analysis, Data Mining*
DOI: 10.24818/issn14531305/26.4.2022.04

1 Introduction

Health experts have predicted that the aftermath of COVID-19 pandemic may initiate a wave of mental health dilemma. The aim of this study is to paint a clearer insight of mental health state post the COVID pandemic era. In this research paper, we considered the mental health as a major public health emergency and hence not only analyzed the suicidal tendencies, altered behavior, anxiety, depression, post-traumatic stress disorder, acute stress disorder etc. but also found learned how a suicidal suspect could be recognized from keywords used in social media platform such as twitter, inspected multiple data from WHO and other research findings. Although an improvement of the epidemic is in sight, the outbreak of mental health caused by it are in the initial stage. We present alarming data using Python programing language (PPL), NLP, Nvivo, Maxqda, Numpy and conducted data filtering, cleaning, subjectivity classification, polarity, neutral analysis and sentiment analysis to portray a picture on the post pandemic mental health status. This is a public health crisis that we still have at large which may continue for a while on the planet in this post COVID-19 era.

2 Literature Review

Heitzman's (2020) research on the impact of COVID-19 on mental health reveals the severity of the mental disorder. In addition, a comparison of the historical and current conditions of post-traumatic stress disorder (PTSD) and acute stress disorder (ASD) is presented. The research indicates that the trend of PSTD and ASD has diverged over the past four decades. There is a possibility that COVID-19 will introduce a new type of specific mental disorder in the near future.

A groundwork conducted by Gobbi, et al. [1] let us know about the worsening psychiatric condition caused for COVID-19. The research reveals that during the COVID-19 pandemic, there was an increase in anxiety, depression, and other psychopathologies. In relation, rapidly deteriorating mental health conditions have been associated with a greater risk of suicide attempts. The number of mentally disordered patients has also increased in mental health care.

A study by Zhao, et al. [2] on the correlation between mental health disorders and the number of days people maintain social isolation during the COVID-19 pandemic. Those who have stayed at home for a prolonged period and resisted social gatherings suffer more mental distress than those who have stayed at home for a shorter period.

Gavin, et al. [3]'s research demonstrates the connection between mental health and the COVID-19 pandemic. Aside from the pandemic, mental health conditions were on the rise. Following the pandemic, it has gone beyond the obvious. It has also been observed that the workload of frontline workers for adjusting to the new situation guided by COVID-19 is substantial. Suicidality among the general public and frontline workers increased significantly due to mental illness due to the COVID-19's economic constraints, changing lifestyles, and decreased mental healthcare resources.

An interpretation was shown by Robinson, et al. [4] about how social media user express their suicidal thought on social media. In this study, the authors reveal several aspects, such as the age of the users influencing subjects. Mostly, young adults who are sorrowful tend to express their suicidal feelings on social media. People share their suicidal thought on social media to meet others with similar problems, and people judge others anonymously.

A study conducted by Vindegaard, et al. [5] about the COVID-19 pandemic and mental health consequences. The authors demonstrated that those with preexisting mental health issues reported deteriorating conditions in this study. Health care workers have endured more hardships than anyone else. They suffered from depression, anxiety, and poor quality of sleep. After the COVID-19, the study also revealed a significant increase in mental health patients.

Xiong, et al. [6] conducted a study on the impact of the COVID-19 pandemic on mental health. The authors examined the general population's mental health in this research paper. They discovered alarming statistics, including the increasing prevalence of anxiety (6.33 percent to 50.9%), depression (14.6 percent to 48.3%), post-traumatic stress disorder (7 percent to 53.8%), psychological distress (34.43 percent to 38.3%), and stress (8.1 percent to 81.9 percent).

A groundwork was conducted by Standish [7] on the coming wave of suicide based on gender after the COVID-19. This study demonstrates how the mental effects of COVID-19 have contributed to male suicide. Multiple factors, including unemployment, anxiety, and mental trauma, contributed to their demise.

Zalsman, et al. [8] investigated suicide during the time of COVID-19. This empirical research predicted that during COVID-19, the suicide rate might not increase immediately, but factors such as the global health system and economic loss will lead to a long-term increase in suicide rates. During quarantine, the older adult likely to live alone received less physical assistance. It hindered their mental state. Additionally, this factor may account for the rise in suicide rates in the post-covid era.

An investigation on suicide behavior during the COVID-19 pandemic conducted by Dubé, et al. [9] informs us that during the COVID-19 pandemic, younger, female, and from democratic countries are most susceptible to suicidal ideation. It has been observed that suicidal behavior is prevalent among suspicious individuals is alarming. As a national issue, the government should act to safeguard this issue.

Berardelli, et al. [10] discuss the impact of suicide ideation and attempt because of the COVID-19 pandemic in their research paper. They compared two issues: whether psychiatric patients attempt suicide and whether they seek medical care during the COVID-19 pandemic. Their findings indicate an increase in suicide attempts rather than suicidal ideation. In addition, mood-changing behavior has increased during this period.

A research made by Manzar, et al. [11] on youth and adolescent suicide during the COVID-19 epidemic. The authors have collected samples from several nations. According to the published news, they have collected the sample. Males exhibited a high rate of suicide behavior, with most instances resulting from mental health difficulties. Suicide was primarily caused by psychological distress caused by Tiktok addiction, followed by academic distress.

Sher [12] researched the impact of COVID-19 on suicide rates. According to studies, the COVID-19 outbreak is connected with discomfort, anxiety, fear of infection, melancholy, and sleeplessness in the common person and among healthcare staff. Stress-related psychiatric problems, such as mood and substance use disorders, are linked to suicide conduct. After the epidemic, suicide behavior may be more prevalent than during the pandemic.

A study conducted by Coppersmith, et al. [13], and Kabir, et al. [14] on natural language processing (NLP) of social media and identify the suicide risk. Authors have explored the frequency and impact of suicide deaths on society. Using NLP and machine learning, they examined users' social media posts and came up with a number. That quantitative signal surrounding suicide attempts and creating an automated system for estimating suicide risk are considered.

Seah and Shim [15], Kabir, et al. [16] conducted a study by data mining from social media and tried to detect the suicide issue. In this method, the authors collected data from Reddit posts and comments and used natural language processing to comprehend the various facets of human existence associated with suicide.

Du, et al. [17] performed research on extracting phycological stressors for suicide from different social media using deep learning. This study demonstrated how suicidal suspects could be recognized, examined, and quantified their behavior through keywords. Data cleansing from the suspect's social media posts assists in obtaining the real sample result.

The research was undertaken by Luxton, et al. [18] on social media and suicide showed the public health perspective. People who express their diverse perspectives on social media are victims of cyberbullying. Occasionally, chat room conversations and media consumption harm the minds of the general public. People in general share suicidal thoughts on social media.

Sedgwick, et al. [19] developed knowledge on the relationship between social media, internet use and suicide attempt among young adults. The authors revealed that suicide is the second leading cause of death in youth aged 10-24 years. More screen time and cyberbullying cause poor mental health. As a result, young adults trapped in the suicidal ideation and post it on social media as potential victims of suicide.

Le, et al. [20] researched the phycological consequences of lockdowns because of COVID-19. This study revealed that COVID-19 lockdowns are associated with several characteristics that affect the general population's mental health, including anxiety, worry, depression, and general health concerns. This occurred due to food security, housing security, and job security.

[21] examine the emotional, behavioral and psychological impact of the COVID-19 in their study. They intended to demonstrate the altered behavior of humans during that time. In addition, they highlighted how internal and external elements such as economics, human personality traits, and government regulation affect human perception and the phycological outcome. The prevalence of boredom, stigma, phobia, anxiety, sadness, and rage has increased dramatically.

Le, et al. [20] investigated the psychological impact of COVID-19 severity. The authors analyzed many parameters associated with COVID-19 and mental health using psychological distress as the sole indicator in this study. Anxiety, fear, displeasure, and depression have been identified as factors. If any of these characteristics are present, a person will experience mental health problems. The majority of samples were impacted by one of the study's variables.

Imran, et al. [22] conducted a study based on the mental health of children and young adults during the COVID-19. This study revealed how social separation had harmed the mental health of adolescents. Children's screen time, parental stress, and danger of abuse and neglect increased due to their separation from their friends and school closing. This survey also found that adults were given precedence over children regarding mental health concerns.

Serafini, et al. [23] performed research on the mental health issue of the general public during the COVID-19. According to the authors, the pandemic caused a rapid onset of socioeconomic crises and severe psychological misery across the globe. During the COVID-19 outbreak, psychological disorders and significant mental health repercussions gradually arose, including stress, worry, despair, frustration, and uncertainty.

Prati and Mancini [24] performed a meta-analysis on mental health effects during the COVID-19. Most studies undertaken during the pandemic revealed detrimental effects on mental health. However, this study produced positive results. Due to demographic and geographical characteristics, mental health issues can vary according to the result.

3 Literature Breakdown

Pandemic and Mental Health Context

It was believed that a wave of mental health disorders would be arriving in the post-covid era [7]. Multiple research projects were done to explore the psychological effects of the epidemic. Most studies examined anxiety, depression, concern, parental stress, abuse, and distress. [25], [1, 3, 5, 6]. Due to social separation, social engagements such as birthday parties, religious holidays, and the traditional festival did not occur, resulting in boredom significantly influencing mental health [2]. The government and healthcare system were more concerned with adults' mental health than adolescents. The COVID-19 epidemic substantially impacted the suicide rate, which was rising quickly. [12] [11]. Suicide ideation and attempts were more prevalent among teenagers and young adults. [10]. There was also a positive mental health impact on the general public; it varied because of geographical and demographical changes [24].

Social Media and NLP Context

Due to the maintenance of social distance and lockdowns, it was difficult to collect information for a study through in-person interviews and surveys. During this time, people addressed their emotions on social media platforms. Using Natural Language Processing (NLP) and deep learning to mine text from social media, numerous researchers examined the psychological impact of the COVID-19. They attempted to investigate the possible reasons for suicidal ideation by converting text to numeric values. During the COVID-19, social media users expressed their displeasure and depression. Scholars attempted to extract and analyze these terms from their posts. (Du et al., 2018; Seah & Shim, 2018) (Du et al., 2018) (Coppersmith et al., 2018).

4 Methodology

Consideration was given to secondary data while analyzing the post-covid psychological impact on social media users. There are numerous ways to obtain data from social media platforms. Using the Python programming language and a few lines of code, social media data may be extracted. There is licensed software, such as NVivo Plus and MAXQDA, that can also extract keywords from social media text. However, social media text can be collected manually, but it is time-consuming.

NVivo Plus software has been used to mine text from social media due to its versatility, the possibility of making fewer errors, filtering options, and reduced processing time. The transparent data collection procedure is outlined below.

Identifying Data: In this study, the post-covid era has been considered after February 2022. Because in February, the infection rate of Coronavirus decreased by 21%, and most countries in the world came under the vaccination within February [26]. As a result, the advanced Twitter search option has been used where we set every keyword with the period (February 20, 2022 to May 20, 2022), language option (English) and exclude the reply from the Twitter to minimize the repeated text. For example, in the Twitter search box, "Post Covid lang:en until 2022-05-20 since 2022-02-20 -filter:replies" (in the red frame of the picture).

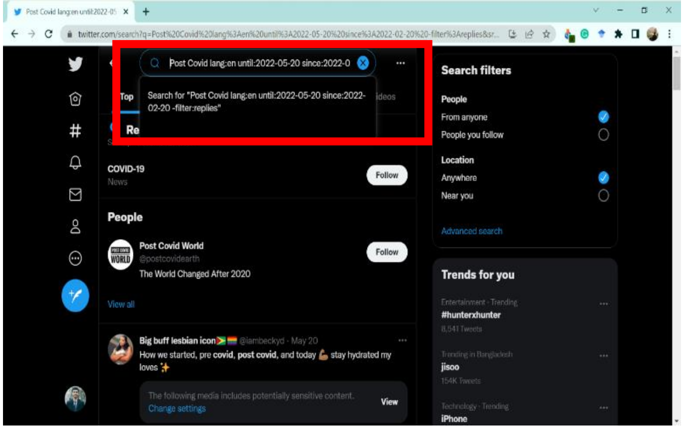

Figure 1: Advanced twitter search

Capturing Data: An addon named 'NCapture for NVivo' integrated with the web browser to capture Twitter's public posts that had already been searched using the advanced Twitter search option. After clicking the capture button, another web browser's tab opens automatically and shows the progress of capturing Tweets for every capture and downloading an NVivo Plus compatible file (File Type: .nvp) for further data filtering.

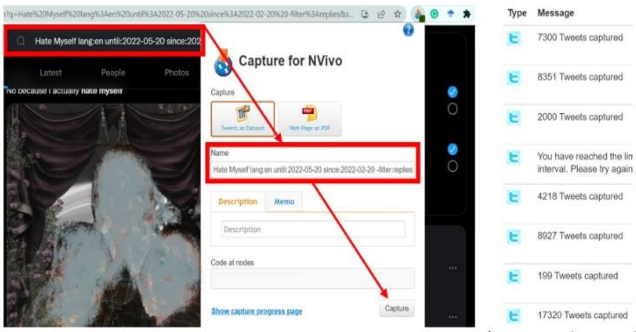

Fig. 2. Data Capture using NVivo software

Filtering Data: The downloaded (.nvp) file opened with the NVivo Plus application for filtering. In the first place, NCapture captures all the tweets and the Retweet. Retweets increase the possibility of text repetition, which might produce a less accurate result of data analysis. All the retweets are ducted from the dataset of one keyword and around all keywords. It decreases a huge number of posts but produces a more accurate dataset.

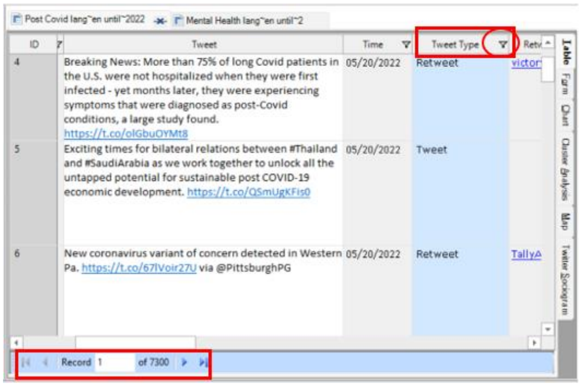

Fig. 3. Filtered data on NVivo software

The first picture showed that the number of data related to post-covid was 7300. After filtering the Retweet, the number decreased by more than two-thirds, which is 1940, shown in the third picture, where the second picture contains the filtering process.

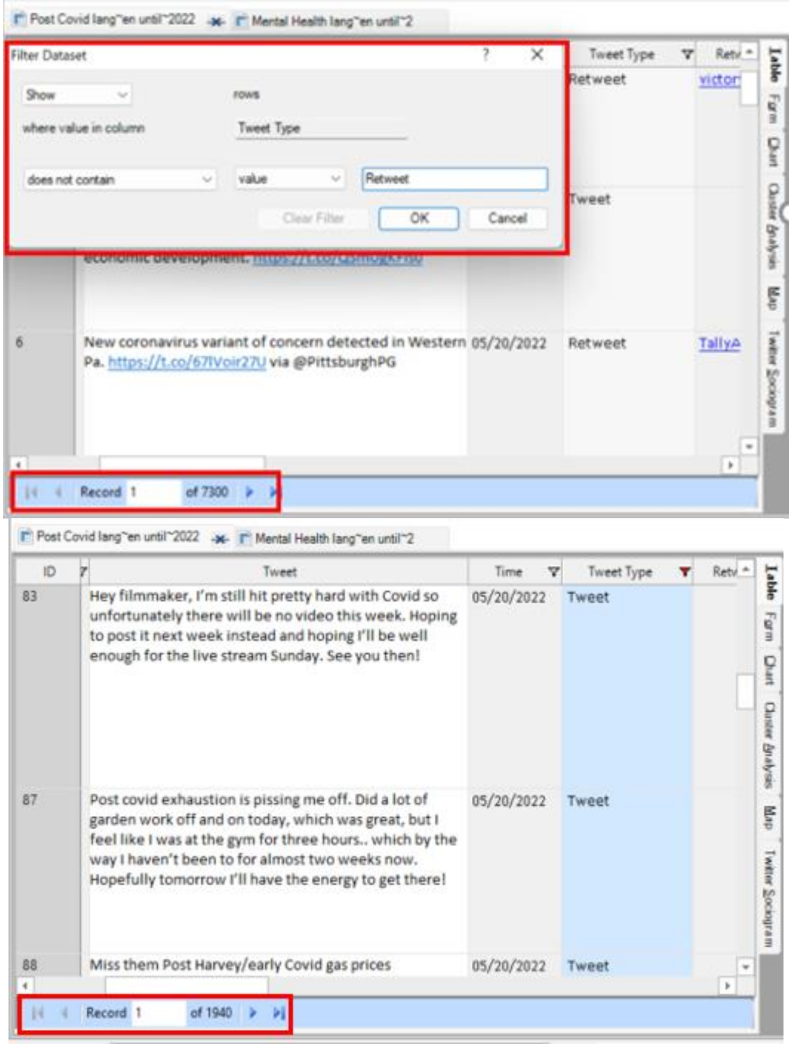

Fig. 4. Data Filtering Process

Storing the Data: Filtering data was applied to the dataset of all keywords (mental health, post covid, hate myself, want to die, kill myself, suicide pate pandemic, suicide in covid) captured by NCapture and exported as a (.xlsx) file. The (.xlsx) file contains the tweets and other information such as Row ID, Tweet ID, Username, Tweet Type, Time, Location and others. Only the Tweet column of every dataset of keywords was transferred to the 'final dataset.xlsx' file with the heading named Tweet. The first picture shows a dataset of a single keyword in the (.xlsx) file. On the other hand, the second picture shows the extracted data of the 'Tweet' column of every dataset of the keywords. Finally, the total Tweet in the final dataset was 17877, which would be used for sentiment analysis to know the psychological impact of post-COVID.

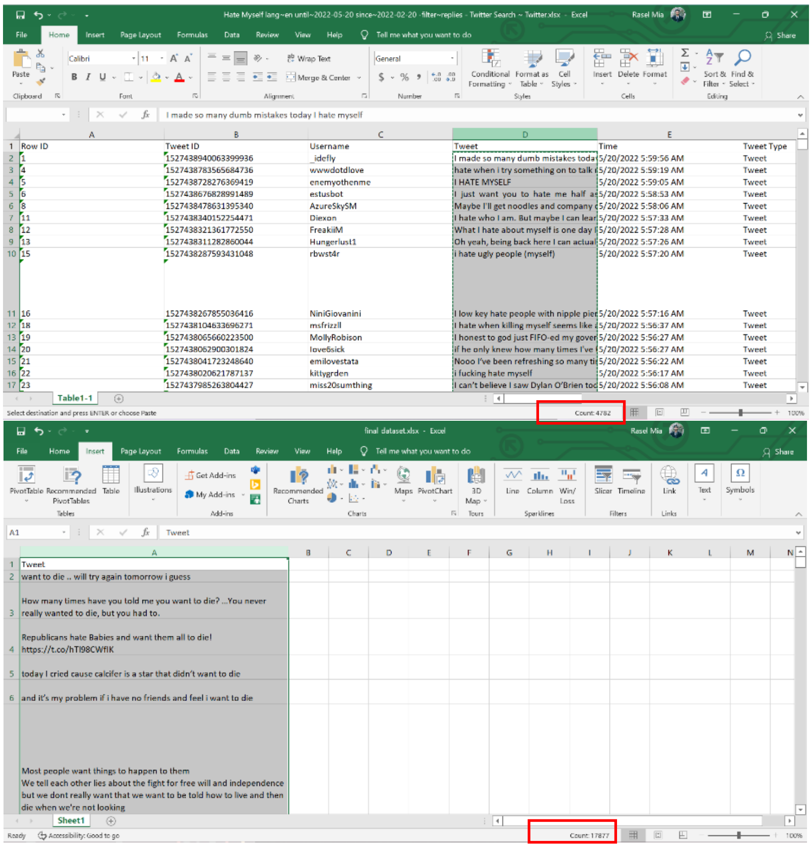

Fig. 5. Data storing process on Microsoft Excel

5 Analysis and Discussion

All the collected data from social media has been analyzed by the Python Programming Language (PPL), namely 'Sentiment Analysis'. The most useful aspect of using PPL is its built-in library. The sentiment analysis is finding authors' opinions in a particular arena. It is the most fine-grained analysis of review articles and social media posts related to an object and its aspects [27]. Numerous Python built-in libraries have been deployed to explore the data, including the Matplotlib library for immersive and rigid visualization, concerning Natural Language Processing (NLP) TextBlob is used. It allowed access to necessary text processing operations [28]. In addition, the Pandas library has been accessed to handle and analyze data. It assisted with manipulating data from the numeric table and producing a data frame.

```
# Import the libraries

from textblob import TextBlob
from wordcloud import WordCloud
import pandas as pd
import numpy as np
import re
import matplotlib.pyplot as plt
plt.style.use('fivethirtyeight')
```

Fig. 6. Importing Python library

NumPy was used to perform the mathematical operation. Another built-in library named re (Regular Expression) has been imported for analysis. Regular Expressions, often known as "regex" or "regexp", are utilized to match text strings containing specific characters, words, or character patterns. We can match and extract any string pattern from the text with regular expressions. The imported word cloud gave a visual representation of text data. Typically, words are single words, and the

importance of each is indicated by font size or color.
The Python code was executed in Google Colab employing a Python version (3.6.9). This platform was selected because of its simple data import, processing, and analysis capabilities. The sample data comma-separated value (.csv) file can be imported using the Google Drive path link. First, we must connect Google Drive with Google Colab. Next, we must place the (.csv) file in any area of Google Drive and copy its path using a line of code path = "*paste the copied path link". Google Colab is now prepared to read and analyze the file.
Data cleansing is essential for achieving optimal results. Data filtering provided us with accurate raw data, whereas data cleaning enabled us to obtain data ready for analysis. Our unprocessed data contains mention signs, various symbols, URLs, and hashtags and may contain more languages. These are all ineffective for gauging subjectivity and polarity. To assure more reliable data, we added a line of code to eliminate Non-ASCII characters from English-language tweets.

```
#Create a function to clean the tweets

def cleanTxt (text):

  text = re.sub (r'@[A-Za-z0-9]+',", text) # Removed @mentions

  text = re.sub (r'#', ", text) #Removing the '#' symbol text= re.sub (r'RT[\s]+', text) # Removing RT

  text = re.sub (r'https?:\/\/\S+',", text) # Remove the hyper link

  text = re.sub(r'[^\x00-\x7F]',' ', text) # Remove all language except english
```

Fig. 7. Data cleaning using Python

Figure 8 shows the way how the clean data looks. Here, we have 17,876 cleaned data in one column. We need to add two more columns named Subjectivity and Polarity accordingly.
A ruled-based method to feed that helps to provide training data for subjectivity. Sentience will be subjective if two or more strong subjective clue is presented in the sentence [29].
Subjectivity classification can be expressed in numeric value, specifically absolute value, which lies in (0,1). Large absolute value is associated with the highly opinionated concept [30]. This means if a tweet gets the subjectivity of 1, the subject of the tweet is mostly dogmatic of the keyword. The same goes for the lower value of subjectivity; if a tweet is close to 0, the post maker is not making any sense of the keywords we are finding.

	Tweet
0	want to die .. will try again tomorrow i guess
1	How many times have you told me you want to di...
2	Republicans hate Babies and want them all to d...
3	today I cried cause calcifer is a star that di...
4	and it s my problem if i have no friends and f...
...	...
17871	Police label anyone attacking Judson Almeida a...
17872	Could two followers please copy and re-post th...
17873	CW: transphobia, suicide. \n \n They often do...
17874	On this Throwback podcast episode, I speak wit...
17875	Workplace suicide prevention requires upstream...

17876 rows × 1 columns

Fig. 8. Cleaned data

The polarity supports a subjective opinion. It measures how strong the opinion is. Polarity is classified into three categories: positive, negative, and neutral, and the numeric value for each classification is 1, -1 and 0, respectively. The number can also measure whether the tweet is less positive or positive, less negative or more negative. Suppose a tweet gets the value of 0.20 polarity, which means it is positive but less in number, and again 0.80 is more positive. For the negative polarity, it is the same as the positive polarity. When the polarity of a tweet's number is very close to -1, it indicates the tweet is more negative and vice-versa.
The image below (Figure 10) shows the subjectivity, polarity in numeric value and their analysis of whether the tweets are positive, negative or neutral. It can be easily understood that when a tweet is not opinionated at all, the subjectivity and polarity both get the value of 0.00 and the analysis column shows the tweet as neutral.

	Tweet	Subjectivity	Polarity	Analysis
0	want to die .. will try again tomorrow i guess	0.000000	0.000000	Neutral
1	How many times have you told me you want to di...	0.350000	0.200000	Positive
2	Republicans hate Babies and want them all to d...	0.900000	-1.000000	Negative
3	today I cried cause calcifer is a star that di...	0.000000	0.000000	Neutral
4	and it s my problem if i have no friends and f...	0.000000	0.000000	Neutral
...	...	...	...	...
17871	Police label anyone attacking Judson Almeida a...	0.000000	0.000000	Neutral
17872	Could two followers please copy and re-post th...	0.000000	0.000000	Neutral
17873	CW: transphobia, suicide. \n \n They often do...	0.000000	0.000000	Neutral
17874	On this Throwback podcast episode, I speak wit...	0.666667	-0.233333	Negative
17875	Workplace suicide prevention requires upstream...	0.444444	0.244444	Positive

17876 rows × 4 columns

Fig. 9. Subjectivity and polarity

After plotting the polarity and subjectivity, it was seen that there were only a few less opinionated tweets. The number of negative tweets seemed higher than the positive tweets. Most opinionated tweets lie between 0.4 to 0.80.

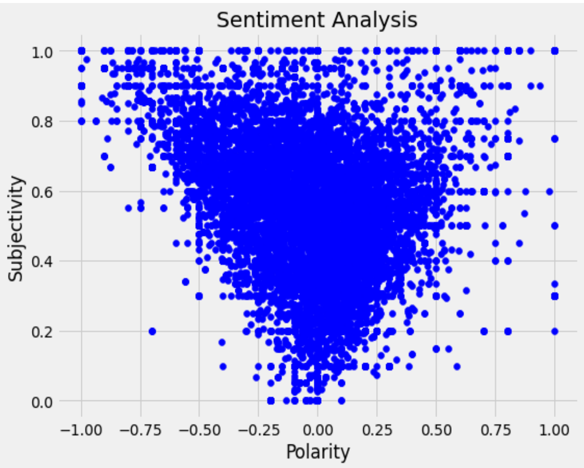

Fig. 10. Sentiment analysis report.

Neutral analysis indicated; that the tweeter users did not have any post-covid psychological impact. They were not bothered expressing their opinion regarding mental health issues. Positive impact means that the users were not dissatisfied in our considered post-covid era. Users who posted the negative tweets in the analysis were vulnerable mentally. Keywords which was related to the suicidal ideation and attempt, such as kill myself, want to die, suicide, mental health issue, suicidal ideation, and hate myself [31], were in our consideration to identify the phycological impact of suicidal ideation.

Those who used these keywords for subjectivity and got the negative polarity might be in a position for a suicidal attempt. We also saw how well these sentiments are distributed. A good way to accomplish this task is by understanding the common words by plotting something called a word cloud, and a word cloud is also known as tag cloud or text cloud. It is a visualization where the more specific word appears in the text as the bigger and bolder in the word cloud [32].

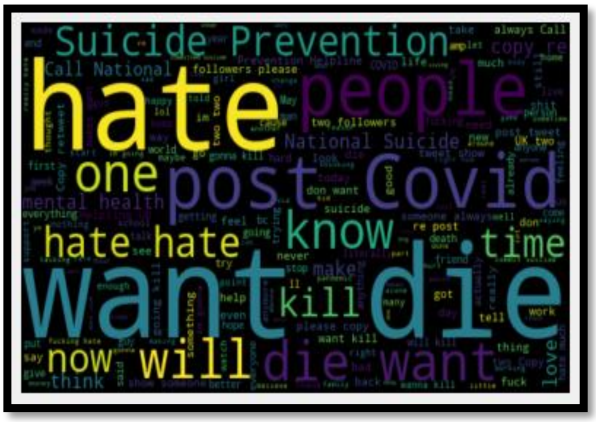

Fig. 11. Generated word cloud.

In the word cloud, we can see hate, die, Covid, kill, want, Suicide Prevention, people are pretty big. That means the mentioned word appeared a lot in the text. Among the word in the word cloud, many seem like people were frustrated after the Covid-19. Some words like 'people, post, know, and time' seem like neutral words. Suicide prevention appeared as a big word, and it is a positive word people used frequently in the post-covid era.

We tried to generate the percentage of positive, neutral and negative tweets. In the analysis, the number of negative tweets was significantly higher than neutral and positive tweets. The percentage of positive and negative tweets was almost similar, but the positive tweets were slightly higher than the neutral ones.

```
[ ]  # Get the percentage of Neutral tweets
     nutweets = df[df.Analysis == 'Neutral']
     nutweets = nutweets['Tweet']

     round ( (nutweets.shape [0] / df.shape [0]) *100 , 2)

     27.0
```

```
[ ] # Get the percentage of negative tweets
    ntweets = df[df.Analysis == 'Negative']
    ntweets = ntweets['Tweet']

    round ( (ntweets.shape [0] / df.shape [0]) *100 , 2)

    43.51

[ ] # Get the percentage of positive tweets
    ptweets = df[df.Analysis == 'Positive']
    ptweets = ptweets['Tweet']

    round ( (ptweets.shape [0] / df.shape [0]) *100 , 2)

    29.49
```

Fig. 12. Percentages of positive, negative and neutral tweets.

Positive tweets: 29.49% or 5,272 tweets.
Word Cloud's words might be associated with the positive tweets: Suicide Prevention, love.
Negative tweets: 43.51% or 7778 tweets.
Word Cloud's words might be associated with the positive tweets: hate, suicide, die, hate, kill.
Neutral Tweets: 27% or 4826.52 tweets
Word Cloud's words might be associated with the positive tweets: People, time, national.
Among the 17876 tweets, 10,1099 tweets were positive and neutral, and the rest of the tweets were negative, which was 7778. The number tells us that their mental health is significantly poor in the post-covid era for the general public. It is anticipated that the suicidal ideation number would not be smaller either.

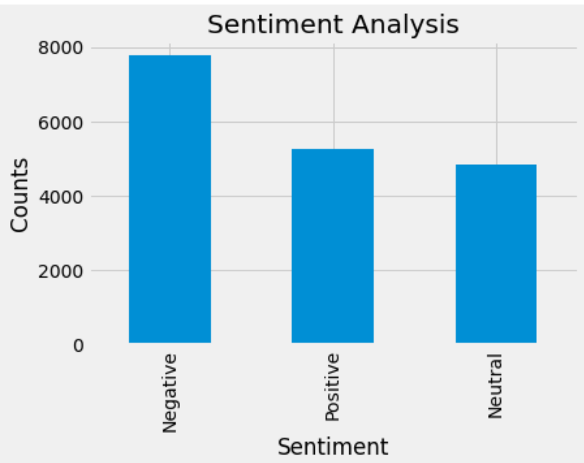

Fig. 13. Visualization of sentiment analysis

6 Findings and Recommendations

The findings from the study provided some evidence to support the null hypothesis that was 'Post-covid phycological impact leads general people to attempt suicide.' Among the whole dataset, we have seen that more than one-third of the tweets are negative and several have suicidal thoughts. Also, people talked a lot about suicide prevention. When the situation goes wrong, people try to protect the situation. Suicide prevention thought would not appear if suicide did not take place. The range of using NPL to measure the broad scenario of a particular subject has become so fascinating, especially in measuring the phycological impact, because accessing data from the Twitter feed is easier than the other sources.

Nevertheless, it has limitations on accessing private accounts, location, and different demographic data. Considering the post-covid era, a specific period was considered, and many tweets have been retrieved that were not opinionated.

The study's recommendations should stem from its limitations. It is strongly suggested to analyze a face-to-face poll and compare the results to the Twitter sentiment analysis. Data that are related to the subject area should be considered. The study only coved the phycological impact on the general population. In the future, some research could be done on preventing mental health issues among Twitter users.

7 Concluding Remarks

Implementing NPL techniques to determine the phycological impact of the general population is advantageous for large data analysis. Even if it has certain flaws, it nevertheless provides some valuable information that may be useful in the future of study. This study's primary objective was to determine the post-covid psychological effects, and the outcome was satisfactory in terms of analysis and findings. However, the popular opinion has been deemed quite worrying. More than one-third of those around us struggle with mental health issues and have suicidal thoughts. Following the

COVID-19 pandemic, the post-covid era may be viewed as another pandemic associated with mental health.

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Md. Rasel Mia is currently employed by United International University in Bangladesh as a Teaching Assistant. Prior to pursuing a career as a teaching and research assistant, he earned his BBA degree in Management Information System (MIS) from the university where he is currently employed. In addition to his undergraduate studies, he worked as a social media analyst for the UIU Marking Forum and developed a keen interest in text and data analysis. Subsequently, this sparked his interest in Natural Language Processing (NLP). His further research interests include Management Information System, NLP, and Data Analytics. Now, he is looking forward to attending an internationally renowned university for his graduate studies to advance his research interest.

Ahmed Imran Kabir is an experienced Faculty Member in the School of Business and Economics at United International University with working experience in the Management Information Systems and Business Analytics subjects. Strong educational background with a Master of Science in Business Analytics from Texas A&M University, United States. He has several research papers published in international and national journals and in ISI and Scopus- indexed journals. His objective is to enroll himself in a successful and progressive academic and research organization where he can use his skills and knowledge to improve himself as well as contribute to the goodwill of that organization and make it more efficient. His research interest areas are – Management Information System, Big Data Analytics, Blockchain Technology, and Multi-disciplinary studies.

Abdullah Al Fahad is a Faculty Member of MIS in the School of Business and Economics at United International University. Abdullah completed his "BBA with a Finance concentration" from University of North Texas and "MS in Information Technology Management" from University of Dallas, Texas, in The United States. Abdullah's corporate experience also speaks volume about his in-depth knowledge as he placed himself with prominent Fortune 500 giants such as J P Morgan Chase in Arlington, Texas, where he started a journey as a "Financial Analyst" and climbed the ladder to "Quality Control Analyst" and a "Subject Mater Expert". After his Masters, Abdullah were positioned as a "Software QA Tester" at "CVS Health" in Richardson, Texas. Abdullah Also hold a directorship at Greenland Group, in Dhaka, Bangladesh. Abdullah's objective now is to have a progressive academic career and contribute his knowledge in research and hence improve his efficiency as an educator. His research interest areas are – Management Information System, Data Analytics, Data Visualization, Python Programming etc.

Appendix - Python code used for the analysis

```
# Import the libraries
from textblob import TextBlob
from wordcloud import WordCloud
import pandas as pd
import numpy as np
import re
import matplotlib.pyplot as plt
import nltk
nltk.download('punkt')
from nltk import word_tokenize
from nltk.stem.snowball import SnowballStemmer
import requests
plt.style.use('fivethirtyeight')

from google.colab import drive
drive.mount('/content/drive')

from os import pathconf
path ="/content/drive/MyDrive/Research Paper/final_dataset.csv"

df = pd.read_csv(path)
Tweet = pd.read_csv(path)
df = pd.DataFrame(Tweet)
df.head(10)

#Clean the text
#Create a function to clean the tweets
def cleanTxt (text):
    text = re.sub (r'@[A-Za-z0-9]+','', text) # Removed @mentions
    text = re.sub (r'#', '', text) #Removing the '#' symbol text= re.sub
(r'RT[\s]+', text) # Removing RT
    text = re.sub (r'https?:\/\/\S+','', text) # Remove the hyper link
    text = re.sub(r'[^\x00-\x7F]',' ', text) # Remove all language except english
    return text

#Cleaning the text
df['Tweet']= df['Tweet'].apply(cleanTxt)

#Show the cleaned text
df

# Create a function to get the subjectivity
def getSubjectivity (text):
    return TextBlob(text). sentiment.subjectivity

# Create a function to get the polarity
def getPolarity (text):
    return TextBlob(text). sentiment.polarity

#Create two new columns
df['Subjectivity'] = df['Tweet'].apply(getSubjectivity)
df['Polarity'] = df[ 'Tweet'].apply(getPolarity)

#Show the new dataframe with the new columns
df

# Plot The Word Cloud
allWords = ' '.join( [twts for twts in df['Tweet']] )
wordCloud = WordCloud(width = 500, height=300, random_state = 21,
max_font_size=119).generate (allWords)
plt.imshow(wordCloud, interpolation = "bilinear")
plt.axis('off')
plt.show()
```

```
#Create a function to compute the negative, neutral and positive analysis
def getAnalysis (score):
    if  score  < 0:
       return 'Negative'
    elif score == 0:
       return 'Neutral'
    else:
        return 'Positive'
df['Analysis'] = df['Polarity'].apply(getAnalysis)

#Show the dataframe
df

#Print all of the positive tweets
j=1
sortedDF = df.sort_values (by=['Polarity'])
for i in range(0, sortedDF.shape[0]):
    if (sortedDF['Analysis'][i] == 'Positive'):
        print(str(j) + ') '+sortedDF [ 'Tweet'][i])
        print()
        j = j+1

# Print all of the negative tweets
j=1
sortedDF = df.sort_values (by=['Polarity'])
for i in range(0, sortedDF.shape[0]):
    if (sortedDF['Analysis'][i] == 'Negative'):

       print(str(j) + ') '+sortedDF [ 'Tweet'][i])
        print()
        j = j+1

#Plot the polarity and subjectivity
plt.figure(figsize=(8,6))
for i in range(0, df.shape[0]):
    plt.scatter(df['Polarity'][i], df['Subjectivity'][i], color='Blue')
plt.title('Sentiment Analysis')
plt.xlabel('Polarity')
plt.ylabel('Subjectivity')
plt.show()

# Get the percentage of positive tweets
ptweets = df[df.Analysis == 'Positive']
ptweets = ptweets['Tweet']
round ( (ptweets.shape [0] / df.shape [0]) *100 , 2)



# Get the percentage of negative tweets
ntweets = df[df.Analysis == 'Negative']
ntweets = ntweets['Tweet']
round ( (ntweets.shape [0] / df.shape [0]) *100 , 2)

# Get the percentage of Neutral tweets
nutweets = df[df.Analysis == 'Neutral']
nutweets = nutweets['Tweet']
round ( (nutweets.shape [0] / df.shape [0]) *100 , 2)

#Show the value counts
df['Analysis'].value_counts()
#plot and visualize the counts
plt.title('Sentiment Analysis')
plt.xlabel('Sentiment')
plt.ylabel('Counts')
df['Analysis'].value_counts().plot(kind='bar')
plt.show()
```