Impact Analysis of COVID 19 Response Measures on Social Media Postings

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Research Article

Keywords: Data and knowledge visualization, Natural Language Processing, Sentiment analysis, Social and Behavioral Sciences

Posted Date: January 5th, 2022

DOI: <https://doi.org/10.21203/rs.3.rs-1217984/v1>

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Abstract

Declared a pandemic in March 2020, SARS-COVID19 has become a health emergency of global concern. The World Health Organization has directed the countries all over the world to take measures to stop the spread of disease. There was a public outburst for policies like lockdown and a mixed review for Working from Home on social networking platforms. By analyzing this change, we can identify the sentiment of people about different policies. A lot of work has been done on sentiment analysis of Covid19 tweets. This is an in-depth impact analysis of COVID-19 response measures on sentiments of tweets. It can help us understand the social media trends revolving around COVID19. For achieving the goal, Google Mobility Report has been used for obtaining data about the mobility in different countries. A huge collection of tweets is extracted using Twitter API. Both datasets are used to analyze multiple trends over a period of more than a year. This article shows the change in social media sentiments with the evolving state of pandemic and the steps taken by authorities. Although, number of cases have more impact on Sentiments, the impact of changing mobility of residential and non-residential areas is also not negligible because average sentiments have seen significant up and down trends because of changing government policies.

1. Introduction

Coronavirus or SARS COVID19 has changed our lives drastically after it was declared a pandemic. It gave a 180 degree turn to our daily routine and has a great impact on our economy, health, education, politics, sports, business and every other field of life. This change in our lives has not only impacted our physical health and mentioned areas but has also affected almost every one of us mentally and emotionally. Mental Health itself is an issue of global concern and the pandemic situation in the world made it worse. People couldn't go out to earn their bread and butter because of the pandemic. There were days when we were not able to do the very basic things like travelling in a bus, attending a class and watching a movie in the theatre. The Standard Operating Procedures (SOPs) and response measures directed by World Health Organizations (WHO) and implemented by the governments globally, restricted us in several ways and it was like a cage for the whole world where everyone was locked up in his home for his health, well-being of his family and stopping the spread of the virus in his proximity. This change in the routine and not being able to do our usual stuff has a very strong mental response from individuals on various social networks especially, the microblogging site, Twitter. Social Media was already being used by a big portion of the world's population and everyone at home during the pandemic gave it more users and usage. Everyone there is sharing his opinion on the current pandemic which is the reflection of how he feels about the change he has experienced. It can be used to determine his mental state because of the response measures taken by the authorities worldwide. We can use this data to analyze the mental health and sentiment of individuals in different countries against the response measures taken. It can help us identify the response measures that are more effective for the public and have a better effect on global and local mental health than those disturbing the people mentally and emotionally. We can also find out how these measures impacted the sentiments in different stages of pandemic. This can also provide us a

general public opinion on the effectiveness of a response measure. Mental health awareness programs for those suffering issues because of COVID 19 restrictions is the need of time and for achieving it, an in-depth analysis of people's approach towards it can play a significant role.

2. Literature Review

Many researches have used the social media as a source for understanding it and used it to estimate the mental response of people to the pandemic. In the work done by Alaa Abd-Alrazaq, Dari Alhuwail, Mowafa Househ, Mounir Hamdi & Zubair Shah [1], the authors have used Twitter Application Programming Interface to study the topics shared by social media users which has some relation with COVID 19 pandemic. They have achieved this objective by using unigram and bigram models which helped them in identifying the main topics discussed in the tweets fetched. Before using the mentioned models, a data preprocessing has been performed like removal of retweets, tokenization and lemmatization. In a study conducted in Blavatnik School of Government [2], a Response Tracker is introduced which shows the measures and steps taken by the government to contain the novel coronavirus spread in different subnational regions of different countries and the whole country over time. The data required for the analysis is collected from multiple publicly available sources like press releases, briefings and news articles with the help of more than one hundred students in Oxford University. In the research done by Cindy Cheng, Joan Barceló, Allison Spencer Hartnett, Robert Kubinec & Luca Messerschmidt [3], a dataset of 13,000 announcements by the government has been considered for identifying the aspects of the data of response measures taken by the government. It can help the researchers and policy makers in assessing the effectiveness of policy. In the study conducted by Gopalkrishna Barkur, Vibha and Giridhar B. Kamatha [4], a sentiment analysis has been performed for the tweets related to coronavirus specifically the lockdown in India to analyze the response of people about the ongoing lockdown in the country. Giliberto Capano, Michael Howlett, Darryl S.L. Jarvis, M. Ramesh & Nihit Goyal [5] analyze the policy making and how it is affected by the current politics and people's behavior of the nation. Datasets are collected from multiple public sources. These datasets are used to identify the nature of the problem of coronavirus and policy responses against it, the uncertainties in the current pandemic and how we can apply the mix of policies to stop the spread of the deadly disease. It also showed the difference in the making of the policies and their timings and how they affect the situation in different countries. CoronaTracker [6] is a predictive model that is used to predict the deaths, recoveries and spread of the virus. Beside predicting the model, the researchers also worked on assessment of economic and political influence of the virus by analyzing the sentiments of the general public and the trends in those sentiments.

In the study conducted by Sijia Li, Yilin Wang, Jia Xue, Nan Zhao and Tingshao Zhu [7], an analysis is performed for the mental health of the general public in response to the declaration of COVID 19 Pandemic. The data is collected from a social media site called Weibo. The posts related to the topic are collected from active users of the social network using machine learning predictive models for analyzing the frequency and emotions of words. People are more inclined towards their health and wellbeing of their family than their friends and other daily activities. It can help the authorities in conquering the COVID

fight with minimal impact on public mental health. The data is collected from a Chinese Social Network, Weibo. The social media posts from Weibo users are analyzed for understanding the sentiments. An OER is used for automated recognition of psychological traits. Word Frequencies and Predictive models for cognitive indicators are used for this recognition. In the analysis done by May Oo Lwin, Jiahui Lu, Anita Sheldenkar, Peter Johannes Schulz, Wonsun Shin, Raj Gupta & Yinping Yang [8], four emotions Anger, Fear, Sadness and joy are taken in consideration for examining the sentiment of twitter users. Tweets are collected in English language containing words like nCoV, Covid19, Wuhan etc. These tweets are extracted using Twitter's official Application Programming Interface and to analyze the emotions on these tweets, an algorithm called CrystalFeel is used.

The work done by Emily Chen, Kristina Lerman & Emilio Ferrara [9] is based on the techniques we can use to collect data from twitter for tweets related to the COVID19. Twitter search API is also utilized to fetch the recent tweets and add them in the datastore. Junling Gao, Pinpin Zheng, Yingnan Jia, Hao Chen, Yimeng Mao, Suhong Chen, Yi Wang, Hua Fu & Junming Dai [10] used a survey approach to analyze the change in mental health. It is found that the increase in social media exposure during the time of pandemic has a major impact on Mental Health especially problems like anxiety and depression.

3. Methodology

The proposed framework in Figure 1 shows how the analysis is done after collection and preparation of the data and sentiment calculation and aggregation.

3.1 Data Collection

There are three different types of data required in this study. For the response measures we need the data about the steps taken by the government of each country against COVID19. For the sentiment calculation we need the tweets related to COVID19 on which we have to do the sentiment analysis and aggregation and visualize these 2 datasets on the basis of date and time. Both the datasets have variables for Time and Location to do temporal and spatial analysis. Another dataset has been used for supporting the visualizations and making them more meaningful. It is a World Health Organization's Official dataset [11] which contains details about number of cases and vaccination details.

The datasets generated and analysed during this study are available from the corresponding author on reasonable request.

3.2 Data Preprocessing

For the twitter dataset, the filtering is done by the Twitter API. The API fetches tweetIds of tweets with the specific keywords. These tweetIds are stored in GitHub Repository from where we are timely fetching the tweets' text and other attributes on which we can perform Sentiment Analysis. Mobility Reports have been filtered out for countries and dates. The data collected from WHO for number of cases and vaccination is

also cleaned. It has been used occasionally in visualization for number of new cases and number of vaccinations.

3.3 Sentiment Analysis & Aggregations

Each tweet is then evaluated to mark it with a sentiment value based on the emotion and opinion of the twitter user. This value is calculated using VADER Algorithm and sentiment lexicon. Now there are tens of thousands of tweets against each day. These tweets are now aggregated using an average (mean) to identify the daily aggregate sentiment of twitter users for a specific region or the whole globe.

VADER algorithm has been used for sentiment analysis of the tweets. Each tweet has been observed for this purpose. Each word as token has been marked with a sentiment value. After scoring each word the average of each word in tweet is calculated to assign a score to the tweet.

3.4 Timelining

Timelining for both the dataset will be done using the daily aggregates from both sets. The aggregate sentiment score against the tweet also has the date which will be used to do the timelining. In the case of google mobility report's response measures data, we already have the data attached to each row. The timeline for sentiments will help us identify the daily sentiment change and the response measure timeline will help us in analyzing the daily ups and downs in the response measure values. Timelining is also done for COVID19 cases to add more insights in the work.

3.5 Visualizations

Visualization is a very good approach to identify more trends in the data. Visualization makes the interpretation of the data easier and the easier it becomes to interpret the data, more trends and patterns in the data can be extracted. We also need this step to identify the phases of pandemic and evaluate the sentiment on these phases. In this step, we have used different plots and graphs to extract insights from data and use these insights in our analysis and conclusion.

3.6 Trend Analysis

This is the step where we analyze different trends present in the data. These trends are analyzed by placing response measures and sentiments on a timeline. This can help us identify the areas we need to work on and measures from which we have more positive public feedback.

For trend analysis we have used Microsoft PowerBI on which we have created several graphs and plot that have been discussed in results parts. PowerBI is a powerful tool for analyzing trends in data. It not only visualizes the data in plots and chart but also allows us to merge, transform, filter and examine the data and creates a set of insights to identify the relationships between different variables of data, correlations and variance.

4. Results

After we are done with analysis, aggregation and visualizations. We have to identify the trends and patterns in the data.

4.1 Global Sentiment Change

Globally we have seen a massive change in public opinion because of COVID19 on tweets. The analysis in this part covers the global change in these sentiments over the period of one and a half year. In Figure 2, there are 7 variables that are changing over time grouped by month on twitter that shows the public opinion on the scale of -1 and 1. Here -1 is the negative opinion and 1 is the positive opinion while 0 is neutral.

Following are some interesting insights from the response measures and sentiments from all over the globe.

- From where we started observing the data, the sentiments are already at the negative side because of the ongoing situations that time, the initial fear and lack of knowledge about dealing the situations. They are at -0.14 in March 2020 already and dropped by 0.4 further in April 2020.
- The sentiments have a slight uptrend in May 2020 but they again have a significant drop from -0.12 in May 2020 to -0.32 in July 2020 because of the increasing number of cases.
- There are several uptrends in these Average Sentiments. Major uptrends are between July 2020 and August 2020, September 2020 and November 2020 and the most recent major uptrend in January 2021 to March 2021.
- Average sentiments touched the peak in March 2021 at 0.27 because of the decreasing number of cases and increasing mobility. Average sentiments are at their steepest and are the lowest in July 2021 at -0.43 because of the mobility going back to normal even after the increasing number of cases.
- Between March 2020 and August 2021, Retail and Recreation has the largest increase (110.93%) while Daily Sentiment has the largest decrease (152.96%).

Most of the Mobility variables have the inverse relation with Sentiment Average. Park have a correlation value of -0.45 indicating the inverse relation of the mobility of Parks and AverageSentiment. Whenever we see a rise in mobility of Parks, the sentiments have dropped significantly. Other non residential areas also have the same relation but with less impact.

Residential Mobility is the only parameter with which the sentiment increases and decreases. The value of the correlation between Average Sentiment and Residential Mobility is 0.12 as shown in Figure 14. Although, it doesn't have a very strong correlation but increasing the mobility in residential areas increases the sentiment. Whenever the restrictions are imposed on residential areas, the sentiments drop to some extent because most of the people are living at their homes in the times of pandemic and this frustration of not coming out of their homes or leaving home to go back to offices, reflects in their social media postings and sentiments.

The response measures taken by government do have relation with each other too. These relations are stronger than other relationships we have analyzed. They have high impact on each other which makes sense because increased mobility in certain areas will definitely impact the mobility in others. Whenever there is an increase in mobility of Residential Areas, we have seen a decline in mobility of others. In Figure 14, the correlation between these variables has been shown in a correlation map.

Retail and Recreation and Transit Stations have the highest positive correlation of 0.97 because whenever there is an increase in mobility of Retail and Recreation people have used Transit Stations equally to commute to these places of Recreation. Grocery and Pharmacy has the similar relation with retail and recreation with a correlation value of 0.95 followed by Parks with correlation value of 0.88 and Workplace with correlation value of 0.64. Workplace is less significant in comparison to others.

When we talk about residential areas, the mobility of them has a negative impact on all other non-residential areas. Whenever there are restrictions at public places, parks, workplaces the number of people in homes and societies are bound to increase any way. That is the reason behind this negative relation of residential areas with others. The most contributing places on residential mobility declines are workplaces and transit station with the correlation value of -0.89, followed by retail and recreation with correlation of -0.83, Grocery and Pharmacy with correlation of -0.74 and Park with -0.7.

Workplace Mobility have lesser impact on other places in comparison to others except Residential Mobility. The correlation of workplaces with other no residential lies within the range of 0.5 and 0.75.

Transit Stations are way to commute to different places, that is the reason they have more significant relation with others. Grocery and Pharmacy has correlation of 0.91 with Transit Stations, Parks with correlation of 0.89 and workplaces with correlation of 0.74. Parks have a correlation of 0.8 with Grocery and Pharmacy which also is a strong relationship.

4.2 Regional Sentiment Change

In different countries, the response measures have different impact on Sentiments and we have only seen the sentiments change till now in different regions of the world. Now we are going to see the response measures taken by governments of the major countries around the globe and how they have impacted the sentiments.

Canada

In Canada, Parks are the most mobile areas throughout the pandemic. None of the response measure has a significant impact on sentiments. Parks have the highest impact of them all on Sentiments and that too is a very small correlation value of -0.13. Residential Mobility has a very small positive relation with Sentiments. Mobility of all other places has a negative (not significant) impact on it. The most noticeable trend in this country is the increased mobility of Parks and that too with a very small impact on Sentiments that means people are okay with parks opening in the pandemic and very few of them have issues with it. Sentiments in this country are also slightly positive which shows people are fine with the

policies. They are not very happy but not sad too with the response measures taken by Canadian Government as shown in Figure 3.

United States of America

In United States of America, Parks are less mobile than Canada but are the places with the highest mobility when compared to other places in the States. There is a negative correlation of -0.38 between the mobility in Parks and AverageSentiments that means Sentiments in this country decreases with increasing mobility in Parks. Likewise, Transit Station and Grocery and Pharmacy have the same relation but with less impact and correlation of -0.19 and -0.17 respectively. Workplace and Retail and Recreation have negligible negative correlation while Residential Mobility has the positive correlation of 0.16. So, we can say Americans are not happy with the increasing mobility in the parks and have slightly sliding and not so strong opinions about other response measures taken by the Government of different states in the country as shown in Figure 3.

Brazil

People in Brazil have no strong opinion about the response measures taken by the Brazilian Government. Grocery and Pharmacy and Residential areas are the most mobile places in this country. Transit Stations, Parks and Retail and Recreation are the least mobile as shown in Figure 4. Mobility of all areas in Brazil has the correlation of almost 0.05 either positive or negative and Brazilian are not irked with their government even if they are not happy.

Russia

Like Brazil, Russia also has very small correlation for response measures and sentiments. All of the variables have these small, non-significant correlation with Sentiments but all of them are positive and Sentiments of tweets from Russia are increasing with increase in mobility of them. Sentiments of Russia are also stable on the positive side with a little distance from zero. Parks are the areas where mobility is highest in Russia and trends of which are very similar to Canada where Parks have a mobility much higher than baseline after the initial months of pandemic as presented in Figure 4.

France

Like many other countries, Residential areas are the only areas where Average Sentiments increase with the increase in their mobility in France. Beside that all other places have a negative impact on Sentiment and they drop with increasing mobility. Parks have the highest correlation with Sentiments in case of Park. This is a negative correlation of -0.25 followed by Transit Station with correlation of -0.22 and Retail and Recreation with correlation value of -0.2. Parks in this region have experienced a rise in mobility in mid of both the years and it also has a negative impact of public opinions. People there, are not very happy with French Government when they decided to remove restrictions from parks, Transit Stations and Retail and Recreation because they feel it can be a potential cause of increasing number of cases in France. Trends of France can be seen in Figure 5.

United Kingdom

In United Kingdom, the impact of mobility is more significant than United States, Canada, France and Russia. Among the mobility of all places, Transit Station Mobility has the highest correlation of -0.3 with a negative impact on Sentiments, followed by Retail and Recreation with correlation value of -0.24, Parks with correlation of -0.22 and Workplace Mobility with the correlation of -0.18. Residential Mobility is on the positive side with correlation of 0.27. Sentiments increase with the increase of mobility in Residential areas and decrease in all other places as presented in Figure 5. The least impact is of Grocery and Pharmacy that is a correlation of -0.12. People in United Kingdom are not fine with the increasing mobility of the Transit Stations, Parks, Workplaces and do not agree with government's decision of removing the restrictions on these places when the number of cases are rising.

Italy

Italy is one of the countries most affected by the COVID 19 and Sentiments down the zero line are the proof of the impact it has on the public. Like many others, mobility in parks has a massive increase in Italy too after the initial months of the pandemic and sentiments also has a drop whenever the mobility in parks has increased as shown in Figure 6. Italians have considered mobility in not just parks, but other places except the Residential areas too, a big reason behind the spread of the virus. The mobility of Parks has correlation of -0.26 followed by Transit Stations with correlation of -0.22, Residential with correlation of 0.21, Retail and Recreation with correlation of -0.18 and other two places which have a non-significant correlation with the Average Sentiments. So, we can say that people in Italy are discontent and a little disappointed with the increasing mobility in Parks and Transit Stations ordered by their government.

Spain

Spain has almost the same trends for mobility like Italy. Although lesser than Italy, but Spain also has higher mobility in Parks after the start of the pandemic and after mid of 2021 and this increase is aligned with the decrease of the sentiments but this impact is very minimal in case of Spain when compared to Italy as seen in Figure 6. The correlation of Parks with Sentiment is of -0.04. There are differences in Spain for the relation of mobility and Sentiments. Mobility of all areas have a very small correlation. Residential and Parks mobility have a negative, very small and negligible correlation. Mobility in other areas has a positive correlation and increase with increase in Average Sentiment. Workplace Mobility is the most significant in Spain which increases with sentiment increase and it has a small correlation of 0.12. People in Spain have a mixed reaction and an average, close to zero response to the steps taken by their Government for COVID 19.

Australia

Australia has a different impact of response measures taken by the government which is inverse of what we have seen in most of the countries. Here Residential Mobility has the negative impact on Sentiments which is positive in other countries. Mobility of others has a positive impact on Sentiments in Australia

but negative in other countries. Transit stations has the highest impact which is a small correlation value of 0.17. Residential and Grocery and Pharmacy are the most mobile places in Australia as show in Figure 7. While mobility of other areas has dropped from the baseline. People of Australia have a slightly positive opinion about the steps taken by the government and are satisfied if not happy with the response measures.

India

Like Australia, People in India are also in favor of increased mobility. Whenever the mobility of residential areas increases, the sentiments have dropped. Residential Mobility has the highest impact with correlation of -0.25 followed by Workplace Mobility with correlation value of 0.23, Grocery and Pharmacy with correlation of 0.21, Transit Station with correlation of 0.19, Retail and Recreation with correlation of 0.15 and Park with correlation of 0.1 with AverageSentiments. Indians have shown some negative sentiments when the mobility of the areas decreased. Whenever the mobility of non-residential areas rises, the sentiments from India are positive. Residential and Grocery and Pharmacy are the most mobile areas in India and have mobility more than baseline after the initial days of pandemic which can be seen in Figure 7.

Turkey

In Turkey, Parks, Residential and Grocery and Pharmacy are the most mobile areas as shown in Figure 8. None of the areas in this country have significant impact of AverageSentiment. Mobility of Retail and Recreation, Transit Stations and Workplaces never came back to baseline after it dropped with the start of the pandemic in March 2021. Mobility of Grocery and Pharmacy increased tremendously between March 2020 and August 2021. People in Turkey are not very opinionated about the response measures taken by the government because the correlation of Average Sentiments with Mobility of any place is very minimal and never exceeds 0.1 on both positive and negative side. As far as the Sentiments are concerned, they are slightly positive in Turkey after seeing minor drop from zero line in the initial months of the pandemic and increased on more in late 2020 and early 2021.

United Arab Emirates

In United Arab Emirates, Parks are the most mobile areas while Transit Stations and Retail and Recreation are least mobile and both of them have uptrends after 2021. Sentiments in United Arab Emirates are lowest in mid of 2020 as shown in Figure 8. Most of the areas have increase in mobility after 2020. The impact of Transit Station Mobility on Average Sentiments is highest with correlation of 0.17 followed by Retail and Recreation with correlation of 0.13 and Residential Mobility with correlation of -0.11. Parks and Grocery and Pharmacy has a same impact with correlation of 0.11 and Workplace mobility with correlation of 0.08. Residential Mobility has a negative impact on Sentiments and Sentiments decline with the increase in Residential Mobility. People in United Arab Emirates are not in favor of sitting at home and are a little more interested in going out.

Government Response measure have some impact on sentiments for sure although small but not negligible. Mobility of Parks has the worst impact and Residential mobility has the best. These highs and lows for sentiments have changes for different countries. The relationship of mobility of different areas is very impactful. These are very few insights and the more we dive in data, the more we will explore.

5. Conclusion

Response measures do have an impact on mental health. The decrease in mobility in public places because of the COVID 19 Pandemic and lockdowns have affected the mental health and taking timely and efficient measures can improve the mental health globally. This impact is less significant than the impact of number of cases and deaths but it does have some significance and undeniably affects the people.

Different response measures have different impact on mental health. Mobility Increase in Residential areas have positive impact on Sentiments usually, while other non-residential places have negative sentiments with increasing mobility there. Increase in restrictions in Parks has the best impact and whenever parks have been reopened for public the sentiments have seen the lows. While restriction in residential places, societies, and neighborhood have the worst impact on social media postings. It shows that people are more inclined to stay at home then going to a park. Initially, people were happy at homes but then comes a period when people started feeling caged in their homes and the sentiments dropped too.

These are the global trends which can change if we talk about countries individually. Western countries are more inclined toward lockdowns and staying at home. Countries like United States of America, Canada, Italy, United Kingdom, France and Spain have a good opinion about lockdowns and ban on public places. While on the other hand, Eastern Countries like India, Australia and United Arab Emirates are not in favor of lockdown and have positive sentiments when mobility is increased in public places. There are some countries where people have very insignificant and negligible opinion about the restrictions and response measures taken by government.

Governments' response measures have certain impacts on global mental health. Sometimes, they have a positive impact and other days they have negative impacts. Different response measure have different impact and they change significantly due to local, cultural and societal factors. Vaccinations are of some relief to public. Identifying the response measure that are not working in favor of public mental health can surely work in improving that and suggesting better alternatives. Still, there is a lot of scope of enhancements in this work. As this is a task of Data Mining, there is no limit of discovery. The more you dive in the data, the more you discover. The more you discover, the more you can contribute to efficient policy making for the pandemic, new variant and it can help us in planning and defeating Pandemics in future too.s

Declarations

Conflict of Interest

On behalf of all authors, the corresponding author states that there is no conflict of interest.

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Figures

Figure 1

Architecture Diagram

Figure 2

Average Daily Sentiment and Mobility by Month

Figure 3

Sentiments and Mobility for Canada and United States

Figure 4

Sentiments and Mobility for Brazil and Russia

Figure 5

Sentiments and Mobility for France and United Kingdom

Figure 6

Sentiments and Mobility for Italy and Spain

Figure 7

Sentiments and Mobility for Australia and India

Figure 8

Sentiments and Mobility for Turkey and UAE