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Mental Health and the COVID-19 Pandemic: Analysis of Twitter Discourse

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Completed Research

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Abstract

This study analyzed Twitter discourse to understand the association of the COVID-19 pandemic with mental health. The study compared tweets' volume over time, tweets' volume per mental health category, emotions, and the top hashtags on mental health before and after November 2019, the month on which the first COVID-19 case was reported. We analyzed a total of 273 million English tweets on mental health collected from 56 million unique users. Results and analysis showed a significant shift in trend for the volume of tweets on mental health over time. There was also a notable increase in the volume of tweets on depression, anxiety, stress, and suicide mental health groups. The volume of tweets posted by males and females was comparable. Finally, there was a noticeable increase in the average daily tweets that mention suicide prevention and mental health during the COVID-19 pandemic.

Keywords

Mental Health, Social Media, Twitter, Pandemic, COVID-19

Introduction

The COVID-19 pandemic has impacted different aspects of the population's daily life. The pandemic forced millions of people to work from home and avoid social gathering. Furthermore, the pandemic had its impact on the economy and caused the highest unemployment rates since decades. Overall, COVID-19 impacted people's life directly or indirectly, creating an environment of fear, anxiety, and stress among the developed and developing societies (Singh et al. 2020). Accordingly, the population's mental health during the pandemic requires a significant attention to understand and characterize its prevalence.

With the pandemic and associated lockdowns, social media platforms have been increasingly used as a result of limited opportunities for gathering and being socially connected (Wahbeh et al. 2020). Recognizing the importance of social media, a number of studies (Chen et al. 2020; McClellan et al. 2017; Roy et al. 2020; Zhou et al. 2021) have used social media platforms to understand and characterize population's mental health. However, there are no studies that leveraged social media (SM) to explore and understand COVID-related mental health in a manner that can provide insights to priority issues and guide public health campaigns. In essence, the analysis of mental health discourse on social media can shed light into the magnitude of the issue, the prevailing topics, and the overall extent of the crisis. Identifying prevailing mental health issues can also help in prioritizing intervention and mitigation strategies.

In this research, we analyze mental health discourse on social media, namely, Twitter, during the COVID era and compare trends of mental health issues before and after the pandemic. Such analysis could help design and adjust campaigns that promote mental health and reduce anxiety, depression, and stress. Such campaigns are necessary for people with history of "psychiatric disorders, COVID-19 survivors, and older adults" (Sher 2020). The remainder of the paper is organized as follows: the next section provides an overview of existing literature related to mental health and social media analytics. The research design and methodology section discusses data collection, preparation, and analysis. The results and discussion sections summarize the findings. The paper concludes with a summary of contributions and limitations.

Literature Review

A number of studies have relied on social media to analyze and predict various mental health related phenomenon. A systematic literature review by Karmegam, Ramamoorthy, and Mappillairajan (2020) addressed the feasibility of using social media data for mental health surveillance, especially, during disasters. A total of 18 studies were included in the review. The review showed that Twitter is widely used for mental health surveillance during disasters. Furthermore, mental health surveillance in a number of studies was done by studying sentiments and emotions using machine learning methods. Along these lines Amir et al. (2019) proposed a social media-based cohort for the surveillance of mental health. The cohort was developed by sampling Twitter users at random and infer key demographic from those users. The cohort was then used to develop a classifier that can be used to measure relative rates of post-traumatic stress disorder (PTSD) and depression in a sample population. Results showed that disaggregating differences per demographic group helped make a clear distinction on how PTSD and depression vary across different parts of the population. Makita et al. (2020) analyzed Twitter discourse during a mental health awareness week. The authors collected a sample of tweets based on a search query based on mental health related terms. A content analysis approach was followed, and results showed that 'awareness and advocacy', 'stigmatization', and 'personal experience of mental health/illness' are the central discourses within the sample.

Research also aimed at using social media data to detect potential adverse effects of mental health issues. For example, Kumar et al. (2015) analyzed the change in suicide content on social media following celebrity suicide. The authors collected social media data from a suicide forum on Reddit. The authors analyzed the posting volume as well as the content right after the death of ten high-profile suicides. Results showed that after the death, posting activities increase and was associated with increase suicidal ideation. Another study by McClellan et al. (2017) used *Crimson Hexagon's ForSight software* to collect 176 million tweets from 2011 to 2014 directly related to mental health based on a number of hashtags related to depression or suicide obtained from *hashtagify.me* website. The authors used the *autoregressive integrated moving average (ARIMA) model*, specifically *a natural log transformation*, to analyze tweets' frequency and trends in the volume of tweets. Results showed heightened Twitter activity regarding depression or suicide. Luo et al. (2020) showed that Twitter could be used to early detect latent suicidal factors. The factors are shown to be correlated with ground truth surveillance and survey data and can reflect the suicidality trend in time. Roy et al. (2020) proposed a machine learning algorithm based on neural networks to forecast future risk to suicidal thought from Twitter data. Authors used suicide related terms like burden, stress, loneliness, hopelessness, insomnia, depression, and anxiety to collect Twitter data. Results showed a significant correlation between regionally Twitter data and county-wide suicide death rates across 16 days.

Social media has also proven useful in analyzing the impact of calamities on mental health. In that regard, Gruebner (2016) proposed the need to use social media as a tool to identify populations during and after disasters. More specifically, the use of sentiment analysis and space-time syndromic surveillance can be effective tools to detect "geographically concentrated emotional reactions after traumatic events". Such approach can help identify affected population and provide a pro-active approach for developing the necessary intervention to promote the general population mental health after disasters and incidents. More recently, Zhou et al. (2021) proposed a novel classification model to identify depression polarities in Twitter during the COVID-19 pandemic. The model is based on multimodal features from tweets. The tweets were represented using the well-known term frequency-inverse document frequency weighting scheme. Results showed that the proposed model is effective for detecting community depression dynamics during the COVID-19 pandemics. Furthermore, the results indicated that people become more depressed in association with increased confirm COVID-19 case.

The COVID-19 pandemic as well as policies and guidelines that followed to minimize the impact of the pandemic on the general population health have impacted mental health. However, such impact on mental health is inadequately understood (Gloster et al. 2020). To better understand such impact, there is a need to analyze the general public discussions on social media before and after the pandemic. According to the literature and up to the knowledge of the researchers, there are no studies that characterized the impact of COVID-19 on mental health by comparing and analyzing online discourse related to mental health before and after the start of the COVID-19 pandemic. The ability to characterize changes in mental health related discourse on social media can help provide more guidance for the provisioning of mental health services (Gruebner 2016).

Research Design and Method

Figure 1 shows the methodology followed in this study for analyzing Twitter data related to mental health.

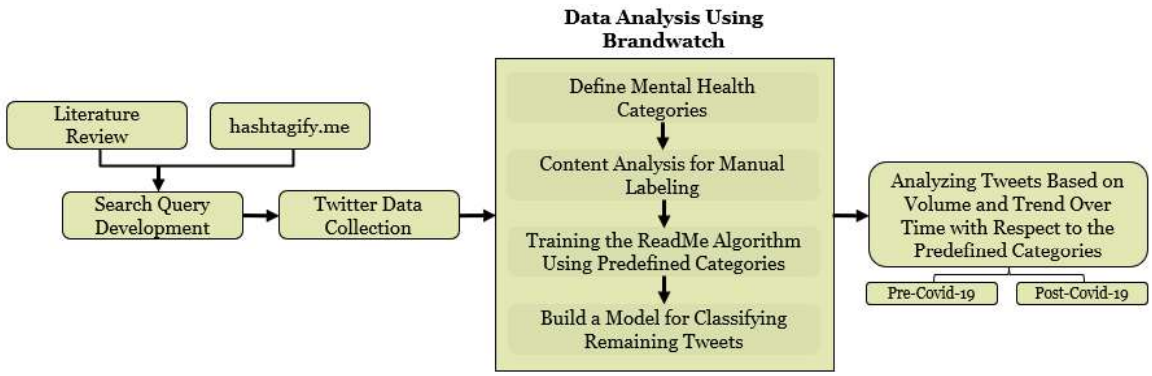

Figure 1: Research Methodology for Mental Health Discourse on Twitter

The methodology starts by reviewing the existing literature on mental health as well as searching through the hashtagify.me Website to identify a set of commonly used and relevant terms to be used for searching Twitter for relevant tweets related to mental health. The search query in figure 2 is used to search Twitter using Brandwatch to extract tweets between July 1st, 2017 and February 1st, 2021. The query takes into consideration any non-relevant tweets that could match the identified search terms. A total of 273 million English tweets were collected from a total of 56 million unique users. These numbers were made possible because Brandwatch social analytics platform provides access to every public tweet posted in any language and geographic locations as long as the tweet matches the search query.

```
((depression  OR depressed OR stress OR anxiety OR "mood disorder" OR PTSD OR suicide  OR bipolar
OR "mental health")
 OR
(#mentalhealth* OR #mindfulness OR #depression OR #depressed OR #PTSD OR #suicide OR #mentali
llness OR #sad OR #Posttraumaticstressdisorder OR #suicideprevention OR #mooddisorder))
AND - (bomb* OR "great depression" OR "economic depression")
AND - (RT OR http*)
```

Figure 2: Search Query

Once the data was collected, it was analyzed using Brandwatch's ReadMe algorithm (Hopkins and King 2010). The algorithm requires a training set of documents. Such training set is hand-coded by the researchers into a set of predefined categories . In this study, the mainly defined categories related to mental health are stress, depression, anxiety, suicide, PTSD, and bipolar. The tweets represent the set of documents for training purposes. Once the categories were defined in Brandwatch, a sample set of tweets were analyzed manually by one author and confirmed by a second author in order to determine tweet's relevancy with respect to the categories to which a tweet belongs to. After the sample tweets were manually classified into the predefined categories, the algorithm ran on the remaining tweets in an iterative fashion, ensuring that the examples clearly outline each category. Then, based on the training phase, the resulting model was used to classify the remaining tweets into the six categories. Trends of tweets volumes over time, trends of tweets per mental health category, top ten hashtags, and emotional analysis were automatically generated by

Brandwatch and compared before the start of COVID-19 (November. 17, 2019 is the date on which the first COVID-19 case was reported (Bryner 2020)) and after that date up to February 1st, 2021. The top ten hashtags were analyzed and compared for the periods before and after November 2019. For emotional analysis, we focused on four emotions: sadness, fear, anger, and disgust. Furthermore, for the comparative analysis, we normalized the volume of tweets for each emotion and each hashtag by the number of days and calculated the average tweets per day for each separate analysis.

In order to assess the impact of COVID-19 on the volume of tweets over time, a time series analysis was conducted using the Time Series Modeler procedure (IBM 2013). The procedure "estimates exponential smoothing, univariate Autoregressive Integrated Moving Average (ARIMA), and multivariate ARIMA models for time series, and produces forecasts" (IBM 2013). The Expert Modeler part of the procedure is used to "automatically identify and estimate the best-fitting ARIMA or exponential smoothing model for one or more dependent variable series" (IBM 2013; Jakasa et al. 2011). The Model produces the forecasted values, the Lower Confidence Limit (LUL), and the Upper Confidence Level (UCL) of the confidence interval. In addition to the time series analysis, a trend line was generated in order to further assess the impact of COVID-19 on the volume of tweets over time. A dummy variable reflecting the first date COVID was introduced. Statistical significance of the dummy variable coefficient at 5% was used to test for statistically significant change in the slope of the trend line coinciding with the start of COVID-19.

Results

A total of 273 million tweets from 56 million unique users were analyzed with respect to the predefined categories. Among those who shared their gender identity, 2,739,032 authors (49%) were males, and 2,807,842 authors (51%) were females. Figure 3 shows the distribution of the volume of tweets on mental health over time split by gender. As shown in the figure 3, we can notice a similar pattern in terms of the number of tweets shared by male and female after November 2020, the month on which the first COVID-19 case was reported (Bryner 2020).

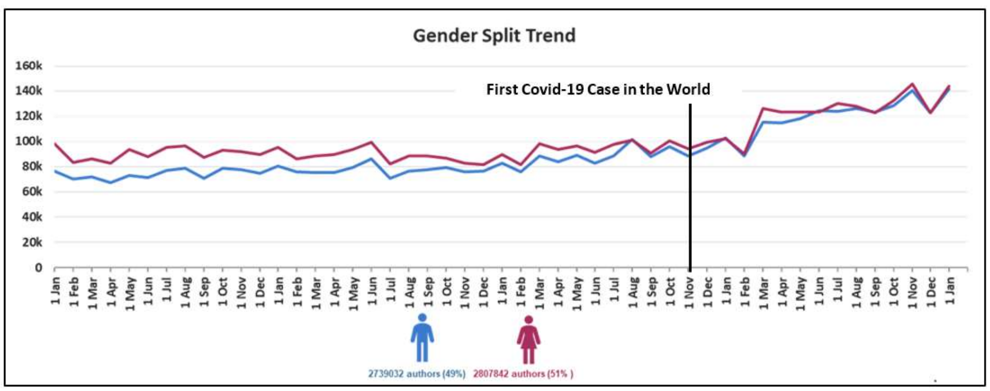

Figure 3. Volume of Tweets on Mental Health Over Time Split by Gender

The distribution of the volume of tweets over time is shown in figure 4. The figure also shows the result from the time series analysis. Actual tweets volume values are represented by a solid red line. The forecasted values are presented using a solid orange line based on the Winters' Additive model selected and generated by the Expert Modeler in SPSS, with the 95% prediction interval dotted lines (green dotted line for UCL and gold dotted line for LCL). As shown on the figure, after March 2021, the date where the WHO declared the COVID-19 a pandemic, the actual volume of tweets exceeded the prediction interval. Such difference may reflect a significant event that was not accounted for by the model (McClellan et al. 2017), which could be explained by the introduction of COVID-19.

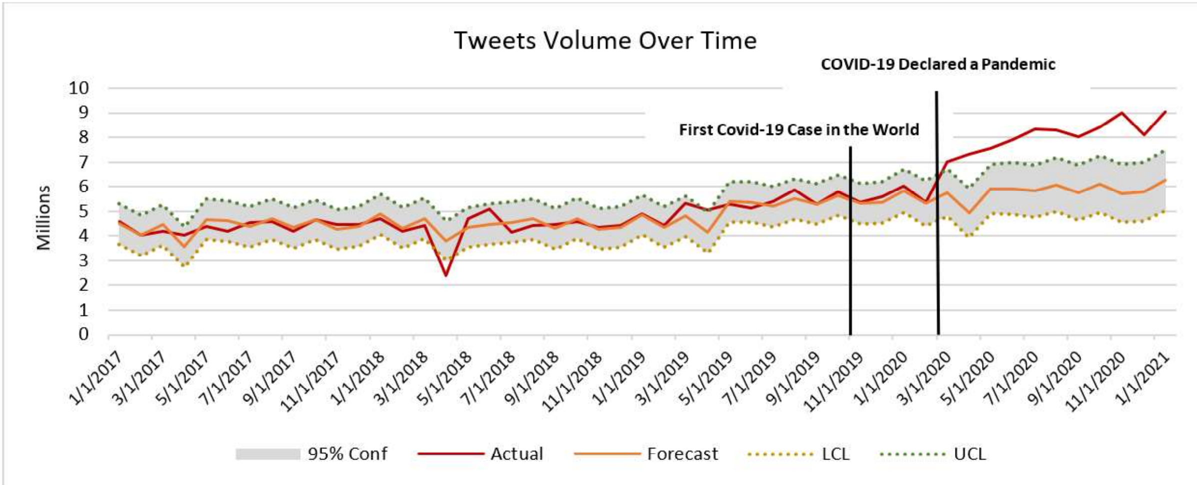

Figure 4. Volume of Tweets on Mental Health Over Time

Figure 5 depicts the trend line against the actual volume of tweets for the analysis period. The R^2 is 0.9 with the kink representing the start of COVID-19. The coefficient for the dummy variable is highly significant with a p-value < 10^{-8}.

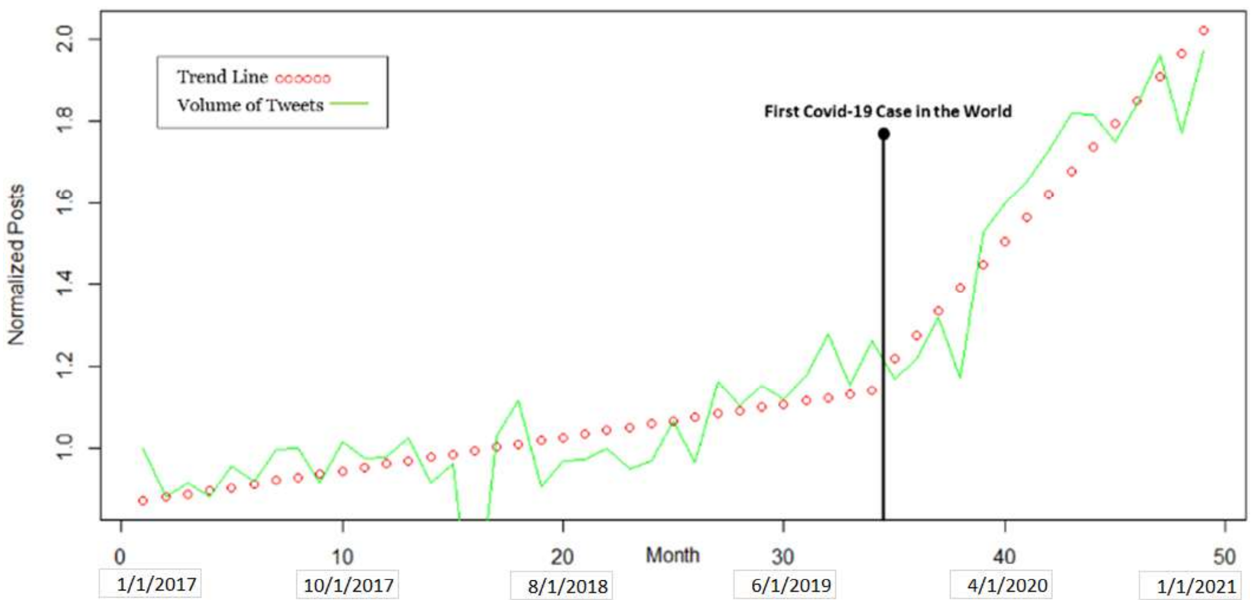

Figure 5. Trend lines for each of the preCovid and postCovid

Figure 6 shows the volume of tweets over time by category. These categories were mainly related to *stress, depression, anxiety, suicide, PTSD,* and *bipolar*. Overall, the number of tweets posted increased noticeably after February 2020. We can see a large increase in the volume of tweets related to depression starting March 2020. Similar pattern could be inferred for stress, anxiety, and suicide. Finally, the volume of tweets related to PTSD and bipolar remains pretty much the same over time.

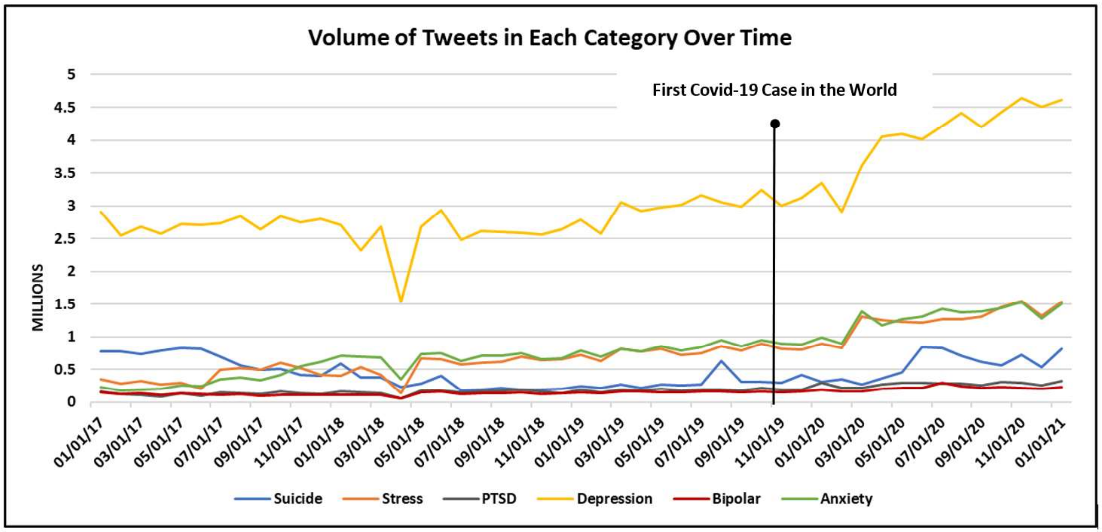

Figure 6. Volume of Tweets on each Mental Heath Category Over Time

Table 1 shows the average number of tweets per day for the top ten hashtags related to mental health before November 01, 2019. As shown in the table, the top hashtags are sad, mental health, depression, bellletstalk, anxiety, mindfulness, mentalhealthawareness, mentalhealthmatters, kcapinoystar, and ptsd. The table also shows the average number of tweets per day for the top ten hashtags related to mental health after November 01, 2019. The top hashtags are mentalhealth, sad, mentalhealthmatters, depression, covid19, mentalhealthawareness, suicideprevention, anxiety, mindfulness, and bellletstalk.

According to the table, we can notice a substantial increase in the average number of tweets with hashtags on depression, mentalhealth, mentalhealthawareness, and mentalhealthmatters after November 01, 2019. In the same time period, we can notice a major decrease in the average number of tweets with hashtags on sad. Furthermore, after November 01, 2019, two new hashtags 'covid19' and 'suicideprevention' are widely used on daily basis in tweets related to mental health. These hashtags were not present in the top ten list before November 01, 2019.

Top Hashtags Before Nov. 01, 2019	Average Tweets Per Day	Top Hashtags After Nov. 01, 2019	Average Tweets Per Day
#sad	923	#mentalhealth	1,152
#mentalhealth	690	#sad	563
#depression	246	#mentalhealthmatters	325
#bellletstalk	224	#depression	312
#anxiety	217	#covid19	284
#mindfulness	203	#mentalhealthawareness	263
#mentalhealthawareness	155	#suicideprevention	249
#mentalhealthmatters	138	#anxiety	244
#kcapinoystar	110	#mindfulness	211
#ptsd	105	#bellletstalk	201

Table 1: Average Number of Tweets for Top Ten Hashtags Before and After November 01, 2019

Table 2 shows the emotional analysis of the average number of tweets per day before and after November 01, 2019. As shown in the table, the average number of tweets per day for each emotion group has increased significantly. The average number of tweets per day has increased by 6,075 (77%) tweets for anger emotion followed by 2,619 (68%) tweets for disgust, 18,310 (66%) tweets for fear, and 58,064 (56%) for sadness.

Emotion	Average Tweets Per Day Before Nov. 01, 2019	Average Tweets Per Day After Nov. 01, 2019
Sadness	103,397	161,461
Fear	27,914	46,224
Anger	7,921	13,996
Disgust	3,836	6,455

Table 2: Average Number of Tweets for Top Ten Hashtags Before and After November 01, 2019

Discussion

The collected data from Twitter and data analysis show that social media can help reveal an important shift in trend analysis over time, emotions, and the top tags on mental health during the COVID-19 pandemic. Gender is considered an important factor when addressing the pandemic impact on mental health disorder on the general population (Yazdavar et al. 2020). The results show the impact of the pandemic on the number of daily tweets posted by both genders, where smaller gap exists between the number of tweets posted by males and females after November 2019. Overall, there is an increased trend in terms of number of tweets related to mental health after November 2019, the month on which the first COVID-19 case was reported globally. This demonstrates the potential impact of the COVID-19 pandemic on the general discourse about mental health. Interestingly, this increase in tweets volume on mental health after March 2020 could be associated with the fact that on March 11, 2020, the world health organization (WHO) declared COVID-19 as a pandemic because there was concerns related to the alarming levels of spread and severity of the virus (WHO 2020).

Similar trend for the volume of tweets over four out of the six categories was also evident. The four categories are depression, anxiety, stress, and suicide. In general, there could be a prevalence of a major depression after major incidents and disaster (Person et al. 2006). This is evident in the analysis where the volume of tweets in the depression category has increased substantially compared to other categories in the analysis. During the pandemic, people have developed mild, moderate, and severe depression; where the prevalence rates of depression in a sample population were 19.8% (Choi, Hui, and Wan 2020) and 48.3% (Gao et al. 2020). Anxiety has also increased after the pandemic. The prevalence of anxiety in a sample population was 20.4% (Li et al. 2020) and 14.0% (Choi, Hui, and Wan 2020).

Evidence for stress has also increased after the pandemic. Such stress could be related to more than one factor such as stress regarding economy and jobs (Crayne 2020), getting infected (Shen 2020), or the health of loved one (Husky et al. 2020). Finally, the volume of tweets on suicides has also increased. This also aligned with the current literature where suicidal thoughts and online discourse on suicide were more frequent after disasters (Kumar et al. 2015; Woo et al. 2015), especially among COVID-19 survivors (Sher 2020).

The analysis shows a shift in the average number of tweets per day for top ten hashtags before and after November 01, 2019. Interestingly, there was a shift in tweets with hashtags that include the keyword mental health. Furthermore, new hashtags, #covid19 and #suicideprevention entered the top ten hashtags list after the pandemic. The change in the average number of tweets as well as the prevalence of more tweets with hashtags related to COVID-19 and suicide prevention clearly show the impact of the pandemic on mental health, whether directly or indirectly. According to Killgore et al. (2020), there is a potential for increased suicide risks during the COVID-19 pandemic. Furthermore, the measures taken by many countries to reduce the virus spread and the impact of the pandemic have led to social isolation, which is associated with increased anxiety, depression, and suicidal behavior (Calati et al. 2019; Nomura et al. 2021). Finally, COVID-19 survivors may also be at elevated suicide risk (Sher 2020).

Emotion analysis of tweets related to mental health before and after the pandemic shows a significant increase in the average tweets per day after November 01, 2019. Overall, tweets with sadness, fear, anger, and disgust emotion have increased (+50%) on an average daily basis after COVID-19. The increase in negative emotions after the pandemic supports the side effect of pandemic on public emotions, which could be used to predict the long-term mental health need (Gruebner 2016). Furthermore, the emotion analysis supports the need for monitoring emotional responses to pandemics, identify the most impacted populations, and develop solutions that can help reduce the psychological effects of pandemics (Martín-Brufau et al. 2020).

Limitation and Future Work

This work is not without any limitations. First, the sample tweets were manually labeled into the predefined categories by two non-expert persons. Second, even though the tweets represent the general population of Twitter user, such tweets do not necessarily represent the public opinion in general. This is because social media use is biased in different ways based on demographics, preferred social media platform, geographic location, and different age groups. Third, a more in-depth analysis that focuses on different aspects of mental health disorder can help better understand the impact of the pandemic and focus effort on the adverse psychiatric symptoms. Fourth, this study utilized Twitter as a social media platform. Future studies need to characterize the impact of pandemic on mental health by analyzing data from multiple social media platforms. Fifth, the research demonstrates potential correlation as it could be that people had only social media as a medium of communication (due to self-isolation or social distance) leading to the increase in the number of tweets on mental health that we observed. Therefore, as a future work, it could further compare the increase of tweets on mental health with the change in the number of tweets on any other topic pre-post COVID-19. Moreover, from a methodological perspective, stronger econometric methods (such as difference in differences (DID)) could be employed to establish a causal effect. Finally, different text preprocessing techniques like n-grams could be explored.

Conclusion

In this study we analyzed the Twitter discourse on mental health and compared the trends analysis over time, emotions, and the top tags on mental health pre- and post- the COVID-19 pandemic. Results showed that there was a significant increase in the volume of tweets after the COVID-19 pandemic. Furthermore, there were more concerns on suicide prevention as well as mental health during the pandemic. Emotion analysis showed a significant increase in tweets related to sadness, fear, anger, and disgust emotions. The study demonstrates that social media platforms could be used to understand the shift in adverse psychiatric symptoms due to pandemics and disasters. Furthermore, the analysis calls for more focused interventions mental health programs and tools that need to be in place in early stages of the pandemic to reduce the adverse effect of pandemics on mental health, especially for the affected population. Finally, there is a need to develop and promote new practices that improve access to cost-effective mental health services to individuals with existing mental disorders as well as those who developed such disorders during the pandemic (Moreno et al. 2020).

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