COVID-19 Impacts on Public Attitude towards Mental Health Services — A Twitter-based Study

CB&B750 Final Project Report

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Abstract

This paper explores the impact of COVID-19 on mental health services, focusing on public sentiment. Sentiment analysis was conducted using VADER and TextBlob on 7,440 tweets from 2017 to 2022, with temporal analysis identifying trends of different sentiment levels during pre-COVID and post-COVID periods. We performed and compared multiple topic modeling methods, including BERT, PCA, K-means clustering, LDA, and BERTopic, and ultimately proceeded with results from BERTopic, while customizing parameters such as stopwords and n-grams to elevate final model performance. Additionally, data visualizations, including topic word score charts and intertopic distance maps, showed specific hot topics and level of variety among different topics. Results show that tweets elicit a more positive sentiment overall. However, attitudes towards certain topics shifted completely over time. These results provide valuable insights regarding what specific aspects of mental health services have been impacted by COVID-19 and direct further endeavors in policy and decision making.

Keywords: Tweets, Sentiment Analysis, Temporal Analysis, Mental Health Services, Topic Modeling, BERTopic, TextBlob, VADER

1. Introduction and Background

With the rise of COVID-19 pandemic and the implementations of relative Health preventative measures, mental health's prevalence, which had already been one of the big issues existing among the population, tremendously increased. It is stated by the World Health Organization (WHO) that "[c]ovid-19 pandemic triggered 25% increase in prevalence of anxiety and depression worldwide"[1] solely by March 2nd 2022. Therefore, the demand for Mental Health visits has grown even stronger. Telehealth visits for mental health and substance use disorders have increased significantly since the pandemic, and made up nearly 50% of total visits for behavioral health.[2] Accompanied by such inclined preference from the public to seek help for mental health issues as well as the relatively convenient barrier of entries and opportunities for service providers to fulfill such needs, the number of mental health service platforms surged, including Telehealth and in-person visits, which still continues even today. With the potential of continuous growth of such prevalence, analysis towards the association between COVID-19 pandemic and mental health services are of great significance to be performed.

Throughout literature review and meta-data analysis, there are nearly 3,000[3] researches with regards to the association of COVID and mental health, along with analysis that resembles sentiment analysis. Nonetheless, research gaps exist in sentiment analysis, temporal analysis, and topic analysis on how the pandemic impacts the general public's perspectives towards Mental Health Services. As a result, we perform sentiment analysis, temporal analysis along with topic modeling in an attempt to analyze scraped Tweets from 2017 to 2022 related to mental health services.

2. Methods

2.1 Data Scraping

We employed Snscrape for data extraction, focusing solely on tweet content and hashtag information. By establishing a time window of three months for a duration of six years, spanning from January 2017 to December 2022, we collected data for each keyword quarterly. For each keyword, we gathered 30 tweets, resulting in a total of 7,440 tweets. This approach aimed to provide a balanced representation of data for each segment of mental health services while minimizing the impact of advertisements. However, it is important to note that this data collection method may not accurately reflect the real-world distribution of each keyword.

2.1.1 Keywords Selection

Keyword selection is performed to support sentiment analysis on the extracted Twitter data pre-COVID and post-COVID. In order to refine our final corpus from Twitter data extraction, we established pre-screening methods to consolidate our selection process. First, frequency is analyzed within a time range with advanced search on words that stand strongly for sentiments on specific keywords derived from our initial corpus. The appearance of advertisements from official accounts and their frequency is then evaluated to reduce limitations derived from marketing materials, despite the inability of fully disregarding inclusion of advertisements. Accordingly, keyword base is categorized into 3 tiers regarding priority of usage when extracting posts from Twitter on their respective relevance to our research, which is shown in the table below.

Tier 1 (Most Relevant)	Tier 2	Tier 3 (Least Relevant)
mental health provider mental health facility mental health professional mental health assistance mental health funding mental health insurance coverage mental health crisis mental health apps mental health recovery mental health legislation mental health education mental health equity mental health self-care mental health care mental health support mental health resources mental health access mental health policy	mental health barriers mental health reform mental health advocacy mental health waiting times mental health telehealth(ads) mental health online therapy(ads) mental health first aid(ads) mental health cultural competency	mental health clinic mental health helpline mental health peer support mental health workplace mental health experiences

Tier 1 (Most Relevant)	Tier 2	Tier 3 (Least Relevant)
mental health stigma mental health awareness mental health therapy mental health service mental health psychiatrist mental health clinics mental health professionals mental health treatment		

2.2 Data Preprocessing

Before diving into the analysis, it is essential to preprocess and clean the tweet data to ensure its quality and improve the accuracy of the results. Redundant information is removed from the tweets to focus on the text content. In this case, we use the preprocessor library (imported as p) to perform the cleaning. The preprocessor is customized to exclude the hashtags and other elements such as URLs, emojis, mentions, and numbers. We also manually replace non-alphanumeric characters with a single space, as well as replace all the consecutive spaces with a single space. By conducting this preprocessing and cleaning, we can ensure that our analysis will focus on the relevant information present in the tweets.

We believe that data preprocessing is crucial when working with textual data from social media platforms like Twitter, as the presence of unnecessary elements and noise can adversely affect the results of the analysis. In the context of mental health service data, it is particularly important to extract meaningful insights that can help us better understand public sentiment and needs in this critical area.

2.3 Sentiment Analysis

In our analysis, we implemented sentiment analysis using two widely used Python libraries: VADER (Valence Aware Dictionary and sEntiment Reasoner) and TextBlob. VADER is a lexicon and rule-based sentiment analysis tool specifically designed for social media text, while TextBlob is a more general-purpose NLP library that offers a simple API for various text processing tasks, including sentiment analysis. Both methods were employed to analyze the sentiment of mental health service-related tweets and to compare their performance on this specific dataset.

To visualize and compare the performance of both VADER and TextBlob, we plotted bar charts representing the distribution of sentiment polarity scores for each method. We then customized the polarity value thresholds for each method to find the best match between the sentiment classifications provided by both VADER and TextBlob. This step allowed us to determine which sentiment analysis tool performs better on our dataset of mental health service-related tweets.

2.4 Temporal Analysis

In our study, we conducted a temporal analysis to investigate potential shifts in public sentiment regarding mental health services over time. We plotted line charts to visualize the levels of positivity from January 2017 to December 2022. Given the significant impact of the COVID-19 pandemic on social media during this six-year period, we divided our dataset into two equal three-year periods: pre-COVID and post-COVID. We defined the breakpoint as the first day of 2020, which allowed for a balanced distribution of data across both periods.

It is important to note that there are two plausible ways to determine the breakpoint for the COVID-19 pandemic. One option is December 2019, when the first case was reported, and the other is March 2020, when the WHO declared a global outbreak.[4] We opted for the former approach, as we are analyzing Twitter data rather than healthcare data. The term "COVID" rapidly became one of the most frequently mentioned tokens on Twitter following the initial reports of the virus. By choosing this breakpoint, we aimed to capture the impact of the pandemic on public sentiment regarding mental health services as reflected on social media.

2.5 Topic Modeling

In our study, we employed various topic modeling techniques to analyze the data. Initially, we constructed a model using BERT embeddings, followed by Principal Component Analysis (PCA) for dimensionality reduction, and subsequently applied K-means clustering. As a second approach, we implemented Latent Dirichlet Allocation (LDA) directly after the data cleaning process. Finally, we utilized BERTopic as our primary model for topic analysis.

The primary distinction between the first two methods and BERTopic lies in their topic representation generation. The former methods rely on probabilistic approaches, whereas BERTopic leverages c-TF-IDF to generate topic representations. This implies that BERTopic's topic generalization is founded on dense vector embeddings and contextual information, which enables the capture of semantic similarities and linguistic nuances without necessitating identical terms. Moreover, BERTopic is more intuitive and cost effective than LDA, and it does not require manually tuning the hyperparameters.

In the process of constructing our topic modeling, we made several customizations to parameters, such as stopwords and n-grams. While we removed URLs during the data cleaning phase, some URL-related redundancies, like "amp", "http", and "https", still required manual exclusion. Additionally, we excluded tokens directly related to mental health, as they would not provide significant information in the topic modeling. These customized stopwords were then combined with the existing English stopwords provided by the NLTK library during model construction.

Regarding the n-gram parameter, we experimented with unigrams, bigrams, and trigrams individually. Ultimately, we chose to utilize unigrams for building the model. The rationale behind this decision is that social media platforms often employ shorthand, abbreviations, and emojis, which are typically single-word representations.

We applied BERTopic multiple times, considering both time series data and the sentiment analysis results from VADER. Our goal was to examine the changes in topics from the pre-COVID to post-COVID periods, as well as to analyze public sentiment on different topics. Based on the topic clustering outcomes, we employed various data visualization techniques, including word score bar charts, cloud maps, inter-topic distance maps, and so on.

3. Results

3.1 Data

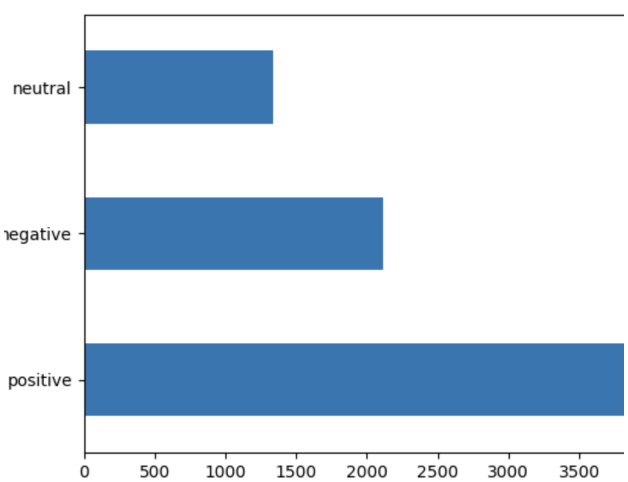
As mentioned, data was scraped from Twitter using the Snscrape library in Python. They were then preprocessed and organized before being fed into our analysis tasks. After preprocessing, we have a total of 7,442 tweets, spanning from Jan 1, 2017 to Dec 31, 2022. Furthermore, we divide the tweets into 2 groups, tweets from the pre-COVID period (defined as 2017-2019) and the post-COVID 2020-2022 (defined as 2017-2019). In the end, we have 3,721 pre-COVID tweets and 3,721 post-COVID tweets.

3.2 Sentiment Analysis

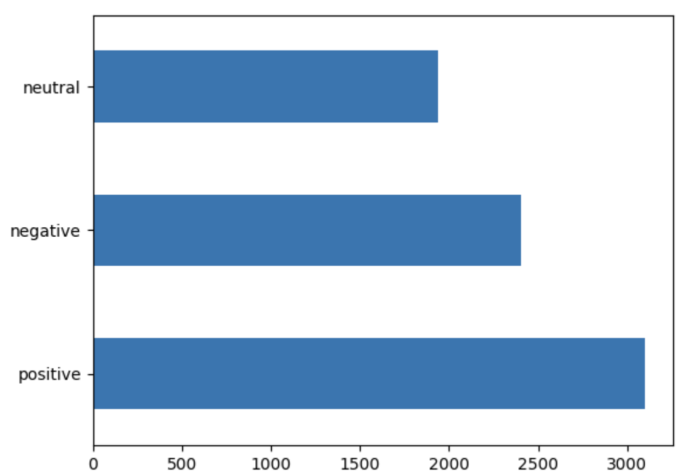
As mentioned, we apply 2 different kinds of methods, VADER and TextBlob, to perform sentiment analysis in order to see how different the results are. Distribution of different sentiment classes from different time periods and using both methods are plotted. Figures 1 and 2 show the distribution of each sentiment class using all data with both methods, whereas figures 3, 4, 5, and 6 divide the data into the 2 time periods and plot their sentiment distributions using both methods.

3.2.1 Results of all tweets

Overall, they gave similar sentiment distributions, since the results from both methods for all tweets show that there are more positive tweets than negative ones, and then followed by neutral tweets. VADER shows that there is a larger number of positive tweets and a slightly smaller number of negative tweets than TextBlob did.



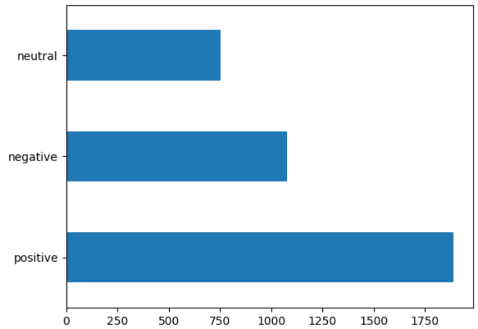
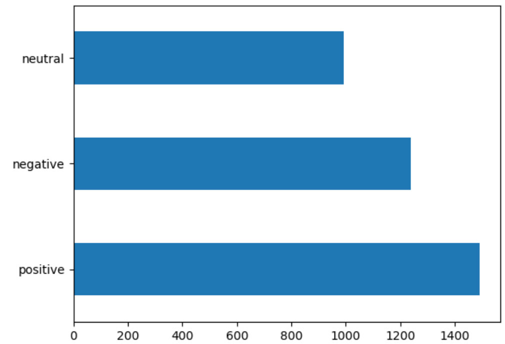
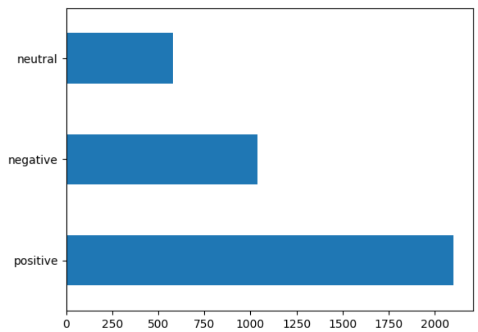
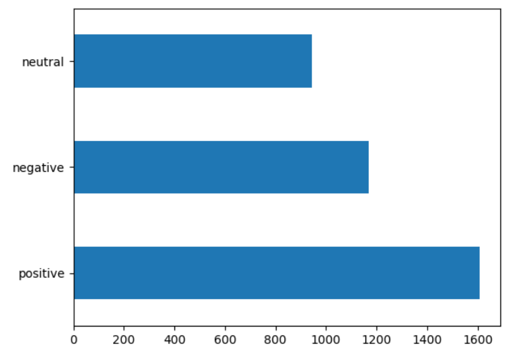
(Figure 1: Number of tweets by sentiment for all tweets using VADER)



(Figure 2: Number of tweets by sentiment for all tweets using TextBlob)

3.2.2 Results of tweets divided by time period

Overall, there are more positive tweets than negative ones, and then followed by neutral tweets in both time periods and in different methods, which is the same as the case when all tweets from both time periods are plotted together. One interesting result is that both methods show that there are larger numbers of positive tweets in the post-COVID era than in pre-COVID times.

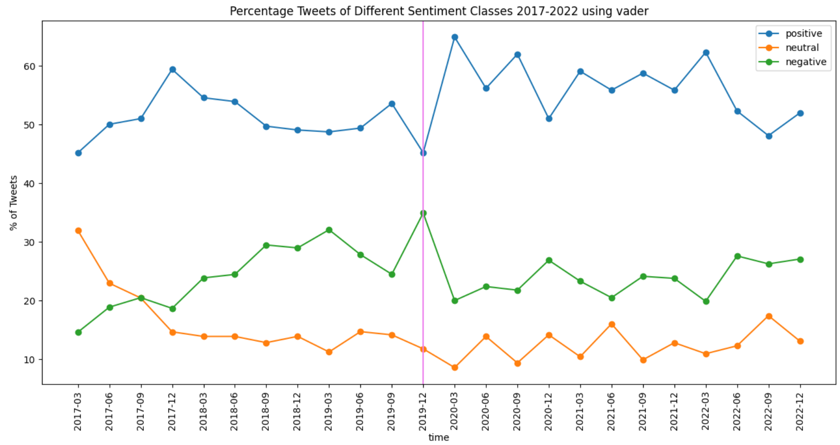
	VADER	**TextBlob**
Pre-COVID	 (Figure 3: Number of tweets by sentiment for pre-COVID tweets using VADER)	 (Figure 4: Number of tweets by sentiment for pre-COVID tweets using TextBlob)
Post-COVID	 (Figure 5: Number of tweets by sentiment for post-COVID tweets using VADER)	 (Figure 6: Number of tweets by sentiment for post-COVID using TextBlob)

3.3 Temporal Analysis

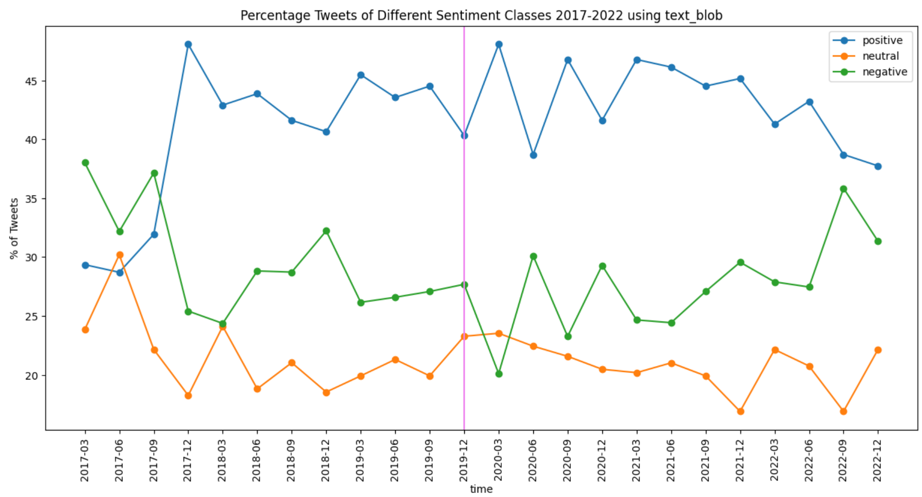
As mentioned, tweets are scraped by season (e.g Jan-Mar, Apr-Jun, Jul-Sep, and Oct-Dec) in every year. Therefore, in addition to looking at the distribution of different sentiment classes in different time periods, we also wanted to do a temporal analysis to look into how positivity rates in tweets change over time from 2017 to 2022. Percentages of negative and neutral tweets are plotted as well for reference and comparisons. The positivity rate of tweets are calculated and plotted by season based on the formula as shown below.

$$positivity(s) \ = \frac{number\ of\ positive\ tweets\ in\ season\ s}{number\ of\ all\ tweets\ in\ season\ s}$$

Figure 7 shows the results from using VADER, and Figure 8 shows the results from using TextBlob. Overall trends look similar, except for the positivity rates in the first year – 2017. TextBlob shows a drastic increase in positivity year within the first year, including a time period where the number of positive tweets is smaller than the number of neutral and negative tweets whereas VADER's results show a much smoother increase in positivity rates, and positive tweets are constantly more than neutral and negative rates.



(Figure 7)



(Figure 8)

3.4 Topic Modeling

After retrieving results from sentiment analysis and how sentiment distributions change overtime, we further analyze towards what topics do people hold relatively more positive or negative views. In order to do this, we extracted the topics through topic modeling. As mentioned, BerTopic allows us to understand the common topics being discussed in the data we collected.

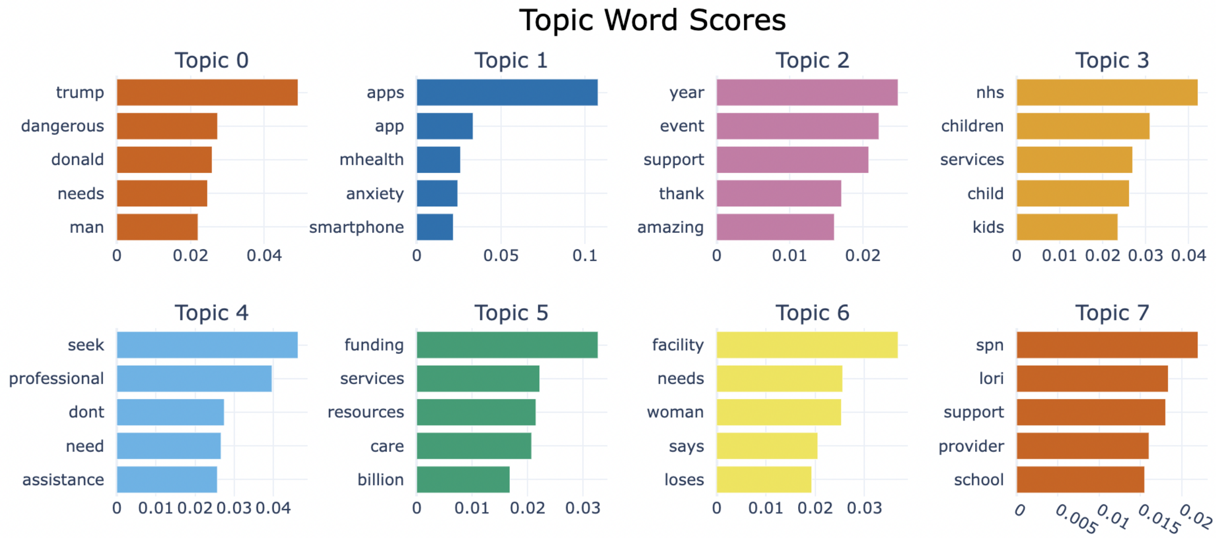
As mentioned, we continue our topic analyses based on results from using VADER, and we performed 2 rounds of analyses. During the first round, we divided our dataset into 2 subsets (pre-COVID tweets and post-COVID tweets) before conducting topic modeling in order to facilitate comparisons. During the second round, we further divide the datasets by sentiment class (positive vs. negative, we ignore tweets marked as neutral in this step) and specifically look at the intertopic distance maps to explore topic distributions between the 2 sentiments.

3.4.1 Pre-COVID vs. post-COVID

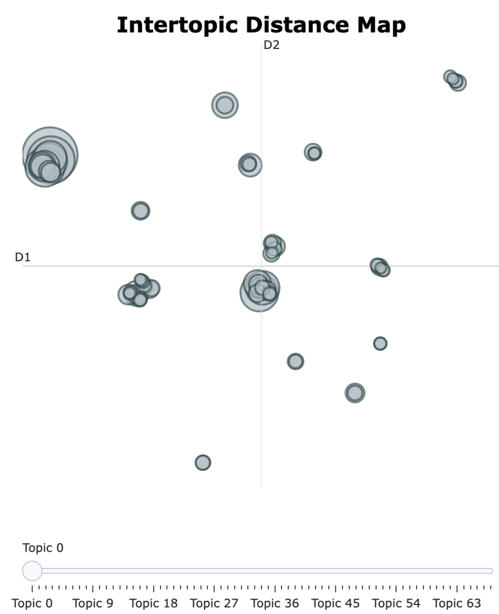
Regarding visualizations, the topic word scores and intertopic distance maps for each time period are shown in figures 9-10 (pre-COVID) and figures 11-12 (post-COVID). With topic word score bar charts, we are able to see the top 8 hot topics discussed on Twitter related to mental health services in the corresponding time period. These charts also include information of individual word scores for each word, which is the c-TF-IDF scores. The score shows how well a specific word represents the corresponding topic, with a higher score indicating higher representativeness. On the other hand, intertopic distance maps include all the topics extracted from our dataset, which gives us a broader view showing how dispersed and how much level of variety there is among the different topics being discussed. The two dimensions of the topics are from calculations from Umap, which reduces the dimensions of the c-TF-IDF representations to 2D, which effectively helps to visualize all the topics.

(Figure 9: Topic word scores for topics pre-COVID)

(Figure 10: Intertopic distance maps for topics pre-COVID)



(Figure 11: Topic word scores for topics post-COVID)



(Figure 12: Intertopic distance maps for topics post-COVID)

Looking at the word score bar charts, we can see the difference between hot topics for pre-COVID and post-COVID periods. Some topics remain as one of the top 8 hot topics, for example, discussions about “trump”, “seeking professional help”, “mental health apps”. Additionally, the level of discussion in some topics changed after COVID started. For example, discussions related to “mental health apps” used to be the 7th hottest topic before COVID but then became the 2nd hottest topic, which makes sense because after COVID started, individuals shifted more attention to online resources regarding mental health services. Looking at the inter-topic distance maps, we can see that during both time periods, the topics are dispersed overall.

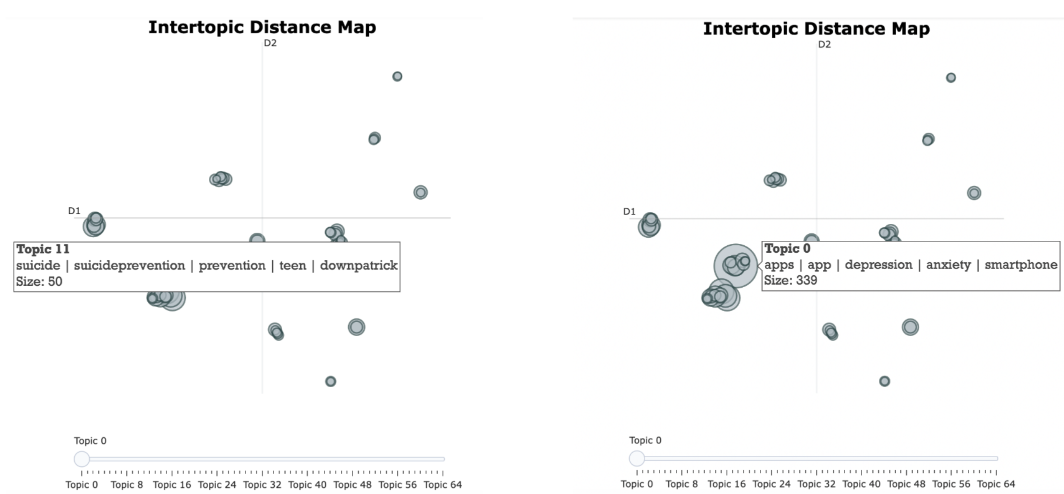
We also generated additional visualizations, including table views and cloud maps of the topics, as shown in Appendix 1 and Appendix 2.

3.4.2 Topic analyses by sentiment

We then moved onto the second round of topic analysis, which is to look at topics by different sentiment classes. After dividing the datasets by sentiment class and keeping only positive and negative ones, the specific numbers of tweets in each sentiment class in each time period are shown in the table below. There are more positive tweets than negative ones in both time periods.

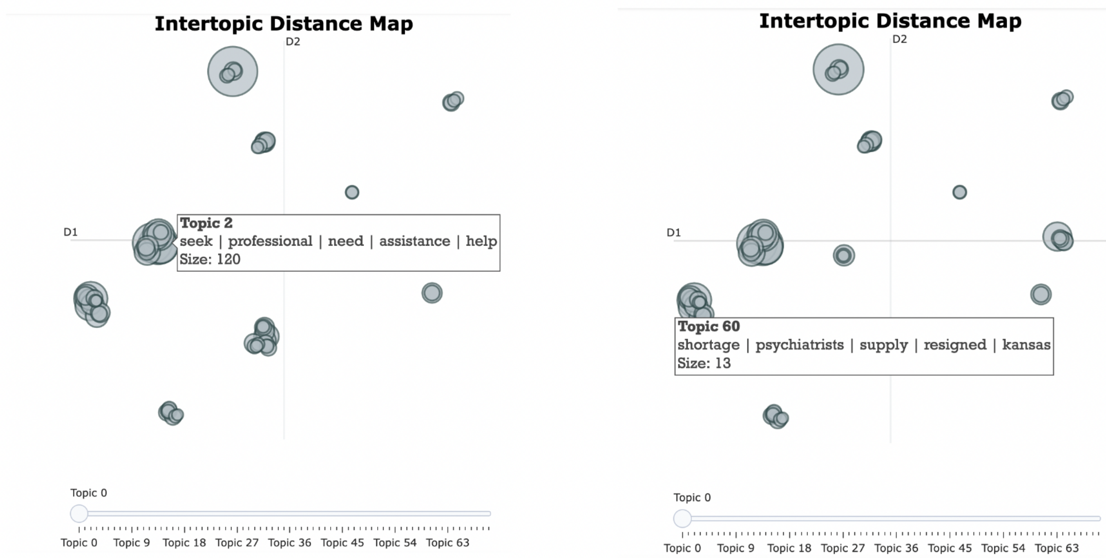
Number of Tweets	Positive	Negative
Pre-COVID	1889	1077
Post-COVID	2101	1038

Topic analyses are performed using the same method on these 4 datasets. We specifically look at the intertopic distance maps in this round of analysis. Results below show topic examples from different sentiment classes and time periods. For each dataset, we extract 2 examples, one of which is a relatively hotter topic while the other one has a relatively smaller discussion level in order to present the scope of the discussions. We specifically extracted examples that showed interesting patterns of attitude change when comparing the two time periods.



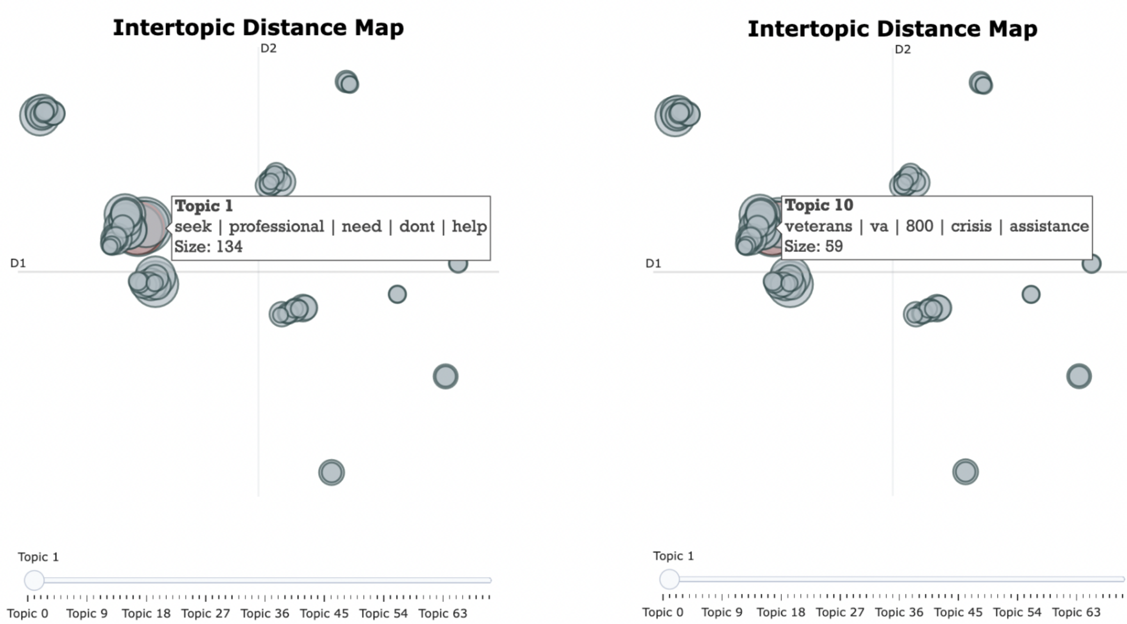
(Figure 13: Topic examples of pre-COVID positive tweets)

Above maps show that there is an overall positive attitude towards “teen suicide prevention” and “depression and anxiety smartphone apps” before the COVID-19 pandemic.



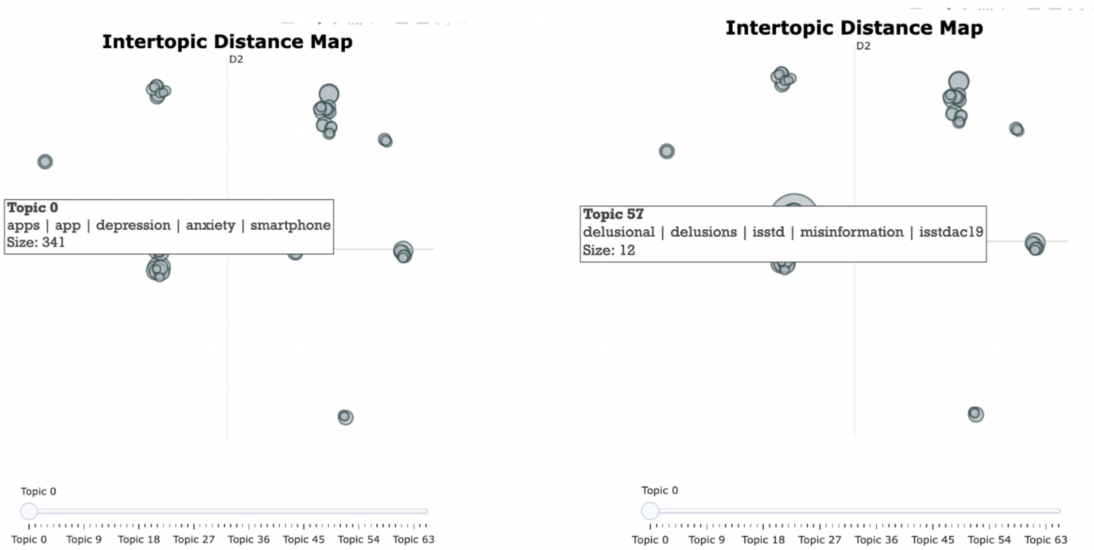
(Figure 14: Topic examples of pre-COVID negative tweets)

Above maps show that there is an overall negative attitude towards “seeking professional help” and “psychiatrists supply shortages” before the COVID-19 pandemic.



(Figure 15: Topic examples of post-COVID positive tweets)

Above maps show that there is an overall positive attitude towards “seeking professional help” and “veteran crisis assistance” after the COVID-19 pandemic started.



(Figure 16: Topic examples of post-COVID negative tweets)

Above maps show that there is an overall negative attitude towards “depression and anxiety smartphone apps” and “delusional/misinformation” after the COVID-19 pandemic started.

4. Discussion

4.1 Sentiment analysis over time

Sentiment analysis results are further inspected using temporal analysis, including the pandemic factor into the analysis. The temporal graphs show how positivity levels change and develop over time. The graphs are divided into two sections, pre and post pandemic. The discussions about mental health services have relatively the same level of positivity, ranging around 50% throughout the years 2017-2019 before the COVID-19 pandemic started. The separator marks the month when the first case of COVID-19 occurred[5]. According to the graph generated by using VADER, this month marks the lowest point of positivity level in the tweets related to mental health services. Moving on to the season after that (Jan 2020 to March 2020), which is when the COVID-19 pandemic started to spread globally[6], the positivity level in tweets increases drastically, and reaches its highest point in March 2020 when WHO declared COVID-19 as a pandemic[6]. This is an interesting pattern in attitudes towards mental health services, since we would expect the public attitude to contain more negativity under the influence of the pandemic, while our results show a sudden surge in positivity during this quarter of the year. However, during the time period after the COVID-19 pandemic started. The positivity level shows an overall decreasing trend up until the end of 2022. This shows that the COVID-19 pandemic might be a factor in why positivity rates show the pattern as discussed.

4.2 Topic modeling

Based on our results from intertopic distance maps, we are able to observe how spread out the discussion groups are and how different they are from each other. Pre-COVID and post-COVID intertopic distance maps show relatively the same variety levels. However, for post-COVID, the largest discussion cluster is slightly larger than that during the pre-COVID time period.

By dividing the dataset by positive and negative tweets help us understand what specific aspects people are satisfied or complaining about. In addition, stratifying the dataset by time period, it is interesting to see existing cases where attitudes towards a certain topic has shifted completely from pre-COVD to post-COVID. For example, from intertopic distance maps, we can see that discussions related to “professional help” are one of the hot topics in both time periods, but the results show that people’s attitudes towards this topic has shifted from negative to positive, comparing results from pre-COVID and post-COVID. Another example is discussions on “depression/anxiety smartphone apps". Similarly, this topic is also one of the hot topics before and after the pandemic started. However, results show that people’s attitudes towards this topic has shifted from positive to negative.

These results provide valuable information on how mental health services have been influenced by the COVID-19 pandemic, according to how the public’s attitudes have shifted or changed over time. Looking at the results stratified by sentiment class provides us with more information on specific aspects or factors of mental health services and how they individually have improved or worsened over time, which can help inform policy makers and direct future efforts to develop effective mental health services.

5. Conclusion

Topic modeling, temporal analysis and sentiment analysis on scraped data from Twitter from 2017 to 2022 allow holistic visualizations and representations of general public’s perspectives on mental health services, which reflect the trends of changes in such perspectives resulting from pre-covid and post-covid periods. This is a pivotal aspect that can also greatly contribute to the analysis of outcomes from other societal changes, such as policy-making, public health measures and preventative methods, that could be mirrored from pre-covid and post-covid periods. Apart from analysis of the pre-existing social climates, our study also provides a window for indicating demands for mental health services, advocating public acts, and immediate response to any drastic changes in the general public’s sentiments related to mental health services in order to ensure sufficient accessibilities to mental health service providers under sophisticated regulations.

6. Limitation and Future Work

Our study faced some limitations, including the inability to entirely eliminate the effect of advertisements on Twitter data. Future research could involve manually tagging advertisements to remove them to further reduce noise in the dataset. Additionally, the averaging of keyword weights during data scraping may have introduced selection bias.

Further improvements could be made by increasing the number of tweets analyzed. People could further enhance the accuracy of the sentiment analysis model which involves manually tagging the sentiment classes. We should also consider the multilingual aspects of the data by using models capable of handling multilingual information. Future study may also consider integrating BERTweet and BERTopic when constructing topic models. Pretraining existing models on our dataset could also potentially increase the accuracy of topic modeling results. Future researchers could also include geographic information in the analysis which would enable the exploration of attitudes towards mental health services across different locations. Using the official Twitter API to extract location information could be a valuable approach, although it is challenging since many tweets are posted without disclosing their geographical information.

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Appendix

Appendix A Pre-COVID(a) and Post-Covid(b) Topics Table View

	Topic # 01	Topic # 02	Topic # 03	Topic # 04	Topic # 05	Topic # 06	Topic # 07	Topic # 08	Topic # 09	Topic # 10	...
0	trump	seek	funding	facility	spn	facility	apps	resources	school	resource	...
1	dangerous	professional	services	needs	support	lodge	track	visit	schools	tons	...
2	donald	need	resources	woman	supporting	dunsmuir	anxiety	near	teachers	awesome	...
3	needs	assistance	care	says	school	prepares	mood	online	pupils	info	...
4	case	dont	country	loses	efficient	site	best	informedimmigrant	districts	resources	...
5	man	help	america	shes	connect	new	use	aging	pupil	mentalhealthawareness	...
6	psychiatrists	nearest	people	child	assistance	maps	free	link	bullying	nowwearestronger	...
7	facility	try	billion	assistance	provider	conversation	list	organizing	allies	deer	...
8	president	don	gt	ford	wellness	building	improve	zip	counselors	trends	...
9	professionals	really	loan	hope	lori	open	stats	resource	prison	red	...

10 rows × 70 columns

A(a)

	Topic # 01	Topic # 02	Topic # 03	Topic # 04	Topic # 05	Topic # 06	Topic # 07	Topic # 08	Topic # 09	Topic # 10	...
0	trump	apps	year	nhs	seek	funding	facility	spn	facility	suicide	...
1	dangerous	app	event	children	professional	services	needs	lori	dunsmuir	suicideprevention	...
2	donald	mhealth	support	services	dont	resources	woman	support	lodge	prevention	...
3	needs	anxiety	thank	child	need	care	says	provider	prepares	teen	...
4	man	smartphone	amazing	kids	assistance	billion	loses	school	site	downpatrick	...
5	facility	improve	awareness	youth	help	people	shes	585	maps	selfcare	...
6	case	mobile	improv	childrens	nearest	country	child	6486	new	depression	...
7	president	track	charity	young	finding	gt	ford	mentalhealthto	old	youth	...
8	psychiatrists	effective	excited	schools	feeling	loan	assistance	efficient	building	support	...
9	professionals	free	join	brexit	like	budget	professional	connect	open	prosocialresearch	...

10 rows × 69 columns

A(b)

Appendix B Pre-COVID(a) and Post-COVID(b) Cloud Map

B(a)

B(b)

Appendix C Topic model clustering result using BERT+PCA+K Means by sentiment