Advances in Journalism and Communication, 2022, 10, 170-198
https://www.scirp.org/journal/ajc
ISSN Online: 2328-4935
ISSN Print: 2328-4927

How People Show Their Emotions towards COVID-19 on Twitter Platform

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How to cite this paper: Zhao, L. (2022). How People Show Their Emotions towards COVID-19 on Twitter Platform. *Advances in Journalism and Communication, 10,* 170-198.
https://doi.org/10.4236/ajc.2022.102012

Received: March 21, 2022
Accepted: June 4, 2022
Published: June 7, 2022

Abstract

The pandemic that has lasted for more than three years exerted a significant influence on the life of people, especially on their physical and mental health of people. The study intends to find out how people express their sentiments on social media platforms—Twitter. It will adopt the quantitative methodology in analyzing the data. The secondary data will be collected from the Web page via the Chrome extension with WDRA software. By means of making the analysis, the study shows that there was a great change before and after the pandemic.

Keywords

Social Media, COVID-19, Sentiment Analysis

1. Introduction

1.1. COVID-19 on Social Media

As COVID-19's effects are felt globally, social media networks and platforms are getting overwhelmed with content related to the virus. According to Lwin et al. (2020), since the novel infection COVID-19's identification as well as reporting in China's Wuhan, it has spread to numerous regions and countries throughout the entire continent and has hence become a serious global pandemic. Further, the WHO declared the outbreak of COVID-19 on 11th March 2020. As of 30th June 2020, the pandemic had infected over 10 million individuals globally and had resulted in about 503,000 deaths at that time (Boon-Itt & Skunkan, 2020). To contain COVID-19's spread, several countries implemented quarantine and lockdown measures and enforced travel bans, limiting individuals' movement. Schools were also closed; several workers became unemployed and many people were locked down within their homes. Therefore, with millions of individuals' lives impacted by the pandemic, Twitter, an important social media platform became a pivotal outlet and medium for users to exhibit and express their sentiments, opinions, feelings, and concerns regarding COVID-19.

Amongst these social networks, the Twitter platform has been pointed out as a popular and accepted platform for brief messages. For example, as of 2021's second quarter, Twitter had about 206 million active daily users worldwide and this platform is especially popular in the US followed by Japan and the UK. Every Twitter message known as a tweet is limited to only 280 characters. According to Moran (2022), this setting fulfills the need for swift updates thereby making Twitter increasingly popular. Notably, Twitter's interactive nature has attracted scientists to employ it in evidence-informed health policy. It is worth bearing in mind that the Twitter platform's representativeness could be prejudiced. According to Ahmad & Siddique (2017), a survey undertaken by Pew Research Center within the US revealed that grown-up Twitter users' median age was 40 years, which was less than people living in the US's median age. Further, Twitter might erroneously identify and remove harmless and non-dangerous Twitter messages and content.

Therefore, social media platforms especially the Twitter platform has surfaced as a crucial channel for medical-related information. Chandrasekaran et al. (2020) assert that most individuals across numerous nations utilize some social media form. Pew Research studies assessing numerous nations pointed out social media networks as a pivotal source of medical and health information. Over the last few years, sharing as well as consuming medical information through social media platforms has become widespread. It is not surprising that social media has become an outstanding channel for individuals to share and exchange feelings and information regarding COVID-19. According to Shi et al. (2020), the science recognising and understanding medical-related information, which is shared through a digital channel like social media or the internet to notify public policy and public health is referred to as infodemiology. Further, as a related phrase, infoveillance talks about public health-related concerns' syndromic surveillance that is diffused and expressed on the web via digital channels. Notably, infoveillance has especially helped point out outbreak patterns as well as examine public perceptions and awareness of many diseases including the Ebola virus, Zika virus, and H1N1 influenza. Thus, analysing health event information shared on social media offers first-hand proof of medical event happenings and enables quick access to actual-time information, which may assist policymakers and health professionals frame proper responses to medical-related events.

Further, not long ago, researchers tried to employ big data analytics in evidence-based health policy. According to Saunders et al. (2020), big data could assist in evidence-based health policy decision-making. Notably, in the modern era of the pandemic, there is a pressing need for lower human effort and fast data gathering approaches. Researchers have tried to develop and establish data gathering approaches and strategies based on different social media platforms like Twitter to deal with these challenges (Dunn et al., 2018). The simplicity of accessing an enormous amount of actual time data from social media platforms grants social media distinctive advantages for evidence-based health policy. Ratkiewicz et al. (2011) assert that the Twitter platform is a dynamic social media platform that enables researchers to examine huge populations. Notably, Twitter's actual-time nature enables quick data processing to evade delay and lag caused by traditional approaches. Such features and elements enable policymakers to gather actual-time evidence effortlessly. This upper hand is pivotal to evidence-informed health policy, particularly in this era of COVID-19.

1.2. Evidence-Informed Health Policy

Policy-appropriate evidence's significance for assessing the likely influence of policies of public health has been extensively acknowledged. According to Vanagas (2017), an evidence-informed policy of public health seeks to enhance public health through the full utilisation of accessible data and information for purposes of decision-making. Notably, public health researchers have created several approaches within this field. Further, these techniques utilise evidence from numerous sources like medical literature, health data databases, survey results, and clinically collected information. The accomplishment of employing evidence-based health policy robustly encourages scientists to further analytical techniques for example public health surveillance, systematic reviews, and health impact assessment (Aarons et al., 2011). Data collection is one common major element of these techniques, which is thus far a challenging stage. Data gathering is mandated to fit the related and relevant policies' time frame. According to Spangler & Caldwell (2007), systems of policy surveillance should examine the associated policy influence's trends and patterns. Such systems require that the data and information be gathered both efficiently and feasibly. Regrettably, it is challenging to completely fulfill such requirements utilising conventional approaches such as case studies and major informant interviews because of the time lag caused by most of such approaches' inefficient processing phases.

The outbreak of COVID-19 has impelled an emergent series of studies, which have explored public perceptions, concerns, and thoughts regarding this pandemic utilising social media information and data. The majority of these studies depended on data and information from Twitter and examined data from the initial periods of the pandemic. Further, the amount of information and data employed in this research differs from several hundred tweets to several million. Such studies have jointly offered a rich knowledge base on how users of Twitter have responded to the COVID-19 pandemic along with their concerns during the outbreak's early stages. Several of these research studies failed to differentiate between tweet sources, like whether the users' tweets emanated from an organisation like a health agency or news channel, or an individual. From the perspective of inforveillance, it is pivotal to understand and appreciate the social media discussions concerning COVID-19 amongst the general public instead of by press agencies or other entities. Additionally, there is a narrow understanding of how people express themselves on social media concerning public health policy measures and events aimed at curbing the pandemic's spread. Therefore, to address these gaps, I studied COVID-19 public health policy measures and events-related tweets utilising a much bigger set of data covering a period from 1st January 2020 to 30th June 2020.

1.3. Research Questions

The following dissertation seeks to answer three different research questions identified below.

1) How did people express themselves on Twitter in response to policies of public health and events evident in their attitudes?

2) Were Twitter users' expressions helpful in disseminating information regarding COVID-19?

3) How do people's expressions in Tweets towards public health events and policies help in predicting their attitudes towards those events and policies?

1.4. Study Objectives

This study's objective is to assess how social media platforms, through their online accessibility, have facilitated the expression of people's attitudes in the context of the world epidemic. Notably, the study pays particular attention to two specific objectives. First is the sentiment regarding COVID-19 on Twitter evident in their tweets and expressions. Secondly, it is how people particularly Twitter users express their attitudes towards public health policy as well as events within the 19^{th} century. Further, the study seeks to analyse the link between the changes in sentiments in pandemic-related user tweets and policies of public health and events.

2. Literature Review

2.1. People's Expression on Social Media Platforms

Social media might resemble an artificial world where individuals' lives entirely comprise photogenic and healthy meals, thriving friendships as well as exotic vacations. People utilize social media platforms to express themselves by especially utilising platforms to build their identity and show the world what they care about (Himelboim et al., 2020). Further, people increasingly depend on the web, especially social media for health-associated information. Twitter users, the ultimate mode of expression in brief social interaction and engagement have been devising some creative means to express themselves and communicate their thoughts (HT Tech, 2022). Further, individuals are growingly depending on social networks to express themselves and their thoughts negatively and positively. People's expression both negatively and positively elicits corresponding positive and negative emotions and sentiments among other users.

Social media includes a wide array of networking sites including Facebook and microblogging services including Twitter. People utilize such platforms along with others to create and publish information concerning the prospective disease and health dangers and interventions, and efficient health strategies and policies (Al-Dmour et al., 2020). Contrastingly, the campaigns instigated via social media always fruitfully convert information and knowledge on various health-related subjects into every day successful web-based conversations and discussions and it is through these discussions that people express themselves. Giustini et al. (2018) argue that another major benefit of internet-based social media information and data apart from a growingly huge volume of data's availability is that it is extremely networked and contextual. For instance, Porumbescu (2016) argues that there would be a strong temporospatial sentiment towards an advanced vaccine whether negative or positive. Risk factors like poor diet, smoking, drug abuse, lack of physical activity, and their connected diseases are usually determined to be concentrated within a population.

Social media comprises a powerful communication medium that people can utilize to raise public awareness and consciousness of contagious diseases, especially novel ones regarding dates of the outburst as well as spreading developments. According to Allgaier & Svalastog (2015), the general public turns to social media to acquire information on emergent contagious infections, which constitute unrivaled hazards to the people. The public attitude and perceptions of such risks and hazards are formed based on how information is disseminated and communicated throughout various social media platforms, which in turn impacts individuals' behaviours and the decisions they undertake. Apart from information dissemination via social media platforms and networks, these platforms' users take part in conversations and discussions by giving their sentiments and their experiences. Nonetheless, information propagated via social media platforms usually lacks reliability since it is usually user-generated themselves instead of and not generated by professional medical care institutions themselves (Lin et al., 2020). Therefore, while information that users spread on social media while expressing themselves might often lack credibility, social media offers a platform for individual users to express themselves, particularly in the pandemic's context.

2.2. Social Media Platforms within the Health Domain

Bennett & Glasgow (2009) in their study examined how people try to consume health information and content and how the Internet transforms the connection between members of the public and health professionals. Contrastingly, Moorhead et al. (2013) in their article reviewed research that was undertaken to examine social media platforms' uses, benefits, and limitations in attaining successful communication between patients, healthcare professionals, and the public at large. Although social media platforms' advantages within medical communication were pointed out in several relevant studies. Notably, there is an absence of research that discussed the evaluation of social media platforms' effectiveness and adjusting practices of health communication in the interim and longer terms.

According to Zadeh et al. (2019), research on social network campaigns and active and healthy behaviour has revealed that campaigns on social media can evoke positive changes of behaviour and even stop negative behavioural changes in people. Thus, social media may be employed in reducing pandemic's spread thus, minimising the levels of anxiety and fear amongst the general public. Scientists have contended that social network communication may transfer helpful information regarding contagious infections based on pointing out and tracking the behavioural patterns of users (Al-Dmour et al., 2020). Also, it is worth noting that social media coverage controls disease prevalence. Behavioural changes associated with contagious disease via campaigns initiated by social media are restricted to a lesser population of literate and educate individuals. Thus, by enabling people to express themselves on social media regarding different health-related topics, social media platforms evoke behavioural changes amongst the general public.

2.3. Discussions on Twitter about COVID-19

Twitter has attracted practitioners' and researchers' attention within the health domain. According to Giustini et al. (2018), researchers have in recent times considered the use of Twitter to monitor peoples' discussions about infectious diseases. Further, Twitter is used in detecting contagious disease outbreaks, forecasting disease trends, monitoring emergencies as well as assessing the public's understanding, awareness as well as responses. According to Xue et al. (2020), as of June 2020, over 4 million individuals were confirmed to have tested positive for coronavirus across 110 nations. Social media's widespread usage including Twitter speeds up the process of information exchange and expression of opinions and viewpoints regarding health crises and public events.

Even today, COVID-19 is among the top trending discussion on the Twitter platform since its outbreak in 2019. Since measures of quarantine were implemented throughout most nations, such as the US's Shelter-in-Place directive, individuals have been growingly depending on various social media networks and platforms to get news as well as express viewpoints and opinions. Mackey et al. (2020) assert that Twitter data and information are helpful in disclosing public discourses and opinions to interesting subjects and actual-time news updates within global pandemics like Ebola and the H1N1 influenza virus. Within the present COVID-19 epidemic, several individuals globally are utilising the Twitter platform as among the key channels of communication to express their views and opinions regarding COVID-19 (Sharevski, 2022). The various keywords that people use to express themselves and their opinions include COVI19, COVID-19, COVID_19, SARS-COV-2, SARSCOV2, SARS_COV_2, stay-at-home, and lockdown. Kouzy et al. (2020) in their study gathered 22 million tweets associated with COVID-19 from 1st March 2020 to 21st April 2020 and the popular hashtags in their results included coronavirus, quarantine, COVID-19, virus, lockdown, new cases, and social distancing.

2.4. COVID-19 Public Health Policy and Events

The following section presents the run-through of various health policy events along with social measures regarding the pandemic. All countries' overarching goal is to manage COVID-19 by halting the virus' transmission and staving off related illness and mortality (Ayouni et al., 2021). The WHO (2020a) reveals that an exhaustive strategy to manage COVID-19 will also constitute other health policies together with social measures and actions, which comprise actions by communities, institutions, individuals, national and local governments, and global agencies to stop or suppress COVID-19's community spread. Therefore, public health as well as social measures play a part in stopping individual transmission chains and stopping outbreaks and are hence pivotal in restricting further COVID-19 spread especially, whilst therapeutics and vaccines are not available yet.

According to Maqbool & Khan (2020), public health policy and events include personal measures designed to restrict person-to-person transmission, safeguard people together with their contacts and minimise regularly touched surfaces' contamination. Personal measures thus comprise social distancing, mask usage if ill as well as environmental cleaning. Further, the World Health Organization (2020c) reveals that social measures also comprise social and physical distancing within public and open spaces to prevent spread between infected people and those that are not infected. Notably, social distancing measures shield individuals at risk of contracting a serious illness. Thus, social and physical distancing measures entail physical distancing, cancellation or reduction of mass meetings and gatherings, and steering clear of congested spaces in various settings for example public transport, bars, theatres, and restaurants.

Public health together with social measures also entails movement measures that seek to stop introduction as well as restrict the virus movement from one point to the other. According to Semenza et al. (2021), movement measures comprise limiting persons' movement nationally or locally, providing guidance concerning travel, arranging systematic and orderly travel beforehand to avoid overcrowding at travel centers including airports, bus terminals, and train stations, and taking into account a *cordon sanitaire* or any other chosen measures whilst rationalised by the domestic and local COVID-19 epidemiology. Padidar et al. (2021) argue that public health policy measures and events offer a package of interventions that nations must choose and realign based upon their respective local contexts.

According to Semenza et al. (2021), each public health and social measures category including personal, movement, and social distancing measures consists of an assortment of interventions that must be chosen, calibrated as well as implemented depending on the domestic intensity and degree of COVID-19 spread (see **Table 1**). The WHO (2020c) recommends that public health interventions must be commensurate with COVID-19 transmission's intensity and whatever measures that nations seek to execute must be carefully adapted to make sure

Table 1. Chosen public health policy measures and events within the context of the pandemic.

Personal measures	Movement measures	Social and physical distancing measures
Seek to restrict person-to-person transmission, protect people together with their contacts as well as minimise regularly touched surfaces contamination	Seek to prevent the virus introduction from infected points to uninfected ones.	Seek to guarantee safe physical distancing via reduced crowding

they are sustainable, acceptable, and feasible within the domestic context. Further, national authorities must apply or recommend measures sub-nationally or nationally depending on their particular context, the extent of spread, or risk and assess the situation frequently as COVID-19 evolves. Communities may as well adapt social measures as required, keeping in mind local culture, access to services and resources, and living environments.

Amirthalingam et al. (2021) assert that public health policy and events primarily seek to safeguard health. Nonetheless, the utilisation of specific measures comprising stringent social and physical distancing as well as movement measures might have detrimental. Tan et al. (2020) argue that addressing such concerns at local and national policy levels will aid in alleviating possible burdens related to putting into effect public health policy measures and events and support conformity to the stated measures. Also, it is pivotal to adapt social measures and policies to the domestic context and take into account the duration they may be in place. Further, closer coordination of social services and public health is also needed to make sure everybody is aware of how to seek medical attention or testing and isolate. According to Daoust et al. (2021), no single approach exists for what measures to incorporate or how to put them into action considering the extensive range of economic and social contexts and epidemiological situations where COVID-19 is occurring.

2.5. Sentiment Analysis

Amongst the several applications of tweet analysis within public health, sentiment analysis is an application that has already gotten considerable research attention. According to Thelwall et al. (2011), sentiment analysis comprises a computational natural language processing tool for analysing the public's attitude on a given subject. In the recent past, machine learning strategies have made inspiring advancements within sentiment analysis. Thelwall et al. (2012) argue that Twitter offers an enormous number of tweets, nearly all of which are short, unstructured, public text messages, which allows employing tweets' sentiment analysis in several areas. Part of those applications dealt with public health concerns.

In the media and communication studies field, sentiment significantly contributes to the system of social media. Several studies have been undertaken to examine the connection between the public's sentiment and opinion on social media platforms and events. Thelwall et al. (2013) in their survey of levels of sentiments in tweets regarding major news found a connection between surges in the number of users' tweets associated with major happenings and a smaller surge in negative sentiments. Further, even positive happenings are mostly accompanied by a moderate increase in negative sentiments (Pavlatos & Vita, 2016). Other analyses also stress the pivotal role of social media sentiment in health-associated issues. Seeman & Rizo (2010) in their research examined the attitude of the Canadian public toward the safety of the Swine flu vaccine. They established that 23.4% and 41.4% of the study respondents considered the vaccine safe and unsafe respectively. This implies that 41.4% of respondents' opinions that spread largely via social media and Twitter were negative. Additionally, Himelboim et al. (2020) in their study also concluded there was significantly more negative footage on YouTube regarding the vaccine compared with positive videos, and the negative ones are likely to lead the public attitude astray and even get more likes.

Feedback is another pivotal social media role in disseminating information regarding key events. Twitter is a platform for distributing and promoting information as well as getting the public's feedback including comments, retweets, and tweets regarding particular topics being discussed. According to Shen et al. (2019), researchers can draw out keywords from an enormous volume of Twitter data comprising largely of textual information via text mining and afterward visualise key trends and connections between the keywords. Park et al. (2018) in their study utilised text mining to identify variations and similarities of topics amongst the three sub-Reddits; namely PTSD, depression, and anxiety. They found an overlap of this subject discussed within three different societies and identical patterns of discussion, which exhibited positive sentiments and appreciation for emotional assistance was shared as well.

The latest COVID-19 pandemic resolutely encouraged researchers to employ Twitter sentiment analysis to associated areas of public health including the perception of precautionary and preventive courses of action for COVID-19, COVID-19's social life influence, concerns regarding the pandemic, and emotional responses towards the COVID-19 pandemic. According to Chun et al. (2020), to undertake the sentiment analysis, such previous studies either utilised pre-trained models of sentiment analysis or manually developed annotated collections for training the models of sentiment analysis. It is worth noting that either model has limitations.

3. Methodology

3.1. Data Preparation

On February 28th, 2020, the World Health Organisation set COVID-19's risk assessment to "extremely high". Since 1st January 2020, I used WDRA to access Twitter APIs, to gather actual-time tweets. Further, from 1st January 2020 to 30th

June 2020, I gathered actual-time tweets.

During this period, I searched Twitter using several keywords and queries and later downloaded the search results using WDRA, a kind of software for data scrapping. Thereafter, I imported the data I gathered using WDRA into Senti-Strength. SentiStrength software can analyse the tweets that are either negative or positive or the emotions that account for the majority. Finally, I went back to the initial Excel data to screen and filter tweets associated with the greatest sentiment portion, utilising Voyant. According to Dickerson (2018), using the Voyant tool for mining Twitter text helps in identifying outlying or emerging trends within specific datasets. Thus, Voyant helped me to get visual results and outcomes of the prevalence of Tweets utilised words as well as semantic network amongst words in every aspect of attitude.

3.2. Sources of Data

By means of using the WDRA software, the researchers collected data from the website and used the records from the website of Twitter to collect various information, including the use of the data. Besides, based on the emotions and sentiments, the data is ranked from 1 to 5. For instance, some of them are negative sentiments, and some of them are positive sentiments. There are various topics, such as how users used Twitter to gain information and how they used Twitter to express their emotions.

3.3. Data Collection

Data collection is the initial research stage. The WDRA software abstracts information and data from the Web page via the Chrome extension. This is hinged on API that provides a link between the data extraction instrument and the Twitter platform itself. According to Hernandez-Suarez et al. (2018), Twitter's Application Programming Interface is public as well as accessible via accounts that have queries. In the following research, the queries took into account several scenarios as plausible to get more possible accessibility and access to Twitter data. While gathering the data, I searched key words including "coronavirus", "pandemic", "COVID19", "Social Distancing", "COVID-19", "COVID_19", "SARS_COV_2", "SARS-COV-2", "SARSCOV2", "isolation", "lockdown", and "stay-at-home". These search queries and keywords emanated from the virus and disease's official names as well as public health measures and events. Further, to evade confusion, this research did not employ other terms or names as search keywords and queries during tweet gathering. Slang was maintained whilst links and emojis in the gathered tweets were filtered out. On the day of collection, I gathered 3737 original tweets by specifically searching the above queries and keywords. To ascertain correct and valid search queries, I at the onset searched for COVID19 as a search to point out the most frequently utilised expressions associated with this talking point from the Twitter search results. Following countless search validations, I set the queries in this research as "COVID-19", another spelling "COVID_19" and similar words "SARSCOV2", "SARS-COV-2" and coronavirus. Considering hashtags' characteristics, COVID-19 comprised one word that needed to be written as "COVID19" or COVID_19 with the underscore character. Thus, in this study, "COVID-19" is generally utilised in referring to the pandemic, SARS_COV_2", "SARS-COV-2", "SARSCOV2 and COVID_19, COVID19.

4. Data Analysis

4.1. Sentiment Analysis

After gathering the data utilising the WDRA software, I carried out sentiment analysis to study how Twitter users express themselves on social media and their general attitude towards COVID-19 public health policy and events. This was done using SentiStrength. According to Thelwall (2017), sentiment analysis comprises a technique of employing a software system to assess the sentiments presented by people's text. The application utilised in this research is of the initial sentiment analysis strategy: machine learning, which learns by offering the program examples of negative and positive phrases and words known as a sentiment analysis dictionary, hence the algorithm may differentiate their usual sentimental characteristics and elements (Thelwall, 2018). A score from 1 depicting neutral to 5 depicting very positive or a score from −1 depicting neutral to −5 depicting extremely negative respectively is used to measure the negative or positive attitude of every phrase in the SentiStrength software's lexicon (Thelwall et al., 2013). Before text analysis, I initially scrutinised the data to ascertain validity. Especially, I removed Tweets with missing information, and several codes generated by the different hashtags within the "Sanitised Text" column were rectified.

This research categorised the gathered tweets into five levels of sentiments including extremely negative, negative, neutral, positive as well as extremely positive. **Table 2** below shows sample tweets depicting the various levels of sentiment.

Table 2. Selected tweets depicting various levels of sentiment.

Level	Selected Tweet
Extremely negative	Electronic monitoring companies refuse to touch coronavirus-positive inmates. That means they can't go home.
Negative	When your sister in law is in isolation but still has to deliver a box "Social distancing delivery"
Neutral	You can't catch coronavirus if you never stop eating and drinking. Fact!
Positive	This is the scenario that L.A. County health officials most feared—that reopening would coincide with sudden jumps in coronavirus transmission.
Extremely positive	If you have coronavirus stay home. Stop going out and acting like it's okay to infect everyone else.

Following an initial analysis, I discovered that for the different search queries, the final outcomes did actually mirror the precise sentiments because of the particularity of COVID-19 expression. For example, the word COVID-19, which largely refers to coronavirus or the pandemic caused by SARS-CoV-2 has several positive emotions and sentiments in this research.

After concluding the preliminary step of the analysis, I sorted the tweets in a work sheet based on negative emotions' value. Thereafter, I progressed to the next stage of sentiment analysis. The sentiment analysis procedure is also called sentiment mining or opinion mining considering it aims to mine opinions and sentiments from data within texts (Liu, 2012). Nevertheless, it is insufficient to just recognise opinions' sentiment tendency. The following research also further examined the factors and elements of every kind of sentiment via text mining. Ampofo et al. (2015) assert that text mining is an assemblage of or single process where software draws out meaningful patterns, trends, and associations from an enormous amount of Twitter text. I used Voyant, a tool of text mining to process filtered and processed tweets with negative and positive sentiments. Further, I used Semantic link and WordCloud to demonstrate the results and findings to reveal the aspects of COVID-19 public health policy and events users of Twitter are most concerned and interested about in every category of sentiments and how they express themselves regarding those topics. Eventually, I categorised these key topics and talking points and went back to the initial tweets for

The data collected in the following study was all posted and tweeted on the Twitter platform by individual Twitter users. It is worth noting that this research was not responsible in any way to notify any user of the Twitter platform to get consent while utilising the set of data from Twitter. Nonetheless, I paid particular attention to certain scenarios that might have involved ethical concerns that some Twitter users might have concerned the Twitter platform as a special and private space and may be reluctant to share their Tweets with other users. In the meantime, sensitive and vulnerable groups possibly comprised COVID-19 patients, which I paid particular attention to as well. Notably, I steered clear of directly containing private data like location and name in this study report. I blurred the personal information and rephrased the tweet content while quoting certain tweets where needed.

4.2. Results

Sentiment analysis is the initial part. With data correction as shown in **Table 3**, along with the WDRA software, I got an aggregate of 3737 valid data. Further, as shown in **Table 3**, every tweet's sentiment score contains two different components including the negative and positive aspects, for instance, −1 and 2. Considering 1 and −1 depict neutrality, I for the most part analyse the percentages from −2 to −5 as well as 2 to 5 within this section. In the figure above, I noticed that the proportion of users' tweets with negative sentiments solely was 28.82% of the sum total. This was less than the aggregate of the positive user tweets (29.98%). The negative sentiments were concentrated and amassed in the levels

Table 3. Data correction.

Raw Labels	1	2	3	4	Grant Total
−4	2.20%	0.70%	0.40%	0.40%	3.70%
−3	4.74%	3.00%	3.00%	0.00%	10.74%
−2	7.61%	5.61%	0.51%	0.71%	14.44%
−1	55.47	7.86%	6.59%	1.20%	71.12%
Grand Total	70.02%	17.17%	10.5%	2.31%	100%

of −2 as well as −3, which depicts a lighter percentage of negative sentiments with 10.74% and 14.44% respectively. Likewise, the key aspects of positive emotion and sentiment are also at a modest level of 17.17% and 10.50%. Nonetheless, just fewer numbers 0.40% and 3.70% of extremely negative and positive sentiments appeared in users' tweets. Generally, the gathered tweet data largely conveyed people's positive attitudes towards COVID-19 public health policy and events as they express themselves on Twitter. Notably, people expressed themselves towards COVID-19 public health policy and events with a modest attitude.

Results of Sentiment Analysis

The present analysis used excel to calculate the aggregate sentiment scores provided in Figure 1. The remainder of the following section summarises the results of the analysis of the COVID-19 public health and policy events including stay-at-home orders, social distancing, lockdown, and isolation. The results of the analysis offer pivotal information for global public health officials and policymakers for assessing people's opinions and sentiments towards related policies.

Results of Analysis of Stay-at-Home Orders

Figure 2 shows the average opinion scores for tweets associated with stay-at-home orders. From the analysis of the tweets, the sentiment scores, as well as tweet numbers associated with stay-at-home orders, peaked on 29th June 2020. Further, as shown in Figure 2, the average opinion scores for stay-at-home orders-related tweets were negative. A manual evaluation revealed that the peaks in tweets associated with stay-at-home orders were strongly connected with the stay-at-home recommendation granted by different governments and public health institutions across the globe. Most related and affiliated tweets were against this suggestion. For example, one user tweeted on 29th June 2020, "Gov. Greg Abbott with this about Dallas County Judge Clay Jenkins asking for authority to issue stay at home order: "He seems to want to continue to force poverty on people by having a stay-at-home order…" On 30th June 2020, related tweets revealed that most users agreed with this recommendation by different governments and health authorities. Similarly, during this period, I manually interpreted the related tweets and found that the increases in the number of tweets compared to other periods reflected the general public's attitudes towards

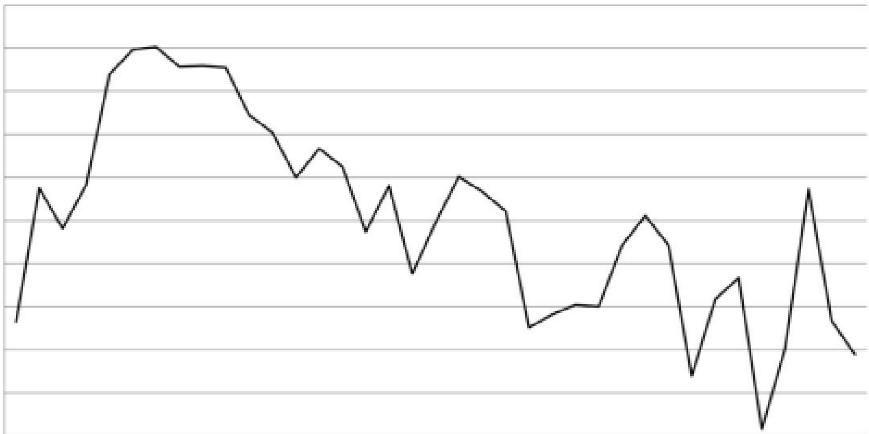

Figure 1. Users' overall sentiments and opinions concerning COVID-19 public health policy and events from 1st January 2020 to 30th June 2020.

Figure 2. Average sentiment score for tweets associated with stay at home orders.

those stay-at-home orders announced by over 50 countries this time. These tweets strongly supported this policy. Thus, the expression of individuals regarding stay-at-home orders comprises negative and positive sentiments. The associated tweets expressed users' and people's concerns about this policy's negative influences.

Results of Analysis of Social Distancing

Figure 3 shows the mean sentiment scores along with the number of tweets associated with social distancing directives. According to Le et al. (2020), as of 13th April 2020, there were 1,916,284 cases as well as 119,467 mortalities from the pandemic within the 181 impacted territories and countries. This saw several countries introduce social distancing directives to minimise COVID-19's spread. Tweets related to social distancing that was gathered between January 1st, 2020 and June 30th, 2020 reveal that several users were against this policy hence the higher negative average sentiment score as shown in **Figure 4**. I noticed the number of tweets associated with social distancing increase between June 29th and 30th. Further, I analysed the related tweets manually and noted that the increase in users' tweets was because of a surge in people's concerns regarding

Figure 3. The average sentiment scores and the number of tweets associated with social distancing policy.

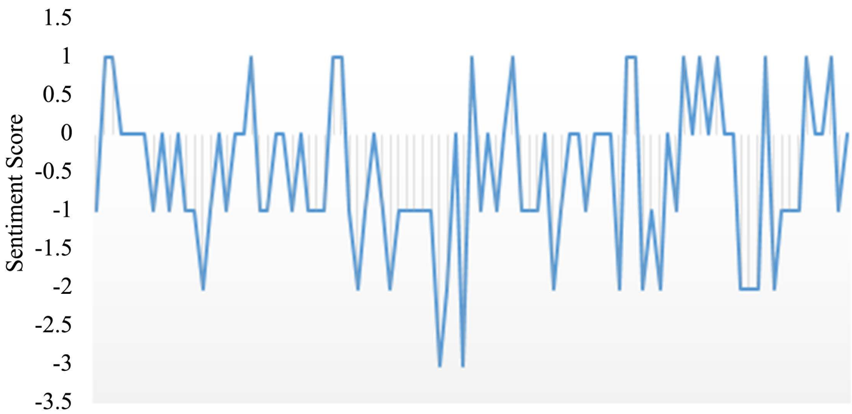

Figure 4. The average sentiment scores and number of tweets associated with isolation directives.

the need to practice social distancing while others were equally opposed to the orders.

Results of Analysis of Isolation

Figure 4 depicts the average opinion scores as well as the number of tweets associated with the isolation topic on the Twitter platform. On 16th March 2020, the World Health Organisation through its Director-General while briefing the world on COVID-19 announced that every case must be tested and if an individual tests positive for COVID-19, then they must be isolated to discover the persons they have in close connection and contact with up till 2 days before developing symptoms (World Health Organization, 2020b). Most users in their tweets asserted that isolation would be useful. This caused the mean sentiment score as well as the number of tweets tweeting under that hashtag to increase during that period, especially between March and June. Further, manual analysis, revealed that associated tweets expressed people's concerns of isolating once tested positive to avoid infecting others. Comparatively, lower opinion scores with a commensurately higher number of users' tweets were noted around 29th June. Most associated tweets also supported the isolation directive by the WHO.

Further, several associated tweets showed readiness for isolation, which was motivated by related tweets. For example, one user tweeted, "We need to make a psychological shift, New Zealand: mandatory isolation and quarantine is not a holiday, it's a service that returning New Zealanders commit to in order to keep the rest of us safe."

Results of Analysis of Lockdown

Figure 5 shows the average opinion scores together with the number of users' tweets associated with the topic of lockdown. Hundreds of regulations have been made worldwide in response to COVID-19 and most of them can only be characterised as "lockdown regulation." For example, in the UK the initial lockdown was implemented across the country in March 2020. Most Twitter users in their tweets stated that lockdown had denied them several opportunities by being unable to go out and continue with their daily normal lives. Therefore, they posted and shared negative sentiments regarding what was absent from their respective local areas and expressed a yearning for different amenities found within their workplaces. A manual analysis of the gathered tweets associated with lockdown also revealed that there was an increase in the number of tweets associated with lockdown between early March and late June at the same time when various governments were implementing such measures. The surge in tweets can be attributed to the implementation of lockdowns as people expressed their opinions regarding the same. For example, one user tweeted, "I'm going to ignore the reinstituted lockdown rules, and I encourage you all to do the same. If rioters get a pass, so must we." This tweet expresses negative sentiment because the user is opposed to the reinstituted lockdown measures and further encourages others to ignore such measures.

Results of Analysis of COVID-19 and SARS_COV_2-Related Tweets

Figure 6 shows the average sentiment scores as well the numbers of associated tweets associated with COVID-19 and SARS_COV_2. According to the WHO (2020b), COVID-19 dominated 2020. On 9th January 2020, the WHO announced inexplicable coronavirus-associated pneumonia in China's Wuhan. Nonetheless, at this point in time, the WHO still had doubts regarding the origin of what

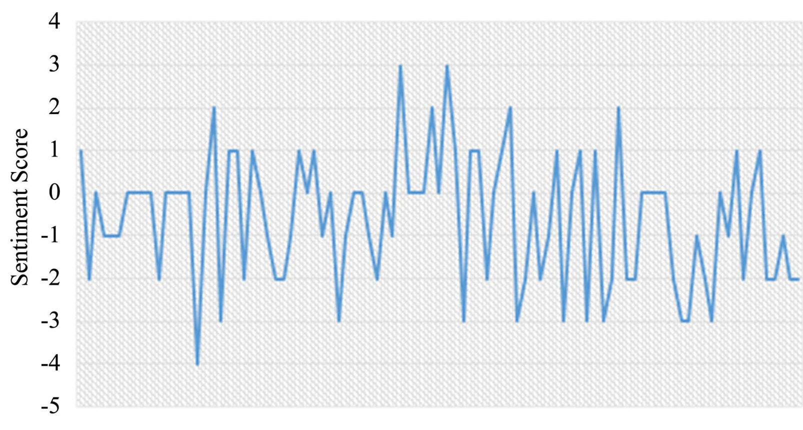

Figure 5. Average sentiment scores for tweets related to lockdown.

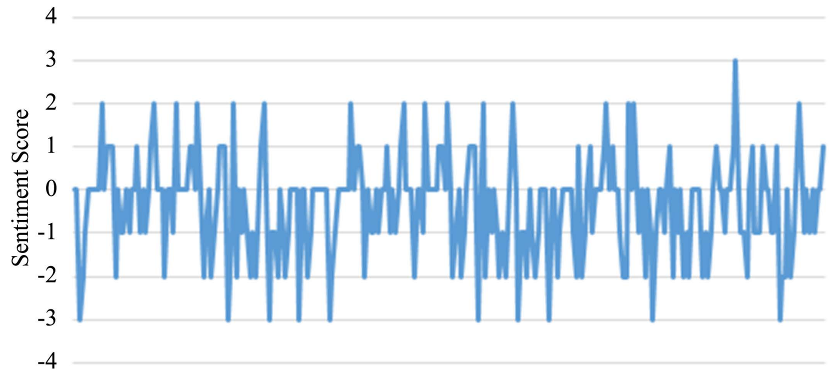

Figure 6. Average sentiment scores for tweets related to COVID-19 and SARS_COV_2.

would become the pandemic, stating that the outbreak of pneumonia-like cases within Wuhan could have emanated from a novel coronavirus. During this period, 59 cases were confirmed and several travel measures and precautions were already at the cutting-edge of experts' interests and concerns. It is during this period that users began to express themselves regarding the COVID-19 pandemic especially its origin and the likely causes. This was evident in the surge in the number of tweets associated with COVID-19 on the Twitter platform. Therefore, a manual analysis of COVID-19-related tweets revealed that the surge was caused by people's increasing concerns about this novel virus. Also, on June 30th, 2020, the WHO warned that new cases of COVID-19 could hit 100,000 persons per day. This also saw an increase in COVID-19-related tweets among Twitter users as people expressed themselves and their opinions regarding this new happening.

Further, following the discovery of the COVID-19 in Wuhan, the WHO stated that severe acute respiratory syndrome (sars), a viral respiratory infection was caused by a SARS-related coronavirus. From a manual analysis, there was an increase in the number of tweets associated with SARS_COV_2 on Twitter between 7th February 2020 and 14th April 2020. For example, one user tweeted, "Our researchers &, a company that grew from describing their rapid, versatile method for improving detection of SARS-CoV-2 to improve testing, especially when sample viral loads are low" while another one tweeted "Hoping he can mitigate the SARS-CoV-2 Health pandemic, put the economy on the right path & address systemic racism & unequal justice in the US. Obviously, Trump is incapable of addressing any of these issues or he would have done so." This shows Twitter users' expression of their opinions towards SARS-CoV-2. By doing so, they shared important information regarding the pandemic and also created awareness about it with other users of Twitter.

After concluding SentiStrength analysis, I returned to the earliest tweets for exploratory analysis. I noted that several tweets with positive sentiments and attitudes explicitly supported public health measures and events designed to curb the spread of COVID-19. For example, one user tweeted, "Couple of things. Eliza cut my hair and I think she did a wonderful job. If you have to venture out, be mindful of others, wear a mask, maintain social distancing and don't be racist. That's it." Further, another user tweeted, "These times are really going to test people's respect for the boundaries of others. "I'm social distancing," or "We can't make it," will need to be met with understanding, not pressure or ridicule." Also, another user tweeted, "Go get a test! If you are positive stay home until you are negative! If you are negative continue to practice social distancing and stay that way! Why is this so difficult?" All these users in their tweets expressed support for the World Health Organisation's advice for the general public. Particularly, there was no immediate and direct target audience for the public health policy measures and events such as COVID-19 patients and medical care practitioners to query. Additionally, negative sentiments revealed by other social media tweets were not directed at public health policy and events themselves. Instead, they were aimed at public health-related issues like people's refusal to follow the provided public health measures such as social distancing, stay-at-home, and isolation policies. These sorts of tweets were shared on the Twitter platform by handles ranging from global public health organisations like the World Health Organisation and common users of the platform. These Twitter handles preferred to express themselves by the sentence pattern, "stressing the risk of COVID-19 and appealing to adherence to stated public health policy measures and events".

To further analyse Twitter users' concerns and considerations behind every emotion, I undertook text mining utilising the Voyant software. According to Sampsel (2018), Voyant tools, an internet-based reading as well as an analysis environment, are designed to aid the analysis of digital texts.

WordCloud and term frequency form in Figure 7 and Figure 8 reveal that the topmost nine terms appearing for the most part in the tweets associated with positive and negative sentiments were pandemic, covid, social, distancing, people, masks, health, new and cases (Refer to Figure 8 and Figure 9). Notably, to make sense out of such terms in the specific context, I explored the term link consolidated by extremely high-frequency terms respectively. As shown in Figure 8, COVID-19 was strongly related to social distancing. From the text of

Figure 7. WordCloud on the most appearing terms.

	Term	Count	Trend
1	pandemic	968	
2	covid	765	
3	social	711	
4	distancing	677	
5	people	445	
6	new	394	
7	cases	302	
8	masks	289	
9	health	275	

Figure 8. Frequency of the terms.

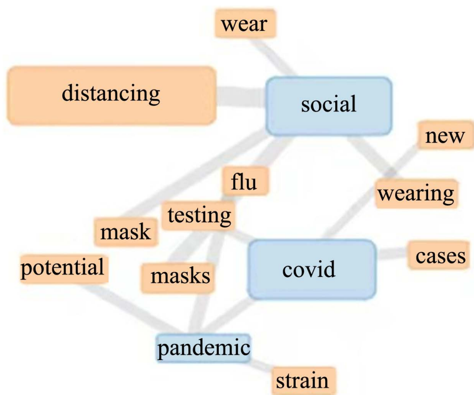

Figure 9. The relationship between the terms.

the tweets, I could establish that public health policy measures and events work effectively when individuals adhere to them. This implies that it is up to other Twitter users to make up their minds whether they should embrace the public health policy measures that other user recommend on their Twitter handles. Further, it was evident that in several negative tweets several users still do not accept the recommended public health policy measures and events. For example, one user in his Twitter handles posted, "Feeling very disconnected atm. I'm trying to engage but seem to be totally inept and devoid of any kind of interaction, isolation is an alien concept to me and I fear it is messing with my head!" Concerning the justification for some people's disregard of recommended public health measures, I had determined two elements including belief in public health measures' efficiency. Another element I noticed was the link between COVID-19 and social distancing measures (see Figure 10). As shown in Figure 9, the word "COVID-19" oftentimes appeared alongside the term "social distancing", emphasising that social distancing, a public health measure is also pivotal for the general public. The key concern of negative users' negative attitudes in their tweets was the absence of broad awareness of the effectiveness of public health policy measures.

	Term	Count	Trend
1	pandemic	968	
2	covid	765	
3	social	711	
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5	people	445	
6	new	394	
7	cases	302	
8	masks	289	
9	health	275	

Figure 10. Top 10 intersected with users' negative tweets.

Eventually, I undertook text mining for users' positive and constructive tweets to discover what was the major information in tweets with a constructive sentiment. As shown in Figure 10, the topmost 10 terms intersected with users' negative tweets although they differed in sentimental and narrative focus (see Figure 10). The increasingly used term in users' text was social distancing appearing 711 times. As may be noted in text analysis, users' positive tweets approving and endorsing public health policy measures focused on protection against the spread as well as contraction of COVID-19. These are two measures that prevent the general public from contracting the pandemic along with other people's safety. That is the key reason and justification why these positive tweets promote public health measures and events.

4.3. Noticeable Trends within Opinions and Sentiments of Users' Tweets

We further explored the trends and patterns in the opinion scores for talking points and subjects underlying the wider queries. This analysis helped me to comprehend and understand sentiments' progression for particular topics and queries over the duration we studied. Notably, to understand the differences in users' sentiments, we studied the tweets for the periods where changes were noted. Sample user tweets for every one of the queries and themes are shown in Appendix A below.

My analysis disclosed a consistently positive score for the subjects and queries for the entire duration studied. I noticed that users of Twitter often referred to the pandemic's geographical origin in their expressions and discussions. When I studied COVID-19's origin I found many tweets regarding the origin. For example, one user tweeted, "A new strain of a flu virus with 'pandemic potential' found in China by scientists. It emerged recently and is carried by pigs, but can infect humans. Researchers are concerned it could mutate and spread easily from person to person" while another one tweeted, "Coronavirus live updates: WHO team to search for Covid-19 origin in China as chief says he fears worst to come." The average opinion scores remained positive throughout my study period. The positive trends within users' tweets are attributable to tweets supporting COVID-19 public health policy and events between 1st January 2020 and 30th June 2020. During their expressions, users circulated these public health policies and events to encourage other users to embrace them. Additionally, the increase in the positive score in users' tweets during the study period is partially attributable to an enormous number of users' tweets with references to the pandemic as a way of challenging people on earth and across the globe how to live with it. For example, there was one tweet stating "WHO says worst of pandemic 'yet to come': Coronavirus latest" These kinds of tweets offer qualitative justification for the users' positive opinion scores I observed in the data analysis like;

"*Health officials in L.A. County issued a dire warning Monday that conditions amid the COVID-19 pandemic are deteriorating rapidly and the highly contagious virus is spreading swiftly in the nation's most populous county*".

"*Arizona Gov. Doug Ducey shuts down bars, movie theaters, gyms, and water parks Monday as leaders in several states order residents to wear masks in public in a dramatic course reversal amid an alarming resurgence of coronavirus cases nationwide*".

"*If you have coronavirus stay home. Stop going out and acting like it's okay to infect everyone else*".

5. Discussion

5.1. Key Findings

This study's findings closely agree with earlier studies that employed sentiment analysis to examine individuals' attitudes concerning public health policy and events (Ji et al., 2015; Du et al., 2017). Although these studies' algorithm details are different, they all found that sentiment and opinion scores could show and reflect individuals' attitudes. Further, this research joins the increasing amount of inforveillance research on COVID-19 that explores social media, especially Twitter data, and information to reveal how people express themselves towards public health policy and events, particularly their opinions regarding the same. I employed a corpus of more than 3,737 tweets from 1st January 2020 to 30th June 2020 to reveal the trends in opinions concerning numerous topics and themes. This present research is comprehensive comprising 12 different topics and queries underlying pandemic-related tweets. Liu et al. (2020) in their study employed sentiment analysis to examine the trends within opinions for different topics and themes over a specified duration. Likewise, in response to a request put forward by Liu et al. (2020), I employed sentiment analysis to observe how people expressed themselves on Twitter regarding public health policy and events. By analysing the collective sentiments and opinions of numerous Twitter users, I found fascinating trends in how they expressed themselves regarding opinions and sentiments of topics and themes of pandemic-related tweets.

I utilised the WDRA software to gather publicly available and accessible data from Twitter thereby creating a unique set of data with English-language tweets regarding different themes and topics linked with COVID-19 public health policy and events. I further employed SentiStrength software to analyse the tweets that are either negative or positive or the emotions that account for the majority. I also employed the Voyant tool for mining Twitter text thereby identifying outlying or emerging trends within the specific datasets.

My major finding is that users of Twitter use the platform to express themselves positively towards COVID-19 public health and policy-related topics and themes. Further, public health policy and events as well as the pandemic's origin were the issues that Twitter users discussed most during the research period. The number of positive proportions and number of users' tweets on the theme of COVID-19 public health policy and events theme was considerably higher compared with negative opinions. Also, users were positive regarding governments and global public health organisations call for the embracement of public health policy and events. This means that Twitter users were feeling positive regarding governments' responses to curb COVID-19 including isolation, social distancing, and stay-at-home.

From my study, Twitter users tended to express themselves positively towards public health policy and events, whilst comparatively few of them exhibited negative attitudes towards those public health policy measures. Contrastingly, Twitter users' negative expression of opinions on COVID-19-related themes on Twitter was largely conveyed in criticism of public health policy and events associated with the pandemic, as opposed to direct objection to such measures. The degree of two types of users' opinions in this present research had considerably changed since Figueira et al.'s (2021) study. The general public's acceptance of public health policy and events as evident in their expressions increased evidently and positive sentiments moderately became mainstream and recognised during the study period.

Nonetheless, it cannot be disregarded that there are sections of Twitter users and the general public with doubts regarding public health policy measures and events. As discussed in the findings section, this group of users was confused regarding the effectiveness of these public health policy measures because of the absence of knowledge on the same. Such groups did not acknowledge the need for public health policy and events towards curbing the spread of the pandemic during the study period. Other aspects that users took into consideration were belief in public health measures' efficiency and effectiveness as well as the impact of other users on the general public's compliance with various public health policy measures and events. Further, as stated in the findings chapter, although several users while expressing their opinions explicitly opposed public health policy measures and events, these criticisms had an enormous influence on other users' opinions and sentiments since they were made by known internet users. It is challenging for other users to disregard the opinion when known Twitter handles say public health policy and events are not effective in curbing the pandemic's spread.

Another important finding of my study is that whilst other users express themselves positively and negatively towards COVID-19 public health policy and events, other users find it noble to share information regarding mental health despite the challenges people face because of the pandemic. Research shows a major surge in the number of adults that report symptoms of depression, insomnia, anxiety, and stress during the COVID-19 times. Notably, after living in COVID-19 for very long, one might feel fed up, exhausted, anxious, and depressed. Therefore, other users of Twitter express themselves by encouraging individuals to take a watch of their mental health. For instance, one user tweeted, "With this pandemic, do not forget to prioritise your mental health" while another posted "Today I conquered my pandemic-induced fear of going on long outdoor walks. Beyond enjoying the fresh air, I also enjoyed these flowers. A gentle reminder to do what you can to take care of your physical and mental health in these difficult times". This shows that these users are mindful of others who might face mental health challenges during COVID-19 and hence encourage them to stay woke.

My study provides various insights and understanding for health administrators, officials, and policymakers who are managing the spread of the pandemic through the implementation of public health policy measures and events. Identifying topics and related sentiment and opinion changes offer indicators to how ordinary people throughout the globe are responding to particular measures and initiatives taken to deal with COVID-19 since its discovery. Differences in the sentiment scores evident in users' tweets act as a mechanism of feedback for evaluating public opinions of different measures recommended and taken regarding social distancing, isolation, and stay-at-home orders. My study reveals that observing overall opinions in people's expressions and changes within those opinions via users' social media, particularly Twitter posts can provide a timely, valuable and cost-effective mechanism to measure public perceptions and opinions concerning recommended public health policy and events to address COVID-19.

5.2. Limitations of the Research

The following research has a couple of limitations that must be acknowledged whilst interpreting the study results. I depended on a huge set of data that I compiled by myself. My data source comprised tweets from different dates and employed varying search terms and queries to collect the tweets. My analysis might have inadvertently and mistakenly omitted specific CIVID-19 and public health policy and events-related tweets that the data sources did not capture. Additionally, I did not take into consideration any or whatever geographical boundaries while assessing the tweets. Research and studies paying particular attention to tweets from particular nations may find varying sentiments and topics that reflect nation-specific concerns and opinions regarding COVID-19 public health policy measures and events. Further, I also restricted my research to tweets with the English language as well those tweets posted and shared by individuals. It is worth noting that the WDRA software helped me in identifying tweets shared by individuals via their respective Twitter handles. Additionally, it is likely that several individual users of Twitter shared tweets in support of organisations and such tweets are included in my set of data. To address the stated limitation, a more effective and refined method with machine learning techniques to point out individual tweets might help in assembling and categorising a data set of tweets with enhanced accuracy. Further, as a future study extension, tweets shared by organisations could comprise another reference frame to recognise and understand their sentiments and concerns. Another essential limitation of research limitation is that my findings are pensive and reflective of users of Twitter, who are relatively well acquainted with social media as well as technology usage. Therefore, the results might not generalise to the wider population of individuals and the general public that does not utilise the Twitter platform.

6. Conclusion

The present study shows that tweet data's general sentiment score might reflect users' attitude changes and shifts towards COVID-19 public health policy and events. As the pandemic continues impacting millions of individuals worldwide, my research clarifies dominant topics, themes, and sentiments evident in Twitter users' discussions as they express themselves. According to Figueira et al. (2021), with COVID-19's outbreak, an overmuch of information associated with the pandemic was released via social media and the scenario worsened across the globe, individuals started depending more considerably on the direction and advice offered by other users and public health institutions. Therefore, based on the fact that social media plays an important role in information transfer notwithstanding other users' feedback, it is pivotal to take into consideration social media initiatives for CIVID-19 public health policy and events promotion. The impact and influence of official Twitter handle and accounts on the Twitter platform is nowhere near other users holding contradicting opinions. Thus, official Twitter handles especially those of global public health organisations and agencies like the WHO can modify and adjust content to social media features. Social media especially Twitter content may be short, informative, easy to comprehend, and pay particular attention to visual expression. This content will enhance tweets' attraction and widen the publicity scale of positive content and information on public health policy and events.

Considering the argument regarding users' call for public health policy and events including social distancing, it is evident that several governments have urged the general public to embrace these measures. For example, the UK government has implemented several public health policies and measures to minimise COVID-19 incidence. Talic et al. (2021) in their study found that several social measures especially social distancing are linked to decreases in COVID-19 incidences. Notably, they recommend that efforts of public health to execute public health policy measures and events must take into consideration community health as well as sociocultural needs. Thus, by assessing the trends and sentiments surrounding different topics and themes as users express themselves on Twitter, government agencies, leaders, businesses, and health care organisations that are putting their efforts towards addressing the pandemic can be aware of the wider public opinion regarding the virus along with the public health policy measures and events that have assumed so that corrective courses and adaptations can be employed to control and prevent COVID-19's spread. It is also worth noting that Twitter users' call for people to take care of their mental health amidst the pandemic is a reminder to health authorities that whilst their efforts are solely focused on curbing the spread of COVID-19, they should not forget the impact of mental health just like the pandemic.

Conflicts of Interest

The author declares no conflicts of interest regarding the publication of this paper.

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