Public Sentiments towards the COVID-19 Pandemic: Insights from the Academic Literature Review and Twitter Analytics

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ABSTRACT

The recent COVID-19 pandemic has severely impacted nations across the globe. Not only has it created economic shocks, but also long-term impacts on the social and psychological behaviors of the public. This can be attributed to the severity of the pandemic and because of the preventive and control measures such as global lockdowns, social distancing, and self-isolation that the governments imposed. Previous studies have reported significant changes in human emotions and behaviors are used to measure public sentiments about certain phenomena (such as the recent pandemic). The present study aims to study the public's sentiments during the COVID-19 outbreak based on an analytics review of public tweets highlighting changes in emotions. A dataset of 58,320 tweets extracted from Twitter and 61 academic articles was explored to analyze behavioral and emotional changes during previous and current pandemic situations. We chose the RPA – COV (Research Process Approach – COVID-19) approach,

which was combined with the LBTA (Literature-Based Thematic Analysis) and the COVTA (COVID-19 Twitter Analytics). The sentiments' analysis results were coupled with word-tree analysis and highlighted that the public showed more highly neutral, positive, and mixed emotions than negative ones. The analysis pointed that people may react differently on Twitter as compared to real-life circumstances. The present study makes a significant contribution towards understanding how the public express their sentiments in pandemic situations.

Keywords: Sentiment analysis, Pandemic, COVID-19, Twitter analytics, Thematic analysis

1   Introduction

Pandemics represent a massive public health threat given their death toll in quite a short period (Taylor et al., 2001). The WHO report 1 (Organization, 2020a) on COVID-19 confirmed 282 cases in four countries on January 20, 2020. This number drastically rose from 282 cases (January 20, 2020) to 2,798 cases (January 27, 2020) in 12 countries (reported in the WHO report 7 (Organization, 2020b)). As per the current WHO report 83 (Organization, 2020d), 1.7 million were already infected, with 0.11 million deaths globally. COVID-19 has taken a toll on the economy, arousing the highest decline in the financial market since 1987, a high record on unemployment, and a major hit to the travel industry with multiple restrictions (Jones et al., 2020). Over the past centuries, pandemics such as Swine flu, Ebola, SARS, MERS, etc., have been persistent, but the COVID-19 pandemic has taken the entire world by storm. Pandemics can cause a high number of fatalities and account for a severe public health risk (Mukherjee, 2017). The COVID-19 outbreak's impact will be long-lasting on people's psychology and physiology (Kecmanovic, 2020). Social isolation is very likely to change the immune system and the sleeping pattern of the world population (Higgins, 2020). The COVID-19 pandemic is expected to cause psychological distress on frontline health workers (Ho et al., 2020). In view of recent statistics, the COVID-19 impact could appear as the deadliest pandemic affecting the

entire World. There is also widespread concern about its effects on mental health. Fear, anxiety, worry, and stress are natural in the prevailing circumstances (WHO). This study aims to explore changes in the sentiments of people as a result of emotional distress caused by COVID-19.

Twitter, a microblogging site, is considered a rich source of information that can be used to identify patterns and observe the reactions/ sentiments of the general public (Ahmed, 2019). Past research has explored the use of Twitter to gain insights into pandemic outbreaks (Signorini et al., 2011; Kostkova et al., 2014; Oluwafemi et al., 2014; Chew and Eysenbach, 2010). Qualitative content analysis, also known as thematic analysis, is a widely used quality-based technique (Kuckartz, U., 2019). The researchers aim to investigate how Twitter users have been reacting to the pandemic crisis. In doing so, we performed a qualitative analysis of past research papers published on pandemics to comprehend people's emotions during such emergencies and then provide the historical context. The sentiments of people towards the COVID-19 outbreak, as expressed on the Twitter platform, were captured and the data collected were analyzed. This was followed by a thematic and content analysis of published research papers. When we compared the results from the content, thematic, and cluster analysis performed on research papers on pandemics with the results from the sentiment, content, and network analysis performed on Twitter data, we gathered insights into people's feelings about pandemics across regions/countries and over time. We have classified tweets according to whether they express positive, negative, mixed, or neutral sentiments to establish polarity scores for judging feelings about pandemics.

This study has significant implications that the study is of its first unique study to test the RPA-COV framework by examining the people's sentiments during a pandemic by understanding the change in sentiments as an outcome of COVID (Min et al., 2021). To the best of our knowledge, this is the first research that involves a qualitative analysis of past studies on

pandemics and social media analytics of Twitter data on the COVID-19 pandemic. In this study, the thematic and content analysis of the literature review depicts the way people feel and think about pandemics. In contrast, social media analytics attempts to explore people's sentiments about the COVID-19. It has been observed that sentiments are the core form of interest of an individual, and the current study examines the effect of the dynamics on an individual's sentiments. Thus, this study contributes to the temporal effect of an event; therefore, this study depicts the progression of people's sentiments towards pandemics over time. Overall, the study attempts to explore the following research questions (RQs):

RQ1: What are the various sentiments shown by the general public towards the COVID-19 pandemic across multiple geographies?

RQ2: How does previous literature investigate the sentiment of the general public towards pandemics?

RQ3: What are the emergent topics and themes highlighting the general public's sentiment towards COVID-19?

The findings of this research are expected to help different health care stakeholders, including policymakers and health workers, in their daily actions. In particular, health workers specialized in psychological and mental healthcare are specially targeted, as they work tirelessly to ensure the physical and mental wellbeing of people during pandemic outbreaks. Following the introduction, the literature review makes a thematic analysis of past research and social media analytics in research. Then, the methodology section highlights how data was extracted from Twitter, how research papers are being identified and what research methods were used. This is followed by a detailed data analysis section and another one summarizing

and discussing the findings. The last section is the conclusion, with implications, limitations, and future research directions.

2   Literature review

In recent times, social media usage has witnessed exponential growth, leading to huge volumes of data, and the accumulated data is known as social media big data. Many social media platforms wherein the general public can communicate, share ideas, and exchange relevant information (Kim et al., 2014). Of all the social media platforms, Twitter is one of the most widely used social media to study interactions and communication (Sinnenberg et al., 2017). Data from Twitter (referred to as Twitter analytics) can be captured and analyzed to provide intelligence (Tricco et al., 2017). Twitter analytics can then be used for discerning trends and insights into a particular issue (Golder and Macy, 2011). Past studies have mined and analyzed the social media data but have been restricted to defined time frames and issues (Kim et al., 2016). As per Lischke et al. (2017), Twitter is like a gold mine of frank and voluntary opinions of the general public. Often, communication on social media leads to an efficient capture of personal thoughts and opinions (Godes and Mayzlin, 2004). Social sciences research studies have highlighted that the time spent on social media platforms influences human behavior (Statista, 2019). The social media platforms have voluminous data in the form of user-generated content. This user-generated content has a psychological influence (both negative and positive) on people's lives (Crawford, 2009). It has also been observed that nowadays, people are paying a lot of attention to the opinions and suggestions shared online, social media users tend to share their opinions, ideas, and emotions (sentiments ranging from irony and negation, sadness and happiness, surprise, confusion to name a few) (Ali et al. 2017; Ji et al. 2016). These sentiments tend to influence critical business decisions and policy-related developments from an organization and government perspective. The extraction of these large-

scale posts containing public sentiments is referred to as sentiment analysis, and the technique is known as opinion mining.

Sentiment analysis is gaining a lot of popularity nowadays. It helps uncover the latest events and dynamic trends as people express their sentiments candidly on social media platforms (Chaudhary and Naaz, 2017). Sentiment analysis is used extensively by researchers across various fields such as marketing, for human behavior (Al-Yafi et al., 2018; Hamouda, 2018; Odoom et al., 2017; Rathore et al., 2017; Zeng et al., 2010), the analysis of customer dissatisfaction (Fan and Gordon, 2014) and learning (Leonardi, 2017; Li et al. 2017). With the advancement of information and communication technologies (ICTs), we can provide ample information on the spread of infectious diseases. Many studies have highlighted the role of ICTs in aiding sentiment analysis on social media platforms (Singh et al., 2018). Various studies have highlighted that sentiment analysis could have possibly helped in effectively controlling the epidemic outbreaks. Hutto and Gilbert (2014) studied the valence and intensity of tweets on pandemics and discovered that distribution of sentiments changes with time and place (Georgiadou et al., 2020). Ahmed (2019) studied the type of information spread on Twitter during the Swine flu outbreak in 2009. Like other studies, their study demonstrated the importance of Twitter in information dissemination during pandemics (Ahmed, 2018; Ahmed et al., 2018; Alonso-Mu~noz et al., 2017; McClellan et al., 2017; Stokes & Senkbeil, 2017; Wekerle et al., 2018; Hashimy et al., 2021).

As a social media analytics tool, sentiment analysis helps accurately measure the positive or negative bent of public sentiments expressed on social media platforms (Rosenthal et al., 2015). It provides real-time communication channels through which information is disseminated and precautionary measures taken in affected areas (Liu, 2015; Alsudais & Corso, 2015; Bendler et al., 2014; Mirbabaie et al., 2016; Gill et al., 2014; van Gorp et al., 2015). It has also been

effectively utilized to assess product assessments (Pang et al., 2008) and evaluate stocks in financial markets (Nguyen and Shirai, 2015). Researches have indicated a significant impact of social media in disaster response. Disaster relief agencies need to be conscious of the effects of emotional churning by the affected people. This can be judged by assessing the expression of doubts, anger, overall satisfaction, etc., about social media through network analysis (Ji et al., 2015).

In the present study, we attempt to discover various aspects of 'pandemics' that researchers have identified in the past so that these efforts can be used to understand the sentiments of people towards pandemics. We use the published literature to identify dominant emotions through thematic analysis. Thematic analysis is used for understanding and analyzing various themes (Braun and Clarke 2006). The thematic analysis involves searching, reviewing, and defining themes (Sodhi and Tang, 2018). Variables are identified using a thematic analysis of published research papers. Themes are deciphered based on the frequency of words in the research papers (Kuckartz, 2019d). The qualitative descriptive technique includes thematic and content analysis. It is applied to analyze text and interpret themes (Vaismoradi et al., 2016). Past research has investigated Twitter content by employing quantitative techniques for gaining data on pandemics (Nolasco and Oliveira, 2020; Chew & Eysenbach, 2010; Signorini et al., 2011; Kostkova et al., 2014; Oluwafemi et al., 2014). This research fills the gap by providing valuable insights into the sentiments of people towards pandemics over time and geography, using social media analytics for the current COVID-19 pandemic, and employing qualitative research on past published papers on pandemics.
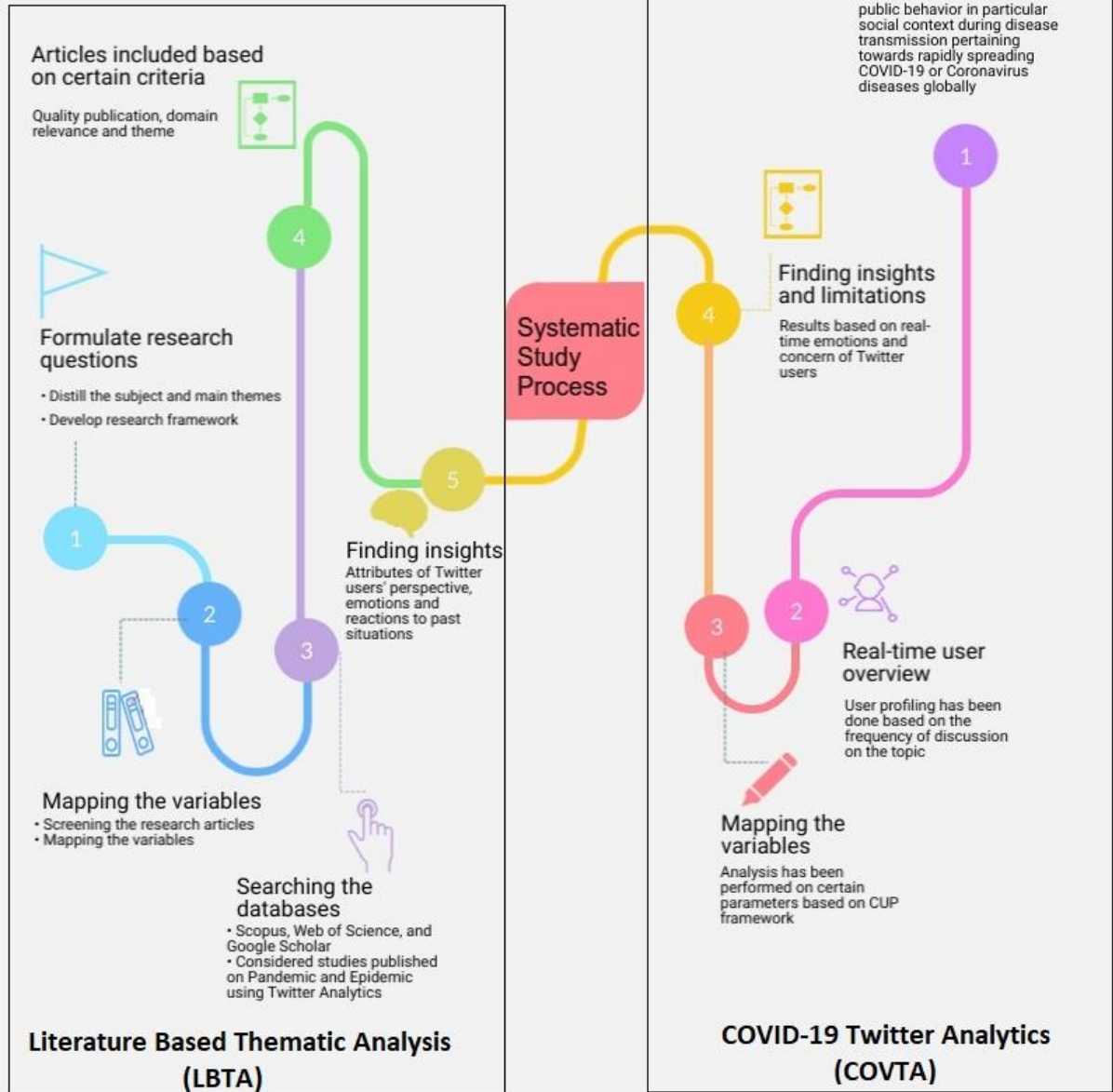
3   Methodology

To explore the public emotions and concerns about the COVID-19, this study made an effort to understand the overall public behavior in a particular social context of disease transmission.

Twitter API was used to extract the data. The study has combined the literature-based thematic analysis (LBTA) with the coronavirus Twitter analytics (COVTA) using Python and NodeXL software, as mentioned in Figure 1, to perform this analysis. Such a combination aims to get a holistic overview of this pandemic situation. Literature-based thematic analysis (LBTA) will provide public emotions, interests, and concerns by taking a historical overview of similar situations. On its part, COVID Twitter analytics (COVTA) will examine the current situation by analyzing the user's sentiments towards the current COVID-19 situation (Figure 1).

Figure 1: Research process approach for COVID-19 (RPA-COV)

Research approach for Analysis

Capture real-time data from twitter

To understand the overall public behavior in particular social context during disease transmission pertaining towards rapidly spreading COVID-19 or Coronavirus diseases globally

Articles included based on certain criteria

Quality publication, domain relevance and theme

Finding insights and limitations

Results based on real-time emotions and concern of Twitter users

Formulate research questions

· Distill the subject and main themes
· Develop research framework

Systematic Study Process

Finding insights

Attributes of Twitter users' perspective, emotions and reactions to past situations

Real-time user overview

User profiling has been done based on the frequency of discussion on the topic

Mapping the variables

· Screening the research articles
· Mapping the variables

Mapping the variables

Analysis has been performed on certain parameters based on CUP framework

Searching the databases

· Scopus, Web of Science, and Google Scholar
· Considered studies published on Pandemic and Epidemic using Twitter Analytics

Literature Based Thematic Analysis (LBTA)
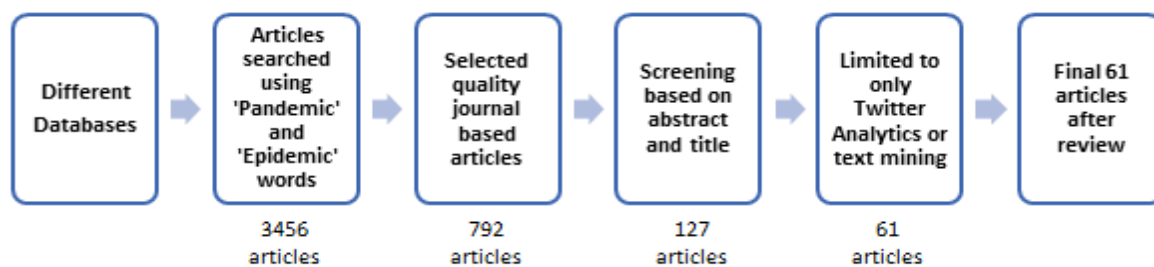
COVID-19 Twitter Analytics (COVTA)

3.1 Extraction of Relevant Articles

Various academic paper databases have been used to extract papers with a clear focus on understanding the COVID-19 situation. After using multiple sources, we eventually extracted a good number of papers till March 2020. Two major search words were used during the search

on different databases: 'Pandemic' and 'Epidemic'. After a preliminary search on google scholar, we selected a total of 3,456 articles. Considering the volume of academic articles, we finally selected articles based on the type of publication journal only. In the second round of investigation, 792 articles were selected. The third step of the work consisted of using another filter (Twitter analytics) to screen the articles further. Figure 2 provides more details on the selection of final articles. Following the basic screening of research articles, obtained only 127 articles, and the final number was reached using abstract screening on these articles. Through Twitter Analytics or Text Mining (the adopted methodology) (Lipizzi, 2016), we were, therefore, able to select all the articles had cited for past pandemic or epidemic scenarios.

Figure 2: Selection method of academic articles

3.2   Twitter Analytics Process

Twitter analytics (TA) will help to understand the emotions and concerns of different users in the Covid-19 crisis. Twitter is an online mediated communication tool (Al-Yafi et al., 2018; Sunday and Vera, 2018) and an effective tool for identifying the user emotional behavior (Brandt et al., 2017) and examining the user interests (Feng et al., 2015) and knowledge sharing (Leonardi, 2017). It will be the right approach to use Twitter analytics for COVID-19 to understand the emotional behavior of users. The CUP framework (Fan and Gordon, 2014) has

been used to perform Twitter analytics in this study. The CUP framework has three major processes: capturing tweets, understanding the data, and presenting the results.

3.3   Tracing of Tweets

The data has been extracted from Twitter using Tweepy API in a specific time framework from January 25, 2020 to April 4, 2020. During this period, approximately 80,420 tweets were extracted using two hashtags, namely "Coronavirus' and 'COVID-19'. We noticed the existence of multiple tweets with low-quality information or less helpful information concerning the coronavirus situation. So, after doing the initial screening of such tweets, we obtained 58,320 final tweets, all of which were used to perform the final analysis on different parameters under Twitter Analytics (TA).

4   Findings and Results

The results and findings of this study were further divided into two significant sub-sections based on the type of analysis performed. In the first subsection of the findings, a detailed thematic analysis was presented based on the literature review, followed by Twitter analytics in the second sub-section of the study. Based on the similarity of the words, the clustering was perfomed in order to fetch the data from the different databases. So, by the process of clustering, the data will generate some specific groups based on similary or dissimarlity and further assignment each object to its closest medoid (Mostafa, 2019). In addition to clustering, the network analysis provided the network (twitter handle) density of the nodes that are highly conncted to each other on the Twitter or the density of handle is very high in nature compare to other handles. So, the network analysis is applied to select a specific dataset on twitter and create a certain range to measure the centrality, density and modularity of the data (Grandjean, 2016)

4.1   Insights from thematic analysis

Various academic articles were extracted from different databases using the search string, as mentioned in table 1. A total of 61 articles were extracted from Web of Science, Scopus, Taylor & Francis, and further analyzed based on the type of pandemic and epidemic situation cited in the paper.

Table 1: Data extraction details

Database	Search String Used
Web of Science	TOPIC: (Pandemic) AND TOPIC: (Epidemic), TOPIC: (Pandemic) AND TOPIC: (Social media), TOPIC: (Epidemic) AND TOPIC: (Social media)
Scopus	(TITLE-ABS-KEY (Pandemic) AND TITLE-ABS-KEY (Epidemic)), (TITLE-ABS-KEY(Pandemic) AND TITLE-ABS-KEY (Twitter)), (TITLE-ABS-KEY (Epidemic) AND TITLE-ABS-KEY (Twitter))
Taylor and Francis online	[All: Pandemic] AND [All: Epidemic], [All: Pandemic] AND [All: Twitter], [All: Epidemic] AND [All: Twitter]

RQ1: What are the various sentiments shown by the general public towards the COVID-19 pandemic across multiple geographies?

Figure 2 explains the number of instances for the recorded pandemics according to the type of situation. These pandemics include Flu Epidemic, Ebola Epidemic, Zika Epidemic, Dengue, Chikungunya, Diphtheria, H1N1 Flu, HIV Epidemic, and Measles. Figure 3 explains the distribution of type of flu (in numbers across various years) wherein figure 4 describe the distribution of specific fluw from duration prespective (in years) of pandemics or epidemics in

respect to the current situation. These two figures examine the historical evidence mentioned in the research articles by using the text mining method. They then showcase a substantial amount of insights about each crisis. The maximum number of research articles have been found to relate to the Flu epidemic scenario, followed by those on the Zika virus epidemic and finally those concerning the Ebola epidemic. All the studies have been performed between 2009 to 2020.
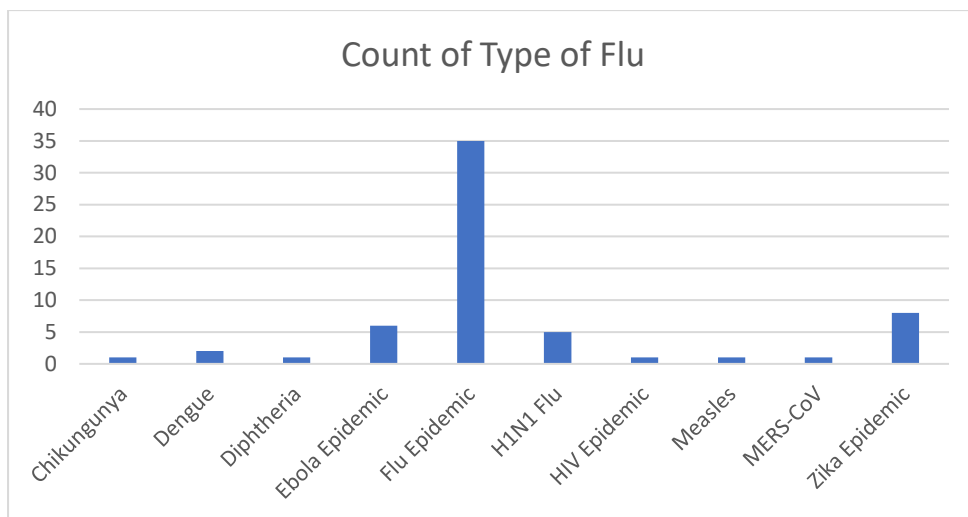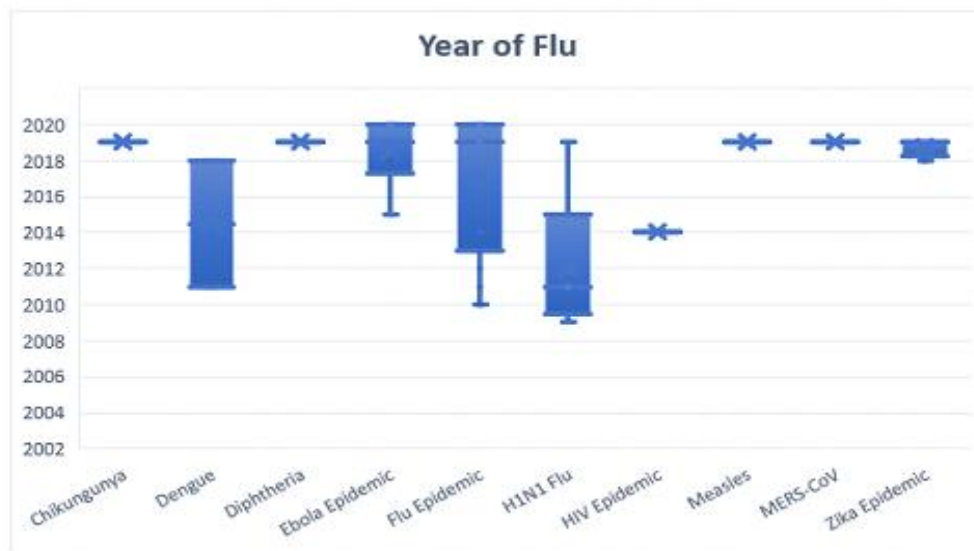
Figure 3: Distribution of types of Flu (number)

Figure 4: Distribution of Flu (years)

RQ2: How does previous literature investigate the sentiment of the general public towards pandemics?

The current study has focused on analyzing the emotions and concerns of people in already published academic studies and comparing findings with results from the current Covid-19 context. Our investigation went through several processes, including a word cloud analysis to understand the frequency of words related to the topics under study. The word cloud analysis revealed the significant words with high frequency: information, social, media, health, and influenza. Moreover, the word frequency enabled us to detect the important words translating a negative and positive intention or internal emotion. Figure 5 presents the results of the word cloud analysis based on the traditional academic literature (Boon-Itt & Skunkan, 2020). In word cloud, the whole analysis is based on the frequency of one specific word (unigram) in the mining text and display their frequencies through the word cloud representation. The words,

such as positive, accessed, prevention, and value, featured among the top positive ones in the word cloud analysis.

During the word cloud analysis, negative words with high frequency appeared in greater numbers than positive words with high frequency. In contrast, outbreak, influenza, infectious, epidemic, virus, infection, and transmission pertained to the top negative words. Therefore, it can be concluded that, according to the previous literature, the public expressed negative feelings about different pandemics or epidemics at a specific point in time. .
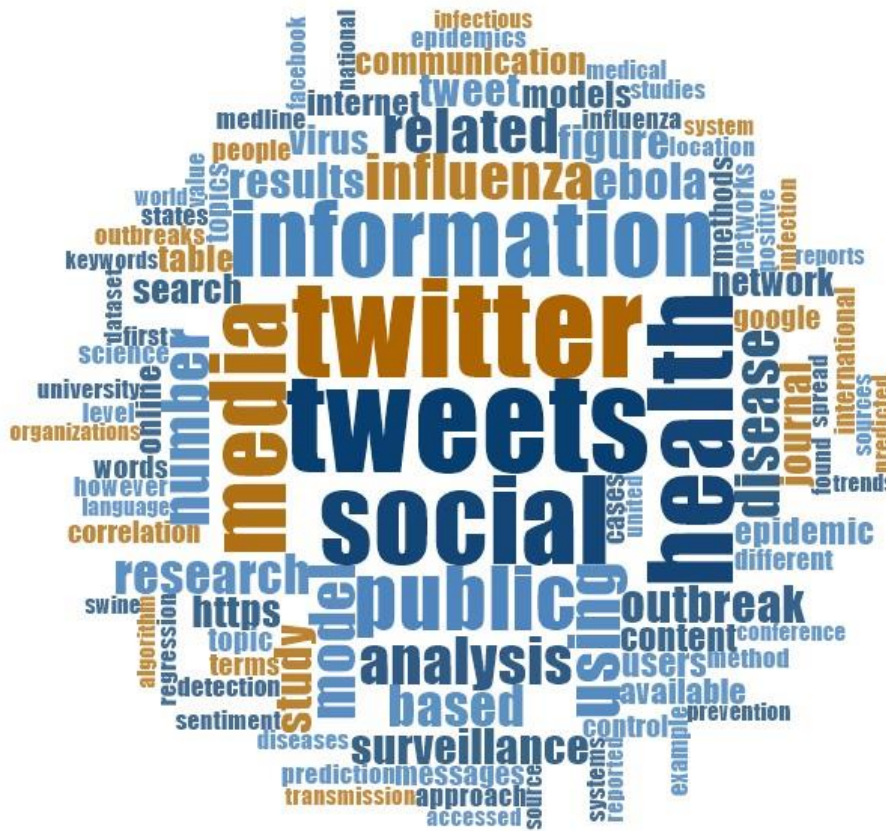
Figure 5: Word cloud analysis – LBTA

Table 2 depicts that the major available academic research on the flu epidemic. To the best of our knowledge, the classification presented in Table 2 is exhaustive; the first column represents the type of flu studied, followed by the most frequent constructs used in the study, the research

methodology used, and the size of the samples. On the other hand, Table 2 provides further details about 61 articles based on the type of flu per article.

Table 2: Flu-specific classification of literature

Type of Flu	Author(s)	Constructs Used for Results	Research Methodology	Sample Size
Dengue	Gomide et al. (2011)	Volume, location, time and public perception	Sentiment analysis	493,102 tweets
	Kraemer et al. (2018)	Disease dynamics, Gravity model, Human mobility, Radiation model	Spatiotemporal analysis	Tweets
Chikunguny a	Rocklöv et al. (2019)	Air passenger, virus transmission	Quasi real-time, geolocated Twitter activity data and computed mobility patterns of users.	Tweets
Ebola Epidemic	Odlum & Yoon (2015)		Content analysis, NLP	54 million tweets
	Tully et al. (2018)	Non-profit organizations, communication, organization, news media, influencers	Qualitative textual analysis	Tweets from non-profits
	Joshi et al. (2020)	Public health & symptoms	SVM and SVM-Perf	Tweets from December 2011 to December 2014
	Roy et al. (2020a)	Figure of blame, government, health communication, outbreak	Inductive thematic analysis approach	Twitter and Facebook
	Roy et al. (2020b)	Epidemic management, African Cup of Nation, soccer	Qualitative thematic and frame analysis	Facebook and Twitter

	Guidry et al. (2020)	Communications, the larger ecological context, and the associated risk perception	Quantitative content analysis	700 Pinterest posts & tweets
	Bempong et al. (2019)	Big data, mHealth, modelling, novel technologies and remote-sensing technologies	Systematic Literature Review	82 research articles
Flu Epidemic	Baker et al. (2020)	Valid category (influenza signs) and invalid category (other category) tweets	Data mining SVM, Naive Bayes (NB), K-nearest neighbor and Decision Tree	54,065 tweets
	Hellsten & Leydesdorff (2020)	Social media debate	Social network analysis and semantic network analysis	72,077 tweets
	Hellsten et al. (2019)	Stakeholder's participation	Social network analysis and semantic network analysis	2,139 Twitter messages
	Huang et al. (2013)	Co-location and social tie	Cosine similarity, standard deviation metrics, dynamic Bayesian Network	35.3 million tweets
	Wakamiya et al. (2019)	Social media, infodemiology; infoveillance	Machine learning and natural language processing	Tweets
	Deiner et al. (2019)		Temporal search and scan analysis of Google searches	135 candidates' tweets
	Rubin (2019)	Newspapers, Internet, Deception, Disinformation, automation, education, regulation	Literature review	Conceptual framework

Diaz-Aviles et al. (2010)	Tweets related to medical conditions	Personalized Tweet Ranking algorithm for Epidemic Intelligence, semantic analysis	7,710,231 tweets
Zadeh et al. (2019)	Public health, Social media, Behavioural analytics, Location analytics	Big Data technologies	Twitter data
Glowacki et al. (2019)	Food safety and illness	Text analysis and content analysis	13,000 tweets
Wegrzyn-Wolska et al. (2013)		Text mining, social network analysis	100,000 tweets
Lamb et al. (2013)	Word classes used	NLP	1.8 billion tweets
Alessa & Faezipour (2019)	Social networking site posts on well being	Sentiment analysis (text classification, mapping, and linear regression)	8,400,000 tweets
Wakamiya et al. (2018)	Patient, urban areas, rural areas, information	Natural Language Processing Module	7 million influenza-related tweets
Xue et al. (2019)	Preventive measures, control measures, departments	SVR for prediction	Twitter data
Hu et al. (2018)	Public health	Artificial tree algorithm	CDC data set and Twitter data set.
Barros, Duggan, & Rebholz-Schuhmann (2020)	Diseases, Medical Conditions, and Health Topics	Systematic Literature Review	162 research articles
Wang et al. (2020)	Flu prediction	PDE model	Geotagged Twitter streaming data
Aramaki, Maskawa, & Morita (2011)		Machine learning, SVM, text mining	300 million tweets

Devika, Sinduja, & Subramaniyaswamy (2019)		Text ranking, min-cut algorithm, SVM	800 tweets
Santos & Matos (2014)	Flu indicator tweets	Naïve Bayes Classifiers	2,704 tweets
Kallur et al. (2020)	Healthcare provider, alternative medicine provider, company, media, or professional society	Least mean scores based on GQS	Youtube videos from 28 January to 5 February 2017
Molaei et al. (2019)	Contagious disease prediction	Nonlinear methods including ARX, ARMAX, NARX, DeepMLP, CNN	Tweets and Centers for Disease Control and Prevention (CDC) data
Samaras et al. (2020)	Social media, precision, severe	ARIMA method	Google and Twitter
Li et al. (2020)	Sentiments, Media attitudes, Range of influence and dissemination, Media credibility and influence, Netizen attitudes and influence	SIR virus propagation model, Social network analysis, Complex system simulation	China's Sina Weibo
Culotta (2010)		Text mining, Regression	574,643 tweets
Sadilek, Kautz, & Silenzio (2012)	Negatively and positively weighted features	SVM, tokenization	16 million tweets
Achrekar et al. (2011)		Correlation and auto-regression with exogenous inputs	4.7 million tweets
Li & Cardie (2013)	Flu indicator keywords such as influenza	Unsupervised Bayesian algorithm basedon a 4 phase Markov Network	3.6 million tweets

|				
	Ng (2014)	Flu indicator terms and emoticons	Correlation	1,055,460 tweets
	Broniatowski, Paul, & Dredze (2013)	Categorization of tweets based on health data	Supervised classification model, time series analysis	0.3 billion tweets
H1N1 Flu	Chew & Eysenbach (2010)	Tweet categorizations Resource, personal experience, personal opinion and interest, jokes/ parody, marketing, spam	Info-veillance using twitter data analysis and survey	2 million tweets
	Ahmed et al. (2019)	Emotion and feeling, health related information, general commentary and resources,	Thematic analysis	214,784 tweets
	Lampos & Cristianini (2010)		Textual analysis	26.8 million tweets
	Szomszor et al., (2010)		Correlation	3 million tweets
	Signorini et al., (2011)		Bayesian classifiers, SVM	5,150,863 tweets
HIV Epidemic	Young et al., (2014)		Binomial regression	553,186,061 tweets
Measles	Meadows et al. (2019)	Health beliefs and vaccine attitudes	Descriptive statistics (frequencies and percentages)	3,000 tweets systematically selected
	Tang et al. (2018)	Public, social media, communication	Semantic network analysis	Twitter discussion before, during, and after the outbreak
MERS-CoV	Yoo & Choi (2019)	Social networking sites, social media, health information, predictor,	Hierarchical regression analyses	Web survey of South Korean adults

		psychological factors		
	Khatua et al. (2019)	Patient symptoms	Word embedding method	0.095 million tweets
	Bora et al. (2018)	Informative, misleading, and personal experience videos	Case study	101 videos from Youtube
	Daughton & Paul (2019)	Linguistic and psychological inquiry	Keyword filtering and machine learning classification	29,386 tweets
	Nolasco et al. (2020)	Technology, influence, humans, articles	Topic modelling algorithms	Twitter datasets of Zika related posts
Zika epidemic	Wirz et al. (2018)	Blame, GE mosquitoes, SARF	Combined machine learning with human coding to analyse and sentiment analysis	Facebook and Twitter
	Darrow et al. (2018)	Zika Knowledge, Attitudes, and beliefs	Survey	139 students' tweets
	Mamidi et al. (2019)	Public sentiment	Machine learning techniques and algorithms	48,734 tweets
	Masri et al. (2019)	Disease surveillance and Disease forecasting	Cloudberry, Time-series analysis	874 million tweets
	Gallivan et al. (2019)	behaviour and intention	Netnography and chi-square tests	15,818 tweets
Diphtheria	Porat et al. (2019)	Policy, misinformation	Correlation	722, 974 tweets

4.2 Insights from Twitter Analytics

In this sub-section, COVTA has been performed using the CUP framework (Fan and Gordon, 2014) in three steps, i.e., capture the data, understand the data through different analyses, and present the results. Figure 6 has provided the complete details about the CUP framework that

was used for COVTA with each step description. We retrieved Twitter data in different periods to grasp the change in emotions with time, if any. We then established scores to quantify our conclusion.

**Figure 6: CUP Framework - COVTA**
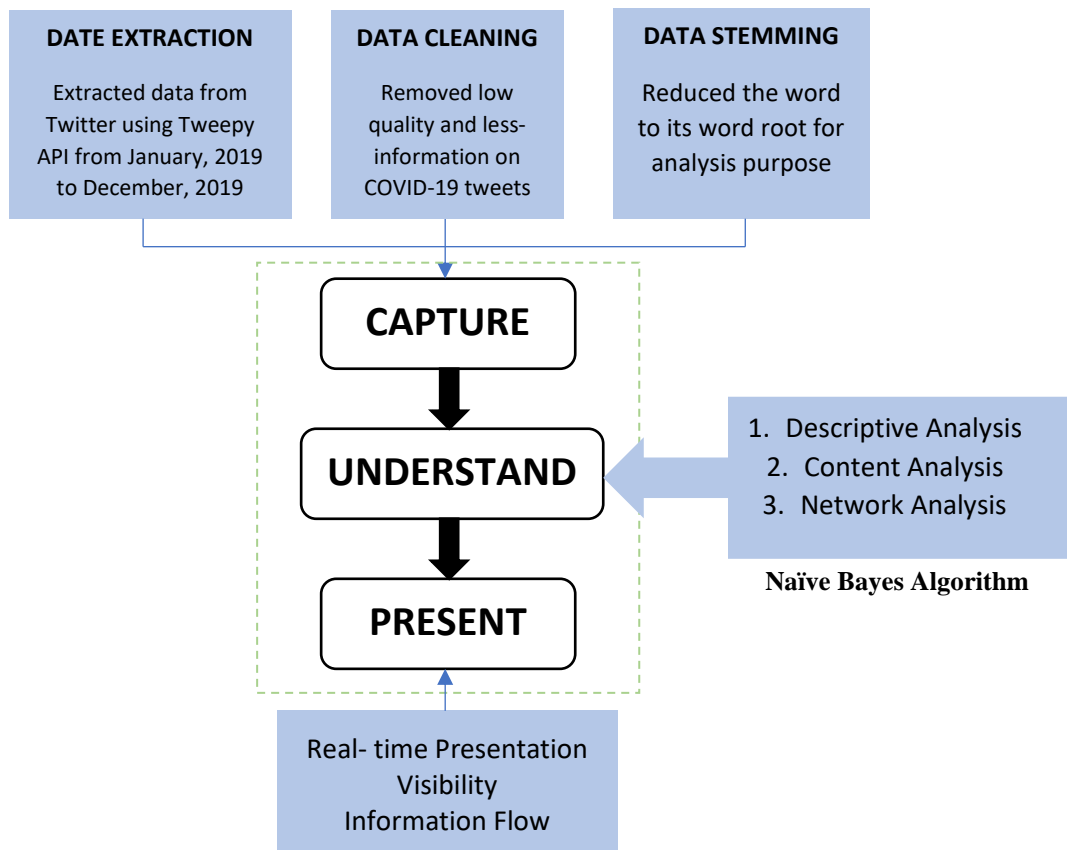
After screening, a total of 58,320 tweets concerning 'COVID-19' or 'Coronavirus' were finally retained using Tweepy API from January 25, 2020 to April 4, 2020. Figure 6 presents details of the analysis performed under COVTA in three major steps. The first step of the CUP framework consisted of extracting, cleaning, and stemming data using capture. Step 2 analyzed the data at three levels: descriptive analysis, content analysis, and network analysis.

RQ3: What are the emergent topics and themes highlighting the general public's sentiment towards COVID-19?

Twitter content regarding the Covid-19 was studied by measuring the user frequency on tweets under descriptive analysis. Based on user frequency, hashtags were selected to perform further content analysis and network analysis. Figure 7 describes the words cloud analysis of COVTA by using tweets by different users. The word cloud analysis disclosed different positive outcomes through words such as health, government, information, social, weather, pollution, believe, unintentional, gracious, support, happy, accept, thank (Boon-Itt & Skunkan, 2020). In contrast, negative words included discrepancy, contagious, sad, crisis, emergency, pandemic, clueless. Word cloud analysis showed a marked disparity between the emotions and concerns of people during the COVID-19 crisis and people's feelings during past pandemic and epidemic outbreaks. In the current Covid-19 times, people's behavior has shifted from negative (according to the literature review) to neutral. The cloud analysis indicated that words like positive, increased, information, media, and discrepancy are being more frequently used, which suggests that social media is the main source of information and that misinformation or discrepancy in information may experience changes according to such media sources.

Figure 7: Word cloud analysis of COVTA
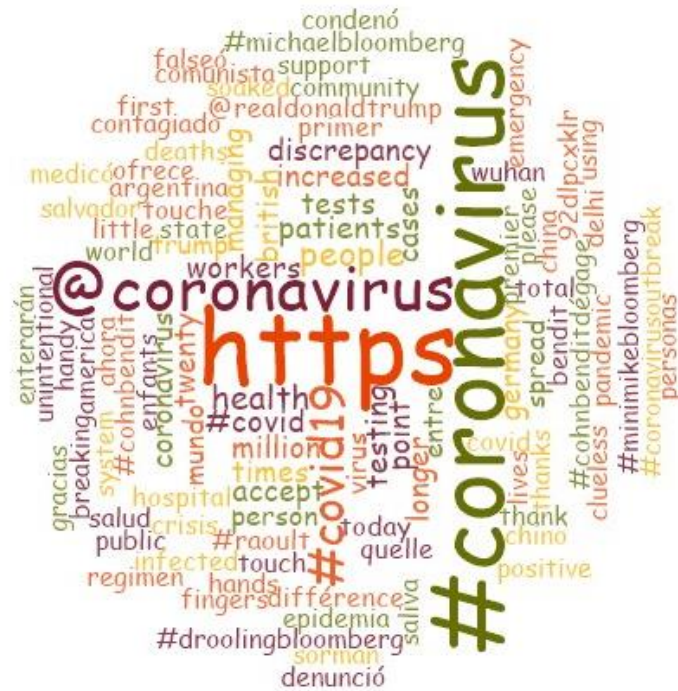
The word cloud analysis displayed few words, like information, social, health, and public, and the results from the literature review looked similar to those of the word cloud analysis.

COVTA user frequency shows information that is similar to those of the actual scenario. A full understanding of the user behavior required a review of user frequency based on the words that are being frequently used in people's tweets. Based on the time frame, the tweets were divided into three categories. In the first place, user frequency was investigated from January 25, 2020 to February 14, 2020. In this period, London appeared as the area with the highest number of tweets about coronavirus or COVID-19, followed by France and Madrid, as indicated by Figure 8. During the same period, the number of Covid-19 cases rose in Europe. As per WHO data (Organization, 2020c), the first case of coronavirus in Europe was discovered on January 24, 2020, and thereafter French officials announced three confirmed cases. So, the high user frequency during this period seemed to map the facts.

Figure 8: User frequency based on location from January 25, 2020 to February 14, 2020
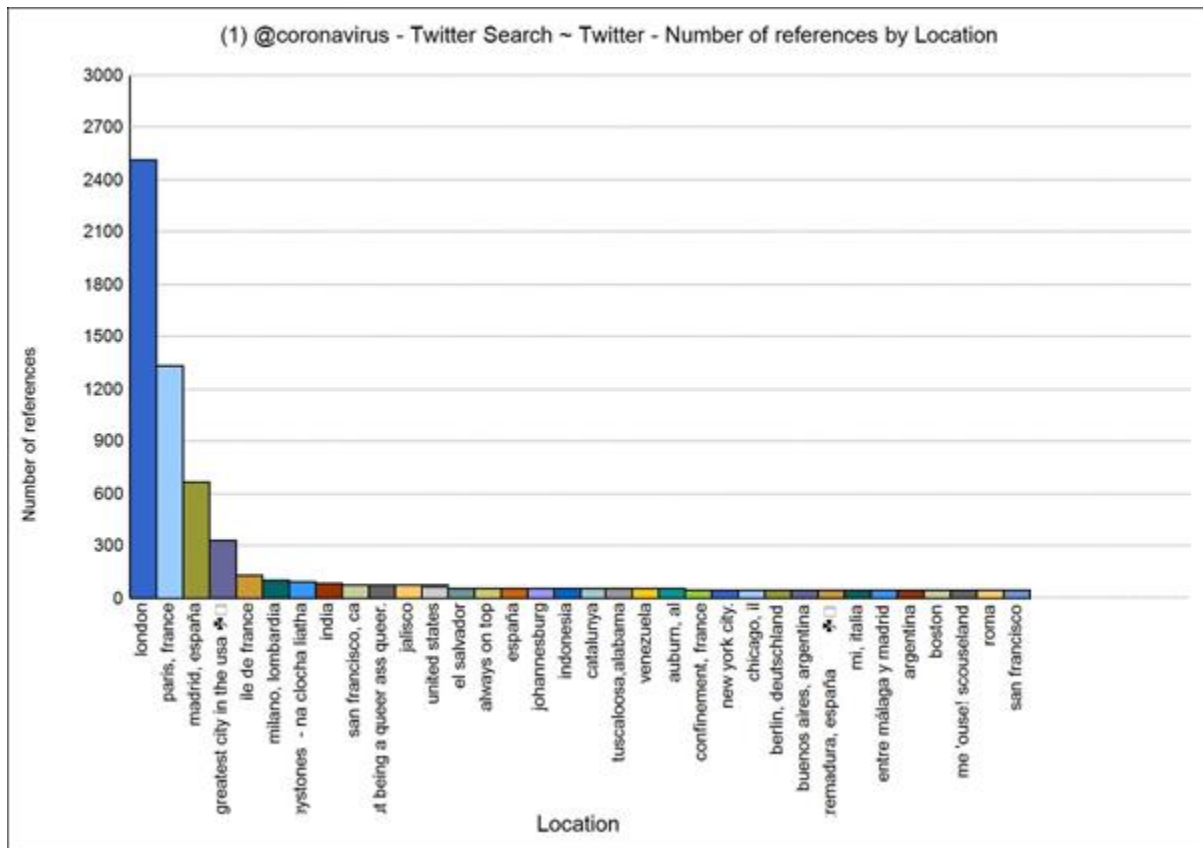
Following the verification of user frequency, cluster analysis relied on the same data for the time mentioned above period. It showed that people from different parts of the World are expressing themselves on social media. We observed that clustering is analogous to the spread of COVID-19, which means that expressing their feelings did so only if they had faced similar types of crises in terms of quantum and severity. The data presents the clustering of users based on their feelings, emotions, and concerns. All the clusters prove the coding similarity index based on Pearson's correlation coefficient.

From February 15, 2020 to March 14, 2020, user frequency was examined in various locations. This accounted for the second step of the process. As shown in Figure 9, the United Kingdom (UK) produced the highest number of tweets pertaining to the coronavirus or COVID-19, followed by India—with Delhi (Capital of India) in the first row. COVTA user frequency

describes insights similar to the actual scenario, mapping the occurrence of the first coronavirus case confirmed on January 30, 2020 by the WHO (Organization, 2020c).

Figure 9: User frequency of tweets per location from February 15, 2020 to March 14, 2020

(1) #coronavirus - Twitter Search ~ Twitter - Number of references by Location
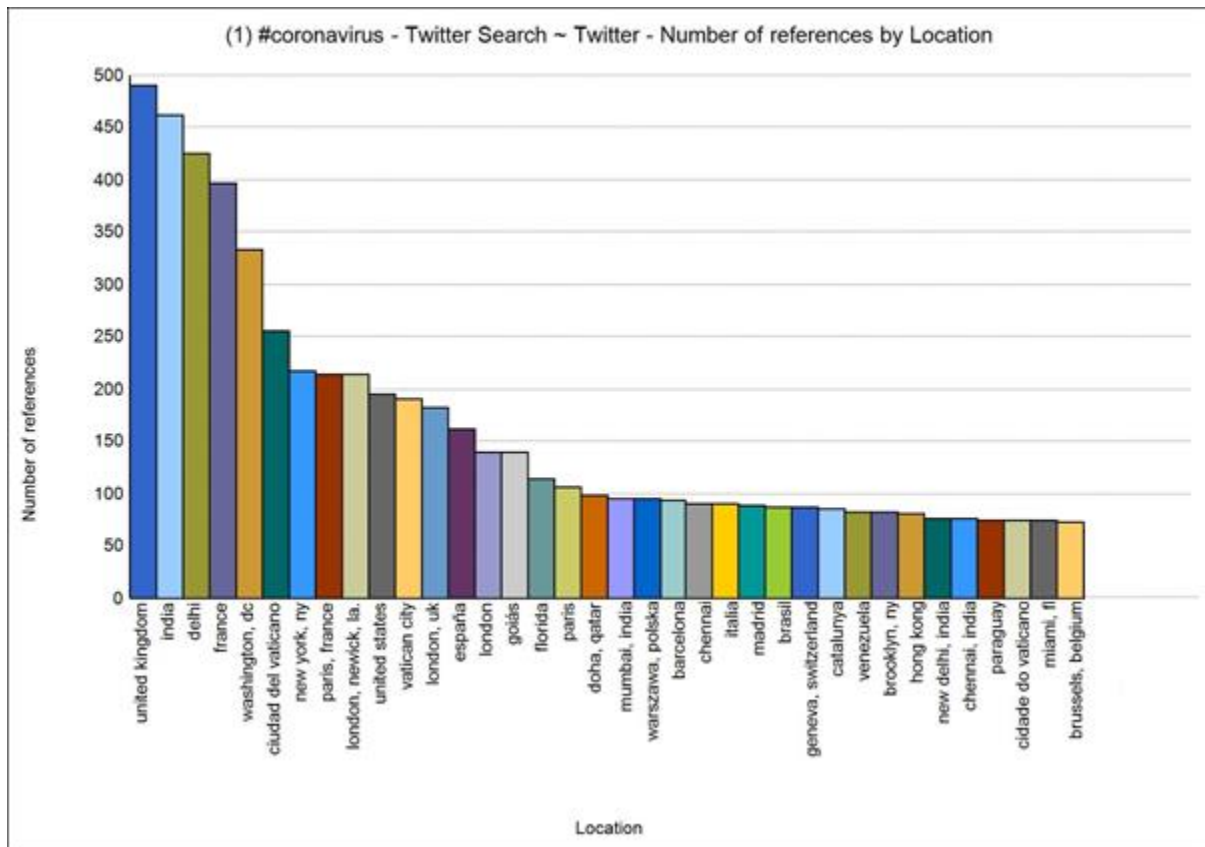
The data describes the cluster analysis as conducted between February 15, 2020, and March 14, 2020, and it shows that people from different parts of the World tend to express similar emotions and concerns.

In the last step of the process between March 15, 2020 and April 4, 2020, user frequency was reviewed based on locations. As indicated in Figure 10, Florida (USA) recorded the highest number of tweets on coronavirus or COVID-19, followed by Los Angeles and New York. The COVTA user frequency evidenced similarities with the actual scenario, and major coronavirus cases were recorded during this period in Florida, Miami, and other parts of the United States (Organization, 2020c).

Figure 10: User frequency based on locations from March 15, 2020 to April 4, 2020
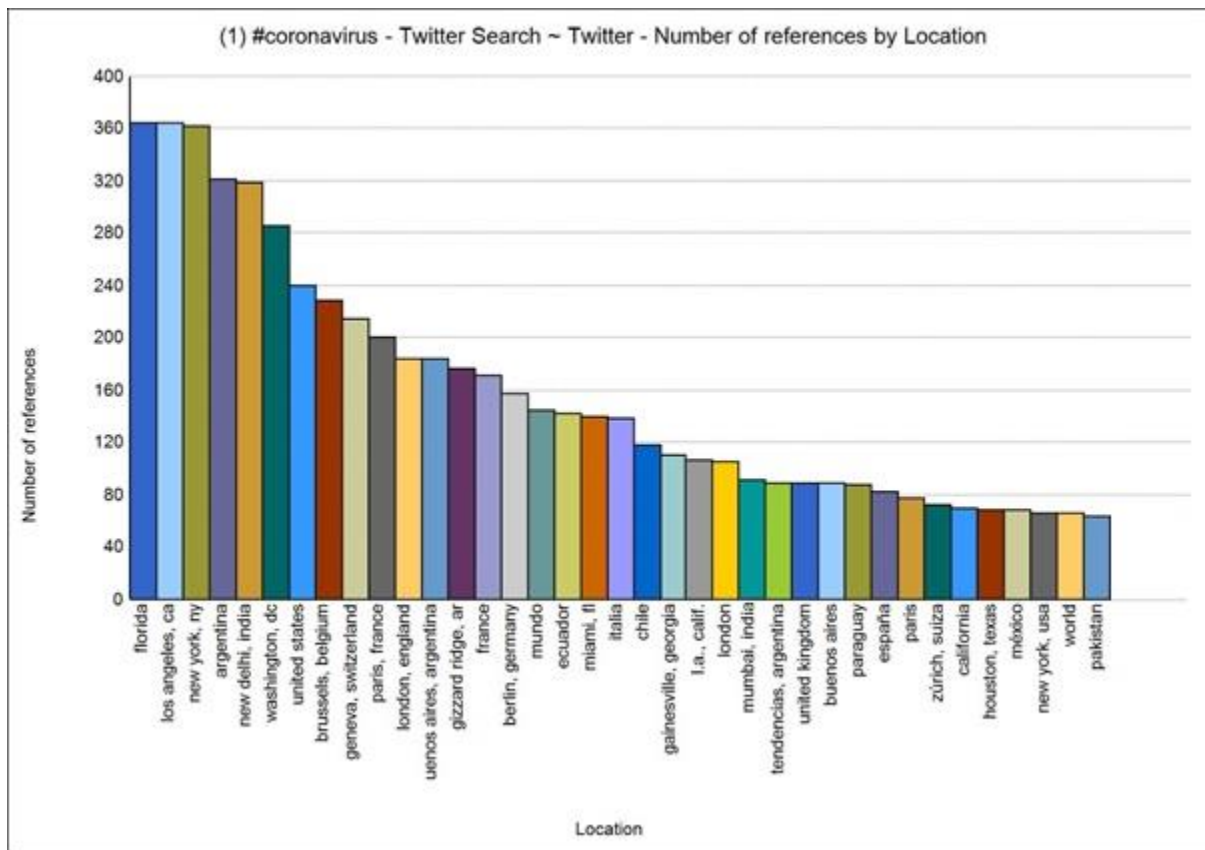

The further analysis presents results from the cluster analysis conducted from March 15, 2020 to April 4, 2020. Such clusters show similarities in people's emotions and concerns.

During the content analysis of COVTA, the sentiments of people as expressed in the selected tweets were examined using the Naïve Bayes Algorithm. People's perception was underscored

through a user classification and classified their feelings into negative, positive, neutral, and mixed feelings. Figure 11 describes the sentiment analysis based on the polarity of emotions and feelings. Sentiment analysis showed a maximum number of neutral, positive, and mixed sentiments, and fewer users expressed negative feelings. Moreover, it disclosed a high propensity of optimistic sentiments (a high number of tweets with neutral and mixed sentiments) and a behavioral shift from negative to optimistic sentiments.

Figure 11: User sentiment analysis
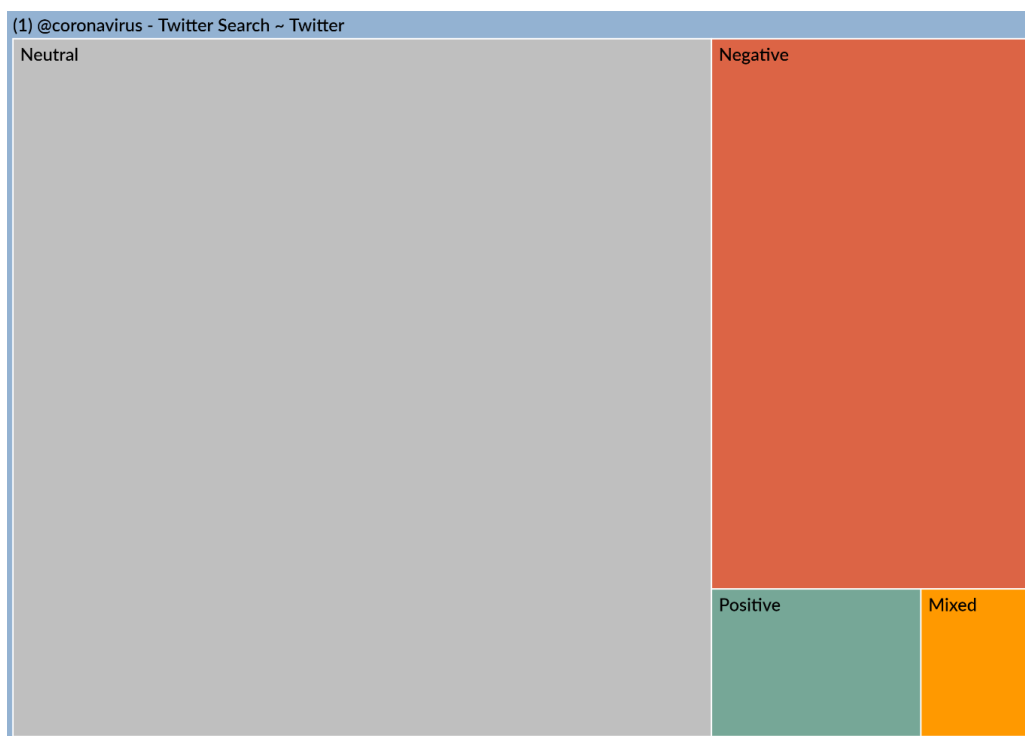
Next, the various types of sentiments were classified to understand the different emotions carried along. Figure 12 presents the related network diagram based on the outcome of the user sentiment analysis.

Figure 12: Network diagram based on user sentiments

The network analysis shows that there are eleven common codes between positive and negative sentiments, and they have a relationship with each other. However, all the codes show positive and moderately positive sentiment in these codes by different user handles. The frequency of hashtag and word cloud analysis provides deep insights into the frequently used words related to positive and negative sentiments.

(1) #coronavirus - Twitter Search ~ Twitter - Hashtags Clustered by Word similarity
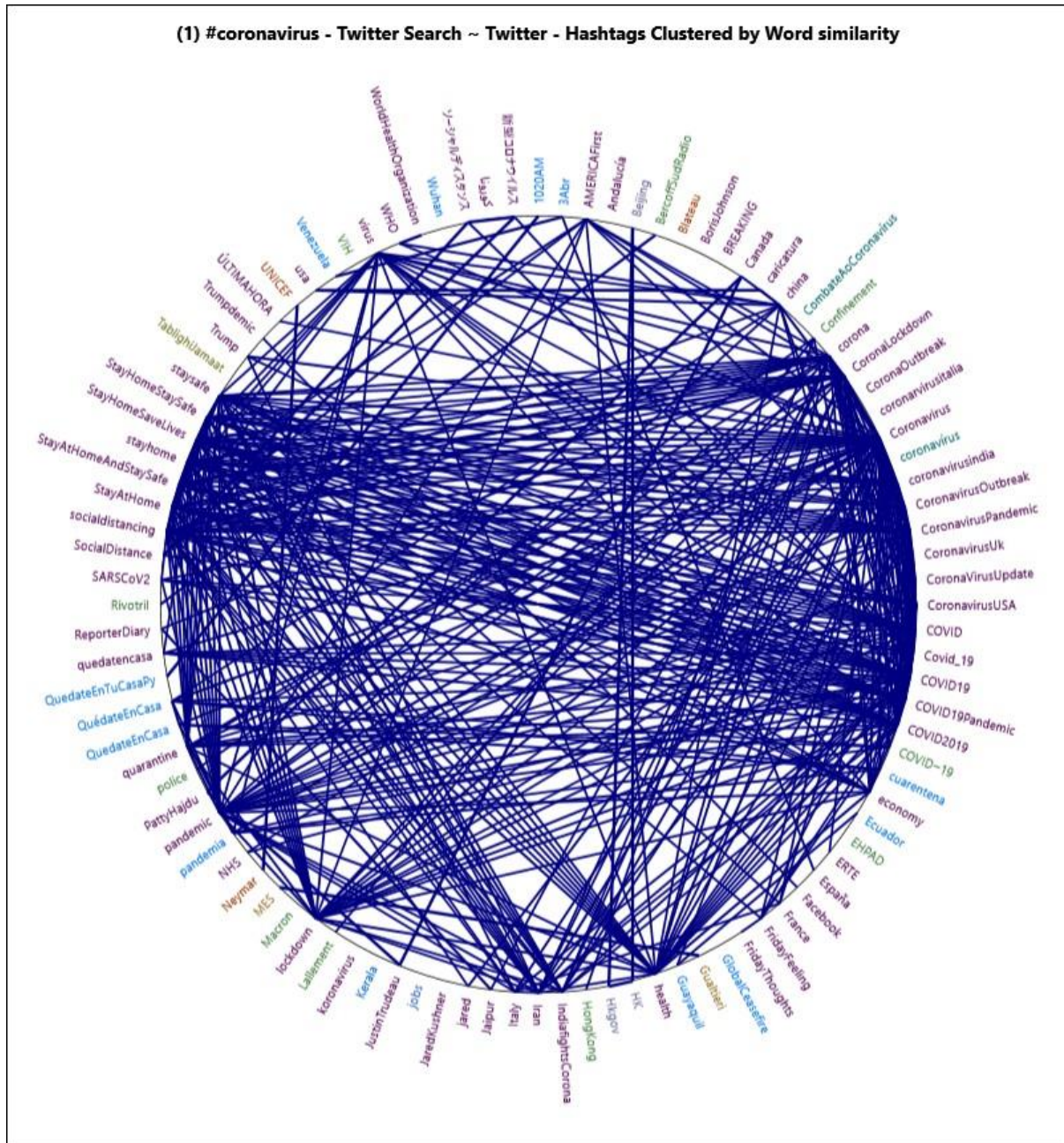
The diagram, as mentioned above, shows the major words expressing positive and negative feelings as indicated by the sentiments analysis. The same sentiments led to positive and negative emotions, but also neutral feelings for some cases. Further, the word-tree analysis was performed based on the top three positive and negative words to understand the sentiments of people.

Researchers have investigated online reviews to observe user sentiments (Joseph et al., 2017). The study also processes the sentiments of people through the extracted tweets. It provides negative and positive verbatim based on the sentiment analysis. Very positive sentiments are related to health and economy, and it expresses the people feeling through the posting during the COVID-19 situation. Very negative sentiments refer to lockdown, about pandemic and breaking of virus that emphasize the polarity scoring to understand people's emotions better.

The word-tree analysis relied on people's top positive and negative emotions, as it appeared from the network analysis of sentiments. The said network analysis highlighted top negative-emotion words such as positive, health, and economy and top positive emotion words such as breaking, pandemic, and lockdown. The word-tree analysis shows the verbatim of users based on user frequency. The emotional state expressed through postings contributes to understanding how people feel during the COVID-19 situation. Strong emotions are generally expressed by means of though words (adjectives, superlatives, etc.): "these dark days, let's stay positive"; "to keep them informed & stay positive"; "The UK is not testing its health" (with health-related terms); "facts and the device of health"; and "health professionals are worth more than," etc. User verbatim may also rely on economic terms, such as: "lives are as normal and their economy"; "save lives and economy"; and "prioritize people's lives than the economy." A critical remark is that health-related terms typically express neutral emotions, whereas economic terms express mixed and positive emotions in COVID-19. Negative emotions have

also been observed, which was expressed through concepts like breaking, pandemic, and lockdown. Terms related to "breaking" include "another virus breaks out" and "time of exercises to avoid," while those related to "pandemic" include "any knowledge over handling pandemic," "severe seasonal influenza or pandemic," and "human can be blamed for the natural pandemic." The "lockdown" has been expressed through expressions such as "fewer people than an indefinite lockdown," "lockdown is better to save peoples," and "cases decreases because of a city lockdown." Expressions of negative emotions look not very negative by nature, as they show more mixed or neutral behavior towards COVID-19, with some degree of hope. Text content with polarity scoring in terms of sentiments helps better understand people's emotions and concerns. So, the various performed analyses (thematic analysis, content analysis, and sentiment analysis) show a strong shift in people's emotions over the years. Through COVTA, it appeared that people are more optimistic about the current COVID-19 situation.

5   Discussion

Pandemics have generated considerable interest among researchers across the World, as shown in Figure 1 and Table 1. Researchers have extensively used data from Twitter to study various aspects of pandemics such as public perception, emotions, feelings, communication, health information, etc., as illustrated in Table 2. It should be noted that social media analytics has already been used to study people's negative emotions (Tsugawa et al., 2015; Chaudhary et al., 2013). LBTA performed on research articles show that communities worldwide have always expressed their concerns for multiple pandemic and epidemic outbreaks, especially different types of flu, as depicted in Figures 3 and 4. The word cloud analysis (Figure 5) of past research showed that people's sentiments during pandemics are majorly negative. Communications are

mostly concerned with viruses, infections, epidemics, and the seriousness of the disease. As a result, people's emotions in such circumstances are generally negative.

Interestingly, according to the outcome of the word cloud analysis conducted for COVTA based on Twitter data between January 25, 2020, and April 4, 2020, people's emotions witnessed a significant change compared to the emotions expressed during past pandemics (from 2011 to 2019). Despite variations in emotions from negative (sad, crises) to neutral and positive (gracious, positive, pollution, thank, accept, support), noted an increased frequency of comforting words, as shown by the outcomes of the word cloud analysis. Moreover, the presence of words like information and discrepancy in information indicates that social media has emerged as a prominent source of information. However, the prospects for social media information being different from reality cannot be ignored.

Based on user frequency in different time periods and locations, it is established that people tweet more on COVID 19 when they are affected the most (Figures 8, 9, and 10). For example, between January 25, 2020 and Februray14, 2020, people from London tweeted the most on COVID 19 (Figure 8), whereas very few people from India tweeted on the pandemic. People from the United Kingdom, India, and France communicated the most on COVID 19 on Twitter from February 15 to March 14, 2020 (Figure 9). Similarly, from March 15 to April 4, 2020, people from Florida, Los Angeles, and New York (USA) used Twitter to express themselves on the pandemic (figure 10). The cluster analysis conducted on tweets for different time periods revealed a fascinating discovery: people with similar situations express somewhat similar emotions all over the World.

Sentiment analysis performed on tweets related to COVID 19 under COVTA classifies emotions into four categories, namely positive, negative, mixed, and neutral. Figure 11 shows that the propensity of such tweets to be non-negative, as they rather portray neutral, positive,

and mixed emotions. The network diagram (Figure 12) based on emotions suggests that positive and neutral sentiments are connected. This also proves that over the years, Twitter-based expressions of emotions about epidemics have mellowed. Network analysis shows positive emotions (terms related to health and the economy are the top positive words) and mixed and neutral emotions. Terms such as "breaking," "pandemic," "lockdown" are the top words expressing negative emotions. The word-tree analysis (based on the world cloud results) gives further insights into emotions through user verbatim. For example, the user verbatim for positive emotions during the Covid-19 pandemic indicates that people are trying to remain positive. Verbatim for health shows mixed emotions as people are concerned about their health and, at the same time, are grateful to health workers. Verbatim for economy indicates that people are giving preference to lives rather than to the economy. Verbatim of top positive, mixed, and neutral emotions further strengthen our finding that the sentiments towards COVID 19 are predominantly positive, mixed, and neutral.

6 Theoretical and Practical Implications

This study provides new insights into the sentiments of people on pandemics. And better still, it contributes to the general research methodology, relying on a thematic analysis of past studies and Twitter analytics on current data. The study suggests that Twitter data can be used for a better understanding of public sentiments on outbreaks. This can be used to gauge public sentiment in future researches.

The pandemic has not only medical consequences, but also impacts people on a social and psychological level. The findings demonstrate that people reach out to social media to express themselves and to acquire information. This paper makes a theoretical contribution to the literature on social-techno realm during pandemic using twitter analytics. Twitter reflects the real time concerns of social media users and the social media platform is helpful to understand

the psychological health of the users. Our findings that people are more expressive when they are the most affected and people across the World go through similar emotions while dealing with similar situations facilitate further discussions on mental and emotional health during the pandemic and the measures to deal with it. It also offers deliberations on how social media can be a powerful communication medium and a tool to provide social support to the needy during emergencies or pandemics. Yang et al. (2020) found out that social support reduces negative emotions, anxiety, and depression. In contrast, physical distance is recommended in Covid-19 situations; the importance of social support through social media for mental well-being offers some reprieve. The importance of mental well-being cannot be ignored, as World health organization prioritized mental well-being (Adhanom, 2020). The United Nations has particularly emphasized the collective approach by the society to take care of mental well-being (Nations, 2022). An international commission on global mental health is being set up by Lancet (Kola, 2020; The Lancet 2020). As our findings suggest, social media could be the most potent medium to measure people's emotional and mental well-being. Real-time screening and assessing the people's emotions during a pandemic can put health agencies in order; their planning and responses could be need-based. This can also improve trust between the health care agencies and the people.

Even though social media data helps monitor mental and emotional health during pandemics, our findings have important implications. From a theoretical point of view, the findings have enriched the RPA – COV model by identifying that people's emotions towards pandemics are changing and showing a tendency for more positive emotions. This research aims to advance knowledge of the emotions of the people during pandemics and the role of social media in effective communication (Oh et al., 2020; El-Awaisi et al., 2020) during pandemics.

There is a serious need to apprehend the sentiment of people to deal with the connected socioeconomic factors. This would help craft better solutions and policies to combat this global

crisis. All through COVID-19, people from the UK, France, London, Paris, Spain, Italy, India, and the USA mostly expressed their concerns on health, test, economy, support, information, etc.. They were gracious, thankful, and hopeful. Past studies revealed that sentiments of people during Chikungunya, Dengue, Diphtheria, Ebola, Flu, HIV, Measles, Zika breakdown from the year 2002 to 2018 were mostly negative. This is contrary to the sentiments expressed during COVID-19. This suggests that the people stayed hopeful in the course of unprecedented health emergencies. People expressed gratitude towards health workers, police, community efforts, and other frontline workers. However, few keywords such as breaking, contagious, emergency, crises, lockdown, pandemic reported negative sentiments during COVID-19. However, positive sentiments overshadowed the negative sentiments. The study captured manifestations of people during COVID-19 and showed the change of public sentiments over the years towards pandemics.

This is probably the first in-depth study of people's sentiments on pandemics, including the current Covid-19 outbreak. The findings of this study should serve as a starting block for developing strategies to deal with future infectious disease outbreaks. The study shows that people express their feelings and emotions (fear, hope, worry, etc.) by posting on Twitter. Health officials may rely on such information to better take care of people's physical and mental health during epidemics or pandemics. For instance, they can use these findings to formulate strategies that can help to reduce negative emotions among the population concerned. Several researchers (Geßler, Nezlek, & Schütz, 2020; 2019; Moroń and Biolik-Moroń, 2021; Hodzic et al., 2018; Elsotouhy et al., 2021) stated that emotional intelligence of a person can predict his or her mental health. Hence health officials can also offer emotional intelligence training to tone down negative emotions. Such findings are useful not only to health professionals but also to policymakers and other stakeholders in outbreaks. Stakeholders and health officials can access the information and sentiments shared on Twitter in real-time, and accordingly, take

preventive measures to better combat pandemics. Of course, this study can be of interest to researchers as well.

7 Conclusion

This study has shown that, over the years, people's sentiments on pandemics as shared on Twitter are changing. Based on the LBTA and COVTA, The study considered 61 research articles published on pandemics, coupled with data from Twitter (for LBTA). A total of 58,320 tweets on COVID 19 was considered for COVTA. Big data analytics techniques were used for Twitter postings, while thematic analysis was performed on published papers to understand people's sentiments on pandemics. Only tweets posted between January 25, 2020 and April 4, 2020, were taken into account for this study. Future studies may consider analyzing Twitter content on COVID 19 for a more extended period to improve the results. People may react differently on Twitter as compared to real-life circumstances. Hence, this could be the limitation of the study. However, the benefit of employing Twitter analytics is that it evades the biases of the researcher/interviewer.

Overall, the complete analysis posits that people's sentiments towards pandemics have changed over ten years. Following a sentiment analysis for COVID 19 clearly shows a high propensity for optimistic sentiments (high number of tweets with neutral and mixed sentiments). It suggests that people are concerned about their health but are optimistic and show immense gratitude towards frontline workers.

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