PUBLIC HEALTH APPLICATIONS OF TWITTER DURING THE CURRENT COVID-19 PANDEMIC

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ABSTRACT

Health education and promotion tools continue to evolve as new interventions and programs are designed to take advantage of current technology. The widespread use of social media sites across all types of populations make them ideal to serve as accessible platforms for public health campaigns. Understanding the interactions between social determinants of health and various networking sites may also prove crucial to developing strategies that reduce health disparities among vulnerable populations. Equally important is the use of misinformation and spam links to spread false reports and increase public anxieties. Overcoming this barrier is essential during public health crises, such as infectious disease outbreaks, in order to reduce disease transmission and unnecessary panic, which can lead to negative health behaviors. As one of the largest networking sites, Twitter has proven its utility in the public health field in prior research by providing emotional support and acting as a communication and public surveillance system, as well as serving as a tremendous source for data. By analyzing how Twitter has impacted COVID-19 responses for prevention and treatment, and how the site can be effectively used to disseminate information throughout the pandemic to educate and inform the public, improvements on communication strategies and response efforts can be employed during future epidemics or pandemics. Despite the small data sample, this research project can act as a framework for larger investigations focused on social media use and COVID-19 and how Twitter can be used by NGO and governmental agencies during public health crises.

INTRODUCTION: TWITTER AS A HEALTH EDUCATION TOOL

After its establishment in the late nineties, social media sites have slowly become a significant component of daily routine, making it difficult to function without its use. As of 2019, about 72% of U.S. adults use at least one social media site indicating the size of the section within the population exposed to this type of content [19]. While young adults were among the first to adopt social media into their lives, the social media user base has grown and become more representative of the population. YouTube and Facebook are the most-widely used online social platforms- however, Twitter is unique in that it is fast-paced and concise, where posts are restricted to only 280 characters. This limiting quality drives users to make use of each character in order to engage their audience and establish a following. According to a survey conducted by Pew Research Center, 42% of users access the Twitter site on a daily basis [19]. Globally, adults between the ages of 25-34 comprise 28% of the user base as the largest age group to use Twitter, followed by young adults between the ages of 18-24 which make up 24% of the user base [4]. Further geographic user analysis has shown that the U.S. is the largest audience base for Twitter, followed by Japan, then Russia and the United Kingdom as of April 2020 [5]. This data exhibits that populations of upper-middle and high-income countries are more likely to interact on Twitter and consist of most of its users.

Thanks to its widespread use, social networking sites have become a vital resource for various fields of research, including public health. According to Laranjo, "At the population level, they are currently being used for public health surveillance" and "At the individual level, they are able to facilitate access to health-related information and social support promoting better-informed treatment decisions" [13]. A wide range of uses have been discovered for Twitter which is evident in Sinnenberg and colleagues' literature review of Twitter as a tool for health research. The authors of this paper defined a new taxonomy to describe the several categories in which Twitter was utilized such as content analysis, surveillance, engagement, recruitment, intervention, and network analysis [20]. Each category is a prime piece of evidence as to how Twitter can be employed in research, and how this taxonomy can be applied to different studies reviewed in this paper.

Kostkova and colleagues' data analysis of tweets regarding the swine flu would fall within the surveillance category of Twitter analysis. This category is defined as "Monitoring of Twitter traffic for mentions of a particular topic above the normal background level of discussion" [20]. By examining the influx of self-reporting flu tweets and the time at which they were posted, the researchers concluded that Twitter could predict peaks in the outbreak up to two to three weeks earlier than official surveillance data [12]. According to the study, it takes around a week for data to be reported at the national level. By harnessing Twitter as a surveillance system, authorities can implement outbreak containment measures ahead of time, limiting the spread of disease. Thackeray and colleagues' analysis of state health departments' tweets would be categorized as engagement and content analysis. Engagement is defined as "Assessing impact of discussion on Twitter by analyzing presence of an account, number of retweets, favorites, followers, etc." and content analysis is defined as "Assessment of body of tweets for themes in relation to a specific subject" [20]. By studying the content of tweets published by state health departments and measuring the level of engagement the department integrated within their tweets, the researchers determined that the state health departments were ineffective in establishing relationships and developing connections amongst members of the community [24]. The content of the tweets focused on sharing one-way information and rarely engaged with its intended audience. This in turn affects the success of information dissemination through social media sites. Employing Twitter data to measure engagement enlightens officials in the state health department of their unproductive tweets and allows them to develop measures to improve engagement with their target audience. Chandrasekaran and colleagues' research on the utility of social media in providing information on the Zika virus would classify as content analysis. The researchers examined the content of tweets focused on Zika and determined whether the information provided was useful, not useful, or misleading [6]. After analyzing their sample of tweets, the researchers concluded that social media was a useful resource in providing relevant information about the outbreak of Zika and the virus itself. By running content analysis on Twitter data, this provides evidence of the success in using Twitter as a source to circulate information for health education purposes. These examples demonstrate the widespread application of Twitter analysis and its potential use in various domains of public health, particularly health education and promotion.

With its massive reach, social media presents several benefits as a form of health communication. Moorhead and colleagues listed these key benefits for individuals in their review, which included "increased interactions with others, tailored information, increased accessibility to health information, peer/social/emotional support, public health surveillance, and influence on health policy" [17]. In the perspective of public health surveillance, social media can be used to "monitor public response to health issues, track and monitor disease outbreak, identify misinformation of health information, and disseminate pertinent health information to targeted communities" [17]. Organizations, programs, and health officials looking to use Twitter can take advantage of the user's current social networks to increase the spread of information. An additional benefit is the creation of a safe space for users to discuss sensitive health issues and questions without the fear of being stigmatized and condemned by societal norms due to the anonymity of the platform.

Despite the aforementioned benefits, there are a few limitations to using social media for health education. Even though there are established privacy settings in place, there is still the potential for private individual information to be leaked since Twitter is a public forum. Also, the information dispersed throughout the site varies in quality and consistency because the mechanism for collecting, sharing, and promoting information is informal and not regulated, which can lead to the spread of misinformation [17]. While further research needs to be conducted to evaluate the impact of social media on certain groups and its long term implications and information regulation, and security issues must be addressed, it is evident looking at current research that Twitter and other social media platforms serve as useful tools for health education and promotion and should be utilized during public health crises.

COVID-19 HEALTH DISPARITIES AND SOCIAL MEDIA

Health disparities define the occurrence of health outcomes that disproportionately affects different populations due to various factors such as "race or ethnicity, sex, sexual identity, age, disability, socioeconomic status, and geographic location" [18]. They remain a pervasive issue in the current healthcare system and contribute to the elevated morbidity and mortality rates of chronic and acute illnesses within vulnerable populations. The current outbreak of COVID-19 brings these disparities to light and clearly exhibits how the illness is affecting different groups in the United States.

According to the CDC, hospitalization rates are "highest among non-Hispanic American Indian or Alaska Native and non-Hispanic black persons, followed by Hispanic or Latino persons" [2]. This is clearly represented in Chicago where "African Americans account for more than half of all COVID-19 positive test results and 72% of recorded virus-related deaths, even though they represent only 32% of the city's population" [1]. Factors related to this phenomenon include the higher prevalence of diabetes, asthma, hypertension, and other chronic conditions within this group, which may aggravate the symptoms of COVID-19 and increase the risk of mortality. On the other hand, factors such as "social determinants of health, bias, and historical mistrust of America's health care system," [1] may play a significant role in affecting the health and treatment of the African American population during the epidemic. Miles and colleagues pointed out that clinicians might be contributing to the health disparities and excess in deaths due to their bias and decision-making skills. Scarce resources and high pressure circumstances influence healthcare professionals as they make decisions regarding the implementation of life-prolonging measures for this group.

Implicit bias is defined as the stereotypes for or against particular groups of people which affects individuals' attitudes and actions in an unconscious manner. This type of bias is especially harmful because individuals are unaware that they harbor these prejudices, creating a barrier when attempting to identify and change this behavior. Milam and colleagues claimed implicit bias may affect the treatment African American COVID-19 patients receive due to the conversations that medical personnel hold with these patients and their families about code status and disease management. These researchers posit that this bias will "result in a smaller number of critically ill African American patients with COVID-19 being placed on a ventilator—a virtual death sentence" [16]. Another possibility is to reduce resource expenditures on Black patients, clinicians may be persuading patients to sign DNRs. The present lack of statistics on the rates of DNRs and African American COVID-19 patients means that the aforementioned conjectures remain unproven for the time being. Further data collection and analysis is required to explain the disparities in COVID-19 cases among different populations. Looking to social media sites, there is also the possibility that vulnerable groups may experience disparities due to the information and discussions shared on these sites.

With respect to health disparities, is there a difference in the information shared by people of different race and ethnicity? For example, at the start of the COVID-19 pandemic, there was a message shared that "Black people can't get coronavirus because of the melanin in their skin". The tweets go back to late February, early March stating how African Americans were immune to the illness and observing the significant lack of reported COVID-19 cases in the Black community. Simple home remedies were also recommended within the community on Twitter, which included chicken noodle soup, vapo rub, robitussin, and ginger ale. Now, it seems that Black people are not only contracting the virus but dying from it at higher rates. This leaves questions of whether or not this message did harm to this population; if it delayed their reaction and behavior change to prevent the spread of coronavirus and affect their motivation to seek treatment from healthcare professionals.

There were also messages surrounding Asian Americans and Asian Immigrants and COVID-19, i.e. Kung flu, Chinese virus, etc. These messages were accompanied by violence and characterized by xenophobic overtones. The lack of information and education regarding COVID-19 resulted in large sections of the population blaming the Asian community for spreading the disease and holding onto the belief that Asian Americans were more likely to get sick from the illness. These discriminatory tweets were posted right at the beginning of the outbreak in January, leading to the possibility that individuals may have refused treatment and testing due to this misinformation.

In general, basic Twitter searches using keywords related to the COVID-19 outbreak revealed that discussions within minority groups on the platform often included posts that circulated incorrect information about disease exposure and treatment. A common trend among these posts included conspiracy theories involving the federal government and their role in increasing the spread of the coronavirus and withholding treatment. Minority populations are particularly vulnerable due to health disparities and previous research has shown that they are at an increased likelihood of contracting COVID-19. The misinformation may have exacerbated negative health outcomes and fueled further distrust in the government, which raises the question of the significance of social media as a medium for information and education and how much it really impacts the health of individuals. The lack of previous literature on the subject highlights the need for further research to be conducted to determine the role of social media messaging in health disparities vulnerable populations face during disease outbreaks, specifically COVID-19.

PROPOSED METHOD FOR TWITTER DATA ANALYSIS

Twitter's multifaceted nature allows its use to be extended to the public health field. This social networking site acts as a unique and massive data source for researchers because of the real-time nature of the content and the accessibility of publicly available information [19]. Considering this relatively newfound use of Twitter, it is difficult to establish a consistent method for data analysis because it is an emerging field of study. Previous literature on this subject has provided various tools and resources to analyze the thousands of Twitter entries since different researchers have developed their own methodologies. This prior research can be utilized to develop a combined and efficient methodology in the present investigation of Twitter as a health education and promotion resource during the COVID-19 epidemic.

The simplest design for Twitter analysis appears to be a basic search of certain terms in the platform's search engine and gathering the top results for the data pool. In a study of social media as an information source for the Zika virus, the first 50 results from Twitter, Instagram, Youtube, and Facebook were gathered and categorized by hand. The three main categories were labeled as "useful", "not useful", and "misleading" and these categories were further subdivided based on the content of the tweet [6]. In order to compensate for the small sample size, Fisher's exact test was used to statistically analyze the data. However, this small sample does not appear to be comprehensive of the population that uses social media as a part of their daily routine. Billions of people engage online on various social media platforms, and on Twitter alone, there are "330 million monthly active users and 145 million daily active users" [14]. Even if the size of the data sample were to be significantly expanded, it would be considerably difficult to categorize all of the data by hand in an effective manner.

While Kostkova and colleagues employed a similar method of data collection and classification for their research, their study exposed the impact of spam on data analysis and measures to circumvent this issue. Spammers take advantage of popular topics by posting false links that contain the trending term or hashtag resulting in inaccuracies and bias during data analysis [12]. The researchers identified spam articles by calculating the author-post ratio to determine whether the link was reputable, where 1 is the most reputable and 0 is the least reputable. Users who post the same link frequently are often spammers, which are easily recognized by this model. Discussions on measures for COVID-19 and the epidemic itself were trending topics on Twitter several times which means that the likelihood of encountering spam during the data collection and analysis is high. By implementing Kostkova and colleagues' model for detecting spam, this increases the reliability of the data, improving the quality of the research.

The primary responsibility of state health departments is to promote public health and safety. Their influence extends into policies, programs, and healthcare which affect the population specific to the particular state. As a result of this jurisdiction, Thackeray and colleagues pulled several tweets published by state health departments to analyze their information sharing, engagement, and action. The researchers used a Twitter application programming interface (API), to gather the posts for the data pool.

API's are typically applied by companies and developers in order to share information on Twitter. It acts as a method of communication between computer programs in order to request and deliver information [25]. Since Twitter data reflects public information that users have actively chosen to share, Twitter's API platform helps provide broad access to this data. While there are several applications for this program, for this study's purpose Twitter's API was used to access public tweets and replies. In this methodology, the specific API limited the tweets to 3,200 per account, and the researchers further downsized the data by sampling 10% of the posts gathered by the API for each state health department. The final sample consisted of 4,221 tweets from 39 state health departments with an active Twitter account [24]. All of these tweets were then hand-coded by research assistants into categories based on their focus, content, interactiveness, and various other characteristics. Despite the use of a data collection program, the methodology for separating the data was similar to Koskova and Chandrasekaran and colleagues' studies. Based on the limited time and resources of this study, this methodology is inefficient considering the amount of time required to manually analyze and code each data entry.

Dakkak's study also raises an important note of determining the intent and accuracy of the information in the links attached to the tweets [7]. In their analysis, if a tweet contained any links, they were examined to understand the intent of the user as well as investigate the source of the message. The researchers concluded that sources attached to original tweets had a high likelihood to report negative health outcomes, indicating that the overall intent behind the tweet was negative as well. The intimidating number of data entries raises the question of how to effectively collectively analyze the large number of tweets, retweets, and links attached to the posts. Studies conducted by Househ and Zhang and colleagues provide an answer to this question through the resources the researchers utilized for their Twitter data analysis. Househ's study made use of the site "topsy.com" which is a "social search and analytics organization that provides analysis of Twitter and other web related data", to find occurrences of the word 'Ebola' in tweets across Twitter between the months September and October of 2014 [9]. This resource independently gathers tweets based on the user's defined parameters and provides information by employing analytics tools used by the site. By employing this methodology, the search for COVID-19 related tweets could be significantly accelerated and the preliminary analysis of the tweets can provide avenues of research that might not have been previously considered. Zhang and colleagues used Tweepy, a python library, in order to find cancer-related Twitter accounts and their posts. This methodology requires coding with python to access and interact with Twitter's API in order to gather data. The content of these tweets were then analyzed using topic model, sentiment analysis, and word co-occurrence network and models were used to categorize the accounts as individuals or organizations [26]. While Tweepy may require more effort, additional models and programs can be included in the code to streamline the analysis, and the researchers have full control over the collection criteria, increasing the specificity of the tweets to the focus of the study. Both methodologies present with their own benefits and limitations, however combining the two tools can enhance the data collection and analysis of the current study.

In the present research focused on COVID-19 and Twitter as a health education resource, combining methodologies from Househ and Zhang colleagues' studies will be the best course of action. Data collection should begin with using Topsy, or a similar Twitter data collection site, to initially gather tweets regarding the outbreak. This will provide data for a cursory analysis of the tweets and allow the researchers to define specific parameters for data collection. Then a coding program, such as Tweepy or NVivo, should be used to interact with Twitter's API to collect the tweets focused on health education and COVID-19. Combining this method with the use of the spam detection method will filter out useless and biased data. Doing so, will produce vital results in an efficient manner and significantly strengthen the analysis and conclusions of this study.

THEORY APPLICATIONS FOR HEALTH EDUCATION DURING COVID-19

Health education theories serve as the foundation for developing programs and tools focused on promoting health and increasing education and awareness. Research on the potential use of theory when utilizing social media as a health education resource is limited. According to Tang and colleagues' literature review of social media and outbreaks of emerging infectious diseases, only a few studies employed theories or models to guide their research, however these studies have implemented varying types of risk communication theories as a part of their analysis [23].

The Situational Crisis Communication Theory (SCCT) provides a framework for responding to major crises and communicating information. The main objective of this theory is to protect the public by providing "instructing" and "adjusting" information tailored to a specific response option. Instructing information advises the public on prevention measures they can take to reduce the impact of physical threats while "adjusting information" helps the public cope with psychological threats such as stress, anxiety, and fear [11]. Response options for the SCCT include deny, diminish, rebuild, and reinforce; each option has its own objectives and strategies for informing the public and dealing with the crisis at hand. When examining and comparing the options between each other, rebuild appears to be the most appropriate for crises involving disease outbreaks. This response entails governmental organizations supporting victims and expressing regret for the negative impact the crisis may have. In conjunction with rebuild, the reinforce option is used to highlight past good deeds, praise stakeholders, and help identify themselves as victims in order to build positive relationships between organizations and stakeholders [11]. During the pandemic, governmental organizations mainly provided "instructing information" to educate the public how to remain safe. Organizations within the sample were found to use social media as a quick response method, but their knowledge of how to effectively use social media was limited. They relied on traditional forms of media to provide the public with in-depth information and it was difficult to identify whether the posts were about H1N1 since there was a lack of cues, such as H1N1 or swine flu, to indicate the post was about the crisis. Despite the previous use of the SCCT during the 2009 H1N1 crisis, the theory does not appear to be applicable to the COVID-19 outbreak due to the limited and restrictive nature of the response options, and its inability to provide comprehensive guidelines for communication with respect to the multifaceted nature of disease outbreaks.

The Crisis and Emergency Risk Communication (CERC) model overcomes the limitations of the SCCT by defining specific messages that should be disseminated during different circumstances for risk and crisis situations. This model outlines five common stages during a crisis and provides guidance on the type of messages that should be communicated at each stage. By using social media as a medium for communication, a large audience can be exposed to the information and informed in real-time during an ongoing crisis. Social media also allows for two-way communication so that "health authorities can quickly address public concerns and reduce public panic during the crisis," [15].

This model proposes that the information needs of the public evolve as the crisis progresses, which in return requires strategic messaging to meet these changing needs. At the first stage, otherwise known as the pre-crisis stage, social media posts should be characterized as risk messages, warnings, and preparations [15]. The next stage when the crisis occurs, messages with the aim of reducing anxiety and uncertainty should be circulated to reassure the public by providing situation updates and individual response actions. Communications should continue to remain positive and encouraging during the maintenance stage. In the resolution stage, updates on the developing resolution are released and discussions surrounding the causes of the crisis and associated risks are initiated. Evaluation is the final stage of the CERC where the response and communication measures are evaluated to determine their effectiveness [15]. Lwin and colleagues used this model to examine the use of Facebook for Zika outbreak communication.

At the beginning of the Zika outbreak, the public was initially informed with risk messages, which included mechanisms of the disease, symptoms, and any risk factors. Details about case reports and areas where Zika had been detected were also provided to suspend fears and anxiety. To reduce panic, calming messages were posted about interventions the government was implementing and online sources the public could look into for further information. All of these messages were employed in the first few stages of the CERC to meet the needs of the population. Once the Zika virus was controlled in the post outbreak phase, information about personal prevention measures were further emphasized to promote personal responsibility and increase self-efficacy. While the model highlights that risk messages, warning, and preparations should be the primary focus during the pre-outbreak phase, researchers found that "uncertainty reduction and efficacy" were also present in the pre-outbreak messages [14], which proves that information needs vary and posts should be monitored on social media in order to appropriately respond to those needs. Evidence from the study also proves that constantly updating the public with case reports and information on interventions throughout the duration of the crisis is shown to reduce fear and reassure the public, which is essential in preventing hysteria and panic leading to the negative impacts of psychological threats. As aforementioned, the CERC is a comprehensive model that emphasizes the importance of different types of messages at various stages of an outbreak, and can provide guidance on the type of health education messages that should be shared during COVID-19.

Laranjo and colleagues' literature review included studies that utilized network alteration in their design, where the networks of individuals were slightly altered to promote effective information dissemination and elicit behavior change. The interventions were based on homophily and clustering, which are aspects of offline social networks. Homophily is defined as the "tendency of people to associate with those who resemble them" and clustering is defined as the "tendency for people's friends to be connected to each other through redundant ties" [13]. Centola studied these aspects and various networks in order to determine how social influences can affect health outcomes in a collective manner. Networks composed of strong ties between close friends and relatives fail to provide new exposures from different sources of information since messages become redundant and the same information circulates among the same people. Weak ties, on the other hand, are long distance connections between people that would otherwise be socially remote and strangers to each other [3]. With a network of weak ties, there is a higher frequency of exposures to different treatments and innovations since there is a smaller likelihood that messages are redundant in these types of networks, proving the inefficiency of clustered social networks.

However, when it comes to spreading information and behavior change, close tie networks are beneficial because they can be used to spread information about preventive behavior changes, which is essential during disease outbreaks [3]. Facilitating positive behavior adoption is less challenging with clustered social networks and redundant ties because of the repeated sources of reinforcement. Weak tie networks lack this reinforcement resulting in minimal behavior change. The Healthy Lifestyle Network conducted a study on social networks proving behavior changes spread rapidly in clustered networks in comparison to random networks, and the commitment to the behavior was greater among participants who received reinforcing signals from multiple sources [3]. Laranjo concluded by slightly modifying social networks, homophily and clustering assisted with the diffusion of "easy" behaviors [13]. In close ties networks characterized by the significant presence of clustering and homophily, a few weak ties can be introduced to increase the spread of information and behavior change. These weak ties serve as sources of new exposure as well as connections to other close ties networks, creating a large social network system connecting all types of people. Even though network alterations aren't explicitly mentioned in education theories or models, they can be utilized alongside other recommendations as a means of increasing the reach of information to the public with the purpose of education and behavior change.

Despite not being specifically designed for crises like disease outbreaks, the Health Belief Model (HBM) has potential applications during the COVID-19 outbreak as guidelines for health education and promotion. The objective of this model is to target perceived barriers, benefits, self-efficacy, and threats in order to induce behavior change within the targeted population [10]. Six constructs make up the model; perceived susceptibility, perceived severity, perceived benefits, perceived barriers, cues to action, and self-efficacy; each with the aim of altering the individuals' beliefs to understand the disease and take measures to prevent themselves from contracting it [21]. Certain factors need to simultaneously work together to ensure the success of the HBM, which are sufficient motivation, the perception of threat and vulnerability, and confidence in the benefits of health recommendations. However there are limitations to the model, such as its inconsistency in predictive power and the unaccountability for the impact of cultural factors, socioeconomic status, and previous experiences on behavior [21]. These limitations can be minimized by adjusting the model and using the HBM in conjunction with other guidelines.

While there are several models applicable to the specific characteristics of disease outbreak crises, a combination of the Health Belief Model and Crisis and Emergency Risk Communication alongside network alterations proves to be the most advantageous. The HBM will provide the foundation for developing the health education and promotion program and direct the interventions that will be implemented. To secure the success of this model, the CERC will guide the messages disseminated to the public throughout the crisis to increase motivation, the perception of threat and vulnerability, and acceptance of health recommendations. Network alterations on social media sites can promote the spread of the information and communication between governmental organizations and the public. Functioning together, these various components will increase the adoption of preventive behaviors and hinder the spread of COVID-19.

METHOD

In order to conduct a comprehensive analysis on the evolution of Twitter posts surrounding the pandemic, tweets were sampled from each month starting at the beginning of the outbreak and continuing up until the current month. Discussions of COVID-19 steadily began in February, and exponentially increased in intensity by March. By employing the advanced search engine options, four to five tweets were gathered from the months of March to July for this research project. Search terms used to collect the data included COVID symptoms, COVID-19 testing, social distancing, testing, mask, COVID, and transmission. During the process of data collection, the tweets were organized into two separate Microsoft excel spreadsheets. One spreadsheet was designated for tweets posted on the behalf of organizations and the other spreadsheet was designated for tweets posted by individuals. Additional data was collected regarding the tweets such as the date they were posted, hashtags and links included within the tweets, and keywords used to find the post. A classification system was utilized to tag the Twitter posts according to their content. The labels used within this system were prevention measures, testing, government criticism, social distancing, treatment, symptoms, case rate, recommendations, and exposure. Once all of the data was collected and organized, models were developed for the data analysis.

MonkeyLearn is a platform that aids developers and businesses with data analytics by supplying straightforward, user friendly tools. The site provides a practical alternative to developing algorithms with coding languages for analyses. Despite the limitations with a free account, a topic classification model and sentiment analysis model were created to investigate the data. Prior to running the analysis, a separate excel file with data was made to assist with training the models. The file contained a Twitter post from each label within the classification system, totaling to twelve data entries without distinction between posts uploaded by individuals and organizations. To train the model, the excel was uploaded onto MonkeyLearn, and using the advanced settings in the topic classification model, the column containing the tweet and attached links were used as text while the classification column was used as tags. After training the model, the original excels were uploaded to evaluate the topic classification's model success in appropriately tagging the tweets. For the sentiment analysis model, the same condensed excel file containing twelve data entries was employed for training. On each data entry, the intent of the post was manually determined to be positive, neutral, or negative. Following the training, the original excels were once again uploaded to the site into the model to determine the overall sentiment of tweets posted about COVID-19 and how this may have changed over time. Regardless of the small scale use of these models for the purpose of this research, the topic classification model and sentiment analysis model can prove their utility with larger batches of data during further examinations of COVID-19 and Twitter.

DATA ANALYSIS

The topic classification model was successful in accurately classifying the tweets according to the taxonomy designed for this research project. For the tweets posted by organizations, the model correctly labeled all nine tweets, and for the ones posted by individuals, the model correctly labeled fifteen tweets out of seventeen. An added feature to the model is confidence levels in its classification of the data. It is expected that the tweets with the lowest confidence levels would also be incorrectly tagged. On the excel containing the tweets posted by individuals, the lowest confidence level the model provided was 9.9%, and the label for the post was also incorrect. Instead of being classified as "testing", the tweet was tagged as "prevention measures". The other tweet that was incorrectly categorized by the model had a confidence level of 10.4% and was labeled as "case rate" and "government criticism" instead of "social distancing". "Testing" and "prevention measures" are similar labels because testing for COVID-19 can serve as a prevention measure to reduce infection transmission, making it understandable as to how the model mislabeled the tweet. On the other hand, "case rate" and "government criticism" and "social distancing" are very different categories and have little relation to each other in terms of subject matter. The content of the post focused on virtual meetings in place of social gatherings and maintained a positive tone, providing little reason for the misclassification. Both of these errors can be attributed to the model's limited training. Across the entire sample of data, the confidence levels ranged between 9% and 30%. With further training, the confidence levels and accuracy of the model will increase, creating a practical model for large data sets.

Within the sample, twelve out of the twenty-five tweets gathered were directed towards testing and prevention measures. Nearly 50% of the tweets were focused on educating the public about the importance of testing COVID-19 and informing them of easily accessible testing locations, as well actions to take to reduce the likelihood of contracting COVID-19. Actions included recognizing the symptoms of COVID-19, wearing a mask in public areas, and maintaining social distancing. These tweets display efforts to inform the public, which is the first step of the Crisis and Emergency Risk Communication (CERC) model. As time passed, there were more tweets that focused on case rates and treatments and the management of the outbreak, however there appeared to be a lack of posts aimed at reducing anxiety and fear. This may have contributed to misinformation surrounding COVID-19, in turn affecting testing and treatment rates. Classifying the tweets with a topic classification model on a chronological timeline provides an image of how organizations managed social media communications during an outbreak and how individuals responded to this information. While larger government agencies placed a heavy emphasis on risk messages and personal protection, they failed to recognize the importance of two-way communication and messages to assuage concerns and panic.

The sentiment analysis model categorized the tweets as "neutral", "positive", and "negative" by analyzing their content. Some posts contained overlap and were placed in two categories if the model believed the post was a combination of sentiments. In the excel containing posts by organizations, 44.4% of the tweets were classified as "neutral", 22.2% of the tweets were classified as "positive", and 55.6% of the tweets were classified as "negative". Three of the nine tweets were placed in multiple categories with one tweet labeled as "neutral" and "positive", while the other two tweets were labeled as "neutral" and "negative". In the excel containing posts by individuals, 29.4% of the tweets were classified as "neutral", 17.6% of the tweets were classified as "positive", and 47.1% of the tweets were classified as "negative". Only one of the seventeen tweets was placed in multiple categories where the tweet was labeled "neutral" and "positive". Confidence levels were also provided for each tweet, and across the sample they fall above 50%, which translates to the model having high levels of confidence in its classification and accuracy.

The results of the sentiment analysis model provided several significant observations. First off, it is important to note that the model left some tweets blank to represent its inability to designate a sentiment for the post. For the excel containing posts by organizations, one tweet was left blank while two tweets were left blank in the excel containing posts by individuals. Increasing the training for the sentiment analysis model will prevent misclassification and reduce the model's inability to classify the sentiments of tweets, i.e. the number of blank spaces in the final analysis. Another notable observation is that 48% of the tweets were labeled as negative, which is nearly half of the entire data set. Over the course of several months, a greater proportion of tweets were negative in comparison to positive and neutral toned posts. The content of several of the "negative" tweets included criticisms of government intervention and the limitations of prevention measures currently in place, as well as concerns over the rising number of COVID-19 cases. "Neutral" tweets were more inclined to provide educational information about COVID-19 and self-protective strategies to prevent illness, while "positive" tweets provided reassurance and reduced fears and anxieties by providing updates regarding the pandemic and the success of ongoing interventions. Analyzing the sentiments of tweets provides a clear image of the public's reaction to the health crisis and their response to governmental efforts. The analysis for this research project supplies the conclusion that the public's overall sentiments were negative highlighting the lack of mental and emotional support by governmental organizations. To improve the public's response and overall well-being, social media interactions need to be organized into two-way communication to build relationships and provide the necessary psychological reinforcements alongside the physical interventions and treatment.

LIMITATIONS AND RECOMMENDATIONS

Due to the restrictive nature of this research project, in both time and size, several limitations are present within the method and analysis. The sample was composed of twenty-five tweets, which cannot be expected to be representative of all the tweets published during the COVID-19 outbreak. Each individual has her or his own opinion and experiences different emotions during times of pressure and uncertainty. While it is not feasible to gather each and every tweet posted, the project's sample could not capture the diversity of the population on Twitter. As a result, the conclusions made within the study based on the limited data cannot be generalized for all individuals and governmental organizations during COVID-19. The analysis of this project was hindered by the rudimentary models used to analyze the data. An excel file containing twelve data entries was used to train the models, which is hardly enough to ensure accurate and thorough models. During training, the tweets were also manually classified for the topic classification and sentiment analysis models, which may have introduced bias. Even with these limitations, this research project provided useful insight into the uses of Twitter in public health and how it has impacted the public during COVID-19.

Several recommendations to improve this study can be made to overcome the aforementioned limitations. The first order of business would be to dramatically increase the sample size by using Twitter's API in conjunction with a data collection program that can interact with Twitter's interface. Doing so will ensure that the sample is representative of the population of Twitter users, increasing the generalizability of the conclusions of the study. Extensively training the topic classification and sentiment analysis models will prevent bias from affecting the data and increase the accuracy and confidence of the models. Further research should also be conducted to examine the racial implications of COVID-19 and social media messaging by using tags related to various races and ethnicities. These improvements for studies conducted in the future will significantly enhance the accuracy of the data analysis and provide meaningful results that can be applied in a health education and promotion context.

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