Exploring Sentiment Towards Contact Tracing

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Abstract

In the midst of COVID-19, contract tracing systems are an important tool for governments around the world to control and track the spread of the disease. However, contract tracing requires pubic acceptance and cooperation to be effective. This study provides an overview of contact tracing, including a review of literature and potential privacy concerns that have been identified. In order to measure public sentiment towards contact tracing, over 50,000 Twitter posts (tweets) across a three-month time frame in April, May, and June of 2020 were gathered. Using established sentiment analysis models (Bing, AFinn, and NRC), it was found that sentiment towards the term "contact tracing" became more negative across the time frame and that words associated with the emotion categories of "Anticipation", "Fear", and "Trust" were most prevalent. We also found that retweeted posts have an important impact on the results and that anecdotal examination of specific tweets shows polarizing views on the subject. This study has limitations due to the potential biases of Twitter posts and the potential inaccuracies of sentiment analysis models. Future research could expand on contract tracing research by studying the topic empirically or by examining case studies on specific systems.

Keywords: Contact Tracing, Sentiment Analysis, Privacy, COVID-19, Twitter.

1. INTRODUCTION

Epidemic diseases such as COVID-19, SARS-CoV2 and Ebola have spread worldwide over the past decade. In addition to the various measures (social distancing, wearing masks, shelter in place, vaccine development) to control the growing global health threat from COVID-19, large-scale testing plus *contact tracing* for those who test positive is beginning to be used by public health organizations. Tracking people who may have come in contact with an infected individual can limit the spread of a virus and help to understand how the virus is spreading. With contact tracing, an infected individual is required to share all of his or her travel details with the health care authorities to reliably track and quarantine people who could contract an illness due to one's own physical connection with the infected person (World Health Organization, 2014).

As a contact tracing system requires participation and cooperation to be successful, it is important to understand the sentiment that prospective users feel towards these systems. This study provides a background and literature review of contact tracing systems and the privacy concerns that may arise. Sentiment towards the term "contact tracing" was examined by using extracted Twitter posts across the timeframe of April, May, and June 2020. This time frame was when contact tracing became widely known in the United States and Europe. The sentiment analysis includes three widely used models: Afinn Model (Nielsen, 2011), Bing Model (Bing, Chan, Ou, 2014), and NRC Model (Kiritchenko, Zhu, Cherry and Mohammad, 2014). These were used to analyze the positive or negative sentiment of the words used and the relative percentage of words used in eight different emotional categories.

2. BACKGROUND AND LITERATURE REVIEW

Contact Tracing and Virus tracking

COVID-19 is infecting millions of people and the spread is mainly through person-to-person contact. A group of scientists (Ferretti, Wymant, Kendall, Zhao, Nurtay, Abeler-Domer, Parker, Bonsall, and Fraser, 2020) examined some key parameters involved with the epidemic spread of the COVID virus in order to estimate the contribution of different transmission routes. They found that it predominately spread through personal contact. This being the case, contact tracing would be a way to follow the spread of this and any future virus since it would build a database of proximity contacts. This database could be used to immediately notify people of positive cases with whom they might have come in contact. Thus, helping to control and maybe stop an epidemic. The general notion is that by targeting health sanctions to only those at risk, epidemics could be contained without the need for massive quarantines that can be harmful to the overall social and business environment. The World Health Director-General said at the WHO meeting in March, 2020 (World Health Organization, 2020), "You cannot fight a fire blindfolded. And we cannot stop this pandemic if we don't know who is infected."

Until a vaccine becomes available, the only way to prevent the spread of the disease is to control the spread. Strict social distancing measures are necessary, but difficult to enforce for extended periods of time. The only way to return to a normal life is to keep the spread under control and with active tracing this can happen. The World Health Organization recommends a combination of rapid diagnosis along with immediate isolation and then rigorous contact tracing. A well-designed contact tracing database is needed (World Health Organization, 2020).

This database can be built by digital means such as with the use of smartphone apps and manually with person-to-person contact tracing and reporting. Contact tracing has a history of being a central public health response to infectious disease outbreaks especially in the early stages when specific treatments are limited or unknown (Keeling, Hollingworth and Read, 2020). The manual tracing previously being used for epidemics is slow and difficult to manage a global pandemic such as CoVID-19 so computer applications will be needed to automate a more successful viral tracing and alert system.

With contact tracing, regardless of process, comes the required collection of privacy-intrusive information such as GPS locations, the logging of privacy-sensitive data on a third-party server, or required additional infrastructures such as Wi-Fi Apps with known locations (Hekmati, Ramachandran and Krishnamachari, 2020). Since the contact tracing process involves gathering private and sensitive data, individuals might push back on sharing that data which would hamper the tracing process and therefore expose more people to the virus.

In order to avoid push back from individuals, ethical measures need to be considered with this personal tracing. Researchers from the University of Southern California (Hekmati et al., 2020) examined a number of mobile applications, with wireless technologies and GPS locators but these involve unreliable self-reporting or relying on external trackers which make privacy-savvy people nervous and usually less cooperative. Besides individuals being hesitant to share personal data, there are also laws that can stop or slow down tracing collection. During an outbreak of measles on three international flights to Germany in 2017 (Thole, Kalhoefer, der Heiden, Nordmann, Daniels-Haardt and Jurke, 2019) contact tracing was substantially delayed due to an interpretation of Germany's data protection act. The Public Health Authority had to wait a week to notify Health officials in various international countries who then could notify the passengers of the Measles exposure, which meant that measles had spread among those whom passengers contacted.

Knowing that only a vaccine or contact tracing can control this pandemic technology, governments across the world along with health authorities are working together to find solutions to stop this COVID-19 pandemic. Technology developers are crafting technical tools to help with tracing. Google and Apple have a joint effort to enable the use of Bluetooth technology to help governments and health agencies reduce the spread of the virus, with user privacy and security central to the design (Sainz, 2020).

Privacy Concerns

Maintaining a sense of user privacy is an essential requirement for people involved with contact tracing. A study by Taewoon Nam (2019) discussed how expansion of government surveillance capacities through information and communication technologies (ICT) has grown over the past two decades because of 9/11 and the passage of anti-terrorism laws and with the upsurge of ICTs and the consequential increase of the capability to conduct monitoring. Americans, in particular, are now more aware of government surveillance after the revelations from Edward Snowden, a contractor for the National Security Agency (NSA). Mass media have been reporting on state surveillance since Snowden's exposure of PRISM in June 2013 (Preibusch, 2015). PRISM is a tool used by the US National Security Agency (NSA) to collect private electronic data belonging to users of major internet services like Gmail, Facebook, Outlook, and others. It's the latest evolution of the US government's post-9/11 electronic surveillance efforts, which began under President Bush with the Patriot Act, and expanded to include the Foreign Intelligence Surveillance Act (FISA) enacted in 2006 and 2007.

When it comes to who people trust, Sabin of *Morning Consult* (April 27, 2020) reported results from a survey of 2,200 U.S. adults and found the majority of people trust researchers (55%) and agencies (54%) more with building an effective COVID-19 tracking app than tech companies (41%). In addition, the survey reported that 59% of the public is also at least somewhat uncomfortable with having tech companies share their location with the government to map a viral outbreak.

Government officials in Washington, D. C. have started acting to build privacy safeguards for the new tracking technologies. Sen. Ed Markey (D-Massachusetts) laid out guidelines for establishing a national contact-tracing system, which would call for transparency about what information is collected, voluntary participation and thorough data security processes. Sen. Josh Hawley (R-Missouri) requested Apple Chief Executive Tim Cook and Google Chief Executive Sundar Pichai to take personal responsibility for protecting the data collected by their contact-tracing system. (Sabin, 2020).

Apple and Google (April, 2020) created a collaboration to create a protocol to maintain privacy in contact tracing. The protocol includes the following:

- The Exposure Notification Bluetooth Specification does not use location for proximity detection. It strictly uses Bluetooth beaconing to detect proximity.
- A user's Rolling Proximity Identifier changes on average every 15 minutes, and needs the Temporary Exposure Key to be correlated to a contact. This behavior reduces the risk of privacy loss from broadcasting the identifiers.
- Proximity identifiers obtained from other devices are processed exclusively on device.
- Users decide whether to contribute to exposure notification.
- If diagnosed with COVID-19, users must provide their consent to share Diagnosis Keys with the server.
- Users have transparency into their participation in exposure notification.

Interest in Contact Tracing

As the COVID-19 virus began to spread rapidly in parts of the United States, there were several terms that became a regular part of the public's vocabulary. As shown in Figure 1, interest in "contact tracing" as a Google search term became increasingly popular during the month of May 2020. While a portion of the search interest could derive from job searches related to the term, as shown in Figure 2, interest in the term itself exceeds that of "contact tracing jobs". Another way to demonstrate the increased interest in contact tracing is to compare it with another, unrelated search term that was also part of the COVID-19 vocabulary. Figure 3 shows that searches for "herd immunity" were initially higher than those of "contact tracing" but that interest in contact tracing rose comparatively during the month of May. These charts show that the term was just recently become popular which demonstrates the importance of the topic but also serves as a caveat that understanding of the impact of the term may not be well established.

Figure 1: Google Search Interest in Contact Tracing

Figure 2: Google Search Interest in Contact Tracing vs Contact Tracing Jobs

Figure 3: Google Search Interest in Contact Tracing vs Herd Immunity

3. METHODOLOGY AND RESEARCH QUESTIONS

Sentiment analysis refers to the use of natural language processing, text analysis, computational linguistics, and biometrics to systematically identify, extract, quantify, and study affective states and subjective information. Over the past two decades, various models have been developed and tested to systematically evaluate words to quantify the extent to which a string of text is positive or negative and to quantify the emotions that are expressed in the text. Sentiment analyses have been widely applied to customer reviews, qualitative survey responses, social media, and healthcare materials for applications that range from marketing to customer service to clinical medicine and other fields of study. For example, one such study demonstrated how the analysis of Twitter sentiment was closely correlated to a Gallup poll of public opinion (O'Connor, Balasubramanyan, Routledge, 2010). Another study showed how the moods depicted in tweets can predict stock market trends (Bollen, Mao, and Zeng, 2011).

In this study, three different models of analyzing sentiment were utilized. The AFinn lexicon is a list of English terms rated for valence with an integer between -5 (negative) and +5 (positive). The model was developed by Finn Årup Nielsen between 2009 and 2011 (Nielsen, 2011). The Bing index (Liu, Hu and Cheng, 2005) is a binary model that assigns words as positive or negative. Applied to Twitter entries, each word in a tweet string is tabulated to determine the net positive or negative score. The NRC lexicon (Kiritchenko, et. al, 2014) is an effort coordinated by the National Research Council of Canada. Its model categorizes English words in alignment with eight emotions: anger, anticipation, disgust, fear, joy, sadness, surprise, and trust. When applied to Twitter entries, each tweet's word count for each emotion is tabulated. The emotions are then compared to a total to determine the relative percentage of each emotion that is found in the set of extracted tweets.

To search and extract the keywords "contract tracing" into a dataset, first, a development account on Twitter that provides access to an open API was requested. This development account on Twitter provided access to an open API. Next, an R script that installs an open source application (R-Tweet) was used with its corresponding library to extract all tweets associated with the search term. The code also saved the search results in a csv format that could then be opened in Excel or read by a programming language to score the tweets in accordance with the sentiment models. The resulting csv file contained all of the tweets, along with the user name and various other attributes, including the number of times that the tweet had been retweeted. Next, a macro enabled Excel file with embedded VBA code was used. This computed the results for the set of tweets in accordance with the three sentiment analysis models presented earlier in this paper (AFinn, Bing, and NRC).

Sentiment analyses can be flawed, especially when small sample sizes are used. The models are not able to capture the context or nuances of the words used and thus can misclassify a particular tweet. However, in large data sets, these individual errors in classification are offset by the greater number of classifications that accurately represent the emotions or positivity/negativity of the tweets. For each of the three dates in the April to June 2020 time frame, a minimum of 12,000 tweets that contained the term "contact tracing" were extracted.

Clearly, an analysis using Twitter data does not necessarily represent a universal perspective on a topic. There is an inherent non-response bias and likely polarizing views expressed, especially on a topic such as contract tracing that can have political or privacy implications. There is also a limitaton by the language, as only English tweets were extracted. The United States has the most Twitter users with over 64 million accounts as of April 2020 (Statista, 2020). However, this is followed by Japan with over 46 million accounts and by other countries whose perspectives are not captured in this analysis. To further complicate the analysis, it is very common for users (or even automated bots) to retweet particular messages. Because these retweets can have a significant impact on the overall results of a sentiment analysis, it is important to examine these effects. At the same time, the retweets are an important source of data on a topic, so one cannot simply delete the duplicate tweets and ignore the impact on the sentiment surrounding contact tracing. In this study, the results of the sentiment analysis is shared along with raw data (that includes retweets) as well as an analysis of unique tweets with all duplicates removed. In order to examine retweets more closely, the text of the most commonly retweeted entries is published in this study. Lastly, in order to illustrate perspectives on contact tracing, anecdotal examples that depict differing views as reflected in the results is included.

Research Questions

As a result of the preceding discussion, this study examines the following research questions:

1. What is the average sentiment score for tweets that contain "contact tracing" (including all retweets), using the AFinn and Bing models during the months of April, May, and June of 2020? How have the positive or negative scores changed during the time frame?
2. What are the average percent of each emotion score for "contact tracing" tweets using the NRC model during the months of April, May, and June of 2020? How have the scores for each emotion changed during the time frame?
3. How do the preceding scores for each model differ if only unique tweets are examined?
4. What are the most frequent retweets for the each of the three data sets and how do they impact the sentiment scores?
5. What are representative tweets that depict positive or negative perspectives and particular emotions on contact tracing?

4. FINDINGS

Research Question 1: Positive and Negative sentiment towards "contact tracing" tweets using AFinn and Bing models (including retweets)

As shown in Figure 4, the average AFinn score for tweets (including retweets) that contained the term "contact tracing" were initially positive in April of 2020 with an average of .28. The average AFinn score became negative in May with average of -.10 and fell much further in June with an average of -.54. The Bing scores followed a similar pattern, although with higher averages across the time span (with averages of .76, .22, and -.29 for April, May, and June respectively).

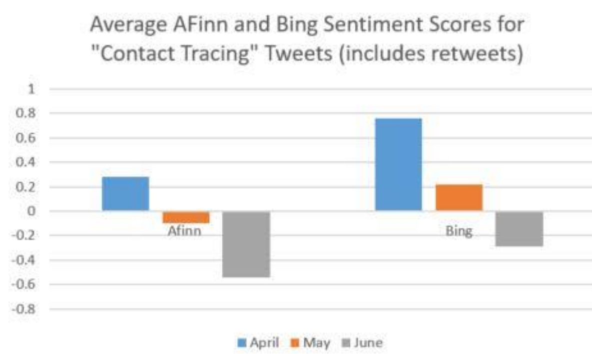

Figure 4: AFinn and Bing Sentiment Analysis for Contact Tracing April, May, June 2020

Research Question 2: Emotional words used in "contact tracing" tweets using NRC sentiment model (including retweets).

As shown in Figure 5, words classified in the "Anticipation", "Fear", and "Trust" categories were most prevalent in the April dataset with 21%, 19% and 22% of the share of the words that were able to be categorized. In May, there was an increase in "Disgust" from 5% to 9% and "Surprise" from 4% to 9% along with modest declines in "Anticipation" to 17% and "Fear" to 14%. In June, there was a sharp rise in the "Anticipation" category to 32% and "Anger" to 15% (from 9% and 10% in April and May). Much of these differences can be explained by the metrics from the mostly commonly retweeted items in the June dataset.

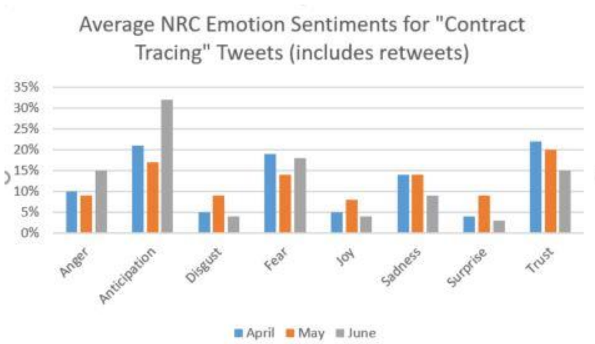

Figure 5: NRC Sentiment Analysis Emotions for Contact Tracing April, May, June 2020

Research Question 3: Differences in results from AFinn, Bing, NRC sentiment scores when only unique tweets are used.
For the same data sets, but retweets removed, as shown in Figure 6, one can see a similar pattern of declining sentiment in the AFinn and Bing scores but with much less volatility in ranges. The AFinn averages fell from .15 to .06 to -.06 across the time frame while the Bing averages fell from .26 to .22 to .13. As a result, once can conclude that the sentiment towards contact tracing became more negative as the popularity of the term became more widespread. However, the magnitude of the decline is impacted by retweets. In the examination of the NRC emotions, comparing the results shown in Figure 5 with those of Figure 7, one can see that the percentages of words classified in each emotional category are much more consistent across the time frame when the dataset includes only unique tweets. As a result, the emotion scores, particularly from June, are impacted to a great extent by the words used in retweets.

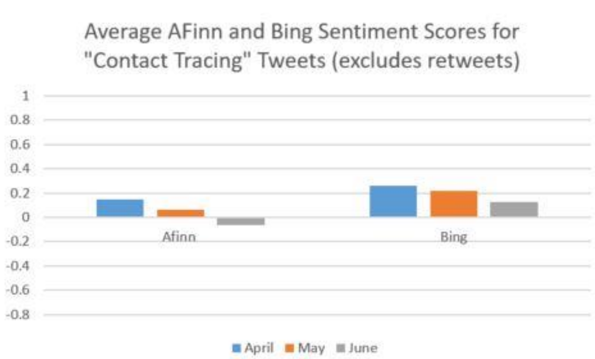

Figure 6: AFinn and Bing Sentiment Analysis for Contact Tracing April, May, June 2020 (excludes retweets)

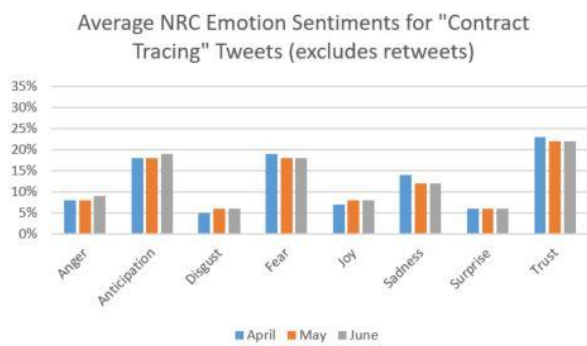

Figure 7: NRC Sentiment Analysis Emotions for Contact Tracing April, May, June 2020 (excludes retweets)

Research Question 4: Most frequent retweets for the each of the three data sets and impact on sentiment score.
In the April dataset, the following entry appeared 1404 times, representing approximately 8% of the tweets: *"Democrats are fighting for our $30 billion plan for a comprehensive national testing strategy. A major new investment that includes bolstering the supply and manufacturing chain, significantly expanding free testing for all, and expanding reporting and contact tracing."* This tweet has a positive AFinn score of 1.5 and Bing score of 2. Interestingly its words are only classified as a 1 in the "Anger" category and a 1 in the "Anticipation" category.

In the May dataset, the following entry appeared 850 times, representing approximately 7% of the tweets*: "Doctors don't think it's safe for schools to re-open. Countries with lower death tolls than ours don't think it's safe for schools to re-open. We don't even have our testing and contact-tracing system set up yet. Why are the govt pushing for something they haven't prepared for?"*. Despite the pessimistic tone to this tweet, the word classifications for AFinn and Bing are actually positive with values of .25 and 2 respectively. The tweet includes words for each of the NRC emotion categories, with 4 words in the "Trust" category, two in the "Anger", "Sadness", and "Joy" categories (one in the other four categories).

In the June dataset, there were two tweets that had a major impact on the sentiment results. The following entry appeared 3154 times, accounting for 26% of the tweets: *"We are paying 45 million pound to Serco for contact tracing. Serco's 18000 call handlers contacted only 10,000 contacts in two weeks. Meanwhile local public health teams contacted 77600 contacts ie almost eight times more according to DHSC Test and Track data."*. This tweet was actually neutral in the AFinn and

Bing scores so it did not affect the overall average decline in those averages for June. However, the quote does have scores of 2 for "Anticipation" and 1 for "Anger" which would explain much of the increases in those averages for month. June also had a tweet that appeared 1843 times, accounting for over 15% of the entries. This tweet: *"Contact tracing: FAIL. Herd immunity: FAIL. PPE: FAIL. Testing: FAIL.Lockdown: FAIL. Care homes: FAIL. Contact tracing, again: FAIL. This government has presided over a serious of failures so catastrophic that it should trigger an overhaul of how things are run in this country*" results in scores of -3 for AFinn and -2 for Bing for each entry, which would have a significant impact on the overall decline in those averages in June. The quote also has an emotion score of 1 in the "Fear" category.

These frequently retweeted quotes should not be ignored (since they would appear in the Twitter feeds and may represent legitimate perspectives on contact tracing), however, the conclusions should be tempered by understanding the potential disparate impact they may have on the overall findings.

Research Question 5: Tweets that depict positive or negative perspectives and particular emotions on contact tracing.

Within the framework of the sentiment analysis models, it is useful to examine polarizing views on contact tracing by examining anecdotal tweets from the data. These quotes show reactions that represent varying levels of support for and against contact tracing systems.

The following quotes represent positive scores from the AFinn and Bing models:

- *"In the absence of a prove. antiviral therapy and a viable vaccine, extensive contact tracing and testing is our best defense. the epidemiologist in me is delighted. HOWEVER COMMA...."* (+3 AFinn)
- *"Japan's official contact-tracing app is out for iOS now. I wonder how much traction this will gain. Hopefully enough to be effective."* (+5 Bing)

The following quotes represent negative scores from the AFinn and Bing models:

- *"Wait the government has f***ed off contact tracing?! At what point can you take a Government to court for negligence and manslaughter?"* (-4 AFinn)
- *"Seriously, why does LEFT seem excited/almost giddy about: - Declarations of Systemic Racism, Police brutality, broken justice system - Spending into bankruptcy -Contact Tracing ?? We HAD a beautiful country of strength & independence. FREEDOM TO THINK/TO BE IS SLOWLY DYING IN CANADA"* (-2 Bing)

The following quotes represent specific word classifications from the NRC emotions model:

- *"They promised a 'World Beating Track and Trace System' on 1st June - more lies from this dishonest and incompetent Government that have had fatal results. UK abandons contact-tracing app for Apple and Google model"* (+4 "Anger")
- *"HUGE win! Government to ditch "world-beating", GCHQ-backed, data-centralising contact tracing app that we warned was a failure from the start - & replace it with a decentralised app. How much precious time was wasted How much public money was wasted"* (+6 "Anticipation")
- *"#DP3T entered as a candidate to so-called PEPP-PT in good faith, but it is now clear that powerful actors pushing centralised databases of Bluetooth contact tracing do not, and will not, act in good faith. PEPP-PT is a Trojan horse."* (+ 5 for "Joy")
    - Note: this is an example of a spurious classification. The entry also has a +6 score for the Bing model.
- *"A lawsuit in federal court is challenging #Texas #ContactTracing efforts. A constitutional law professor said lawsuit is unlikely to succeed, but it remains to be seen whether campaigns against contact tracing will undermine the state's public health"* (+4 "Fear")
- *"If you are diagnosed with COVID-19, expect a call from a County public health specialist. They are not law enforcement agents and will not ask about immigration status. It will appear on your phone as L.A. Public Health please answer. Contact tracing helps us save lives."* (+5 "Trust")
- *"The cost of these failures. Contact tracing: FAILURE LEADING TO DEATHS Herd immunity: FAILURE LEADING TO DEATHS PPE: FAILURE LEADING TO DEATHS Testing: FAILURE LEADING TO DEATHS Lockdown: FAILURE LEADING TO DEATHS Care homes: FAILURE LEADING TO DEATHS Truly shocking !"* (+6 for "Disgust", "Fear", "Sadness")

5. CONCLUSIONS

Contact tracing systems (as well as the concept of "contact tracing") are in their infancy. This study's efforts, to gather and analyze qualitative perspectives on contact tracing should not be viewed as conclusive. Rather, it is informative and interesting to capture and document these sentiments during a time of great change in our world. Based on the perceptions of news reports, it appears that contact tracing is of growing interest as a way to track and prevent disease outbreaks. The rising interest in the term is supported by Google metrics regarding searches of the term. One could speculate that due to the nature of contact tracing, perceptions of the term may change once the public becomes more aware of the potential privacy implications and restrictions placed on the freedoms of individuals identified in these systems.

The use of Twitter as a data source and sentiment analysis models to classify tweets may not be universally accepted as a rigorous scientific approach to academic research. However, this style of research has become increasingly common in both practice and academic studies across a wide spectrum of fields. In this study, it was found that sentiment towards contact tracing tweets have become less positive as depicted in trending results from June vs those from April and May of 2020. Also, emotional word classifications of "Anticipation", "Fear", and "Trust" are most prevalent across the three month time frame.

Clearly there are inherent limitations to using Twitter as a data source since there is a certain motive for sharing a perspective on Twitter and its user base may not represent the same demographics as the public at large. It is noted that specific tweets that have been retweeted many times can influence the sentiment analyses. Moreover, the classification of certain tweets using the sentiment models may not match a common sense perspective of an individual reading the same tweet. Contact tracing is a very diverse and quickly changing subject. In the US, the systems are mostly operated at the state level. Similarly, across the world, there are different systems, technologies, and laws that are rapidly changing that may influence sentiment towards contact tracing. The acquisition of tweets that are only in English is a further limitation of this study. Future research could use this study's results as a foundation for empirical studies that explore perspectives in a more controlled setting. Research using case studies of contact tracing implementations along various stages of maturity to reveal best practices and implementation success factors is recommended.

Lastly, as a topic that has political implications, sentiment regarding a topic like contact tracing, is subject to change as news or opinions on the topic becomes widespread. Conversely, interest in the topic could wane if treatments or vaccines for COVID-19 are developed making contact tracing systems a less pressing priority for governments across the world. However, these systems will become more prevalent as the impact of pandemic diseases are realized. This study makes an important contribution by documenting the perceptions of contact tracing during a notable time period where interest in the term was emerging.

5. REFERENCES

Apple/Google (2020, April). Exposure Notification: Bluetooth Specification. V1.2, 8. Retrieved May 21, 2020 from https://www.apple.com/covid19/contacttracing

Bing, L., Chan, K., Ou,C. (2014) . Public Sentiment Analysis in Twitter Data for Prediction of a Company's Stock Price Movements, 2014 *IEEE 11th International Conference on e-Business Engineering*, Guangzhou, 232-239, doi: 10.1109/ICEBE.2014.47.

Bollen, J. , Mao, H. , Zeng, X. (2011). Twitter moodpredicts the stock market, *Journal of Computational Science*. 2:1, 1-8. Cite as: 10.1016/j.jocs.2010.12.007.

Ferretti, L., Wymant, C., Kendall, M., Zhao, L., Nurtay, A., Abeler-Domer, L., Parker, M., Bonsall, D., Fraser, C. (2020, March) Quantifying SARS-CoV-2 transmission suggests epidemic control with digital contact tracing. *Science*. DOI: 10.1126/science.abb6936.

Hekmati, A., Ramachandran, G., Krishnamachari, B., (2020, April 10). CONTAIN: Privacy-oriented contact tracing protocols for epidemics. Cite as: arXiv:2004.05251

Keeling, M. J; Hollingworth, T. D. and Read, J. (2020) The Efficacy of contact tracing for the containment of the 2019 Novel Coronavirus (COVID-19). Retrieved June 4, 2020 from https://doi.org/10.1101/2020.02.14.20023036

Kiritchenko, S., Zhu, X., Cherry, C., Mohammad, S. (2014). Detecting Aspects and Sentiment in Customer Reviews. *Proceedings of the 8th International Workshop on Semantic Evaluation* (SemEval 2014), 437–442.

Liu, B., Hu, M. Cheng, J. (2005, May 11-15). Opinion Observer: Analyzing and Comparing Opinions on the Web. *Proceedings of the 14th International World Wide Web conference* (WWW-2005), Chiba, Japan.

Nam, T. (2019) What determines the acceptance of government surveillance? Examing the influence of information priacy correlates. *Social Science Jounal.* 56(4). Retrieved June 7, 2020 from https://doi.org/10.1016/j.soscij.2018 .10.001

Nielsen, F. (2011, May) A new ANEW: Evaluation of a word list for sentiment analysis in microblogs. Proceedings of the ESWC2011 Workshop on 'Making Sense of Microposts': Big
things come in small packages 718 in CEUR Workshop Proceedings 93-98. Retrived June 20, 2020 from http://arxiv.org/abs/1103.2903

O'Connor, B., Balasubramanyan,R., Routledge, B. Smith, N. (2010). From Tweets to Polls: Linking Text Sentiment to Public Opinion Time Series. *Proceedings of the Fourth International AAAI Conference on Weblogs and Social Media*. 122-129.

Preibusch, S. (2015, May) Privacy Behaviors after Snowden. *Communications of the ACM*. 58(5), 48-55.

Sabin, S. (2020) Agencies Lead Big Tech by Double Digits on Trust in Contact-Tracing Data Security. *Morning Consult*. Retrieved June 7, 2020 from https://morningconsult.com/2020/ 04/27/contact-tracing-apps-data-privacy-poll/

Sainz, F. (2020) Apple and Google partner on COVID-19 contact tracing technology. Retrived May 24, 2020 from https://www.apple.com/ newsroom/2020/04/apple-and-google-partner-on-covid-19-contact-tracing-technology/

Statista.com (2020) Leading countries based on number of Twitter users as of April 2020. Retrieved June 5, 2020 from https://www.statista.com/search/?q=covid&Search=&qKat=search

Thole, S., Kalhoefer, D.,der Heiden, M., Nordmann, D. ,Daniels-Haardt, I. , and Jurke, A. (2019, May 9) Contact tracing following measles exposure on three international flights, Germany, 2017. *Euro Surveill*. 24(19): Retrived May 30 , 2020 from https://www.ncbi.nlm.nih.gov/ pmc/articles/PMC6518964/

World Health Organization (2020). *Report of the WHO-China Joint Mission on Coronavirus Disease 2019* (CoVID-19). Retrived April 24, 2020 from https://www.who.int/news-room/ commentaries/detail/modes-of-transmission-of-virus-causing-covid-19-implications-for-ipc-precaution-recommendations

World Health Organization (2014). Contact tracing during an outbreak of Ebola virus disease. Retrived April 28, 2020 from https://www.who.int/csr/resources/publications/ebola/contact-tracing-during-outbreak-of-ebola.pdf