How Health Information Spreads in Twitter: The Whos and Whats of Philippine TB-data

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Abstract: Twitter is a popular platform for disseminating health information. Unfortunately, there is no clear way to monitor how information reaches the intended audiences. This research examined how health information spreads on Twitter and identified factors that affect the spreading within the Philippines. We created a process whose goal is to generate results that experts can deeply analyze to reveal insights into information spread. The process consists of crawling Twitter data, transforming the data and applying sentiment identification and topic modeling, and performing Social Network Analysis (SNA). The SNA graphs allow for the study of the interactions between Twitter users and tweets while giving insights on influential users and topics discussed across clusters. The study explored and utilized tuberculosis-related tweets. Though the algorithms were meant to process tweets written in Filipino, the process is mostly language-agnostic and can be applied to Twitter data. The results also help in identifying strategies that can improve health information spread on Twitter in the Philippines.

1 INTRODUCTION

1.1 Background of the Study

Social networking sites (SNS) have emerged as primary forms of communication within the online community, with around 46.03% of the world population using SNS[1]. Furthermore, they have also become the main sources of information online, with almost 64.5% of Internet users receiving breaking news from online platforms, such as Facebook, Twitter, and Instagram, instead of traditional media. Due to their wide use, other domains have also taken advantage of the spread of information found within these sites as mediums to promote and provide awareness[2].

One such domain is that of the medical field as SNS have become popular avenues for publicly sharing information. In fact, Twitter has been called the most popular healthcare communication platform (Pershad et al., 2018). Furthermore, many studies have been conducted to better understand the behavior of information spread within Twitter and its effects on users (Kudchadkar and Carroll, 2020; Liang et al., 2019; Tambuscio et al., 2015).

We found an opportunity for a localized study that focuses on the behavior of information spread in the Philippine context. We focused on health information revolving around tuberculosis (TB), since TB has been characterized as a global health threat[3,4], with around 9 million people acquiring TB in 2017[5]. It is also more prevalent in the global South and the Philippines[5,6], which has been classified as high in both TB and drug-resistant TB[6]. Moreover, in 2017, around 581,000 were diagnosed with and 27,000 died of TB[5] in the Philippines. One of the methods to effective prevention and management of TB is relevant information (Wieland et al., 2013; Brashers et al., 2004). Communicating social support to patients is also important for continuing medication and treatment success (Skiles et al., 2018). Thus, this study would also like to explore how health information regarding tuberculosis is spread on Twitter and determine factors that may be used to better disseminate pertinent and

[1] https://ourworldindata.org/rise-of-social-media

[2] https://conductscience.com/the-impact-of-social-media-on-knowledge-dissemination/

[3] https://www.tballiance.org/why-new-tb-drugs/global-pandemic

[4] https://www.who.int/news-room/fact-sheets/detail/tuberculosis

[5] https://www.who.int/tb/publications/global_report/en/

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important information regarding tuberculosis.

There is a significant amount of Filipinos using social networking platforms as a way of getting news and information (Chua, 2020). However, there is also a lack of dissemination of reliable health information (Sbaffi and Rowley, 2017). While there are alternatives in disseminating information in traditional media, such as televisions and radios, these are proven ineffective because fewer and fewer people are utilizing them (Chua, 2020).

The following are the contributions of this research:

- Identified factors information spread will allow Philippine health organizations to take advantage of the popularity of Twitter to spread important and relevant information, with an emphasis on lesser known diseases or programs that do not receive the necessary attention, effectively and efficiently so that the information reaches a wider audience.
- The formulated process in tracing health information spread is reproducible in other contexts with most of the modules being language agnostic.

2 RELATED WORKS

2.1 Social Network Analysis

Social network analysis is consistently used to learn how information spreads in social networks by characterizing network structures to find unique patterns on how information spreads and determine the potential factors that may affect the spread. A previous study by (Himelboim et al., 2017) has shown that social network analysis can also be used to classify topic-networks on Twitter by using features such as mentions, retweets, and replies. Twitter networks are also directed and have edges flowing towards a certain direction. In social network analysis, these networks are usually represented as graphs, with different metrics applied to measure the spread of information in the network. One of the most commonly used metrics is *centrality*.

Centrality aims to measure the influence of a specific node in a network and is commonly used to identify the source of a spread (Grandjean, 2016). In its application to the analysis of information spread in SNS, the *out-degree* centrality can be used to measure the amount of outgoing information from a certain user and represents the reach in the community in a directed network. The *out-degree* centrality value also represents how often a node interacts with other nodes in the network (Hansen et al., 2020). *Eigenvector* centrality measures the importance of a node based on the importance of its neighbors (Bihari and Pandia, 2015), where its neighbors are also connected to other nodes. Furthermore, *eigenvector* centrality can be used to determine the most influential node in a network (Maharani et al., 2014), as a high *eigenvector* centrality value indicates greater connectivity compared to other nodes, resulting to a wider spread of information flow in the network. Another centrality measure, *betweenness* centrality, is used to measure how frequently a node acts as a bridge along the shortest path between two nodes (Xu et al., 2015).

2.2 Non-textual Factors

As Twitter is being continuously used as a medium for information spread, the factors that affect its spread vary on what metrics are used to compare. A previous study has shown that different types of users play different roles in the dissemination of information on Twitter (Cha et al., 2012). Mass media accounts, ordinary accounts, and even influential accounts such as world leaders, politicians, and celebrities affect the flow of information spread significantly (Cha et al., 2012).

Other features such as retweets and followers are also effective in playing a big role in the retransmission of information. Through the retweet feature, information is spread efficiently, as users who retweeted only act as a middleware in the spreading process (Zhang et al., 2017). This implies that readers on Twitter will be only focused on the original message without taking into account the users who retweeted the messages. Meanwhile, hashtags, commonly used as a metric to measure the popularity, were proven to ineffective in the process of information spread on Twitter (Skaza and Blais, 2017).

Furthermore, these non-textual factors are affecting each other's process, such as when influential accounts' posts trigger the retweet actions from their followers resulting in the spread of the information to accounts connected to the accounts' followers. This effect quickly became a continuous chain of actions, making the information spread faster from one point to the next.

2.3 Tweet Sentiment

There have been some researches done on analyzing the sentiments of different messages and information and how these sentiments affect the spread of this piece of information on SNS (Tsugawa and Ohsaki, 2015; Hansen et al., 2011; Brady et al., 2017).

A study by (Tsugawa and Ohsaki, 2015) investigated the relationship between the sentiment of a message on SNS and its virality, which is defined as the volume and speed of message diffusion. Through extensive analyses, the research found that messages which were perceived to have a negative polarity are more likely to get re-posted significantly, and more quickly and frequently compared to messages with either positive or neutral polarity. This is also supported by the research done by (Hansen et al., 2011), which sought to find out what kind of sentiment would affect the virality of a message on Twitter. The research found that although negative sentiments enhanced the virality of the message in the context of news, this was not the case for the non-news tweets.

2.4 Tweet Topic

Understanding the topic of a tweet is crucial to identifying the information in the text. Previous studies have used topic modeling to identify the topic a tweet falls under.

Studies have made use of topic modeling to try and categorize tweets into different models. A study done by (Pirri et al., 2020) used topic modeling to explore the nature of and extract topics posted by users and organizations on Twitter during World Lupus Day. Meanwhile, (Abd-Alrazaq et al., 2020) also used topic modeling to identify main topics from the tweets related to the COVID-19 pandemic. For the first study, twelve topics were discovered. From the results, tweets that shares additional information is more prevalent compared to awareness messages and informative content. It was also found that the general public was more interested in tweets that made the reader understand the illness and its manifestations. The second study categorized the tweets into twelve categories, which were grouped into four main themes: the origin of the virus, its sources, its impact on people, countries, and the economy, and ways of mitigating the risk of infection. In particular, users were focused on the impact of the virus on people and countries, which consist of death count and emotional and psychological impact of the virus, particularly the fear and stress about COVID-19 and the lack of vaccine treatments to prevent it.

3 METHODOLOGY

Figure 1 shows the process in analyzing the Twitter data.

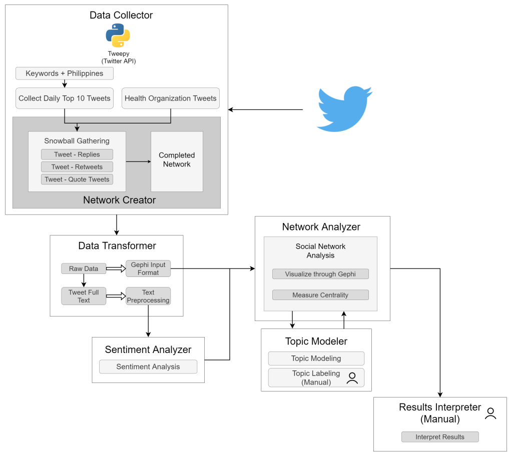


Figure 1: Collection and Analysis Process.

3.1 Data Gathering

The data was gathered from Twitter with Tweepy, a Python library that accesses the Twitter API, from December 4, 2020, to June 4, 2021. The data gathering was conducted with snowball sampling method using custom-made crawlers to extracts tweets every day, filtering the tweets by the geolocation, Philippines, and by a set of health-related keywords — "*tb*", "*tuberculosis*", "*WorldTBDay*", and "*TBFreePh*". The top ten Philippine-geolocated tweets was sorted according to the number of retweets (`retweet_count`) and likes (`favorite_count`). Due to the influence of the official Twitter accounts of the Department of Health (DOH), *@DOHgovph*, and the World Health Organization (WHO) Philippines, *@WHOPhilippines*, as sources of health information, these accounts' tweets were also collected.

3.2 Data Transformation

The data gathered were then converted into a CSV format that is acceptable in Gephi along with other details as the additional attributes for attribute-categorization graphs. The raw Twitter data is converted into graphs where the users are the nodes and another graph where the tweets are the nodes. The edges of both graphs are directed edges representing directed interactions that exist between the users or tweets.

There are two kinds of graph being generated for social network analysis. Graphs with users as the nodes are used to identify the influential users in the network through their interactions with other users in the network, and how they affect the spread of information. During the process, all edges that have the same source and target nodes will be skipped, to direct the focus to the interaction between different users in the network. Meanwhile, graphs with tweets as the nodes are used to see how the attributes of tweets such as keyword, hashtag, and sentiment of the tweet can affect the spread of information.

3.3 Data Cleaning

To remove the ambiguity of the keywords used to extract the Twitter data such as “tb”, the data were further cleaned by generating the graph with tweets as the nodes and importing the generated data in Gephi to see the clusters of tweets built. Each central node of each cluster was manually checked and validated to see if the tweet was related to tuberculosis health information. All clusters with a central node that did not have any relation to health information were removed. Tweets or nodes that did not have any interaction coming out from them were also removed. Finally, the cleaned data was exported and used to filter out the other data used for sentiment identification and topic modeling.

3.3.1 Text Preprocessing

To determine the sentiment of the tweets, tweets that are in Filipino or English were further processed. The `full_text` attribute of the tweet is used to determine the sentiment of the tweet. The preprocessing done to the `full_text` consists of lowercasing and removing handles and hyperlinks. For topic modeling, additional preprocessing consisted of removing single quotes and newlines. Before tokenizing, English tweets underwent lemmatization and Part-Of-Speech (POS) tagging, preserving only “nouns”, “proper nouns”, and “adjectives”. The tweets were then combined and underwent the following preprocessing: removing stopwords for English and Tagalog, converting text to bigrams, creating dictionaries, and converting to Bag-of-Words (BOW).

The social network analysis provides a visualization of the network and analyzes the relationships of the nodes to each other while measuring their centralities. Two types of networks are generated, one where the user is the node and the other where the tweet is the node. Moreover, it is to explore the different factors that might affect the spread of information in the network.

3.3.2 Visualize using Gephi

In the visualization, the username of the Twitter user is displayed. This is done to identify influential users that affect the spread of Tuberculosis information in the Philippines. Furthermore, data privacy is not a concern, since Section 1.2 Public Information in Twitter Privacy Policy states that most activities on Twitter and all users’ information including their profile, tweets, and interactions (replies, retweets, likes, and quote tweets) are considered public data.

3.3.3 Measuring the Centrality

After the network is built, Gephi is used to visualize the network in a form of a graph. Gephi also has built-in features to compute the different centrality measures of the network (Grandjean, 2015).

3.3.4 Sentiment Identification

The sentiment of a tweet is naively determined by checking if the tweet contains a negative keyword. If it contained predefined negative words, emojis, and emoticons. If the words, emojis, or emoticons exist, the tweet is then labeled negative, otherwise it is labeled positive. After the categorization, each node in the network is labeled by its sentiment. Then the sentiment is graphed together with the other attributes of the tweet to see if the sentiment is a factor in the spread of the tb data.

3.3.5 Topic Modeling

To identify the topic of the tweet, a network with tweets as the nodes was generated and plugged into Gephi. The visualized tweets were grouped together according to their modularity class using the compute modularity feature of Gephi to distinguish the different communities that exist within the network, and then were exported to undergo topic modeling. The `full_text` of every tweet from the exported data underwent text preprocessing and were plugged into the unsupervised topic modeling algorithm, Latent Dirichlet Allocation (LDA). The keywords per topic that were generated by the LDA were then used to label each modularity class with its respective topic by a domain expert following a specific framework, with an example shown in Table 1. Afterwards, the labeled community were once again plugged into Gephi to visualize the change in topics across the network.

3.4 Result Interpretation

The different graphs from the SNA were analyzed to see the factors affecting the information spread. Each centrality measure was observed to identify if the nodes with high centrality values were one of the most influential nodes in the network. Influential nodes were determined by being the top source of health information and nodes that cause the most

Table 1: Sample results for topic modeling.

Comm ID	Keywords	Theme
1	traffic, car, road, drive, stop, passenger, park, wheel	Vehicle
2	sick, fever, symptoms, recovery, cough, temperature	Illness
3	shot, efficacy, vaccine, antibody, immunity, dose	Vaccine

propagation of information. Different factors that can affect the spread of information are analyzed by determining which non-textual factors are recurring the most in the influential nodes.

4 RESULT AND DISCUSSION

Different graphs were generated with Gephi, producing different insights regarding the relationships between the users and the non-textual and textual factors of tweets. The aforementioned centrality measures were also explored in Gephi, producing graphs with the respective insights discussed. Analyses of the results were also given by domain experts knowledgeable in SNA and health communication.

4.1 Twitter Interaction Graphs

Figure 2 shows the user interactions, with Figure 2a showing all user interactions while Figure 2b to Figure 2d isolate the retweet, reply, and quote tweet interactions respectively. Notable accounts with high number of users interacting with them consist of *WHOPhilippines*, *DOHgovph*, and fan accounts of Alden Richards, a local celebrity who spoke at a World TB Day event. There is also significant disparity between the number of retweet interactions that make up most of the interactions with the number of reply and quote tweet interactions, which may suggest that replying and quote tweeting are not as strong as retweets in spreading information due to them requiring users to add more information than what is written in the original tweet, rather than retweeting which simply forwards the original message.

The experts also noted that two organizational actors are driving the conversation, both *WHOPhilippines* and *DOHgovph*, while the presence of fan accounts could denote the power of fan bases in driving the conversation as well. Another insight noted is that *WHOPhilippines* and *DOHgovph* did not interact with each other's tweets, instead having some users interact with both their tweets. Another significant finding by the experts is that the same set of actors, namely *WHOPhilippines* and *DOHgovph*, are still prominent regardless of interaction, and there seems to be a lack of prominent medical accounts or media accounts that drive the conversation regarding tuberculosis. One possible explanation for the lack of media accounts is that since tuberculosis is not as relevant to the public, media accounts would instead focus on other news which garners more viewership.

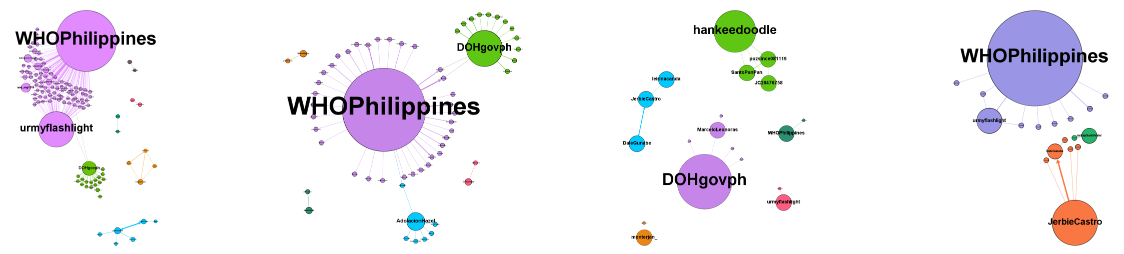
4.2 Attribute-categorized Graphs

In the Attribute-Categorized Graphs, we checked how the following four (4) attributes affect the spread of information as shown in the interactions of the tweets:

1. keywords used in the tweet
2. hashtags used in the tweet
3. media (e.g. video or image) attached in the tweet
4. sentiment of the tweet

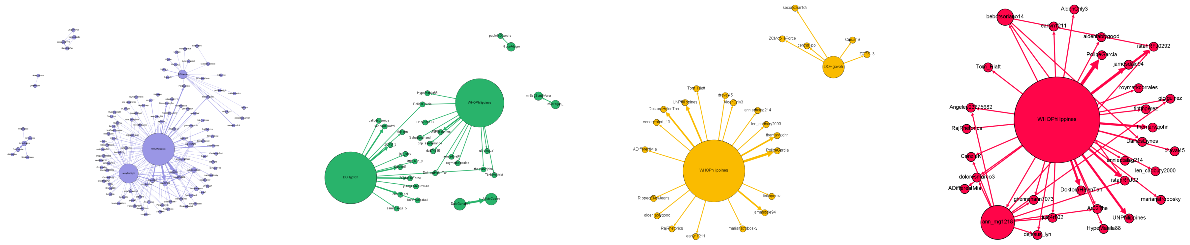
4.2.1 Keyword

The network in Figure 4 shows the interaction of indivudal tweets to each other, with the colors of the nodes denoting the use of specific keyword (i.e. tb, tuberculosis). The sizes of the nodes are based on their out-degree centrality. As seen in the graph, the key-words "tb" is the dominant keyword. The two biggest



(a) All Interactions (b) Retweets (c) Replies (d) Quote Tweets

Figure 2: Twitter Interactions Graphs.



(a) tb (b) tuberculosis (c) TBFreePh (d) WorldTBDay

Figure 3: Keyword Categorized (Users as Nodes).

nodes belong to one cluster, where the root tweet is made by *WHOPhilippines* and the biggest node is a reply *WHOPhilippines* made to its own tweet. The use of certain keywords (in this case, "tb") is essential in propagating the information within the network as more users interact with specific keywords compared to the others.

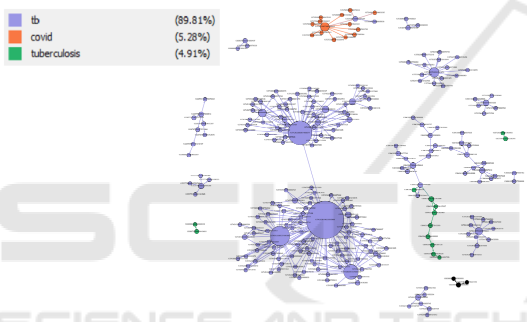


Figure 4: Keyword Categorized (Tweet as Nodes).

To further analyze the effects of keywords in information spread, each tuberculosis-related keyword was plotted wherein the user is the node of the network as seen in Figure 3. The size of the node is the out-degree of the users, which is the number of the users that interacted with them. The "tb" keyword graph has the most number of nodes and edges. Moreover, the difference from the other graphs are drastic. This means that most users used "tb" keyword when they are talking about tuberculosis.

Overall, the use of certain keywords, specifically "tb", is essential in propagating the information within the network, as the majority of the tweets used "tb" when they are referring to tuberculosis. Additionally, more users interacted with this keyword compared to the others.

4.2.2 Hashtags

Figure 5 shows a graph where the nodes are tweets and the color of the nodes represent a group of hashtags the tweets use. The node size is the out-degree

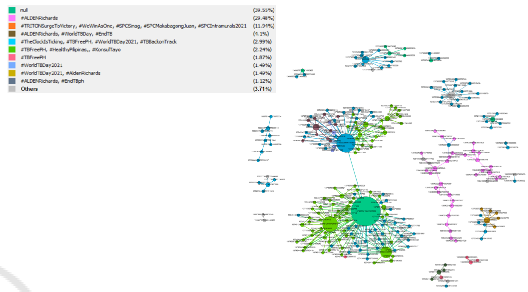


Figure 5: Categorized by the Existence of Hashtags (Tweets as Nodes).

value of the nodes. The majority of the tweets about tuberculosis do not make use of any hashtags in their tweets. However, it can be seen that the most prevalent hashtag is #ALDENRichards. While the original tweet contains nothing about the artist Alden Richards, since he is the ambassador of World TB Day, his fans are using his name as a hashtag in the tuberculosis-related tweets. Moreover, the network shows that not the same hashtag sets are being used in one cluster. Oftentimes, the presence of hashtags decreases per interaction made by the users. Sometimes, there are new hashtags that pop up while the information is cascading, like the "ALDENRichards" hashtag.

4.2.3 Media Attachment

The graph in Figure 6 is a network, where the tweet is the node and the color is categorized by the presence or absence of media attachment. It can be seen that the majority of the tweets don't interact using media attachments. Even though the majority of the root nodes contain media attachments in their tweets, the node with the highest out-degree centrality does not contain any media attachments. Additionally, the 3rd biggest node also does not contain media attachments. This shows that media attachments do not significantly play a role in the spread of information but rather, it is because of the users being influential,

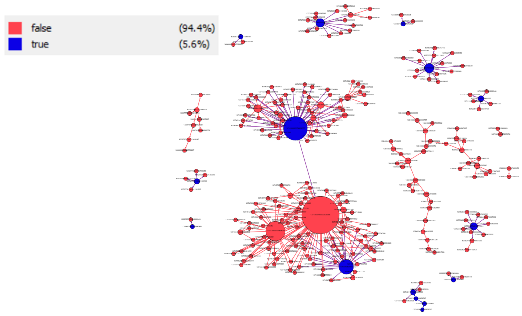


Figure 6: Categorized by the Existence of Media Attachment (Tweets as Nodes).

which is why the clusters are big.

4.2.4 Sentiment

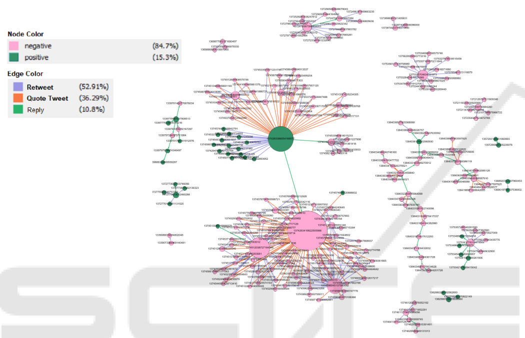


Figure 7: Categorized by Sentiment (Tweet as Nodes).

The graph in Figure 7 shows the tweet as a node network, where the node colors are categorized by sentiment and the edges are categorized by interaction. It can be seen that the majority of the tweets are negative, with a percentage of 84.7% and with retweets inheriting the sentiment of the original tweet. In some cases, the polarity of the tweet changes when the sentiment is changed when replying or quote tweeting.

The second biggest cluster showed that the majority of the children nodes with differing sentiments were made from quote tweeting the parent node. The cluster on the lower right show that the interactions were replies to the original tweet. Upon manually checking the tweets, they contain negative words against the disease. This could be because, in the context of diseases, people naturally disagree or go against it rather than support or encourage it. Overall, the sentiment of the tweet does not affect the spread of tuberculosis information in the network.

4.3 SNA Centrality Measures

Figure 8 shows a set of graphs with users as nodes, where the colors of the nodes are based on the modularity class or the community in the network, and the sizes of the nodes are based on the *out-degree*, *eigenvector*, *betweenness*, and *closeness* centrality.

It can be seen in Figure 8a that when measuring based on out-degree centrality, the top influential users are health organizational accounts and a fan account. As noted by the experts, the difference of impact towards the spread of information between the two health organizations was mainly caused by how often they tweeted, where *DOHgovph* only tweeted once as compared to *WHOPhilippines*. Furthermore, the impact of fan base towards the spread of information can be seen through the network built by *urmyflashlight*.

On the other hand, Figure 8b shows that the influential users are fan accounts or individual accounts, as this type of account were most likely to react or response to anyone who interacted with their tweets, compared to health organizational accounts, thus, raising their centrality value. The experts also noted that health organizational accounts will most likely to have low eigenvector centrality value due to the lack of interactions they had with their followers, making them merely sources of information.

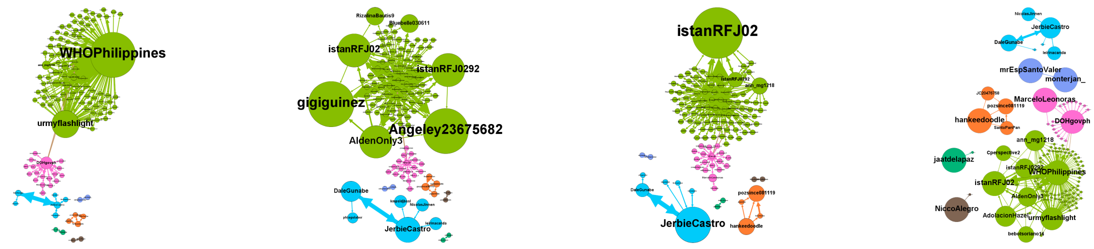
Furthermore, figure 8c shows that the influential users are health professionals and individual users, including the fan accounts, signifying how information are being passed often through the aforementioned user types, and was forwarded to other connected users in the network.

As for the closeness centrality, the experts concluded that the use of closeness centrality as a metric to measure how influential a user in this case was not very useful, as there were too many small and disconnected clusters in the network as shown in Figure 8d.

Furthermore, when it comes to the tuberculosis data, the user with the highest number of followers is *DOHgovph*, and its number of followers is significantly higher compared to the rest of users in the network. This shows how the number of followers of each user does not have significant contribution or effect towards the spread of information in the network.

4.4 Topic Results

As seen in Figure 9, the topics of the interactions between users of the same clusters were not limited to what the central nodes were talking about, as its topic was directed towards a different focus after the interactions For example, the two biggest nodes were the



(a) Out-Degree (b) Eigenvector (c) Betweenness (d) Closeness

Figure 8: Centralities Graphs.

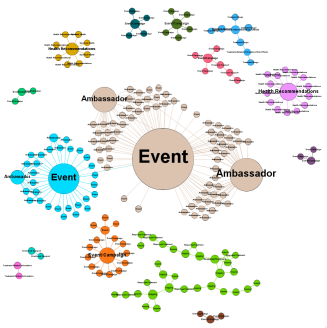


Figure 9: Topic Graph generated from results of Topic Modeling.

tweets by *WHOPhilippines*, reminding people about the virtual event of World TB Day. Even though both central nodes talked about "Event", the topics that were being discussed by most of the tweets that interacted with the central nodes were about "Ambassador", which in this context would be the fan base of Alden Richards as he was the ambassador of the World TB Day on last March 24, 2021. Furthermore, aside from World TB Day, when it comes to tuberculosis health information, other users in the network were also seen to be exchanging information about tuberculosis treatments and health recommendations for people afflicted with tuberculosis.

5 CONCLUSIONS

Twitter is a social media platform that can be utilized to spread information, especially health information. With tuberculosis being identified as a global public health threat, this paper utilized social network analysis, topic modeling, and sentiment identification to analyze the spread of tuberculosis health information on Twitter in the Philippine setting.

The results show that among the interactions available in Twitter, retweets are proven to have more impact in triggering more interactions and spreading information, followed by quote tweets, and replies as the Twitter interactions that are less likely to have any impact when it comes to tuberculosis health information. Furthermore, among the attributes of the tweet only the keyword attribute played a major role in the spread of tuberculosis information in the network.

Meanwhile, the centrality measures show that *WHOPhilippines* is the most influential user in the spread of tuberculosis health information on Twitter. However, with a bigger dataset or a different focus on health information, it is still possible that other health organizations, health professionals, or even individual users might arise as influential users in the network.

6 FUTURE WORKS

Future studies may further analyze the results and confirm whether these findings hold for other similar datasets. The results may also be used as a foundation for other studies which may opt to find information related to tuberculosis health information spread in the Philippines, such as finding efficient ways to spread health information through Twitter. Meanwhile, other studies may also build upon the pipeline created by this study, such as including finding topics commonly used within different clusters, and use the pipeline in other domains outside of tuberculosis and health information.

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