RESEARCH ARTICLE

Epidemiological Modeling of Health Information Dynamics on Twitter

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Abstract: Social media, like Twitter, has become a critical component in promoting public health. Due to the similar nature of information and viruses spreading, there is a new trend of using epidemiological models to study how information spreads on social media. In this study, the SEIR model is adapted to model how health information is disseminated over Twitter. Two models are presented: a basic Twitter interaction model and a model wherein the sentiments of tweets are considered. To our knowledge, these models are the first of their kind to study health information dynamics on Twitter and to understand the behavior of users based on the sentiments of tweets. In the basic interaction model (TwitHComm), we compared the dynamics of health information spreading of @WHO and @DOHgovph and found that the tweet data obtained from @DOHgovph do not achieve an epidemic state where @WHO does. In the model where sentiments were considered (TwitHCommS), despite increasing the number of positive sentiment tweets in the simulation, negative sentiments still influenced Twitter users. Overall, these models provide valuable information for using social media for public health communication.

Keywords: health communication, epidemiological modeling, SEIR, Twitter, reproduction number

In this golden age of communication, people can be widely reached and easily influenced (Knoll, 2016). The use of social media, such as Twitter, has become popular and continues to be studied in health communication (Hawn, 2009). Twitter has become a key part of social media as it is the most commonly used platform by public health agencies (Park et al., 2016). The role of social media in health communication is not only limited to providing health information to people but also connecting the public and healthcare providers (Diddi & Lundy, 2017). Social media also allows healthcare providers to spread information that may help improve health attitudes and behaviors (Hawn, 2009). In health communication, it is crucial to think of strategies that will engage and influence individuals and communities to share quality health information (Schiavo, 2013).

When outbreaks such as COVID-19 (coronavirus disease) become a pandemic, people often start to panic. Throughout the pandemic, false and misleading information spread across social media (Hornik et al., 2021). Hornik et al. (2021) presented how to overcome challenges in misinformation for communicating public health recommendations. Social media provides a significant positive influence on public health protection that can cause positive behavior changes in individuals and, as a result, help reduce the spread of the pandemic by lowering the levels of fear and anxiety among the general public (Al-Dmour et al., 2020). However, without the knowledge of health communication, the information that must be spread may not reach the individuals and communities who need it.

To determine whether health information had its intended effect(s), Freimuth et al. (2011) discussed the employment of modeling strategies to study the dissemination of health information. Mathematical modeling is an increasingly used method in studying the dynamics of how information spreads, evaluating the possible effects of interventions, predicting outcomes of epidemics, and forecasting the course of outbreaks (Villasin et al., 2021).

Twitter is a popular social networking website that allows individuals (called users) to both send and read messages, known as tweets (Skaza & Blais, 2017). Compared to different message functions on Twitter, the study of Park et al. (2016) revealed that retweets and likes were the key engagement indicators for personal health action-based tweets. Although Twitter plays an important role in health communicators, Park et al. (2016) suggested that researchers further capture the engagement of individuals on Twitter to strengthen health-related tweets.

Epidemiological models are used to understand how information spreads on Twitter (Jin et al., 2013). These models divide users on Twitter into groups or "compartments" that reflect the status of users (Jin et al., 2013) and simulate their interaction with each other (Villasin et al., 2021). An example of common compartments classifies users as susceptible (people who are ignorant about the information), infected (people who spread the information), or recovered (people who are removed from the information). Jin et al. (2013) used the SEIZ (susceptible, exposed, infected, skeptic) model to study the characterization of information flow on Twitter resulting from both news and rumors. This model introduces a new state of being exposed (E), wherein a user takes some time to believe in a story or get infected, and a new state of being a skeptic (Z), wherein a user has been informed about the news but chooses not to tweet about it. Their work explores modeling news and rumors on Twitter. Their study demonstrated how capable the SEIZ model is to quantify the compartment transition dynamics and showcased how information facilitates the development of screening criteria for distinguishing rumors from real news happenings on Twitter.

When a severe health issue such as COVID-19 arises to the public, everyone wants to know how to stay safe. Social media, such as Twitter, has become a widely used platform that enables individuals to connect and converse with each other. It is important to determine whether public health official channels are widely disseminating health information on Twitter. In this way, interventions and improvements may be suggested to these public health official channels so the public stays informed during public health crises. In this paper, we study the dynamics of health information spread on Twitter by constructing two SEIR-based health communication models. The first model constructed is a basic interaction model, and the second model is a similar model where the sentiments of tweets were considered. We performed sensitivity analysis and computed the basic reproduction number (R_0) for the first model in this study.

To our knowledge, these models are the first of their kind to study health information dynamics on Twitter and to understand the behavior of users based on the sentiments of tweets. These models provide valuable information for determining the spreading dynamics of information and can be used as a guideline in designing strategies and policies to control information spreading, especially false and misleading information. Likewise, it is helpful in designing public health messages for correcting false and misleading information in social media.

Methods

In this section, we present two mathematical models that capture the dynamics of health information spreading on Twitter. The SEIR compartmental model is adapted to study how health information is disseminated over Twitter. In the process of disseminating a tweet, users have different reactions towards the tweet and switch from different roles/statuses at different time points after a tweet is posted. The users are transferred from one compartment to another compartment of the model as they change their role/status at different time points.

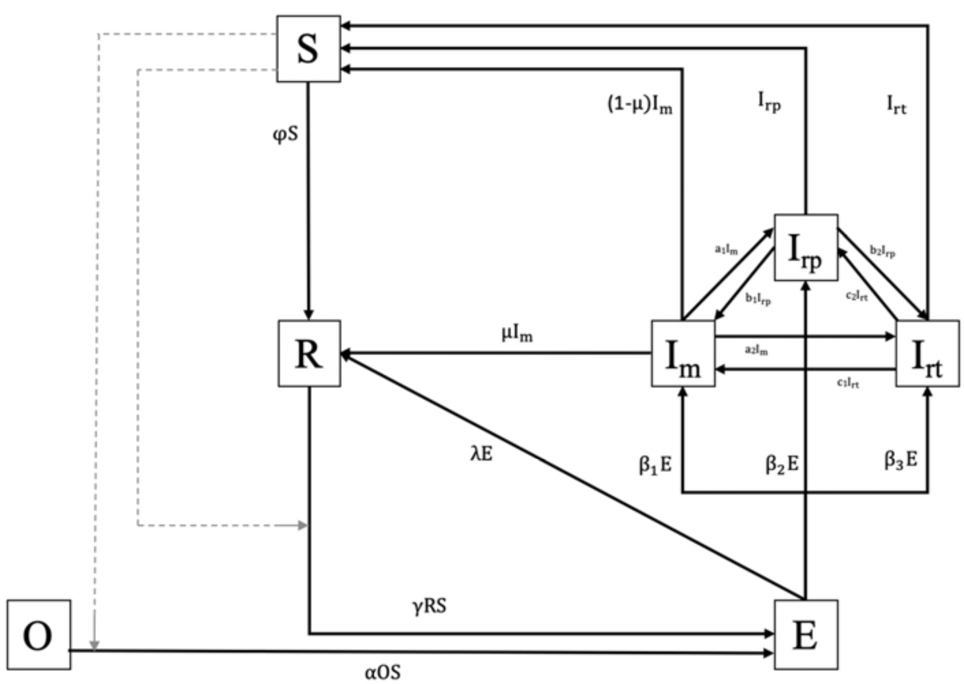
We present two models: a model that describes basic Twitter interaction and a similar model wherein we consider the sentiments of the tweets. In the formulation of these two models, newly added account users are not considered in the assumption of the model. Those who discontinued their Twitter accounts are also not considered in the model. We do not take into consideration the mentions in replies to tweets. Throughout this section, when we say *tweet/s*, we only refer to tweets about health information.

Model 1: TwitHComm

The SEIR model divides the population into compartments: susceptible, exposed, infected, and recovered. To adapt this model for Twitter, we have given new meaning to these terms and categorized each (Twitter) user into compartments based on Twitter interactions.

The first model is called Twitter Health Communication Model without sentiment (TwitHComm), where we classify the users into seven compartments: Oblivious (O), Spreaders (S), Exposed (E), Infected by liking (I_m), Infected by replying (I_{rp}), Infected by retweeting (I_{rt}), and Recovered (R).

The Oblivious (O) or ignorant or susceptible to the information are users who have not come across a tweet (related to health communication information) on their (Twitter) feed. The Spreaders (S) of the information are the users who are tweeting about the information. Users who have come across or read a tweet in their feed are categorized under the Exposed (E) compartment. We have three types of infection in this model, and users are classified based on the three basic interactions they can make on tweets. For users who like tweets, we classify them as Infected by liking (I_m). If users reply to a tweet, they are categorized as Infected by replying (I_{rp}). Lastly, for the infected population, when users retweet a tweet, regardless of whether they add a quote to the said tweet or not, they are classified as Infected by retweeting (I_{rt}). When users no longer interact with tweets for a specific number of time defined in the study, they will be classified into the Recovered (R) compartment. Such a specific number of times defined may be in hours, days, and so forth. The process of transfer of users from one compartment to another is shown in Figure 1. Each compartment in Figure 1 is annotated with the rate at which a user transfers or transitions from one compartment to another. These rates represent the average frequency of a user to transfer from one compartment to another. These rates do not imply an exact rate for a user to transfer from one compartment to another, but rather, they are the expected number of arrivals of users in one unit of time (Miller, 1994). In the long term, the average number of events that occurred in one unit of time would equal the parameter rates (Miller, 1994).



Note. We classify the users into seven compartments: Oblivious (O), Spreaders (S), Exposed (E), Infected by liking (I_m), Infected by replying (I_{rp}), Infected by retweeting (I_{rt}), and Recovered (R).

Figure 1. Twitter Health Communication Model Without Sentiment (TwitHComm)

The parameter α is the rate of transfer of an Oblivious user that becomes Exposed to the information. The outflow αOS represents the successful spreading of information to the Oblivious user, transitioning them into Exposed. The dotted lines pointing to this outflow indicate that αOS is regulated by the Spreader compartment. This means that for the Oblivious users to become Exposed, there has to be an interaction between the Spreaders and the Oblivious. Consequently, αOS is the inflow of Exposed coming from the Oblivious population.

Users in the Exposed compartment may or may not mind or interact with tweets. If users in the Exposed compartment choose not to interact with a tweet, then they will recover from that information. The parameter λ is the rate at which users in the Exposed compartment will become Recovered. Thus, the Exposed compartment has the outflow λE that represents the recovery of Exposed users. The representation λE is the inflow for the Recovered compartment, and it has an outflow of γRS that represents Recovered users to become Exposed if they yet again come across a new tweet in their (Twitter) feed. The rate that Recovered users come across a tweet is given by the parameter γ. For users in the Recovered compartment to become Exposed, there must be an interaction between the Spreaders, and that is represented by the dotted lines pointing to this outflow. Consequently, the Exposed compartment has an inflow of γRS coming from the Recovered compartment.

There are three types of infection: β_1, β_2, and β_3, which are the rates at which Exposed users will become Infected by liking, Infected by replying, and Infected by retweeting, respectively. In return, the outflows $\beta_1 E$, $\beta_2 E$, and $\beta_3 E$ represent the change of Exposed into Infected by liking, Infected by replying, and Infected by retweeting, respectively. As a result, these compartments will have inflows $\beta_1 E$, $\beta_2 E$, and $\beta_3 E$, respectively, that came from the Exposed compartment.

Twitter allows users to have multiple reactions to tweets. A user may like, reply, and retweet simultaneously. The reversible arrows between the infectious compartments indicate the non-mutual exclusivity among compartments. The parameters a_1 and a_2 indicate that users in the Infected by liking compartment may also reply or retweet the same tweet resulting in the outflows $a_1 I_m$ and $a_2 I_m$, respectively. Similarly, users in the Infected by replying compartment may also like, given by the parameter b_1, or retweet, given by the parameter b_2, which results in the outflows $b_1 I_{rp}$ and $b_2 I_{rp}$, respectively. It follows that the Infected by retweeting has outflows $c_1 I_{rt}$ and $c_2 I_{rt}$, indicating that users who retweet a tweet may also like or reply.

When users *like* a tweet, the rate given by the parameter μ means that they recover from that information if they choose not to interact further with a tweet. The outflow μI_m represents users' recovery in the Infected by liking compartment transitioning them into Recovered. Consequently, the Recovered compartment has an inflow of μI_m coming from I_m. On Twitter, likes show on users' feeds when there are no more new tweets from their following list. Thus, there is a rate of $1 - \mu$ of Infected by liking users to become Spreaders, and the outflow $(1 - \mu)I_m$ represents the success of Infected by liking users to become Spreaders. Consequently, the Spreaders compartment has an inflow of $(1 - \mu)I_m$ coming from I_m.

Meanwhile, replies and retweets of users' following list are always shown in their feed so when they reply or retweet a tweet, they will immediately become Spreaders of information. Thus, the Infected by replying and Infected by retweeting compartments have outflows I_{rp} and I_{rt}, respectively, that represent the 100% transfer rate of users in the Infected by replying and Infected by retweeting compartments to become Spreaders. Consequently, the Spreaders compartment has inflows I_{rp} and I_{rt} coming from Infected by replying and Infected by retweeting compartments. The outflow φS represents the recovery of Spreaders, transitioning them to the Recovered compartment. The parameter φ is the rate at which users no longer interact with tweets for a specific number of time defined in our study. Consequently, the Recovered compartment has an inflow of φS coming from the Spreaders compartment.

Therefore, based on the discussion of the model, we obtain the following system of nonlinear ordinary differential equations (ODEs):

$$\begin{cases} \dot{S} = -\varphi S + (1 - \mu)I_m + I_{rp} + I_{rt}, \\ \dot{O} = -\alpha OS, \\ \dot{E} = \alpha OS + \gamma RS - \beta_1 E - \beta_2 E - \beta_3 E - \lambda E, \\ \dot{I_m} = \beta_1 E - I_m - a_1 I_m - a_2 I_m + b_1 I_{rp} + c_1 I_{rt}, \\ \dot{I_{rp}} = \beta_2 E - I_{rp} - b_1 I_{rp} - b_2 I_{rp} + a_1 I_m + c_2 I_{rt}, \\ \dot{I_{rt}} = \beta_3 E - I_{rt} - c_1 I_{rt} - c_2 I_{rt} + a_2 I_m + b_2 I_{rp}, \\ \dot{R} = \varphi S + \mu I_m + \lambda E - \gamma RS, \end{cases} \tag{1}$$

where $S(0), O(0), E(0), I_m(0), I_{rp}(0), I_{rt}(0), R(0) \geq 0$ and $\alpha, \lambda, \gamma, \beta_1, \beta_2, \beta_3, a_1, a_2, b_1, b_2, c_1, c_2, \mu, \varphi > 0$.

Each equation in the ODE system given in Equation 1 is a reflection of the outflows and inflows in Figure 1. The outflows of the compartments indicate a negative term in its equation. Similarly, each inflow of a compartment indicates a positive term in its equation. For instance, E has the equation $\alpha OS + \gamma RS - \beta_1 E - \beta_2 E - \beta_3 E - \lambda E$ because E has inflows αOS and γRS and E has outflows $\beta_1 E$, $\beta_2 E$, $\beta_3 E$, and λE. In Figure 1, the inflow αOS from O to E denotes that S generates the transfer of users from O to E.

@WHO and @DOHgovph correspond to the Twitter accounts of the World Health Organization (WHO) and the Department of Health in the Philippines, respectively. In this model, we consider the parameters α, γ, and μ to have the same values for both @WHO and @DOHgovph. Due to the difference between the number of likes, replies, and retweets, the parameter values for rates in which Exposed users will like (β_1), reply (β_2), and retweet (β_3) a tweet about health information are assigned differently for @WHO and @DOHgovph. In addition, the parameters a_1, a_2, b_1, b_2, c_1, and c_2 on the reversible arrows between the infectious compartments also differ based on the values of β_1, β_2, and β_3 for @WHO and @DOHgovph.

Data was collected from Twitter using the Tweepy library of Python (Yusoph, 2023). Based on the collected data, the average (or mean) number of likes and retweets of a specific user was obtained. This study focused only on the following accounts: @WHO and @DOHgovph. We computed the mean number of likes and retweets of @WHO and @DOHgovph over a total of 200 tweets.

For @WHO, the mean number of likes over time is equal to 133.1, with the transition rate from the Exposed users to Infected by liking represented as $\beta_1 = 0.6655$. As for the Exposed users becoming Infected by retweeting, the obtained transition rate is $\beta_3 = 0.385025$. A similar computational approach is applied to @DOHgovph; the corresponding transition rates obtained are as follows: $\beta_1 = 0.04615$ and $\beta_3 = 0.026275$. For the replies, we take the number of replies of @WHO and @DOHgovph's pinned tweets and obtain the transition rates $\beta_2 = 0.72$ for @WHO and $\beta_2 = 2.87$ for @DOHgovph.

According to Barath (2021), about 42% of Twitter users log on to Twitter daily. In this study, it is assumed that whenever users open their Twitter, they will become Exposed to a tweet. In relation to TwitHComm, if a user posts a tweet related to health communication (users in the Spreaders compartment), 42% of their followers (Oblivious users) will become Exposed. This is used as a basis to set the transition rate of Oblivious users becoming Exposed as $\alpha = 0.42$. Additionally, the parameter γ gives the rate at which users in the Recovered compartment will become Exposed again. In this study, this is assumed to be equal to the frequency at which users open their Twitter accounts. In other words, the parameter γ gives the same meaning as α, and so $\alpha = \gamma = 0.42$.

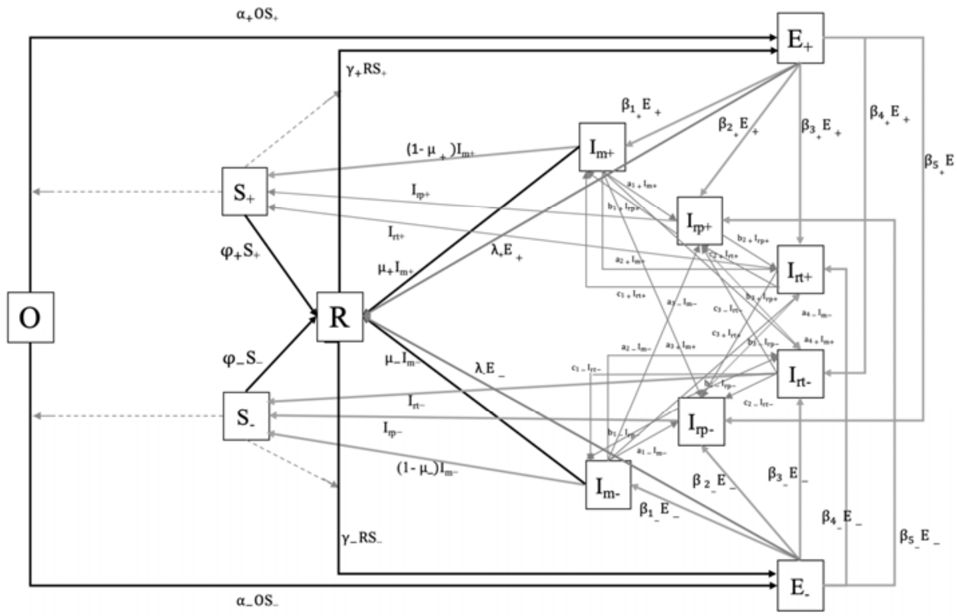
Barath (2021) also mentioned that 34% of Twitter users open Twitter more than once per day. Recall that likes on Twitter are only shown on one's Twitter feed when there are no more new tweets from a user's following list. This means that 34% of one's following list opens Twitter more than once. This information is used to set the transition rate $(1 - \mu)$ of users Infected by liking that become Spreaders as 0.34.

In our model, the parameters for the reversible arrows among the infected compartments are equivalently calculated to the rates at which Exposed users will transition to the infected compartments. For instance, the rate at which a user replies to a tweet after liking it is equal to the rate at which a user who is exposed replies to a tweet. This equivalence in transition rates illustrates that the tendency for users to engage with a tweet, such as replying, is influenced by their current state of exposure to the tweet. Thus, for TwitHComm, $\beta_1 = b_1 = c_1$, $\beta_2 = a_1 = c_2$, and $\beta_3 = a_1 = c_1$.

In this study, we assume that the parameters φ and λ are equal, that is, the recovery rates of users in Exposed and Spreaders are assumed to be equal.

Model 2: TwitHCommS

The second model, the Twitter Health Communication Model with positive and negative sentiments (TwitHCommS), is an extension of TwitHComm by considering the positive and negative sentiments of tweets represented by the "+" and "–" subscripts in the model. Analyzing the sentiment of tweets helps understand the dynamics of health communication and how the users engage in a healthy discussion. This will be helpful in designing better strategies to promote positive sentiment health communication tweets and control negative sentiment tweets. The users are divided into Oblivious (O), Spreaders of positive tweets (S_+), Spreaders of negative tweets (S_-), Exposed to positive tweets (E_+), Exposed to negative tweets (E_-), Infected by liking



Note. The users are divided into Oblivious (O), Spreaders of positive tweets (S_+), Spreaders of negative tweets ($S_–$), Exposed to positive tweets (E_+), Exposed to negative tweets ($E_–$), Infected by liking positive tweets (I_{m+}), Infected by liking negative tweets ($I_{m–}$), Infected by replying with positive tweets (I_{rp+}), Infected by replying with negative tweets ($I_{rp–}$), Infected by retweeting with positive tweets (I_{rt+}), Infected by retweeting with negative tweets ($I_{rt–}$), and Recovered (R).

Figure 2. Twitter Health Communication Model With Positive and Negative Sentiments (TwitHCommS)

positive tweets (I_{m+}), Infected by liking negative tweets ($I_{m–}$), Infected by replying with positive tweets (I_{rp+}), Infected by replying with negative tweets ($I_{rp–}$), Infected by retweeting with positive tweets (I_{rt+}), Infected by retweeting with negative tweets ($I_{rt–}$), and Recovered (R). Users transfer from one compartment to another, as shown in Figure 2. The transfer of users in TwitHCommS shown in Figure 2 is directly similar to the one discussed for TwitHComm.

The following system of nonlinear ordinary differential equations (ODEs) is acquired from TwitHCommS:

$$\begin{cases} \dot{S_+} = -\varphi_+ S_+ + (1-\mu_+)I_{m+} + I_{rp+} + I_{rt+}, \\ \dot{S_-} = -\varphi_- S_- + (1-\mu_-)I_{m-} + I_{rp-} + I_{rt-}, \\ \dot{O} = -\alpha_+ OS_+ - \alpha_- OS_-, \\ \dot{E_+} = \alpha_+ OS_+ + \gamma_+ RS_+ - \beta_{1+}E_+ - \beta_{2+}E_+ - \beta_{3+}E_+ - \beta_{4+}E_+ - \beta_{5+}E_+ - \lambda_+ E_+, \\ \dot{E_-} = \alpha_- OS_- + \gamma_- RS_- - \beta_{1-}E_- - \beta_{2-}E_- - \beta_{3-}E_- - \beta_{4-}E_- - \beta_{5-}E_- - \lambda_- E_-, \\ \dot{I_{m+}} = \beta_{1+}E_+ - I_{m+} - a_{1+}I_{m+} - a_{2+}I_{m+} - a_{3+}I_{m+} - a_{4+}I_{m+} + b_{1+}I_{rp+} + c_{1+}I_{rt+}, \\ \dot{I_{m-}} = \beta_{1-}E_- - I_{m-} - a_{1-}I_{m-} - a_{2-}I_{m-} - a_{3-}I_{m-} - a_{4-}I_{m-} + b_{1-}I_{rp-} + c_{1-}I_{rt-}, \\ \dot{I_{rp+}} = \beta_{2+}E_+ + \beta_{5-}E_- - I_{rp+} - b_{1+}I_{rp+} - b_{2+}I_{rp+} - b_{3+}I_{rp+} + a_{1+}I_{m+} + a_{3-}I_{m-} + c_{2+}I_{rt+} + c_{3-}I_{rt-}, \\ \dot{I_{rp-}} = \beta_{2-}E_- + \beta_{5+}E_+ - I_{rp-} - b_{1-}I_{rp-} - b_{2-}I_{rp-} - b_{3-}I_{rp-} + a_{1-}I_{m-} + a_{3+}I_{m+} + c_{2-}I_{rt-} + c_{3+}I_{rt+}, \\ \dot{I_{rt+}} = \beta_{3+}E_+ + \beta_{4-}E_- - I_{rt+} - c_{1+}I_{rt+} - c_{2+}I_{rt+} - c_{3+}I_{rt+} + a_{2+}I_{m+} + a_{4-}I_{m-} + b_{2+}I_{rp+} + b_{3-}I_{rp-}, \\ \dot{I_{rt-}} = \beta_{3-}E_- + \beta_{4+}E_+ - I_{rt-} - c_{1-}I_{rt-} - c_{2-}I_{rt-} - c_{3-}I_{rt-} + a_{2-}I_{m-} + a_{4+}I_{m+} + b_{2-}I_{rp-} + b_{3+}I_{rp+}, \\ \dot{R} = \varphi_+ S_+ + \varphi_- S_- + \mu_+ I_{m+} + \mu_- I_{m-} + \lambda_+ E_+ + \lambda_- E_- - \gamma_+ RS_+ - \gamma_- RS_-. \end{cases} \tag{2}$$

Results

Model Analysis

For general compartmental epidemic models, Van den Driessche and Watmough (2002) defined the basic reproduction number R_0 to be the threshold parameter for the model. This determines that if $R_0 < 1$, then the associated equilibria are locally asymptotically stable; that is, the infection cannot spread. Conversely, if $R_0 > 1$, then the associated equilibria are unstable, or in other words, the infection will spread among the population. In this study, only the presence of the endemic equilibrium point is investigated. The free-disease equilibrium requires the absence of infection, which, in this case, is the absence of Spreaders. Social media, such as Twitter, requires at least one Spreader to start a communication, and the free-disease equilibrium is irrelevant and excluded in this study.

In relation to analyzing health information dynamics, if the endemic equilibrium is unstable, then this exhibits that health information persists on Twitter. As discussed in section 2, $\alpha = \gamma$ (the parameters in which Oblivious and Recovered users become Exposed) and $\lambda = \varphi$ (the parameters in which Exposed and Spreaders become Recovered) will be substituted in the computations in this section.

In the analysis of TwitHComm, we compute for the endemic equilibrium, where the infection is present. The computations for solving the equilibrium points are done using Mathematica, and the details are shown in the Appendix. In order to compute the endemic equilibrium point, we set each differential equation in Equation 1 to zero, as shown below,

$$\begin{cases} 0 = -\varphi S + (1 - \mu)I_m + I_{rp} + I_{rt}, \\ 0 = -\alpha OS, \\ 0 = \alpha OS + \gamma RS - \beta_1 E - \beta_2 E - \beta_3 E - \lambda E, \\ 0 = \beta_1 E - I_m - a_1 I_m - a_2 I_m + b_1 I_{rp} + c_1 I_{rt}, \\ 0 = \beta_2 E - I_{rp} - b_1 I_{rp} - b_2 I_{rp} + a_1 I_m + c_2 I_{rt}, \\ 0 = \beta_3 E - I_{rt} - c_1 I_{rt} - c_2 I_{rt} + a_2 I_m + b_2 I_{rp}, \\ 0 = \varphi S + \mu I_m + \lambda E - \gamma RS, \end{cases}$$

then, we compute for the state variables.

*Endemic Equilibrium, x**

The endemic equilibrium must satisfy the system of equations above where the presence of infection is considered in the computation for **x***, i.e., I_m, I_{rp}, $I_{rt} \neq 0$. We then solve for the state variables S, O, E, I_m, I_{rp}, I_{rt}, and R, and so we arrive at the endemic equilibrium

$$\mathbf{x}^* = [S^*, O^*, E^*, I_m{}^*, I_{rp}{}^*, I_{rt}{}^*, R^*]$$

$$= \left[\frac{E\beta_1 + E\beta_2 + E\beta_3 - E\beta_1\mu}{\varphi}, 0, E, E\beta_1, E\beta_2, E\beta_3, \frac{\varphi(\beta_1 + \beta_2 + \beta_3 + \varphi)}{\alpha(-\beta_1 - \beta_2 - \beta_3 + \beta_1\mu)}\right].$$

The endemic equilibrium x* is in terms of S and φ, the parameter that gives the recovery rate of users in Exposed and Spreaders. The value for φ is later evaluated in the calculation of the basic reproduction number.

Basic Reproduction Number, R_{EE}

The basic reproduction number for TwitHComm with respect to the endemic equilibrium x* is denoted by R_{EE}. The next-generation matrix is used to compute for R_{EE}. Recall that $a_1 = \beta_2$, $a_2 = \beta_3$, $b_1 = \beta_1$, $b_2 = \beta_3$, $c_1 = \beta_1$, and $c_2 = \beta_2$, and thus substituted in order to simplify the computations.

In TwitHComm, the compartments that contain infection are $\mathbf{x} = [S, E, I_m, I_{rp}, I_{rt}]$, which will be used in the formation of the transmission matrix **F** and transition matrix **V**.

Let $F(\mathbf{x})$ be the 5 × 1 matrix whose entries $F_i(\mathbf{x})$ are the rates of appearance of new infectious individuals in compartment *i*, and let $V(\mathbf{x})$ be the 5 × 1 matrix whose entries $V_i(\mathbf{x})$ are the rates of transfer of individuals into and out of the compartment *i*. The matrix $V(x)$ satisfies $V(\mathbf{x}) = V_i^-(\mathbf{x}) - V_i^+(\mathbf{x})$, where $V_i^+(\mathbf{x})$ is the rate of transfer of individuals into compartment *i*, and $V_i^-(\mathbf{x})$ is the rate of transfer of individuals out of compartment *i*. Thus, we have

$$F(\mathbf{x}) = \begin{bmatrix} I_m + I_{rp} + I_{rt} \\ \alpha OS + \gamma RS \\ \beta_1(I_{rp} + I_{rt}) \\ \beta_2(I_m + I_{rt}) \\ \beta_3(I_m + I_{rp}) \end{bmatrix}$$

and

$$V_i{}^+(\mathbf{x}) = \begin{bmatrix} S + \mu I_m \\ \beta_1 E + \beta_2 E + \beta_3 E + \varphi E \\ I_m + \beta_2 I_m + \beta_3 I_m \\ I_{rp} + \beta_1 I_{rp} + \beta_3 I_{rp} \\ I_{rt} + \beta_1 I_{rt} + \beta_2 I_{rt} \end{bmatrix}$$

$$V_i{}^+(\mathbf{x}) = \begin{bmatrix} I_m + I_{rp} + I_{rt} \\ \alpha OS + \gamma RS \\ \beta_1 E + \beta_1 I_{rp} + \beta_1 I_{rt} \\ \beta_2 E + \beta_2 I_m + \beta_2 I_{rt} \\ \beta_3 E + \beta_3 I_m + \beta_3 I_{rp} \end{bmatrix}$$

and so

$$V(\mathbf{x}) = \begin{bmatrix} S + \mu I_m - I_m - I_{rp} - I_{rt} \\ \beta_1 E + \beta_2 E + \beta_3 E + \varphi E - \alpha OS - \gamma RS \\ I_m + \beta_2 I_m + \beta_3 I_m - \beta_1 E - \beta_1 I_{rp} - \beta_1 I_{rt} \\ I_{rp} + \beta_1 I_{rp} + \beta_3 I_{rp} - \beta_2 E - \beta_2 I_m - \beta_2 I_{rt} \\ I_{rt} + \beta_1 I_{rt} + \beta_2 I_{rt} - \beta_3 E - \beta_3 I_m - \beta_3 I_{rp} \end{bmatrix}$$

For the endemic equilibrium point **x***, we define the transmission matrix **F** and transition matrix **V** to be the respective Jacobian of matrices $F(\mathbf{x})$ and $V(\mathbf{x})$. That is, the 5 × 5 matrices $\mathbf{F} = \left[\frac{\partial F_i(\mathbf{x}^*)}{\partial x_i}\right]$ and $\mathbf{V} = \left[\frac{\partial V_i(\mathbf{x}^*)}{\partial x_i}\right]$ shown below:

$$\mathbf{F} = \begin{bmatrix} 0 & 0 & 1 & 1 & 1 \\ \dfrac{\varphi(\beta_1 + \beta_2 + \beta_3 + \varphi)}{-\beta_1 - \beta_2 - \beta_3 + \beta_1 \mu} & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & \beta_1 & \beta_1 \\ 0 & 0 & \beta_2 & 0 & \beta_2 \\ 0 & 0 & \beta_3 & \beta_3 & 0 \end{bmatrix}$$

$$\mathbf{V} = \begin{bmatrix} \varphi & 0 & -1 + \mu & -1 & -1 \\ \dfrac{\varphi(\beta_1 + \beta_2 + \beta_3 + \varphi)}{-\beta_1 - \beta_2 - \beta_3 + \beta_1 \mu} & \beta_1 + \beta_2 + \beta_3 + \varphi & 0 & 0 & 0 \\ 0 & -\beta_1 & 1 + \beta_2 + \beta_3 & -\beta_1 & -\beta_1 \\ 0 & -\beta_2 & -\beta_2 & 1 + \beta_1 + \beta_2 & \beta_2 \\ 0 & -\beta_3 & -\beta_3 & -\beta_3 & 1 + \beta_1 + \beta_2 \end{bmatrix}$$

The basic reproduction number R_{EE} is then calculated as the spectral radius ρ of the next-generation matrix $\mathbf{FV}^{-1}$ given by $R_{EE} = \rho(\mathbf{FV}^{-1})$. In other words, R_{EE} is the maximum eigenvalue of the next-generation matrix $\mathbf{FV}^{-1}$ in absolute form. The computations are done in Mathematica and are found in the Appendix.

In computing the eigenvalues of $\mathbf{FV}^{-1}$, the values are in terms of φ because it is the only unknown parameter in the model. The maximum eigenvalue of $\mathbf{FV}^{-1}$, such that $0 < \varphi < 1$, is obtained, and thus $R_{EE} = 24.8058 > 1$, with $\varphi = 0.385584$, indicating that the endemic equilibrium is *unstable*. This implies that the information will spread among the population. In relation to health communication spreading on Twitter, this shows that people are engaging in topics regarding health on Twitter.

The computations for the parameters obtained from @DOHgovph are the same for @WHO. For @DOHgovph, the basic reproduction number R_{EE} is equal to $0.13765 < 1$ with $\varphi = 0.71$. This shows that the basic reproduction number is locally asymptotically stable and the information will not spread among the population. The parameters obtained from @WHO and @DOHgovph differ based on the number of engagements they get on Twitter, which is the total number of times a user interacts with their tweet. The engagement of users on Twitter is the key outcome of tweeting for health organizations. Although some tweets may be more engaging than others, based on our results, users on Twitter engage more with the tweets of @WHO compared to @DOHgovph. One factor that explains why the tweets obtained from @WHO are widespread while @DOHgovph is not is because @WHO has a higher user engagement and may also relate to people's trust in health organizations (Bernadas, 2021). It is important for health organizations to build relationships among their users. Trust is critical for public health, especially during vulnerable situations when insufficient, misleading, or even "fake" information are spreading (Bernadas, 2021). It follows from our results that @WHO has built stronger trust among its users than @DOHgovph.

The parameters that differ between @WHO and @DOHgovph are the rates in which Exposed users get infected either by liking (β_1), replying (β_2), and retweeting (β_3); and the recovery rate, which is calculated when the eigenvalues of $\mathbf{FV}^{-1}$ in terms of φ is obtained. To turn the communication based on

@DOHgovph into an epidemic, the parameters can be modified so that the basic reproduction number is unstable. For instance, if we assume the same recovery rate for @WHO and @DOHgovph and adjust the rates in which Exposed users will like (β_1) and retweet (β_2) to both 70%, then $R_{EE} = 1.09136 > 1$ and thus the conversation on Twitter lead by @DOHgovph will turn into an epidemic.

Sensitivity analysis enables us to examine how changes in the parameters of the model can impact the number of users in each compartment of the model (Rodrigues et al., 2013). Sensitivity analysis reveals the significance of each parameter on the spread of disease (Rodrigues et al., 2013). The sensitivity analysis of the parameters with respect to the compartments of the model was conducted on MATLAB, and the results are given by live script shown in Yusoph (2023). Sensitivity coefficients were calculated for each of the parameters with respect to each compartment of the model. These coefficients indicate how much the population of users in each compartment changes in response to a 10% increase and decrease in each parameter while keeping all other parameters constant. We performed a sensitivity analysis for the cases where tweets of @DOHgovph are both endemic and non-endemic and where tweets of @WHO are endemic. For all these cases, the sensitivity analysis results show that the recovery rates, φ and λ, have the strongest influence on all compartments of the model. However, the influence of these rates shows an inverse relationship. That is, an increase and decrease in the recovery rates decreases and increases the number of users in each compartment, respectively. This implies that the number of information spreaders of @DOHgovph decreases as the recovery rate in the model increases, as users become disengaged from the content more quickly, and vice versa.

Discussion

The simulations of TwitHComm and TwitHCommS models are illustrated in this section. Table 1 shows the parameters used for the model simulations for TwitHComm and TwitHCommS.

TwitHComm

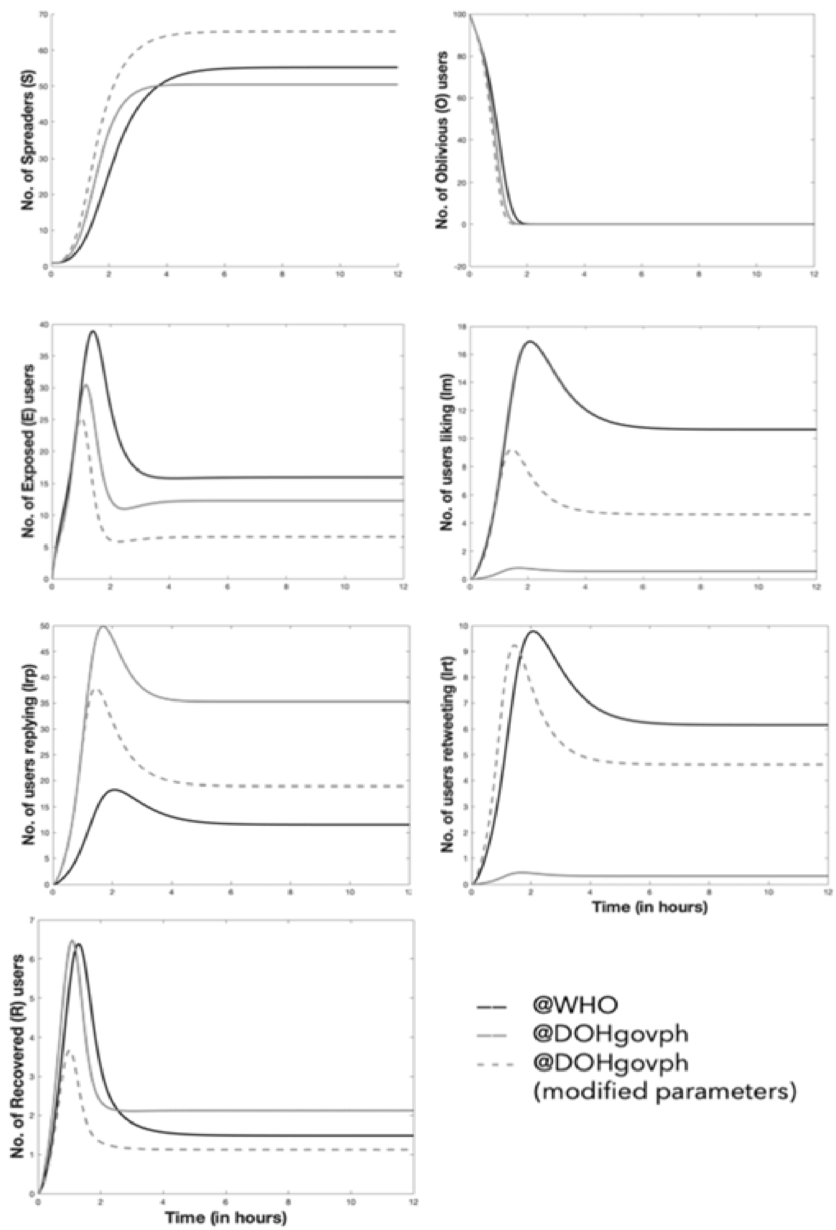
Table 1

Table of Parameter Values Used for the Simulations on TwitHComm and TwitHCommS

Parameter	TwitHComm			
	Original parameter values		Adjusted parameter values	
	@WHO	@DOHgovph	@WHO	@DOHgovph
$\alpha = \gamma$	0.42		0.42	
$\beta_1 = b_1 = c_1$	0.6655	0.04615	0.6655	0.7
$\beta_2 = a_1 = c_2$	0.72	2.87	0.72	2.87
$\beta_3 = a_2 = b_2$	0.385025	0.026275	0.385025	0.7
μ	0.66		0.66	
$\varphi = \lambda$	0.38558	0.71	0.38558	0.71
	TwitHCommS (from @WHO)			
	21% (positive Sentiments)		40% (negative sentiments)	
α	$\alpha_+ = 0.882$		$\alpha_- = 0.168$	
β_1	$\beta_{1+} = 0.139755$		$\beta_{1-} = 0.2662$	
β_2	$\beta_{2+} = 0.1512$		$\beta_{2-} = 0.288$	
β_3	$\beta_{3+} = 0.0\ 8085525$		$\beta_{3-} = 0.15401$	
μ	$\mu_+ = 0.1386$		$\mu_- = 0.264$	
φ	$\varphi_+ = 0.0809718$		$\varphi_- = 0.\ 154232$	

Note. The values were generated based on @WHO and @DOHgovph Health Communication Tweet Data, computed from the Tweepy package using Python (Yusoph, 2023), and sources (Barath, 2021).

For TwitHComm, we demonstrated two simulations to compare the interactions of users based on the Tweet Data obtained from @WHO and @DOHgovph. The scenario portrayed in the simulations is where there is only one Spreader in the population and 100 Oblivious users. As observed in the previous section, the Tweet Data obtained from @WHO exhibits that information about health issues spread among the population on Twitter while @ DOHgovph does not. We calibrated the parameters such that the reproduction numbers for @WHO and @DOHgovph will both yield an epidemic.



Note. The tweets being shown by @WHO are widespread (epidemic, represented by the black lines), whereas the tweets being shown by @DOHgovph are not widely disseminated (no epidemic, represented by the light gray lines), and the parameters used for @DOHgovph are modified for their tweets to be widespread (represented by the light gray dotted lines).

Figure 3. Simulation Results Presenting the Dynamics of TwitHComm

Figure 3 shows the simulations performed for @WHO and @DOHgovph. The black lines correspond to the interactions of @WHO, the light gray lines correspond to the interactions of @DOHgovph with no epidemic, and the light gray dotted lines correspond to the tweets of @DOHgovph being widespread. The x-axis in the graphs represents the time in hours, and so each graph shows the simulations of tweet interaction over 12 hours, and the y-axis represents the population of the compartments in the model. In Figure 3, when @DOHgovph does not achieve an epidemic state, @WHO shows a higher number in the population of Spreaders, Oblivious, Exposed, Infected by liking, Infected by retweeting, and Recovered users, except for the number of users replying. This is because the parameter values set for @WHO are where it exhibits an epidemic state. However, adjusting the parameter values such that @DOHgovph achieves an epidemic state shows a significant change in their interactions.

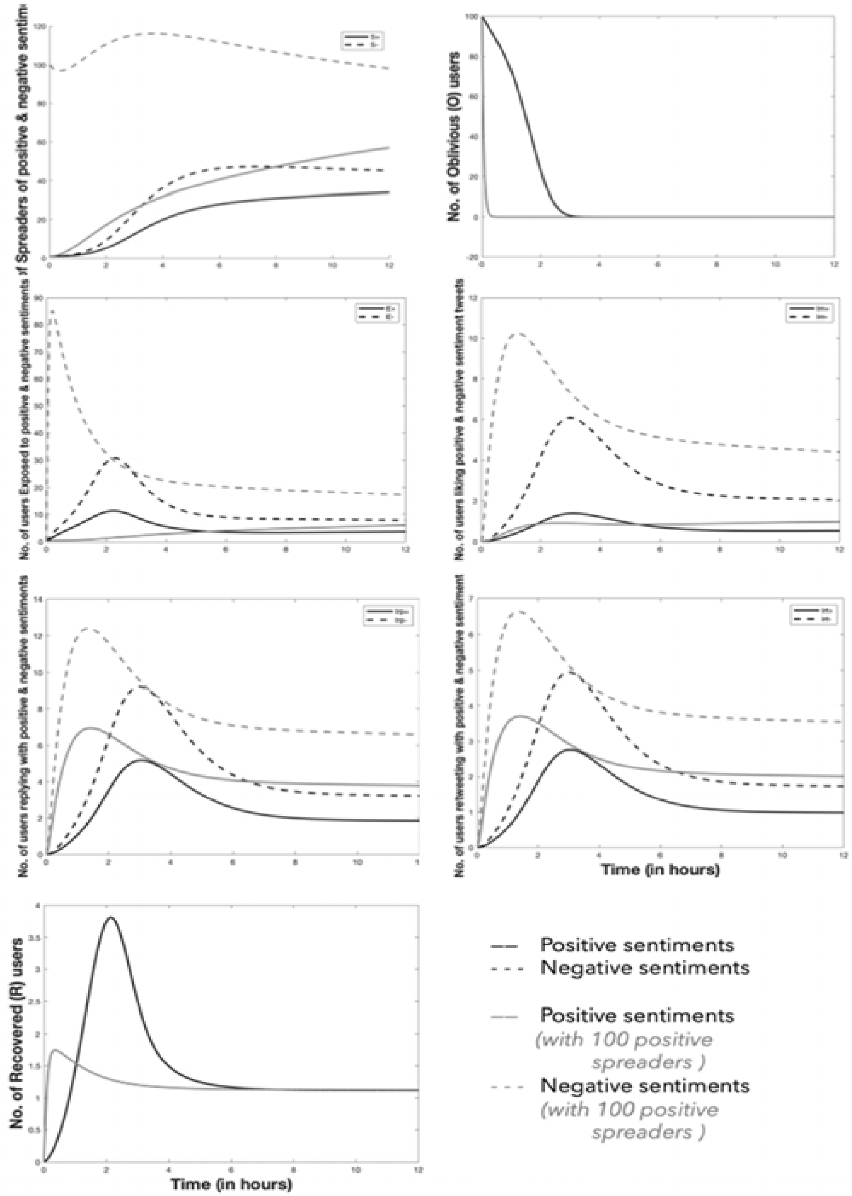
Both simulations from @WHO and @DOHgovph start from one Spreader, and it shows that when we transform @DOHgovph into an epidemic state, it has more interactive followers who spread health communication information compared to @WHO. It can be seen in the graph of Spreaders that @WHO peaked in information spreading later than @DOHgovph by approximately 30 minutes. The simulations started with 100 Oblivious users, which follows the decrease of Oblivious users as they transition into becoming Exposed. There is only a minimal difference between the number of Oblivious users from @WHO and @DOHgovph. This is because the parameter values set for the change in the number of Oblivious users are the same for both Twitter accounts. There are more Exposed users from @WHO than @DOHgovph, which means that users get Exposed faster from the data obtained from @WHO compared to @DOHgovph.

The numbers of infected users from likes, replies, and retweets are based on how many Exposed users transition to becoming Infected by liking, Infected by replying, and Infected by retweeting, respectively. These parameters are given by the βs. @WHO has a higher percentage going to Im from E (66.55%) compared to @DOHgovph (4.615%) when its tweets are not widespread. For the adjusted parameters on @DOHgovph, although it has a higher rate ($\beta_1 = 0.7$) going to Im compared to @WHO, the graph of the number of users liking is higher for @WHO compared to @DOHgovph. This is because more users are getting Exposed from @WHO, and then 66.55% of those become Infected by liking. For the number of users retweeting, @WHO also has a significantly higher number of users retweeting compared to @DOHgovph because @WHO has a higher rate of getting Infected by retweeting (38.5%) compared to @DOHgovph (2.63%). On the other hand, when changing the parameters of @DOHgovph, the number of users retweeting is not that huge because there are more Exposed users for @WHO, but @DOHgovph has almost double the rate ($\beta_3 = 0.7$) of becoming Infected by replying compared to @WHO ($\beta_3 = 0.385025$). For the users Infected by replying, @DOHgovph has a higher rate (287%) of Exposed users becoming Infected by replying compared to @WHO (72%), which explains the big difference in the number of users replying.

In relation to health communication spreading on Twitter, the goal is for users to have a minimal recovery rate so that information persists in the population. It can be seen that both @WHO and @DOHgovph peaked in recovery at the approximately 30-minute mark, and both decreased in the number of Recovered users after an hour and became stable throughout the day. This suggests that users on Twitter recover from health information after 30 minutes of being Exposed and Infected, but when users get Exposed and Infected again, they recover from the information at a slower rate throughout the day. The small difference between the number of Recovered users from @WHO and @DOHgovph (when it is not epidemic) comes from the difference in their recovery rate, where @WHO has a lower recovery rate (38.55%) compared to @DOHgovph (71%). When adjusting the parameter values for @DOHgovph, it has fewer Recovered users than desired. This indicates that among the users in @DOHgovph, where the simulation started with one Spreader and 100 Oblivious users, no more than four users are recovering from health communication information in a span of 12 hours. This shows that when we changed the parameter values for @DOHgovph to its desired values (turning @DOHgovph into an epidemic), even if both Twitter accounts have the same recovery rate, @DOHgovph showed somewhat better results in the simulations for the recovery of the users on Twitter. This indicates that fewer users from @DOHgovph recover, so health communication information persists in the population.

TwitHCommS

In this section, we show simulations for the model with positive and negative sentiments. The scenario portrayed in this section is similar to section 4, where there is one Spreader of positive sentiments, one Spreader of negative sentiments, and 100 Oblivious users. The parameter values used in this section are based on the results of Simanjuntak and Pramana (2021) from Twitter with the query "Indonesian Corona Virus," where it has been found that the positive sentiments amount to 21%, 40% for negative sentiments, and 39% for neutral sentiments. Neutral sentiments are not included in the formulation of TwitHCommS and are, therefore, not covered in this study. The parameter values discussed in section 2 for @WHO are used to assume the rates used in the



Note. The solid lines represent positive sentiments (light gray solid lines represent starting the simulation with 100 positive spreaders), whereas the dotted lines represent the negative sentiments (light gray dotted lines represent starting the simulation with 100 positive spreaders).

Figure 4. Simulation Results Show the Dynamics of TwitHCommS

simulation of TwitHCommS. As the exposure rate ($\alpha = \gamma$) discussed in section 2 is equal to 0.42, then 21% are positive sentiments, and 40% are negative sentiments. Hence, we get the exposure rates for positive sentiments to be 21% of the exposure rate of the basic interaction ($\alpha = \gamma = 0.42 * 0.21$), and so we get $\alpha_+ = \gamma_+ = 0.0882$. The rates at which Exposed users become Infected by liking (β_1) are assumed to be the same (or equal) for users Infected by replying (b_1) and Infected by retweeting (c_1) to become Infected by liking. In other words, the rates for any population to become Infected by liking, Infected by replying, and Infected by retweeting are equal. Hence, we have, $\beta_{1+} = c_{1+} = b_{1+}$,$\beta_{2+} = c_{2+} = a_{1+} = c_{3-} = a_{3-} = \beta_{5-}$, $\beta_{3+} = a_{2+} = b_{2+} = b_{3-} = a_{4-} = \beta_{4-}$, $\beta_{1-} = b_{1-} = c_{1-}$, $\beta_{2-} = a_{1-} = c_{2-} = c_{3+} = a_{3+} = \beta_{5+}$, and $\beta_{3-} = a_{2-} = b_{2-} = b_{3+} = a_{4+} = \beta_{4+}$. In addition, we recall that the recovery rates φ and λ are equal. This is observed in TwitHCommS, and so $\varphi_+ = \lambda_+$ and $\varphi_- = \lambda_-$. Positive sentiments amount to 21% and negative sentiments amount to 40% (Simanjuntak & Pramana, 2021), which explains why users are more inclined to interact with negative tweets. Changing the scenario so that more spreaders of positive sentiments are employed to attract more users to interact with positive tweets, we start the scenario where there is only one spreader of negative tweets and 100 spreaders of positive tweets. Figure 4 shows the model simulations performed for TwitHCommS.

Given that there is one spreader for each of the positive and negative sentiments, negative sentiment tweets attract more negative spreaders in a shorter span of time than positive sentiment tweets. Between the 5th and 6th hour, the number of negative spreaders has already peaked, whereas the number of positive spreaders continuously increases at a slower pace. This result reflects how information with negative sentiments spreads faster than those with positive sentiments. From the projection of the plots, the number of negative spreaders started to decrease as it peaked, whereas the number of positive spreaders continuously increased. Adding 100 times more spreaders of positive sentiment tweets in the simulation shows that negative sentiment tweets still persist in the population. The number of spreaders of positive sentiment tweets is decreasing at a slow pace, whereas the spreaders of negative sentiment tweets are increasing despite starting the simulation with 100 times more spreaders of positive sentiment tweets.

There are also more users exposed to negative tweets than those exposed to positive ones. Users Exposed to positive tweets peaked at the approximate 15-minute mark and swiftly decreased throughout the day. These results are consistent with the work of Simanjuntak and Pramana (2021), where the aspects assessed are in a more negative manner, including opinions on how the country is not responding quickly enough to anticipate this outbreak in the earlier time, having a high number of death cases, less ability to restrict people activity to cease the spread, and so on. The government certainly did not predict the pandemic, but they also have not communicated well with the public (Bernadas, 2021). This may have contributed to the spread of misinformation or negative tweets on Twitter because of government unpreparedness. Bernadas (2021) suggested that health organizations must emphasize that crisis communication is a process so that organizations are relatively prepared to communicate to the public during the early stages of a pandemic.

Users on Twitter react to tweets with negative sentiments more than those with positive sentiments. It can be seen in these projections that more users "like" the tweets containing negative sentiments. Additionally, users reply and retweet negative sentiment tweets more than positive sentiment tweets. The simulations show that tweets with negative sentiments have more impact on Twitter users. The interactions among users Infected by liking, replying, and retweeting show that users interact more in a negative manner. At the 1-hour mark, the number of users "liking" positive tweets peaked and became greater than the number of users "liking" negative tweets. However, as time passes, the number of users "liking" positive tweets decreases, whereas the number of users liking negative tweets gradually increases. Users reply and retweet more with negative tweets than positive tweets. This shows that despite increasing the number of spreaders of positive tweets in the simulation, users on Twitter are more influenced by negative sentiments.

Conclusion

As Twitter gained popularity among public health agencies in spreading health information about health issues to the public, mathematical modeling has increasingly been used as a method in studying the dynamics of the spread of information epidemic on Twitter. The dynamics of information spreading on Twitter were studied in this paper by designing two SEIR-based health communication models of the interactions on Twitter. To our knowledge, these models are the first of their kind to study health information dynamics. The first model (TwitHComm) allowed us to compare and capture the interaction rates of @WHO and @DOHgovph. By calculating the basic reproduction number R0, we found that the tweets of @WHO show that users engage in topics regarding health on Twitter. Meanwhile, @DOHgovph's tweets do not achieve an epidemic state; that is, users do not engage suitably for the information to spread among the population on Twitter.

It is critical for health organizations that are on Twitter to build relationships and develop trust among their users. The trust that is built among healthcare organizations and users on Twitter is important, especially during vulnerable situations when misleading information is spreading (Bernadas, 2021). As Bernadas (2021) suggested, a step towards building trust with users on Twitter is for healthcare organizations to be open regarding their programs and services, especially during times of uncertainty.

Spreading timely and correct health information from the official channels to the general public is essential to avoid panic and the spread of fake news. To improve the information dissemination rate of @DOHgovph, the Philippines' official health communication channel, we have proposed to adjust some of the model parameters for it to obtain information epidemic. Another possible suggestion for @DOHgovph is to invite or identify influential ambassadors to increase the interactions among its users. It is our recommendation for future work to consider adding a compartment to the model for influential spreaders (or super-spreaders) and identify its contributions to the information-spreading dynamics on Twitter. As the interaction of @DOHgovph increases, the behavior of users when it comes to recovery has also improved.

For TwitHCommS, the parameters used for TwitHComm were calibrated in a way that 21% are considered to be positive sentiments and 40% are negative sentiments (Simanjuntak & Pramana, 2021). With a greater rate of negative sentiments, the simulations conducted for TwitHCommS show that users are more inclined to interact with negative tweets. Because the goal is to spread more positive sentiment tweets, we have performed simulations wherein more spreaders of positive sentiments were employed to attract more users to interact with positive tweets. Despite forcing more spreaders of positive tweets, users on Twitter are still more influenced by negative sentiments.

For future work, we suggest the inclusion of neutral sentiments in the model to obtain more information on the spreading dynamics on Twitter. It is intended for future works to perform the stability analysis for the second model where the sentiment of tweets is considered. In addition, we recommend looking at computing the range of values for the engagement rates at which tweets will become widespread or for information to spread among users on Twitter.

Declaration of Ownership

This report is our original work.

Conflict of Interest

None.

Ethical Clearance

This study was approved by our institution.

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