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Twitter vs. Zika—The role of social media in epidemic outbreaks surveillance ☆,☆☆,★

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ABSTRACT

Objective: The risk of global epidemic outbreaks led to the development of epidemic tracking services dedicated to track and warn against them. Despite the usefulness of these services, they suffer from shortcomings that impact their efficiency. This study examines the efficacy of social media in epidemic outbreak surveillance by studying Twitter users' behavior related to the Zika virus outbreak in 2015–2016 and how this behavior can be used to track and predict Zika virus.

Methods: We collected 67,000 tweets in English and Spanish under the hashtag #Zikavirus and #Zika in the period from October 1st, 2015 to February 25th, 2016. We examined the tweets using text analytics techniques and extracted the important concepts. We analyzed the differences in using these concepts from one month to another.

Results: There are significant differences between the numbers of tweets during the Zika outbreak as well as between the concepts used in English and Spanish tweets.

Discussion: The differences in Zika epidemic related tweets evolved with the epidemic outbreak and reflected the different stages of the epidemic. However, those differences also reflected a digital divide between developed and developing communities. The number of tweets was related to the threatened community rather than the severity of the threat.

Conclusion: While Twitter can be used to augment current epidemic tracking systems, it cannot replace them. We identified digital divide and threat of misleading information as two factors that limit the dependence on Twitter as an epidemic tracking system.

Introduction

The improvements in the interconnectedness between societies have led to several benefits, including enhancing cultural exchanges and increasing economic transactions. However, this interconnectedness has also led to an increase in the likelihood of epidemic outbreaks and has caused societies to be concerned, not just with local health problems, but with global health threats as well [1]. Recent years witnessed several such threats to global health including the outbreak of SARS in 2003 which quickly spread from China to seventy-three countries [2]; in 2009, the H1N1 extended to 213 countries [3]; and in 2014, the Ebola virus spread in Western Africa killing thousands and threatening societies all over the world [4]

The most recent virus outbreak is the Zika virus outbreak, which started in Brazil in the second half of 2015 and was declared by the World Health Organization (WHO) as an epidemic in early 2016 [5]. This virus provides a classic example of the importance of global health [6] and the effect of world connectedness on epidemic outbreaks. Zika virus spread from Brazil to most of South America and the Caribbean, then to the United States, Canada, Europe, and few cases have even been reported in Japan and China, which signifies the enormous range of the virus spread.

These epidemic outbreaks raise some important questions: How can these epidemic outbreaks be effectively tracked? And what are

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the most effective ways to inform the public about such outbreaks and how to educate them about the best ways to prevent infection?

The WHO has been doing a reasonable job in tracking epidemics. However, the WHO has been criticized for being slow in issuing its alerts. For example, in the 2014 Ebola outbreak, the WHO was criticized as being slow in responding to the epidemic [7]. Therefore, there is a strong need to have a supportive source for tracking epidemic outbreaks and alerting the public to epidemic spread.

The slow response of WHO and other medical organizations in issuing alarms has led to several attempts to use online presence to track epidemic outbreaks and issue timely warnings. Online activity has been effectively employed in tracking epidemic outbreaks. For example, Google Flu, before its retirement, predicted flu outbreaks in several countries, including the H1N1 outbreak in the USA in 2009 [8,9].

Social media is another source of online activity that can help in alerting the public about epidemic outbreaks. The social exchange that characterizes social networks provides a more rapid and responsive system for epidemic alerts [10,11].

Despite the proposed use of online presence and social media in tracking epidemic outbreaks, there is scarce literature focusing on the efficacy of using social media to track epidemic diseases and even fewer studies focusing on tracking epidemic outbreaks on a global scale rather than a local one. Moreover, studies focusing on some of the previous online and social media presence attempts to track outbreaks studied these attempts from a technical perspective ignoring the social perspective.

This study focuses on the social side of using social media in tracking epidemic outbreaks in a global context. We study the Zika virus outbreak because it was a global outbreak that started in South America, spreading to other parts of the world. We employ Twitter to study the relationship between users' tweets and the Zika outbreak in the period from October 2015 to February 2016.

Literature review

Social media in healthcare

Social media services are Internet-based services where users can create personal profiles and share content with their network of connections [12]. The growth in users' participation in social media in the past decade has been phenomenal with the increase of Internet users' participation from less than 8% in 2005 to more than 67% in 2012 [13].

Because of its widespread use, social media has been widely used to engage the public and create action. For example, users were able to use social media in crisis and catastrophic circumstances such as the use of Twitter to send requests for help when Hurricane Katrina hit the USA [14].

The uses of social media extended to the healthcare domain with patients and healthcare providers alike. For example, healthcare providers have used social media for peer communications and dissemination of knowledge [15], for establishing a connection with patients [16], and for public health communications [17]. Patients have used social media to obtain information about their medical condition [18,19], get peer support [20], retrieve peer opinions on healthcare providers [21], and communicate with care providers [16].

In the area of tracking epidemic diseases, social media played an important role in the Ebola outbreak in 2014. [22,23]. Twitter was also used to track disease activity during the 2009 flu outbreak in the United States [24].

Despite the potential benefits of social media to healthcare providers and patients, there are several challenges associated with its use. These challenges arise from the open nature of social media and the lack of means to validate social media users' information. For example, pharmaceutical companies can use social media to promote their products [25], which may include false information that may impact patients' conditions. Social media sites can also endanger patients' privacy [26,27], given the lack of controls over healthcare providers' use of social media [28].

Most research on the use of social media in healthcare has focused on studying social media for patient support and education, with few studies focusing on the use of social media in disease tracking, especially in a global epidemic outbreak. These studies focused on understanding social media attitudes towards the epidemic and towards medical authorities (e.g. CDC) [29]. They found that misleading information is more common and accepted on social media sites than legitimate information [30]. Hence, in this study, we dig deeper into studying social media user attitudes towards the Zika epidemic and how these attitudes changed with time and with the geographic spread of the virus. In this study we address both these factors in evaluating the global use of Twitter in tracking the Zika outbreak.

Epidemic surveillance

Epidemic surveillance is the ability to monitor and track the outbreak of epidemics using a network of distributed information sources [30]. *Epidemic surveillance can be divided into two categories:* indicator-based surveillance, *which depends on detecting disease indicators using a network of lab systems distributed nationally. This surveillance category is the surveillance method typically used to monitor epidemic outbreaks. It is a trustworthy evidence-based system that provides accurate epidemic data. However, the surveillance data resulting from indicator-based systems may suffer from delays that do not allow creating timely epidemic alarms* [31].

The other category of epidemic surveillance is evidence-based surveillance, which attempts to detect outbreak events by monitoring public information such as newspaper articles, government reports, and online discussions. These systems include independent systems such as the "Healthmap" system hosted at Boston Children hospital that assembles data from various social media sources to track infectious diseases and government moderated systems such as ARGUS and BIOCASTER. These surveillance systems help in provide more timely information and accessing communities with little or no formal healthcare system monitoring [32]. Despite these potential benefits of event-based surveillance systems, they are widespread in North America and Europe and they are lacked where they are most needed in underdeveloped societies [33]. Moreover, these systems rarely use social media data as a source of information because social media services are either closed to their members or require substantial resources to access their data [33].

A sub-category of evidence-based surveillance involves the use of big data, for example, web search queries, to identify epidemic outbreaks. Perhaps the most known attempt in this sub-category is Google flu [9]. This service aimed at tracking flu outbreaks based on Google search terms entered by users in a specific region. Although this service initially worked with acceptable quality, it soon failed in 2013 and was discontinued [34,35]. In addition to Google flu, there were other attempts using social media to track and predict disease outbreaks [22,24]. However, these attempts failed to provide consistent results in predicting disease outbreaks. The failure of these services is because these technologies were not designed with the purpose of disease tracking in mind. They were not designed to provide reliable and valid data but rather to serve the business model of the service provider [36]. Several researchers [37] proposed that social media can be used to supplement, not replace, traditional outbreak predictions. Few studies utilized big data resulting from flight and transport information to detect disease outbreak. For example, flight information was used to detect Zika cases in the United States [38], and to detect flu outbreaks [39].

Unfortunately, there is a lack of research on the use of social media in epidemic surveillance because of the need for substantial resources to access social media data. Most event-based monitoring systems are locally or nationally centered and do not cover communities of most need. Hence, it is important to study the role of social media in surveilling and monitoring epidemic outbreaks and it is also important to study if social media can indeed cover areas that lack formal indicator-based or event-based surveillance systems.

The Zika virus outbreak

Zika virus was identified in the 1950s [40]. This virus causes mild symptoms of fever and rash that last for several days [41]. The Zika virus has been associated with diseases such as Dengue and Chikungunya, which are transmitted by the same mosquito [42]. Because of the mild symptoms of the Zika virus, it did not cause a big concern when the first cases were reported in Brazil in May 2015 [43]. However, the concern about the Zika virus grew with the proposal of a relationship between the virus and Guillain-Barré syndrome (GBS) [44]. By the end of November, a concern was raised on the relation between Zika virus infections and microcephaly [45]. This development caused concern among different countries that issued travel alerts, and tourism in Brazil was seriously threatened. In January, another development was the possibility of transmitting the virus through sexual relationships eliminating the need for the mosquito.

In response to the spread of the virus to other countries, the WHO declared Zika a public health emergency for international concern in February 2016.

Several indicator-based and event-based systems have been used to predict Zika outbreak. An example of indicator-based systems is the Point-of-Care Molecular Test that can detect Zika virus infections in clinics [46]. These point of care tests are expensive and may not be suitable for under-developed communities where Zika first started. Examples of event-based surveillance is the use of spatial video to detect conditions suitable for Zika virus transfer and detect human behavior that increases Zika risks [47], and the use of flight information to detect the spread of Zika virus into the United States [48]. Those event-based surveillance systems are local and cannot be used to track the Zika virus outbreak globally.

Methodology

Data collection

Data were collected using Twitter APIs for the search. Twitter provides some APIs that can return results similar to Twitter.com's advanced search. However, these APIs have the limitation of limited time and results range. Twitter search APIs return the smallest of 18,000 tweets or tweets in the last 9 days. To overcome these limitations, we ran a daily search using the "R" language TwitteR package.

To understand how information about Zika spread through user tweets, we searched Twitter on the hashtags used to discuss Zika virus and we identified two hashtags: #Zika and #Zikavirus. We searched Twitter for tweets related to these hashtags from October 1st 2015 to February 25th, 2016. Because of the large number of tweets associated with these hashtags especially in January and February, the repetitions in those tweets, and the overhead associated with the pre-processing of these hashtags, we randomly selected one thousand tweets per day in January and February and all the hashtags in December, November and October 2015. This process resulted in collecting sixty-seven thousands of tweets for processing. Table 1 below shows the approximate distribution of these tweets to the nearest thousand per month.

Table 1
#Zika tweets samples (to the nearest thousand).

Month	Tweets
February 2016	25,000
January 2016	31,000
December 2015	6700
November 2015	2400
October 2015	2200

Data pre-processing

The data retrieved from Twitter only contained information on the tweet itself, number of likes and retweets, and date of the tweet. To provide proper analysis, we decided to retrieve information regarding the users, including their location and language, to enable us to study the locations of the Zika related tweets. The tweets collected were also in different languages dominated by English and Spanish, (because of where the disease originally started), so we needed to differentiate between these languages for our analysis.

To differentiate between languages, we used a list of the top one hundred words in Spanish as a lexicon and categorized tweets according to these words. That is, if a tweet contained any of these words, it would be categorized as Spanish; otherwise, it would be considered English. We tested the result by going through 1000 random categorized tweets to assess categorization accuracy. The accuracy was 97.6%, which we considered acceptable and therefore, we proceeded with our analysis.

Data analysis

Concept extraction

We identified the important concepts related to the Zika virus that were discussed among users, then we sorted the important words (after eliminating common language words not related to our subject). These words and frequencies were then used to build a word cloud to visually identify the important concepts. To enhance the utility of this analysis, we divided the data according to their dates in 4 categories according to the month of the tweet resulting in four sets of important concepts.

Users' location tracking

The goal of this analysis was to identify the locations of the tweet and to study the relationship between these locations and the spread of the virus.

We categorized users according to their location specified in their Twitter profile. In this step, we were faced with the challenge that not all users entered their locations, and some users provided imaginary locations. We overcame this by only including users with identifiable locations.

Results

Number of tweets

As shown in Fig. 1, although Zika virus cases were reported in Brazil since May 2015, the average number of tweets was significantly small throughout October, November, and December. However, the number of tweets tripled in December compared to

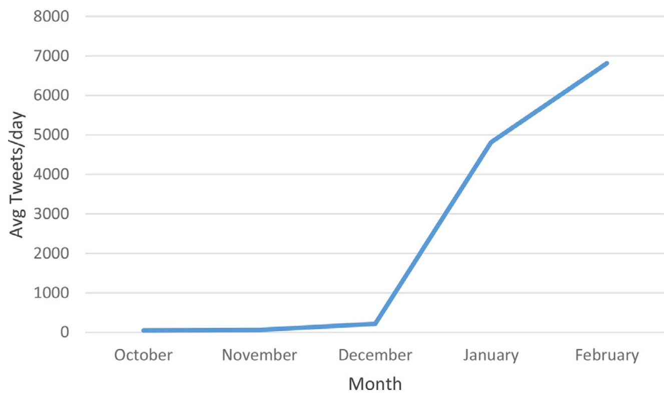


Fig. 1. Average number of tweets per day during the study.

Fig. 2. Important Spanish concepts in October and November 2015.

November. This is probably because of the suggested relationship between the Zika virus and microcephaly proposed by the Brazilian government at the end of November which caused significant concerns among pregnant women. The surge in the number of tweets in January is because by then, the virus had extended to several countries in the Caribbean and an alert was issued by the Centers for Disease Control and Prevention (CDC) for travelers to these locations. The first cases of Zika virus were reported in Florida as travel related cases in January as well. In February, the WHO declared the virus a global concern causing an additional surge in the number of tweets.

The data shows that the number of tweets increases with new developments in the outbreak. The percentage of increase is positively related to the number of people and the geographic region affected by the development. For example, while the number of tweets tripled when the relationship between the Zika virus and microcephaly was proposed, it went up twenty times when the CDC issued a travel warning and when cities in the United States were affected.

Important concepts analysis

Fig. 2 shows the important Spanish concepts prior to December. As with the number of tweets, 98% of the tweets prior to December were in Spanish and Portuguese and therefore, we did not find enough tweets to derive important English concepts. This lack of English tweets is because at that time, the Zika virus outbreak was concentrated in Spanish and Portuguese speaking countries and had not expanded globally.

For Spanish concepts, there was a focus on describing the cases of Zika virus transmission (through mosquito bites), its spread to Columbia and Ecuador (First reported Zika cases were reported in October), symptoms of the Zika virus and reports by the Ministry of Health in Columbia confirming virus cases.

Figs. 3 shows the important concepts during December 2015. The English tweets focused on the transmission and symptoms of the Zika virus. The concerns over traveling to countries where Zika was spreading started to rise in December as well. In Spanish, the most important concept was “microcephaly,” which was proposed to correlate with the Zika virus infections by the end of November.

Users were also concerned about government alerts related to tracking virus development in South America.

In January 2016 (Fig. 4), English tweets focused on travel and how important events such as the Olympics and January carnival in Brazil could have been affected by the outbreak. There was less focus on the transmission of the virus and its effects. In Spanish tweets, the concerns over pregnant women being infected and the effects of the infection on the newborn were evident. Users tweeted on how to avoid mosquito bites, especially for pregnant women.

In February 2016 (Fig. 5), English tweets did not have a specific focus, but they focused mostly on Zika virus-related news, travel alerts, symptoms and transmission of Zika virus. This is probably caused by WHO declaring Zika virus a global concern which raised awareness of the virus dangers and motivated users to seek more information about it. On the other hand, Spanish tweets continued to focus on fighting and preventing the disease with some focus on the WHO declaration.

Tweets location

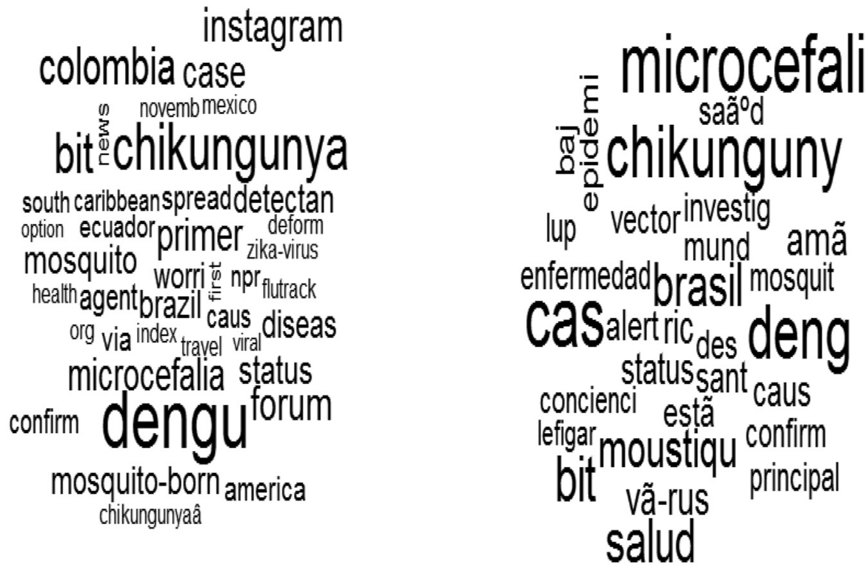
In October 2015, most tweets came from Brazil and Columbia. This is natural given that In October, these two countries were the most affected by the virus. Then in November, when Mexico confirmed the first cases of Zika virus infections, it came second after Brazil, while other countries in South America constituted the third group of locations. In December, the same trend continued as Guatemala, the United States and France appeared in the locations of the active tweets. In December, The first cases were confirmed in French Guyana and Guatemala. United States users were concerned as the disease approached Florida. In January, as the first cases of Zika infections were reported in Florida and Illinois, United States Twitter users were concerned, especially with the CDC issuing travel alerts to the Caribbean and South American countries. In February, as the WHO declared the Zika virus a global concern, tweets spread across the world with the focus still on South America and the United States.

Discussion

Combining the information we obtained from analyzing Twitter data over the months from October to February, we can perceive a potential capability to use Twitter data to support and enhance other alarm systems.

Fig. 6 shows the important events during the current Zika outbreak. As we observed above, there is a relationship between the tweets features (number of tweets, words, and language of tweets), and the geographic origin of the tweets and these events.

For example, when the Zika virus infections were limited to Brazil and Columbia, and before the concerns about the relationship between this infection and microcephaly were raised, tweets were concentrated in Columbia and Brazil, and the focus was on diffusing knowledge on confirmed cases, symptoms, and transmission of this disease. As the Zika spread into new countries, tweets started to appear coming from these locations and covering the same topics. However, when a strong suspicion on the relationship between Zika and microcephaly was raised in December, tweets



a. Important English concepts in December b. Important Spanish concepts in December

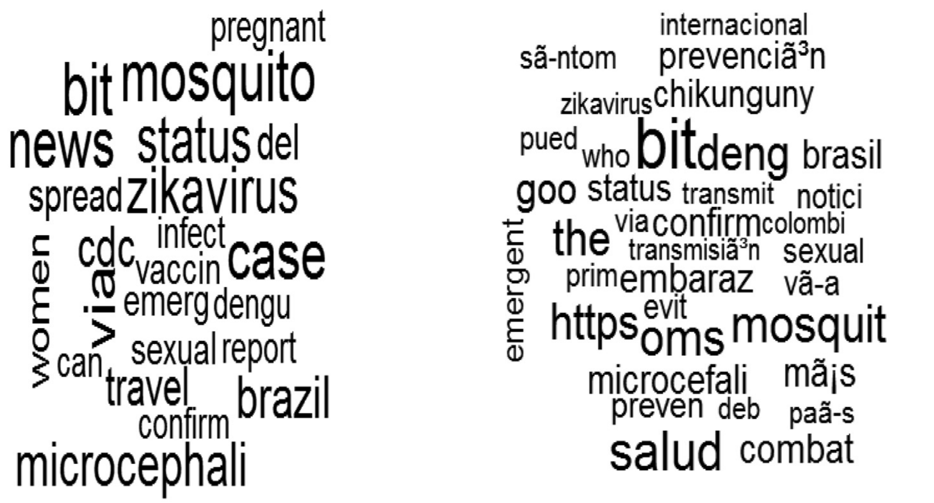
Fig. 3. a. Important English concepts in December. b. Important Spanish concepts in December.

a. Important English concepts in January b. Important Spanish concepts in January

Fig. 4. (a). Important English concepts in January. (b). Important Spanish concepts in January.

tripled with concern over this new disease and fears over babies' health. The rest of the world, where the disease had not spread yet, was more concerned about the potential effect of this disease on Brazil's Olympics and January carnival and on avoiding travel to South American and Caribbean countries. In January, as the virus entered the United States through Florida (travel related cases), tweets soared to twenty times its number in December, United States Twitter users started following up closely on the news related to the Zika virus such as complications, transmission through sexual relationships, and potential effects on newborns. In February, when the WHO acknowledged the Zika virus as a global concern, tweets soared again, but this time they spread across the world and echoed the global concern about the Zika outbreak. It is worth mentioning that the community-based spread of the Zika virus did not take place until late July 2016. Unfortunately, we did not have the resources to continue collecting the data till then. However, when we compare the Zika virus outbreak in 2016 with the Covid-19 virus outbreak in 2020, we would expect a significant change in the number and nature of tweets when localized transmission happened.

However, as we observe Twitter users' behavior, we notice a few things that limit the power of Twitter as a global alert system. First, in most cases, changes in tweeting behavior followed the events and did not predict them. The January surge in United States tweets came after the CDC alert and after cases of Zika infections were confirmed in Florida. Second, the number of tweets



a. Important English concepts in February

b. Important Spanish concepts in February

Fig. 5. a. Important English concepts in February. b. Important Spanish concepts in February.

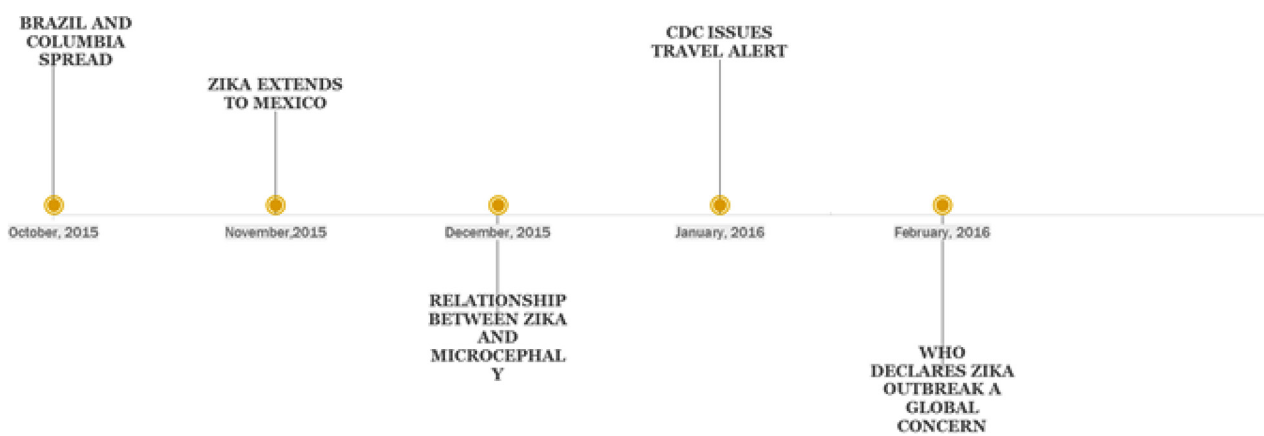


Fig. 6. Important events in Zika breakout timeline.

is not mainly correlated with the seriousness of the event, but with the importance of the country or community that is affected by the outbreak. For example, the increase in the tweets number when the Zika virus became a United States concern is at least ten times the increase when the relationship between the virus and microcephaly was suspected. Third, except for the United States and Brazil, the relationship between the increase in the number of tweets from one country and the spread of the virus into this country is temporary. For example, tweets originating in France, China, and Japan increased only for a few days to report Zika cases in these countries and then decreased again. This may be because only a few cases were reported in each of these countries, but yet this may limit the ability to use Twitter as an early alert system.

In addition to the above observations, depending on Twitter as an alert system is also limited by the possibility of spreading rumors or incorrect information, which can be a serious danger to the public. Although this was not one of the goals of this study, previous studies have warned against this potential danger [28,49,50]. It is worth mentioning though that these rumors or misinformation exist even outside social media, hence reliable healthcare authorities such as WHO and CDC can actually use social media to fight this misinformation. However, this will require a significant effort to win users' trust over the sometimes more attractive misinformation [29]. Recent events signify the potential effects of social media on spreading rumors and directing. For example, in 2018, Facebook data of over fifty-million US citizens have been used to influence them in the 2016 presidential elections. We can perceive the possibility of using a Twitter hashtag, such as #zika, to spread rumors and panic among the public.

Based on the above observations and concerns, we propose that social media faces the same issues faced by other types of epidemic surveillance systems. There is a divide between users of under-developed and developed societies. Moreover, social media is subject to rumors and incorrect information because it is largely unregulated and this can have a negative effect on both patients and the community. Nevertheless, social media can help spread information about disease outbreaks and it can also prevent behaviors that lead to epidemic outbreaks.

Therefore, we propose that social media can indeed be used as an outbreak surveillance system. This agrees with previous studies on Ebola outbreak surveillance [51]. However, social media should be supported by more reliable sources such as the CDC or the WHO to enhance the outreach of their alerts and news. While global and national and healthcare organizations have a significant presence on social media, we propose that these healthcare authorities extend their efforts by monitoring misinformation and public concerns and dedicating part of their presence to respond to these concerns. By being responsive to social media users, healthcare authorities can enhance public trust in them and reduce the spread of rumors [52]. Although this presence will require vast resources, it will pay off by providing an early alarm system and by promoting healthier behaviors in under-developed communities.

The results of this study can be extended to the outbreak of the Covid-19 epidemic. With the spread of Covid-19, social media users posted enormously about the outbreak. For example, over fifteen-million tweets focused on Covid-19 in January alone [53]. Misinformation about Covid-19 was, and still is, a major concern for healthcare authorities and social media sites [54]. The danger of this misinformation is even more aggravated than in the Zika virus case given the novelty of the Covid-19 and the disagreements on how to manage this epidemic. Social media can be used to fight this misinformation. Social media posts can be combined with other sources of information such as GPS data to examine public behavior, their attitudes towards to Covid-19 epidemic and their adherence to social distancing rules. Indeed, one of our future goals is to develop a study to examine the relationship between Twitter posts where users discuss how they are coping with the epidemic and the spread of Covid-19 globally. Healthcare authorities can use such data to demonstrate the effectiveness of social distancing on the virus spread and hence motivate the public to better adhere to social distancing. Furthermore, several countries, including the United States and some European countries, accused China, where the Covid-19 outbreak began of mismanaging the outbreak. It would be interesting to use the same methodology of this paper to examine early social media posts discussing the epidemic and whether they point to intended misinformation.

Conclusion

In this paper, our goal was to assess the value of social media as an event-based surveillance system for epidemic outbreaks using the Zika virus as an example of these outbreaks. We analyzed local tweets (in Spanish and Portuguese) to represent tweets from where the outbreak started as well as English tweets. We attempted to study the relationship between tweets dimensions of volume, location, and concepts with the spread of the virus and whether these dimensions represent the development of the epidemic outbreak.

Our conclusion is that Twitter can be used as a supportive alert and tracking system in addition to more reliable sources such as WHO and CDC alerts. However, For this support to be effective, healthcare authorities need to modify their participation to social media sites to be more responsive to public concerns and to interact more with social media users instead of posting passive information that does not consider the psychological needs of the public. Twitter users should only trust information from reliable sources and avoid unsupported information. Furthermore, our research supports the work of social media surveillance systems such as “HealthMap” [55]. These projects can use our findings to improve their surveillance method to improve early warning of epidemic outbreaks.

Declaration of Competing Interest

None.

CRediT authorship contribution statement

Mohamed Abouzahra: Conceptualization, Data curation, Formal analysis, Visualization, Writing - original draft. **Joseph Tan:** Conceptualization, Data curation, Supervision, Writing - review & editing.

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