RESEARCH ARTICLE

The Utility of Social Media during an Emerging Infectious Diseases Crisis: A Systematic Review of Literature

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ABSTRACT

Objectives: The use of social networking sites for monitoring emerging infectious diseases (EIDs) are on rise. This systematic review examines the available evidence supporting and refuting the use of social media in communicating with the public during the pandemic outbreaks of infectious disease, influencing people's behavior, spreading the awareness, and creating or dispelling rumors.

Methods: PubMed, Google Scholar, and Cochrane Library databases were systematically searched from 2012 till 2019 for studies on the use of social media in detecting the following EIDs: the Ebola virus, Zika virus, Nipah virus, West Nile, Bird flu and Swine flu. The included studies were evaluated and data were extracted and reviewed.

Results: Preliminary search results showed that out of 6224 articles related to social media and EIDs, 49 articles were related to our study objectives. Out of 49 articles, most of the articles were related to the Zika virus (n=24), published in 2017 (n=15) and utilized the Twitter social media (n=26).

Conclusion: The present systematic review supports the use of social media as an important medium for the clinicians, public health practitioners, and laypeople seeking health information for the detection of EIDs. *J Microbiol Infect Dis 2020; 10(4):188-198.*

Keywords: Emerging diseases, Infectious diseases, Information technology, Social media

INTRODUCTION

Emerging infectious diseases (EIDs) are of particular concern to public health. The term was first coined by Lederberg et al [1]. EIDs refer to those new infectious diseases that appeared in the last 20 years. The common route of transmission of EIDs is through insects, water, animals, or from person-to-person but 75% of the EIDs that have affected humans over the last three decades are of zoonotic origin, i.e. they spread from animals to humans [2].

A rise in these outbreaks also coincided with the increased use of social media as a source of public health information [3,4]. Obar and Wildman (2015) defines the social media as "the services that are based on web 2.0 technologies and largely rely on the user-generated content, by which individuals and organizations create profiles, and develop social networks online" [5].

According to the WHO, 51% of the outbreak information related to EIDs was obtained initially from the media sources between 2001 and 2011 [6]. Over the last decade, social media has become a potential tool to predict infectious disease outbreaks across the world and reached far beyond the traditional surveillance system. A systematic review conducted by Korda and Itani has shown the ways through which social media can be applied for promoting health by providing information access, delivering health campaigns, and offering social support [7].

Although social media has uncountable benefits for detecting the EID outbreaks, the generalizability and reliability for all searches are unpredictable as people may not be searching the top posts alone, and misleading information may also be present along with the reliable information, which can misguide the users. Hence, the present systematic review was

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Email: ankita26gupta88@gmail.com Received: 06 July 2020 Accepted: 04 September 2020 Copyright © JMID / Journal of Microbiology and Infectious Diseases 2020, All rights reserved conducted with an aim to examine the available evidence supporting and refuting the use of social media in communicating with the public during the pandemic outbreaks of an infectious disease, influencing people's behavior, spreading the awareness, and creating or dispelling rumors.

METHODS

This article followed the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines [8].

Methodology for Literature Search

This systematic literature review was synthesized by searching databases such as PUBMED, Google Scholar, and Cochrane Library from 2012 till the year 2019. The keywords "Emerging infectious disease" or "Zika virus" or "Swine flu" or "Nipah virus" or "Ebola virus" or "West Nile virus" or "Bird flu" and "Social media" or "Facebook" or "Twitter" or "YouTube" or "Instagram" were used to retrieve the related studies. The above-mentioned databases are readily available for the literature search.

Inclusion criteria

The databases were searched for published studies evaluating the utility of social media for various EIDs. The clinical evidence was searched in the form of original peer-reviewed journal articles published in the English language. Clinical and experimental studies were included and the references of the reviewed articles were also searched for the relevant studies wherever necessary to increase the yield.

Exclusion criteria

Conference papers, book reviews, book chapters, case reports, case series, letters to editors, commentaries, newspaper and newsletter articles, expert opinions, and theses or dissertations were not used. Articles that are not published in English were excluded along with articles that were published prior to January 2012. As before 2012, there were not many articles related to social media use due to the significant changes that have taken place in technology in the 21st century, making these documents to be the most appropriate.

Data Extraction and Management

Data were independently extracted from the included studies by one author using uniform data extraction and any discrepancies were resolved by discussion. Extracted data were independently entered into an Excel spreadsheet.

Data items extracted

The following information was extracted from each study:

-The first author of the study, year of publication, number of enrolled patients, type of EID studied, and method of analysis used in the study

-Reported strength, weakness, and recommendations by various studies

-The utility of social media in handing EID.

Statistical Analysis

The articles were stratified based on the topic studied, the method used, and the major findings. The data obtained was entered in the Microsoft Excel spreadsheet.

Characteristics of the retained studies sorted by the first author name and year of publication were presented in a tabular form. These tables will have information relating to the reported strength, weakness, and recommendations as suggested by various authors of the included studies. Apart from this, we have segregated the studies into various categories based on the application of social media as reported by the studies.

RESULTS

Comprehensive literature search

Our search strategy identified 49 studies. A total of 6224 articles were identified from various search engines such as PubMed (n=4960 articles using the search terms-Emerging infectious diseases or Zika virus or Nipah virus or Bird flu virus or Swine flu or Ebola virus or West Nile virus AND social media or Facebook or YouTube or Twitter), Google Scholar (n=1167 article by using the search term- Emerging infectious diseases and social media), and Cochrane library (n=97 articles by using search term- Emerging infectious diseases and social media). Titles were screened first, followed by the screening of abstracts, based on the inclusion and exclusion criteria. A total of 4126 articles were excluded as they were not able to provide the full text, were non-peer reviewed, duplicate articles, and articles before 2012 excluded. After excluding those articles, abstract screening of 2098 article was done. After screening, more articles (n=1983) were excluded as they were not fulfilling the inclusion criteria (review articles, letter to editor, comments, and irrelevant articles). A total of 115 papers were retrieved for full text reading. Some articles that were published in non-English language were excluded (n=66). In the end, a total of 49 articles were included in this systematic review. The article inclusion flow diagram is shown in Figure 1

Description of the included studies (n=49): A significant number of studies along with the literature reviews have evaluated the impact of the social media on EIDs but we restricted our search to only six EIDs (Ebola virus, Nipah virus, Swine flu, Bird flu, West Nile virus and Zika virus). We got 6224 articles on the preliminary search related to the social media and EIDs, out of them, 49 articles were included in the final

analysis [9-57]. It was found that most of the articles (n=15) were published in the year 2017 and least in the year 2012 (n=1). Out of 49 studies, most of the studies were of the Zika virus (n=24) followed by the Ebola virus (n=15) and the least of the Nipah virus (n=0). Distribution of the studies according to the type of EIDs and their year of the publication is shown in Figure 2.

In terms of the types of social media studied, Twitter was undoubtedly the most scrutinized social media platform and was studied in 26 articles, followed by YouTube (6 articles) and Facebook (3 articles). Detailed information about the articles studying each social media application is given in Table 1. The reported strength, weakness, and recommendations of the social media as reported in the included studies are shown in Table 2. The maximum studies included in this systematic review have reported the strengths of social media as the weakness compared to and recommendations.

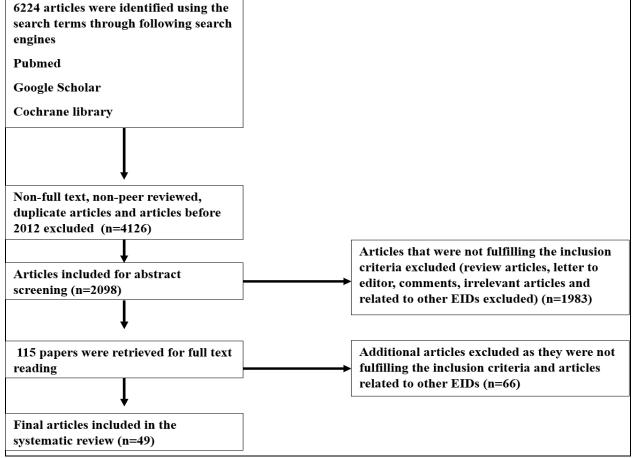


Figure 1. Flow diagram showing the selection process of the articles to be included in systematic review.

Table 1. Types	of social media	a platform studie	ed (n=49).

Types of social media platform studied		No. of article	Studies
Twitter		26	[9]; [10]; [11]; [12]; [13]; [14]; [15]; [16]; [17]; [18]; [19]; [20]; [21]; [22]; [23]; [24]; [25]. [26]. [27]; [28]; [29]; [30]; [31]; [32]; [33]; [34]
Facebook		03	[35]; [36]; [37]
YouTube		06	[38]; [39]; [40]; [41]; [42]; [43]
	Twitter and Instagram		[44]
	Twitter,Instagram, Facebook and YouTube		[45]
	Weibo		[46]
	Google news, Google trend, Twitter, YouTube and Wikipedia search queries.		[47]
	Google searches, Twitter and microblogs	14	[48]
Combinations of all the platforms	Twitter and Google News Trend	14	[49]
	Pinterest and Instagram		I[50]
	Twitter and Weibo		[51]
	Obstetric practice Web sites		[52]
	Twitter and facebook		[53]
	Instagram and Flickr		[54]
	Instagram		[55]
	Twitter, Blogs and Delicious		[56]
	Google Trends		[57]

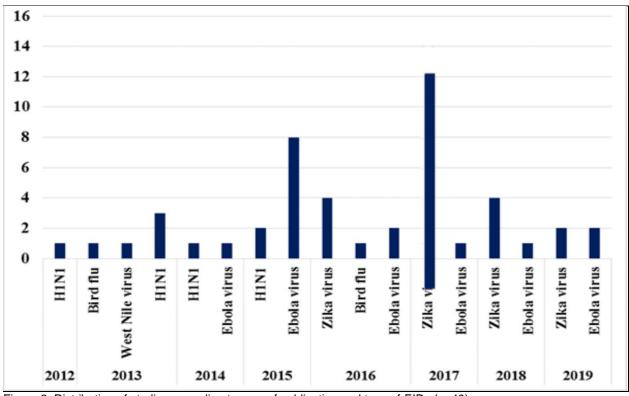


Figure 2. Distribution of studies according to year of publication and type of EIDs (n=49)

	The compared systems showed a good level of correlation The social media was more accurate than Traditional methods	[15]; [19]; [20]; [21]
	The social media was more accurate than Traditional	
		[4 0]
		[18]
	Communication, dissemination of information and disease prediction	[13]; [14]; [17]; [23]; [29]; [30]; [35]; [37]; [39]; [40]; [41]; [42]; [44]; [49]; [50]; [51]; [52]
	Cost-effective	[38]
Reported strengths of social media	Effective medium for health education Debunking rumors and misinformation Increases public interest towards the disease	[9]; [36]; [45] [12]; [28]; [42] [24]; [32]; [47]
	Utility of analyzing temporal variations in the analytic triad of locations, actors, and concepts	[11]
	Web data could improve forecasts	[16]; [33]
	Manages and shares information during the time of crisis	[22]; [27]; 48]; [54]; [56]; [57]
	Useful measure of public awareness	[25]; [31]; [46]; [53]; [54]
	Tweets combine information dissemination with emotional stances and critical views	[34]
	Should analyze the effectiveness of other social media also	[25]; [35]; [44]; [57]
	Source of major potential bias when applying digital epidemiological methodology to emerging disease outbreaks	[10]; [22]
Reported weaknesses of social	Some sources on social media are outdated	[45]
media	Has the potential to spread rumors	[12]
	Misguiding posts were more popular than posts related to information	[26]; [36]; [43]
	lack of verification by authorized healthcare professionals	[39]
	Inability to evaluate non-English videos.	[15]; [32]; [42]
	Should primarily support existing traditional methods	[9]; [14]; [44]; [47]
	Need to develop more tools in future	[49]
	It is important to	
Reported recommendations for	have quantitative methods to distinguish news from	[26]
the use of social media	rumors	
	Public health agencies should consider establishing a larger presence on YouTube to reach more people with evidence-based information about ZIKV.	[42]

Table 3: Categorization of the included studies on the basis of their application and methods of analysis (n=49)

Applications of social media	Authors	Year of publication	EIDs studied	Method of analysis
	[9]	2015	Ebola virus	Time series analysis (exponential smoothing)
	[13] [14]	2016 2018	Zika virus Zika virus	Content analysis Descriptive statistics
	[17]	2015	Influenza virus	Count based technique
	[24]	2015	Ebola virus	Text analysis

	[28]	2017	Zika virus	Network analysis
Communication purpose, public health education and dissemination of the information to the public	[29]	2016	Zika virus	volumetric and text mining analysis
	[30]	2019	Ebola	Descriptive statistics
	[33]	2019	virus Zika virus	Bootstrap resampling
	[34]	2018	Ebola	Quantitative and qualitative
	[35]	2018	Zika virus	analysis Descriptive statistics
	[36]	2016	Zika virus West Nile	Descriptive statistics Inter-rater agreement using
	[39]	2013	virus	Cohen's kappa
	[40]	2015	Ebola virus	Student t-test and Chi-squared test
	[41]	2015	Ebola virus	Descriptive analysis and Kruskal- Wallis one way analysis
	[42]	2017	Zika virus	Kruskal-Wallis H-test and Wilcoxon rank sum test
	[45]	2017	Zika virus	Chi-square test or Fisher's exact
	[46]	2013	Bird flu	test Paired t test for comparing
			(H7N9) Ebola	between baseline and peak
	[49] [50]	2016	virus	Descriptive statistics Chi-squared test and Fisher's
		2017	Zika virus	exact test
	[52]	2017	Zika virus	Descriptive statistics
	[54]	2015	Ebola virus	Descriptive statistics
	[10]	2015	Ebola virus	Mathematical modeling and time series analysis
	[10] [15]	2015 2017		series analysis Tenfold cross-validation
			virus	series analysis
	[15]	2017	virus Zika virus	series analysis Tenfold cross-validation quantitative and qualitative content
Influence public or viewer's behavior	[15] [25]	2017 2017	virus Zika virus Zika virus	series analysis Tenfold cross-validation quantitative and qualitative content analysis
Influence public or viewer's behavior and assess the public's response	[15] [25] [27]	2017 2017 2016	virus Zika virus Zika virus Zika virus	series analysis Tenfold cross-validation quantitative and qualitative content analysis Text analysis and mining
	[15] [25] [27] [31]	2017 2017 2016 2017	virus Zika virus Zika virus Zika virus Zika virus	series analysis Tenfold cross-validation quantitative and qualitative content analysis Text analysis and mining Content analysis Data Annotation Analysis Unpaired Student t test and multivariate logistic regression
and assess the public's response	[15] [25] [27] [31] [32]	2017 2017 2016 2017 2019	virus Zika virus Zika virus Zika virus Zika virus Zika virus Ebola virus Zika virus	series analysis Tenfold cross-validation quantitative and qualitative content analysis Text analysis and mining Content analysis Data Annotation Analysis Unpaired Student t test and multivariate logistic regression analysis Multivariate regression method
and assess the public's response	[15] [25] [27] [31] [32] [38]	2017 2017 2016 2017 2019 2015	virus Zika virus Zika virus Zika virus Zika virus Zika virus Ebola virus	series analysis Tenfold cross-validation quantitative and qualitative content analysis Text analysis and mining Content analysis Data Annotation Analysis Unpaired Student t test and multivariate logistic regression analysis
and assess the public's response	[15] [25] [31] [32] [38] [47]	2017 2017 2016 2017 2019 2015 2017	virus Zika virus Zika virus Zika virus Zika virus Ebola virus Zika virus Ebola	series analysis Tenfold cross-validation quantitative and qualitative content analysis Text analysis and mining Content analysis Data Annotation Analysis Unpaired Student t test and multivariate logistic regression analysis Multivariate regression method Inductive thematic analysis Retrospective analysis
and assess the public's response	[15] [25] [31] [32] [38] [47] [53]	2017 2017 2016 2017 2019 2015 2017 2019	virus Zika virus Zika virus Zika virus Zika virus Zika virus Ebola virus Zika virus Ebola virus	series analysis Tenfold cross-validation quantitative and qualitative content analysis Text analysis and mining Content analysis Data Annotation Analysis Unpaired Student t test and multivariate logistic regression analysis Multivariate regression method Inductive thematic analysis
and assess the public's response	 [15] [25] [27] [31] [32] [38] [47] [53] [55] 	2017 2017 2016 2017 2019 2015 2017 2019 2017	virus Zika virus Zika virus Zika virus Zika virus Zika virus Ebola virus Zika virus Ebola virus Zika virus	series analysis Tenfold cross-validation quantitative and qualitative content analysis Text analysis and mining Content analysis Data Annotation Analysis Data Annotation Analysis Unpaired Student t test and multivariate logistic regression analysis Multivariate regression method Inductive thematic analysis Retrospective analysis
and assess the public's response towards EIDs	[15] [25] [27] [31] [32] [38] [47] [53] [55] [11]	2017 2017 2016 2017 2019 2015 2017 2019 2017 2017	virus Zika virus Zika virus Zika virus Zika virus Zika virus Zika virus Ebola virus Zika virus Zika virus Zika virus	series analysis Tenfold cross-validation quantitative and qualitative content analysis Text analysis and mining Content analysis Data Annotation Analysis Data Annotation Analysis Unpaired Student t test and multivariate logistic regression analysis Multivariate regression method Inductive thematic analysis Retrospective analysis Spatiotemporal and network analysis tools Basic linear autoregressive model Quantitative spatio-temporal
and assess the public's response	[15] [25] [27] [31] [32] [38] [47] [53] [55] [11] [16]	2017 2017 2016 2017 2019 2015 2017 2019 2017 2017 2017 2014	virus Zika virus Zika virus Zika virus Zika virus Zika virus Ebola virus Zika virus Zika virus Zika virus Influenza virus Influenza virus	series analysis Tenfold cross-validation quantitative and qualitative content analysis Text analysis and mining Content analysis Data Annotation Analysis Data Annotation Analysis Unpaired Student t test and multivariate logistic regression analysis Multivariate regression method Inductive thematic analysis Retrospective analysis Spatiotemporal and network analysis tools Basic linear autoregressive model Quantitative spatio-temporal analysis. Pearson correlation coefficients
and assess the public's response towards EIDs	 [15] [25] [27] [31] [32] [38] [47] [53] [55] [11] [16] [18] [19] 	2017 2017 2016 2017 2019 2015 2017 2019 2017 2017 2014 2012 2013	virus Zika virus Zika virus Zika virus Zika virus Zika virus Ebola virus Zika virus Zika virus Zika virus Influenza virus Influenza virus Influenza virus	series analysis Tenfold cross-validation quantitative and qualitative content analysis Text analysis and mining Content analysis Data Annotation Analysis Data Annotation Analysis Unpaired Student t test and multivariate logistic regression analysis Multivariate regression method Inductive thematic analysis Retrospective analysis Spatiotemporal and network analysis tools Basic linear autoregressive model Quantitative spatio-temporal analysis.
and assess the public's response towards EIDs	[15] [25] [27] [31] [32] [38] [47] [53] [55] [11] [16] [18]	2017 2017 2016 2017 2019 2015 2017 2019 2017 2017 2017 2014 2012	virus Zika virus Zika virus Zika virus Zika virus Zika virus Ebola virus Zika virus Zika virus Zika virus Influenza virus Influenza virus	series analysis Tenfold cross-validation quantitative and qualitative content analysis Text analysis and mining Content analysis Data Annotation Analysis Data Annotation Analysis Unpaired Student t test and multivariate logistic regression analysis Multivariate regression method Inductive thematic analysis Retrospective analysis Spatiotemporal and network analysis tools Basic linear autoregressive model Quantitative spatio-temporal analysis. Pearson correlation coefficients and z-test

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	[22]	2016	Bird flu	Intercoder reliability using Cohen's kappa
	[23]	2015	Ebola virus	Bivariate inferential statistics, Content analysis and intraclass correlation coefficients
	[37]	2017	Zika virus	Inter-rater agreement using Cohen's kappa
	[44]	2017	Ebola virus	Content analysis
	[48]	2017	Zika virus	Pearson's correlation
	[51]	2016	Ebola virus	Descriptive statistics
	[56]	2013	Influenza virus	Descriptive analysis
	[57]	2017	Zika virus	Spearman's rank correlation
Helps in spreading and debunking rumors and misinformation, therefore authentication is necessary	[12]	2018	Zika virus	Content and social network analysis
	[26]	2014	Ebola virus	Quantative analysis
	[43]	2018	Zika virus	Quantitative analysis and multiple logistic regression

DISCUSSION

The present systematic review was conducted to evaluate the pros and cons of social media in detecting the pandemic outbreaks of infectious diseases like Zika, Ebola, Swine flu, Bird flu, West Nile, and Nipah virus.

The very first disease studied under this systematic review was Ebola hemorrhagic fever and almost 15 articles of this infectious disease were included in our systematic review. The second EID included in our systematic review was the Zika virus whose first outbreak was reported from the Island of Yap in 2007 [58]. We have included 24 studies of Zika virus infection in our systematic review.

Influenza outbreak (H1N1) or Swine flu disease was first identified in Mexico in April 2009 [59]. A total of 07 studies of Swine flu were included. Nipah virus is a zoonotic virus that causes a range of illnesses from asymptomatic (subclinical) infection to acute respiratory illness and fatal encephalitis. Since the outbreak of the Nipah virus is very recent and occurred in 2018, we could not find any articles related to social media and the Nipah virus.

Bird flu or Avian Influenza is caused by the Influenza bird flu virus subtypes A (H5N1) and A (H9N2). The natural hosts for spreading the avian influenza disease are the birds. We have included 2 articles of Bird flu in our systematic review. The last disease included in our systematic review is West Nile caused by the West Nile virus (WNV). Approximately, 80% of the people who are infected will not show any symptoms. The largest outbreaks occurred in Greece, Israel, Romania, Russia and USA [60]. Unfortunately, we could not get many articles related to West Nile disease; hence, only 1 article was included.

To provide a systematic overview of these studies, we have segregated these studies under four categories on the basis of their application and evaluated them in terms of the EIDs studied, year of publication and method of analysis used (Table 3). The four categories are:

Category 1: Communication purpose, public health education and dissemination of the information to the public

In recent years, social media has become a major source of public health education, communication, and help in disseminating recent evidence-based information. Most of the journal articles (n=22) on this topic used social media for the purpose of communication and providing information to the public for EIDs. In 2016, Fu and fellow-researchers studied data related to the Zika virus with the help of Twitter and concluded that Twitter can be a preferred channel for communication as opposed to the government sites [13]. Wong R et al concluded that Twitter has become the most commonly used communication tool frequently used by

many local health departments to respond to novel outbreaks [23].

YouTube can be used as a significant source of information related to West Nile virus infection and should be used by various healthcare agencies but at the same time, the authors commented on the drawback of the medium as it lacks authentication and so should be used cautiously [39].

Category 2: Influence public or viewer's behavior and assess the public's response towards EIDs

Nowadays, researchers have started to estimate the public interest and response towards any disease on the basis of number or post or messages on social media. The number of social media messages about a disease in a certain time period predicts the interest of an individual towards it. Ten articles were included in this category. Monitoring information dissemination trends on social media can be a effective way of understanding the general public's interests and concerns [25]. Nagpal S et al. used YouTube video as a source of presenting clinical symptoms of infectious diseases (Ebola disease) during the epidemics, and found that these should be included in the high relevance group as it has the power to influence the viewer's behavior [38]. Seltzer EK et al. concluded that image-sharing platforms can be used for the purpose of assessing public fears and misinformation, providing awareness interventions and information exchange about public health crises, like Ebola [54].

Category 3: Predict an epidemic and disease surveillance

Social media allows the health agencies to guide the public during surveillance of an EID. In this category, 14 articles were included. According to a study, twitter can reduce forecasting error by 17-30% over a baseline that only uses historical data [16]. Twitter may allow the detection of disease outbreaks through analysis of data generated by social media [17]. Twitter data can act as a supplementary indicator to gauge influenza infection [18], the high correlation coefficient was found between the trend of our influenza-positive tweets and Influenza likeillness (ILI) trends identified by US traditional surveillance systems [19]. Twitter data is able to detect moderately small outbreaks within a few days and for large outbreaks within hours [20]. Vos SC et al. [22] concluded that tweets related to disease outbreak contained efficacy information that would help individuals to cope up with the crisis. However, social media still cannot be used as an effective platform for distributing information that could contribute to an appropriate response.

Category 4: Helps in spreading and debunking rumors and misinformation

Information about EIDs on social media is not always accurate or useful because it is usergenerated. In this category, three articles were included. Pathak R et al. in their study demonstrated that the majority of the internet videos about Ebola on YouTube were characterized as useful [40].

Social media is becoming the dominant source of information on emerging diseases, their effects on public health measures remain uncertain. Apart from the benefits, there are certain drawbacks of social media that can misguide the users as reported by the studies included in our systematic review. According to Towers et al. [10], social media is a major source of potential bias. Chandrasekaran et al. [45] reported that some sources on social media are outdated. Wood MJ revealed that social media has the potential to spread rumors [12].

According to Sharma et al., misguiding posts were more popular than posts related to information [36]. Tang L et al. concluded that lacked "theorization" social media and "methodologic rigor" and found that approximately 20%-30% of the YouTube videos about EIDs contain inaccurate or misleading information [61]. Oyeyemi S et al. found that more than half of the tweets (58.9%) were and contained misinformation inaccurate regarding the Ebola virus disease [62]. Brownstein JS et al. concluded that the information available from the Internet is evergrowing but lacks sensitivity, specificity, and may not be reliable [63]. Owing to the abovementioned drawbacks, certain steps should be taken by the government and public health professionals to evaluate the reliability and validity of social media information. The coverage of social media would be better if media organizations start designating health

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reporters who are familiar with the subject and issues. Although, social media is a powerful surveillance channel, public health professionals and government institutions must use it with caution.

This study has also some limitations. Although we performed an extensive literature search, several pitfalls do exist in our study. Firstly, we have only included the articles published in the English language. Secondly, we have limited our search only to six EIDs owing to the fact that there are a number of EIDs. Since we cannot include all of them in our systematic review, we have randomly chosen six EIDs. Lastly, there are various synonyms of EIDs such as communicable diseases or transmissible diseases but we have only included EIDs as search term in various search engines which might alter the results and introduce bias in the systematic review. Hence, the above-mentioned points should be kept in mind while performing further systematic reviews on this vital topic.

CONCLUSION

As social media has become a powerful communication channel, social media sites are on the rise with the emergence of EIDs. Enough pieces of evidence are present in the literature favoring the use of social media as a medium to disseminate information. The present review also supports the use of social media as an important medium for clinicians, public health practitioners, and non-professionals seeking health information for the detection of EIDs. Since social media do not have the capacity to replace traditional systems of gathering information about a disease, they should primarily support the existing traditional methods and be viewed as an extension of the traditional system rather than an alternative.

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