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Social media and outbreaks of emerging infectious diseases: A systematic review of literature

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Background: The public often turn to social media for information during emerging infectious diseases (EIDs) outbreaks. This study identified the major approaches and assessed the rigors in published research articles on EIDs and social media.
Methods: We searched 5 databases for published journal articles on EIDs and social media. We then evaluated these articles in terms of EIDs studied, social media examined, theoretical frameworks, methodologic approaches, and research findings.
Results: Thirty articles were included in the analysis (published between January 1, 2010, and March 1, 2016). EIDs that received most scholarly attention were H1N1 (or swine flu, n = 15), Ebola virus (n = 10), and H7N9 (or avian flu/bird flu, n = 2). Twitter was the most often studied social media (n = 17), followed by YouTube (n = 6), Facebook (n = 6), and blogs (n = 6). Three major approaches in this area of inquiry are identified: (1) assessment of the public's interest in and responses to EIDs, (2) examination of organizations' use of social media in communicating EIDs, and (3) evaluation of the accuracy of EID-related medical information on social media.
Conclusions: Although academic studies of EID communication on social media are on the rise, they still suffer from a lack of theorization and a need for more methodologic rigor.

The term emerging infectious diseases (EIDs) was first coined by Lederberg et al[1] to refer to those new infectious diseases appearing in the last 20 years. Some EIDs are caused by newly identified species of pathogens (eg, severe acute respiratory syndrome [SARS]) or pathogens affecting a new population (eg, West Nile virus). Re-emerging infections (eg, measles, drug-resistant tuberculosis) also belong to EIDs.[2] The several global or regional outbreaks of EIDs in the last decade (eg, Ebola virus outbreak between 2013 and 2016, H1N1 outbreak in 2009) coincided with the rise of social media as a source of public health information.[3] Researchers from disciplines such as health communication, public relations, medical informatics, and public health have started to explore social media's role in EID communication. The goal of the current study is to identify the major approaches and assess rigors in published research articles on EIDs and social media. It examines the theoretical

frameworks, methodologic approaches, and research findings in published journal articles. It then provides an evaluation of the current status of research and directions for future research endeavors.

LITERATURE REVIEW

As disease-causing microbes are always evolving, the appearance of new pathogens, the effects of existing pathogens on new populations, and the rise of drug-resistant bacteria (or superbugs) continue to pose a threat to global health in the form of EIDs.[2] In addition to microbial adaptation and change, several other factors also contribute to the rise of EIDs. According to Lederberg et al,[1] human demographics and behaviors, such as increased population density or individual behaviors (eg, sexual activities, substance abuse), can lead to the emergence of new infectious diseases. Modern medicine has benefited the human race at the price of millions acquiring nosocomial infections in hospitals. Food-borne illnesses, such as those associated with *Escherichia coli*, are caused by problems in food processing and handling. Economic development and land use can also lead to EIDs.[1] One example is Lyme disease, a bacterium

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(*Borrelia burgdorferi*) carried by deer whose population and contact with humans increased with reforestation. The breakdown of basic public health and sanitation can also cause deadly attacks of EIDs (eg, Ebola outbreak in West Africa, cholera outbreak in Haiti).[1] Finally, international travel and commerce spread local EIDs (eg, SARS) across national boundaries.[1]

The history of the 21st century is arguably a history of the rise of social media, computer technologies that allow the collaborative creation and sharing of information. Obar and Wildman[4] define social media as services that are based on Web 2.0 technologies and largely rely on user-generated content, by which individuals and organizations create profiles and develop social networks online. According to a recent report of Pew Research Center, the percentage of U.S. adults using social media increased from 7% to 65% between 2005 and 2015.[5] Globally, an estimated 2.34 billion people were social media users in 2016.[6] Health communication researchers and practitioners have recognized the potential of social media in health education and promotion. A systematic review of literature[7] shows that social media can be effectively used in health promotion in a number of ways, including providing information access, delivering health campaigns, and providing social support. Public health organizations such as the World Health Organization (WHO),[8] the Centers for Disease Control and Prevention (CDC), and local public health departments have started to adopt social media in communicating with the public.

Social media are a potentially useful tool for the effective communication of EID outbreak updates and essential medical information to the public. EIDs represent unfamiliar risks to the public, who often turn to both traditional media and social media for information.[9] How these EIDs are portrayed and communicated in media shapes people's perceptions of risks, which in turn have a significant impact on their decision-making process and risk management behaviors.[10] Social media have been instrumental in informing the public about recent EID outbreaks such as the Ebola outbreak in 2014 and the H1N1 outbreak in 2009.[3] Furthermore, social media users not only share EID-related information that they obtain from other sources (eg, traditional media), but also share their own personal experiences and understanding about EIDs. Because information about EIDs on social media are user-generated, such information is not always accurate or useful. It often contains rumors, misinformation, and conspiracy theories.[11] As a result, the WHO calls for social media to be used more proactively in disseminating health messages to journalists, physicians, and the general public, particularly to counter misinformation about EIDs.[8] To better understand the status of existing research on EID communication on social media, we posed the following research question: What is the current status of research on EID communication on social media?

METHODS

Eligibility criteria

This article followed the Preferred Reporting Items for Systematic Reviews and Meta-Analyses guideline. Only original peer-reviewed journal articles reporting empirical studies about social media and EIDs were included. Conference papers, book reviews, book chapters, letters to editors and replies, corrections and withdrawals, newspaper and newsletter articles, opinions and comments, and theses or dissertations were excluded. The main inclusion criteria were (1) must be original; (2) must report empirical studies; (3) must be peer-reviewed and published in English-language journals between January 1, 2010 and March 1, 2016; (4) must involve explicit analysis of social media contents about ≥1 EIDs; and (5) must be focused on user-generated contents that were produced by Web users in natural settings rather than teaching or intervention settings.

Data sources and search strategy

Five medical and health science, psychology, social sciences, and communication databases were searched: PubMed/MEDLINE, PsycINFO, CINAHL Plus, Sociological Abstracts (ProQuest), and Communication Source (EBSCOhost). Based on an exploratory literature search and World Health Organization's "Disease outbreaks by year,"[12] key words used in the search included terms for health crises ("epidemic" or "pandemic" or "influenza" or "virus" or "infectious disease" or "outbreak" or "Ebola" or "measles" or "Zika" or "Cholera" or "SARS" or "flu" or "H1N1" or "H5N1" or "H7N9" or "dengue" or "fever" or "plague" or "MERS" or "malaria" or "polio") and terms for social media ("social media" or "social networking sites" or "SNS" or "Facebook" or "Twitter" or "YouTube" or "blog" or "chat room"). The initial search yielded 569 items. First, the titles of these articles were checked for duplications by one of the authors (B.B.), and 124 duplicates were removed. Next, the abstracts of the remaining 445 articles were screened by an author (B.B.) according to the criteria previously listed. Articles meeting one of the following criteria were excluded: (1) they were not written in English, (2) they were conceptual without empirical research, (3) they did not focus on EIDs, (4) they were only concerned with the contents of nonsocial media Web sites (eg, news Web sites), or (5) the social networking platforms under study (ie, discussion forums and online groups) were established by the research team specifically for teaching or research purposes. Studies on outbreak surveillance were also excluded from the current review. After screening, 71 articles remained in the sample. These articles could not be categorized as eligible based on the information provided in the abstract. Hence, the full texts of these articles were downloaded and read multiple times to ascertain eligibility. Two of the authors (L.T. and B.B.) discussed these articles to decide whether they should be included in the systematic review. Among these, 26 articles met the inclusion criteria. Reference lists from these articles were also screened, and 4 more articles were identified. In the end, a total of 30 articles were included in this systematic review. The earliest article was published in 2010 and the latest in 2016. Figure 1 shows the article inclusion flow diagram.

RESULTS

The 30 research articles were categorized by EIDs addressed, social media studied, and research approaches taken. In terms of the EIDs studied, H1N1 (or swine flu, n = 15) received the most attention from researchers, followed by Ebola virus (n = 10) and H7N9 (or avian flu/bird flu, n = 2). A number of other EIDs, including West Nile virus, measles, Middle East respiratory syndrome coronavirus (MERS-CoV), and enterohemorrhagic Escherichia coli, only appeared in 1 article. (See Table 1 for information about articles studying each EID.)

In terms of the types of social media studied, Twitter was undoubtedly the most scrutinized social media platform and was studied in 16 articles. YouTube, Facebook, and blogs were each studied in 6 articles. Discussion forums were studied in 3 articles, and Flickr appeared in 2 articles. Finally, Instagram, Web site comments, Weibo (a Chinese microblogging platform), and Delicious were each studied in 1 article. (See Table 2 for information about articles studying each social media application.)

To provide a systematic overview of these studies, we evaluated them in terms of the topic studied, theory used, method used, and major findings. We found that these studies typically take one of the following 3 approaches: (1) assessment of the public's interest in and responses to EIDs, (2) organizations' use of social media in EID communication, and (3) assessment of the accuracy of medical information about EIDs on social media. Only 1 article fell into 2
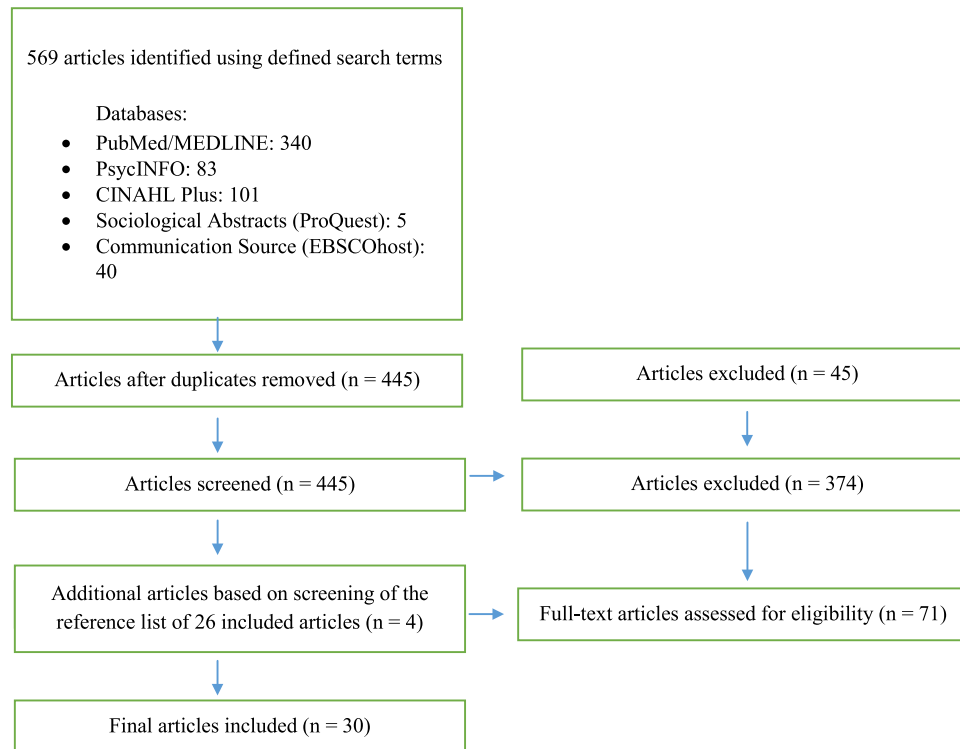
Fig 1. Preferred Reporting Items for Systematic Reviews and Meta-Analyses flow diagram illustrating literature selection process.

Table 1
Types of EIDs studied (N = 31*)

EID	N	Studies
H1N1 (swine flu)	15	Atlani-Duault et al,[13] Biswas,[3] Chew and Eysenbach,[14] Collier et al,[15] Ding and Zhang,[16] Freberg et al,[9] Gao et al,[17] Kim and Liu,[18] Liu and Kim,[19] Luoma-aho et al,[20] Nerlich and Koteyko,[21] Pandey et al,[22] Signorini et al,[23] Tausczik et al,[24] Tirkkonen and Luoma-aho[25]
Ebola virus	10	Basch et al,[26] Househ,[27] Lazard et al,[28] Nagpal et al,[29] Odlum and Yoon,[30] Pathak et al,[31] Seltzer et al,[32] Strekalova,[33] Towers et al,[34] Wong et al[35]
H7N9 (bird flu/avian flu)	2	Fung et al,[36] Vos and Buckner[37]
West Nile virus	1	Dubey et al[38]
EHEC	1	Gaspar et al[39]
MERS-CoV	1	Fung et al[36]
Measles	1	Mollema et al[40]

EHEC, enterohemorrhagic *Escherichia coli*; *EID*, emerging infection disease; *MERS-CoV*, Middle East respiratory syndrome coronavirus.
*The total number is 31 because 1 article[36] studied 2 EIDs: H7N9 and MERS-CoV.

Table 2
Types of social media studied (N = 43*)

Social media	N	Studies
Twitter	16	Biswas,[3] Chew and Eysenbach,[14] Collier et al,[15] Ding and Zhang,[16] Freberg et al,[9] Gaspar et al,[39] Househ,[27] Kim and Liu,[18] Lazard et al,[28] Liu and Kim,[19] Mollema et al,[40] Odlum and Yoon,[30] Signorini et al,[23] Towers et al,[34] Vos and Buckner,[37] Wong et al[35]
YouTube	6	Basch et al,[26] Ding and Zhang,[16] Dubey et al,[38] Nagpal et al,[29] Pandey et al,[22] Pathak et al[31]
Facebook	6	Biswas,[3] Ding and Zhang,[16] Kim and Liu,[18] Liu and Kim,[19] Mollema et al,[40] Strekalova[33]
Blogs	6	Ding and Zhang,[16] Freberg et al,[9] Gao et al,[17] Mollema et al,[40] Nerlich and Koteyko,[21] Tausczik et al[24]
Discussion forums	3	Luoma-aho et al[20] Mollema et al,[40] Tirkkonen and Luoma-aho[25]
Flickr	2	Ding and Zhang,[16] Seltzer et al[32]
Instagram	1	Seltzer et al[32]
Web site comments	1	Atlani-Duault et al[13]
Weibo	1	Fung et al[36]
Delicious	1	Freberg et al[9]

*The total number is >30 because many articles studied multiple social media outlets.

categories.[16] Studies belonging to each of these approaches are subsequently reviewed in depth.

APPROACH 1: ASSESSMENT OF THE PUBLIC'S INTEREST AND RESPONSES

Most journal articles on this topic (n = 17) used social media data to assess the public's interest in and responses to EIDs. They were typically based on manual content analysis with the occasional use of computer-assisted content analysis. Manual content analysis uses human coders to manually assign each text into a set of predetermined categories so that researchers can analyze a set of texts quantitatively.[41] Because of the use of human coders, intercoder

reliability needs to be calculated. Computer-assisted content analysis allows researchers to assess the topics, sentiments, and other contents of large amount of text through the use of computers. Common approaches used in computer-assisted content analysis include topical analysis, semantic network analysis, sentiment analysis, machine learning, and so forth.[41] Occasionally, qualitative thematic analysis and discourse analysis methods were used. Thematic analysis allow researchers to inductively identify themes and patterns within data, whereas discourse analysis focuses on the structure of language.[42] (See Table 3 for a summary of these studies in terms of EID studied, social media studied, theory applied, method used, and major findings.)

Table 3

Approach 1: Assessment of public's interests and responses

Article	EID studied	Social media studied	Theory used	Method and intercoder reliability	Major findings
Atlani-Duault et al[13]	H1N1	Web site comments	Critical theory	Discourse analysis	A discourse about "geography of blame" was present in social media but not in traditional media. This discourse blamed government, pharmaceutic companies, and "figures of otherness" for the outbreak.
Chew and Eysenbach[14]	H1N1	Twitter	None	Manual content analysis for training $k > 0.70$ Computer-assisted content analysis based on key word queries using Structured Query Language Correlation, 0.70	This study identified the frequencies of content (resource, personal experience, personal opinion, jokes, and marketing), qualifiers (humor, relief, downplayed risk, concern, frustration, and question), and links (news Web site, news blog, government, etc) and their longitudinal changes.
Collier et al[15]	H1N1	Twitter	None	Manual content analysis for training $k = 0.86$ Computer-assisted content analysis based on machine learning (SVM and Naive Bayes)	It studied 5 coping behaviors: avoidance, increased sanitation, seeking pharmaceutic intervention, wearing a mask, and self-diagnosis. These behaviors also correlated with the number of CDC-reported cases of flu.
Ding and Zhang[16]	H1N1	Facebook, Twitter, e-cards, buttons and badges, Podcasts, Flickr, YouTube, widgets, Sina blog	Risk communication	Manual content analysis No intercoder reliability	Three types of messages on Sina blog—which represents the public's voice—were experiences and witnesses from grassroots bloggers, comments and criticisms from celebrity bloggers, and prevention information. The discourse on social media rejected the official discourses in traditional media.
Freberg et al[9]	H1N1	Delicious, Twitter, blogs	Crisis communication	Manual content analysis No intercoder reliability	It studied the following variables: source of information (CDC, UK Guardian, etc), types of documents (blogs, Web sites, news, videos, etc), tagged key words (H1N1, swine flu, flu, health, influenza, social media, CDC, etc), and sources bookmarked (Twitter, WebMD, CDC, Google Food Trends, etc). CDC was the most often bookmarked information source. Blog was the most often bookmarked document. H1N1, swine flu, flu, and health were the top 4 most bookmarked key words. Twitter was the most bookmarked source.
Fung et al[36]	MERS-CoV, H7N9	Weibo	None	Counted number of Weibo posts	Chinese Weibo users' interest in H7N9 doubled compared with the previous week (t test) in response to the Chinese government's announcement of a confirmed case, but their interest in MERS-CoV did not increase significantly after the WHO announcement. Overall, Chinese Weibo users responded more strongly to H7N9 than MERS-CoV because the former was closer to home.
Gao et al[17]	H1N1	Blogs	Framing	Manual content analysis $\alpha > 0.80$	It identified 7 frames used in newspapers and health blogs: action, severity, conflict, new evidence, economic consequence, blame and responsibility, and reassurance. It also identified the dominant frame used in news articles or blogs. Blogs were more likely to use the new evidence frame. Sources used were also identified. Overall, newspapers used more sources than blogs.
Gaspar et al[39]	EHEC	Twitter	Families of coping,[43] crisis informatics	Manual content analysis $k = 0.80$	This study coded 12 coping strategies: self-reliance, support seeking, problem-solving, information seeking, accommodation, negotiation, delegation, isolation, helplessness, escape, submission, and oppression. The use of strategies differed in uncertain and certain periods.
Househ[27]	Ebola	Twitter	None	Frequencies of tweets and Google News articles about Ebola	It compared the number of tweets and the number of Google News articles and concluded that the public interest as measured in the number of tweets was related to the number of Google News articles.
Luoma-aho et al[20]	H1N1	Discussion forums	Issue arena	Manual content analysis No intercoder reliability	It used social media data to represent the "citizens' view" in contrast with the organizational point of view presented in governmental media releases. Three topics were identified: symptoms of the flu; safety of the vaccine; and the epidemic, risk groups, and its victims.

Table 3
Continued

Article	EID studied	Social media studied	Theory used	Method and intercoder reliability	Major findings
Mollema et al[40]	Measles	Twitter, forums, blogs, Facebook, and others	None	Frequencies of messages about measles	It found stronger correlation between the weekly number of social media messages and the weekly number of online news articles than between the weekly number of social media messages and the weekly number of reported measles cases.
					Topics of social media discussion of measles were measles outbreak, measles prevention, perceived risks of measles, refusal of vaccination because of religious reasons, criticism toward vaccination, trust, and the role of institutions (in descending order).
				Manual content analysis α between 0.58 and 0.81	Sentiments expressed were frustration, humor, sarcasm, concern, and relief (in descending order).
Nerlich and Koteyko[21]	H1N1	Blogs (cf. traditional newspapers in the UK)	Meta-communication	Thematic analysis (qualitative content analysis)	Three themes in print media stories were blame the official, blame the media, and "we are hooked on hype."
			Crisis communication		The interaction between traditional and digital media contributed to a heightened discourse of blame and counterblame, but also self-blame and reflection about the role of media in pandemic communication.
Odlum and Yoon[30]	Ebola	Twitter	None	Computer-assisted content analysis based on natural language processing	It identified 4 topics in the discussion about Ebola on Twitter: risk factors, prevention education, disease trend, and compassion. No frequency was reported.
Seltzer et al[32]	Ebola	Instagram and Flickr	None	Manual content analysis $r = 0.96$ (Instagram) $r = 0.89$ (Flickr)	Nine types of images were identified, including healthcare workers, West Africa, the Ebola virus, and the artistic rendering of Ebola.
					Types of texts identified were facts, fears, politics, and jokes.
					Instagram images were primarily coded as jokes or unrelated, whereas Flickr images primarily depicted healthcare workers providing care or other services.
Signorini et al[23]	H1N1	Twitter	None	Frequency counts	It used number of tweets to track public interest and disease development.
Tausczik et al[24]	H1N1	Blogs	Health belief model	Computer-assisted content analysis based on key words using LIWC	It used blog posts to monitor public anxiety by examining the language used in personal blogs. In comparison with control blogs, swine flu blog entries had significantly higher use of words related to health, death, and anxiety, and fewer words related to positive emotions. The use of language in blogs was similar to the language in newspaper articles.
Tirkkonen and Luoma-aho[25]	H1N1	Discussion forum	None	Manual content analysis No	Civilians did not trust authorities and the protective actions taken in online forums. The authorities' intervention aimed at correcting false information and shaping opinions in the discussion forums seemed to fail.
Towers et al[34]	Ebola	Search and Twitter, news videos	None	Frequency counts	Ebola-related news videos inspired tweets and Internet searches.
Vos and Buckner[37]	H7N9	Twitter	Crisis and emergency risk communication	Manual content analysis $\alpha > 0.899$ Computer-assisted content analysis based on key words using KH Coder	A large proportion of messages contained sensemaking information, but few tweets contained efficacy information that would help individuals respond appropriately to the crisis.

CDC, Centers for Disease Control and Prevention; *EHEC*, enterohemorrhagic *Escherichia coli*; *EID*, emerging infection disease; *MERS-CoV*, Middle East respiratory syndrome coronavirus; *WHO*, World Health Organization.

Public interest

In the past, researchers have used mainly surveys to measure the public's interest in an issue. More recently, they have started to estimate the public's interest in different issues by examining how much people post about them on social media (eg, Neuman et al[44]). Typically, public interest in an EID was measured in terms of the absolute or normalized number of social media messages about it in a certain time period. Researchers often attributed the wax and wane of public interest to factors such as stages of outbreak (eg, number of cases), official announcements by governmental agencies (eg, CDC) and nongovernmental organizations (eg, WHO), or the amount of coverage in traditional news media.

Fung et al[36] compared Chinese Weibo users' interest in H7N9 after the Chinese government's announcement of confirmed cases and their interest in MERS-CoV after a WHO Global Alert and Response press release. They examined the normalized weekly Weibo post numbers (ratio of illness-related posts and all posts collected) and found that Chinese Weibo users' interest in H7N9 doubled in response to the Chinese government's announcement compared with the previous week, but their interest in MERS-CoV did not increase significantly after the WHO announcement based on *t* tests. They explained this difference by suggesting that Chinese Weibo users paid more attention to H7N9, which affected China, than to MERS-CoV, which mostly affected South Korea. Househ[27] compared the numbers of tweets and Google News articles about Ebola and concluded that the public's interest as measured in number of tweets was related to the number of Google News articles. However, this conclusion was based on observation of graphs only with no statistical support. Signorini et al[23] used the number of tweets to evaluate the public's interest during an H1N1 pandemic and found it to correspond with the reported disease levels. Tausczik et al[24] tracked the public's interest in H1N1 by measuring the cross-correlation of numbers of newspaper articles, blogs, and Wikipedia visits and an examination of the visualization of these 3 time-series measures. They concluded that all 3 measures were correlated; however, the public's heightened interest in the illness was first manifested in Wikipedia searches, then blogs, and finally newspaper articles, and the decline in public interest was first observed in blogs, followed by Wikipedia visits, and finally newspaper articles. Mollema et al[40] studied the Dutch public's interest in measles during an outbreak in The Netherlands by calculating the Pearson correlation among the weekly number of tweets, other social media posts, online newspaper articles, and reported measles cases. They found that the number of social media posts was more highly correlated with the number of online news articles than with the number of reported measles cases. Towers et al[34] studied the number of Ebola-related television news videos on 2 major news networks (MSNBC and Fox News) and the number of tweets and Internet searches. Using the Granger causality test, which is a test of whether one time series is able to predict another time series, they found that the number of news videos could explain 65%-76% of the variances in the number of tweets and Internet searches.

Public response

Researchers examined how social media users responded to EIDs by studying (1) the frames or topics they used in discussing EIDs, (2) their sentiments, (3) their behavioral responses, and (4) public opinion as citizens' views.

Frames or topics of social media posts

Six articles examined the public's response to EIDs by studying the topics or frames used in EID-related discussions on social media. Chew and Eysenbach[14] identified the following 5 types of tweets about H1N1: resource, personal experience, personal opinion, jokes, and marketing. Manual coding of a small selected sample of tweets showed that resource was the most dominant theme, followed by personal experience, personal opinion, jokes, and marketing. They also tested the effectiveness of autocoding based on key word queries using Structured Query Language and were able to achieve around 70% correlation with the results of manual coding. Using the framing theory, Gao et al[17] manually coded 7 frames used in health blog posts about H1N1: action, severity, conflict, new evidence, economic consequence, blame and responsibility, and reassurance. These frames were generated based on existing studies on news coverage of epidemics (eg, Beaudoin,[45] Shih et al[46]). Mollema et al[40] inductively identified and manually coded the following 8 topics about a measles outbreak in The Netherlands on a number of social media and found that these topics were discussed in descending frequencies: outbreak information, prevention, perceived risks of measles, refusal of vaccination because of religious reasons, criticism toward vaccination, trust, role of institutions, and unrelated information. Odlum and Yoon[30] adopted a natural language processing approach, which allowed them to reach 5 computer-generated topics about Ebola on Twitter based on clusters of key words: risks, prevention, disease trend, and compassion. However, they did not report the frequency of each topic. Seltzer et al[32] analyzed the texts embedded in images on Instagram and Flickr about Ebola and manually coded them into 4 inductively generated groups: facts (6%), fears (3%), politics (4%), and jokes (23%). Finally, Vos and Buckner[37] coded the contents of H7N9-related tweets into categories derived from the crisis and emergency risk communication model and found that a large proportion of tweets about H7N9 contained sensemaking information (88.3%), but few contained efficacy information (2%). They used automated coding in KH Coder after a round of manual coding.

Public sentiments

Public sentiments toward EIDs is another topic that has drawn significant attention from researchers. Using a combination of manual and autocoding, Chew and Eysenbach[14] coded several emotions (or what they called qualifiers) in tweets about H1N1, including humor, relief, downplayed risk, concern, frustration, and question. Overall, humor was the most commonly seen sentiment, followed by concern, question, frustration, downplayed risk, and relief. Similarly, Mollema et al[40] inductively identified and manually coded the following sentiments expressed on social media during a measles outbreak: frustration, humor, sarcasm, concern, and relief, in descending frequencies. Tausczik et al[24] used blogs to monitor public anxiety about H1N1. Using LIWC software, they found that compared with non–H1N1-related blog posts, blog posts about H1N1 contained more words about health, death, and anxiety and fewer words associated with positive emotions.[24]

Behavioral responses

How the public cope with EID outbreaks can also be assessed through an examination of their social media postings. Collier et al[15] adopted the typology proposed by Jones and Salanthe[47] and analyzed 5 coping behaviors in the event of an H1N1 outbreak by analyzing the content of tweets: avoidance, increased sanitation, seeking pharmaceutic intervention, wearing a mask, and self-diagnosis. They used a combination of manual content analysis and supervised automatic content analysis using SVM and Naive Bayes. Gaspar et al[39] studied how Twitter users coped with an enterohemorrhagic Escherichia coli outbreak in Europe by manually coding the 12 strategies first proposed by Skinner et al,[43] such as self-reliance, support seeking, problem-solving, and information seeking. They found that people tended to use different strategies in times of certainty and times of uncertainty. Freberg et al[9] took a somewhat different approach by examining the kind of information

about EIDs that people bookmarked online. More specifically, they studied the extent to which social media content of different information sources, of different document types, and on different social media platforms was bookmarked on Delicious through manual coding. They found that the CDC was the most bookmarked information source, blog was the most bookmarked document type, and Twitter was the most bookmarked social media platform.

Alternative views and citizens' views

A few studies examined social media contents about EIDs as alternative or citizens' views in contrast to mainstream or governmental views. Taking a critical perspective, Atlani-Duault et al[13] conducted a discourse analysis of the discussion about H1N1 in the comment section of the Web sites of traditional print and television media in France and identified a discourse of "geography of blame," which was absent in the mainstream media. This discourse blamed the government, pharmaceutic companies, and other groups of elite villains for European epidemics. Ding and Zhang[16] studied the Chinese public's voice about H1N1 by looking at their blog posts on Sina blog and identified 3 types of messages: experiences and witnesses from grassroots bloggers, comments and criticisms from celebrity bloggers, and prevention information. They concluded that the discourse on social media rejected the official discourses in traditional media.

Luoma-aho et al used posts about H1N1 on Finnish online discussion forums to assess the citizens' view in contrast with the governmental point of view as shown in governmental media releases about H1N1. Through manual content analysis, they found that the online public did not trust the government.[25] Furthermore, although governmental messages about the outbreak were timely and factual, they failed to address the fears of the people, whose online discussion was dominated by antivaccine groups and characterized by irrational speculations and exaggerations.[20]

APPROACH 2: ORGANIZATIONS' USE OF SOCIAL MEDIA AND PUBLIC RESPONSES

Organizations, including both corporations and governmental agencies, have started to use social media to communicate EIDs to their different stakeholders. Five articles examined how different organizations used social media in EID communication through the perspective of crisis communication, and 2 articles focused on the public's responses to organizations' EID communication. Most of these studies were based on theories of risk and crisis communication. (For a summary, see Table 4.)

All 5 articles on organizations' social media messages about EIDs used manual content analysis. Among them, only 3 reported the types of social media used and the types of messages posted by organizations. For instance, Biswas[3] studied how the CDC and WHO used Twitter and Facebook in communicating about H1N1 and identified the following 4 types of messages: investigation or diagnosis, prevention, treatment, and update. He also concluded that Facebook facilitated more interactivity because of its technical features, but both the CDC and WHO focused on 1-way communication instead of interacting with the public. Ding and Zhang[16] studied how the CDC and the U.S. Department of Health & Human Services used social media during an H1N1 outbreak and found that Facebook was the most frequently used, followed by Twitter, e-cards, buttons and badges, podcasts, Flickr, YouTube, and widgets. The following types of messages were identified in descending frequencies: updates, policies and guidelines, prevention topics, official actions and efforts, general information, and scientific research, in descending frequencies. Wong et al[35] studied how 286 local health departments in the United States communicated the risks of Ebola on Twitter and identified 4 major types of messages: information giving (78.6%),

preparedness (22.5%), news update (20.8%), and event promotion (10.3%).

However, 2 studies offered more theoretical interest by comparing strategies used by different types of organizations in communicating about EIDs using traditional and social media. Adopting the situational crisis communication theory, Kim and Liu[18] studied how 13 governmental organizations and corporations communicated H1N1 on social media (Twitter and Facebook) and concluded that governmental organizations emphasized risk communication (eg, providing guidelines about how to respond to the outbreak), whereas corporations paid more attention to reputation management. Using the same data set, Liu and Kim[19] examined how governmental organizations and corporations framed the H1N1 outbreak on social media (Twitter and Facebook) and traditional media (eg, websites). They found that these organizations tended to frame the outbreak as a disaster, a health crisis, or a general health issue on traditional media, but tended to frame it as a general crisis on social media.

Two additional studies examined how the public responded to organizations' EID communication on social media and therefore were reviewed here as well. Lazard et al[28] studied the public's response to CDC's Twitter live chat about Ebola using an unsupervised text mining tool (SAS Text Miner) and identified 8 major concerns expressed by the public, such as questions about the science around Ebola and fear of travel. However, they relied on a very small sample of tweets (N = 2,155). Strekalova[33] studied the characteristics of Facebook users commenting on CDC's Facebook posts about Ebola through manual content analysis and found that men wrote more posts per person than women. Neither of these studies was able to shed light on how people responded to the specific strategies or messages used by organizations.

APPROACH 3: ACCURACY OF MEDICAL INFORMATION

Information about EIDs on social media is not always accurate or useful because it is user-generated. Five articles examined the accuracy of social media medical information about EIDs and interestingly all 5 studies in this category focused on YouTube. Among them, 3 studies were about Ebola virus, 1 was about West Nile virus, and 1 was about H1N1. Studies adopting this approach were not based on any specific communication or public health theories. These studies typically examined around 100 videos through manual content analysis. In general, approximately 70%-80% of videos contained useful information (either accurate medical information or outbreak updates) across different EIDs, such as West Nile virus,[38] H1N1,[22] and Ebola.[31] Some studies further examined the types of medical information included in these YouTube videos, such as modes of transmission, screening, treatment, and symptoms.[26,29,38] Very often, these studies tried to establish the relationship between content characteristics and popularity of videos. For instance, Dubey et al[38] found that misleading videos had a significantly higher number of views per day, but Pandey et al[22] concluded that there was no significant difference among useful videos, misleading videos, or updates in terms of views per day. Some of these studies also examined the relationship between the source and the quality of content and the number of views. Not surprisingly, Pathak et al[31] found that independent users were more likely to post misleading videos, and news agencies were more likely to post useful videos. (See Table 5 for a summary of these 5 studies.)

DISCUSSION

Our systematic literature review of published journal articles on EID communication on social media shows increased academic interest in this topic. Researchers studied social media content about

Table 4
Approach 2: Organizations' use of social media in communicating EIDs

Article	Type of EID	Type of social media	Organizations studied	Theoretical approach	Method and intercoder reliability	Major findings
Biswas[3]	H1N1	Twitter, Facebook	CDC, WHO	Outbreak communication	Manual content analysis No	Types of messages: investigation or diagnosis, prevention, treatment, and update. Facebook facilitated more interactivity because of its built-in features. However, both the CDC and WHO focused on 1-way communication instead of interacting with the public.
Ding and Zhang[16]	H1N1	All major social media	U.S. government (CDC and HHS)	Risk communication	Manual content analysis No	CDC and HHS most frequently used Facebook in communicating with the public about H1N1, followed by Twitter, e-cards, buttons and badges, podcasts, Flickr, YouTube, and widgets. The functions served by these social media were updates, policies and guidelines, prevention topics, official actions and efforts, general information, and scientific research, in descending frequencies.
Kim and Liu[18]	H1N1	Twitter, Facebook	13 government and corporate organizations	Situational crisis communication theory	Manual content analysis $\alpha = 0.77\text{-}1.0$	Governmental organizations emphasized providing instructional information to their primary audience, such as guidelines about how to respond to a crisis, whereas corporations emphasized reputation management, frequently adopting denial, diminish, and reinforce response strategies.
Liu and Kim[19]	H1N1	Twitter, Facebook	13 government and corporate organizations	Framing, crisis communication	Manual content analysis $\alpha = 0.77\text{-}1.0$	Organizations were more likely to frame the crisis as a disaster, a health crisis, or a general health issue on traditional media and were more likely to frame it as a general crisis on social media. Organizations relied on traditional media more than social media to address emotions.
Wong et al[35]	Ebola	Twitter	286 local health departments	None	Manual content analysis $r = 0.54\text{-}1.0$	78.6% tweets were information giving, 22.5% were on preparedness, 20.8% were news updates, and 10.3% were event promotion. Each wave of tweets corresponded with a major news event.
Studies of the public's responses to organizations' use of social media						
Lazard et al[28]	Ebola	Twitter	CDC	None	Computer-assisted content analysis based on unsupervised text mining (SAS Text Miner)	This study identified 8 major concerns of the public, such as expert opinions, prevention, and questions.
Strekalova[33]	Ebola	Facebook	CDC	None	Manual content analysis No	Men wrote more comments per person than women on CDC posts about Ebola.

CDC, Centers for Disease Control and Prevention; *EID*, emerging infection disease; *HHS*, U.S. Department of Health & Human Services; *WHO*, World Health Organization.

Table 5
Approach 3: Accuracy of medical information

Study	Type of EID	Sample	Reliability	Coding categories	Major findings
Basch et al[26]	Ebola	100 most watched videos	$k = 0.98$	Video characteristics (source, year uploaded, length, total number of views) Content (coded as yes or no: 19 items, such as modes of transmission, death toll in West Africa, number of cases in West Africa, quarantine, anxiety over infection, public fear, comedy skit, danger for healthcare personnel, conspiracy theory, and need for medical help and resources)	One-third of videos discussed modes of transmission, but few mentioned treatment, and none mentioned the need for U.S. funding of disaster preparedness, coordination between governments on different levels, or beds ready for containment. There was no significant difference between consumer videos and commercial television videos in number of views.
Dubey et al[38]	West Nile	106 videos	$k = 0.95$	Video characteristics (source, days on YouTube, length, total number of views) Content (coded as useful or misleading/ nonuseful; useful videos were further coded in terms of whether they contained the following items: prevention, symptom, and update)	Approximately 80% of videos contained useful information, among which 60% discussed prevention and 35% contained updates. 54% of videos were uploaded by individuals, 41% by news agencies, and 3% by healthcare agencies. Nonuseful videos had a significantly higher number of views per day.
Nagpal et al[29]	Ebola	100 most relevant videos	Third person arbitration	Source (individual or organization) Video information and quality index (5-point Likert scale regarding flow of information, information accuracy, quality, and precision) Medical information and content index (5-point Likert scale regarding components of medical information including prevalence, transmission, clinical symptoms, screening and testing, and treatment and outcome of Ebola infection)	High relevance videos (ranked 1-50) had more views, likes, dislikes, shares, and subscriptions than low relevance videos (ranked 51-100). The difference was attributed to "clinical symptoms" only.
Pandey et al[22]	H1N1	142 videos	$k = 0.97$	Content (coded into 1 of 3 categories: useful, misleading, or update) Source (CDC, UN, WHO, Red Cross, news agencies, and independent users) Video characteristics (total viewership, number of days since upload, length of video)	60% of videos were useful, 16% were misleading, and 23% were updates. No difference was found among these groups in terms of number of views.
Pathak et al[31]	Ebola	108 most relevant videos	$k = 0.68$	Content (coded as misleading or useful) Video characteristics (total number of views, likes, days on YouTube, length) Source (CDC, WHO, Red Cross, NGOs, academic or hospital, news agencies, independent users)	73% of videos were useful; the rest were misleading. Independent users were more likely to post misleading videos, and news agencies were more likely to post useful videos.

NOTE. All 5 articles studied YouTube and used the manual content analysis method.
CDC, Centers for Disease Control and Prevention; *EID*, emerging infection disease; *NGO*, nongovernmental organization; *UN*, United Nations; *WHO*, World Health Organization.

EIDs to understand (1) the public's interest in and responses to EIDs, (2) the use of social media by organizations during an EID outbreak, and (3) the accuracy of social media EID content. Although researchers are making strides in this new area of research, the field suffers from 2 main problems: a lack of theorization and a need for more methodologic rigor.

Lack of theorization

Because of their novelty, studies of EID communication on social media are not very theoretical in general. The most commonly used theories are theories of risk communication and crisis communication; however, very often they are only used to provide a general background for the study without facilitating the generation of research questions or hypotheses (eg, Ding and Zhang,[16] Freberg et al[9]). A few studies used specific theories of crisis communication to guide the construction of their research questions and data analysis. Kim and Liu[18] used situational crisis communication theory, and Vos and Buckner[37] used crisis and emergency risk communication. Other theories used in this group of studies include critical theory,[13] framing,[17] coping,[39] issue arena,[20] metacommunication,[21] health belief

model,[24] and outbreak communication.[3] The wide range of theories used is a testimony of the diverse disciplinary backgrounds of this line of research include public relations, health behavior, media, and psychology.

However, most of the studies reviewed in this article are purely descriptive and atheoretical. This could be attributed to the novelty of this research direction. Atheoretical studies are useful in that they provide readers with an idea of what happened on social media when there is an EID outbreak. However, such studies are only the first step in the scholarly study of EID communication on social media, and their findings are hard to aggregate and compare. The next step in the scholarly inquiry in this area calls for more theoretically motivated studies into the who, what, why, and how of EID communication on social media.

Furthermore, there is little or no current effort in building specific theories about EIDs on social media. Most of the existing studies reviewed here only studied 1 specific EID. Future research could develop theories about EID communication on social media by establishing new typology of message content and typology of communication strategies. Having a widely accepted typology could enable readers to compare the wide range of studies on different

EIDs on different social media platforms. Future research could also create theories about social media users' behaviors related to EID communication.

Need for more methodologic rigor

Research methods used in studies of EIDs and social media range from qualitative methods such as discourse analysis and thematic analysis to quantitative methods such as manual and automatic content analysis. However, most studies reviewed used quantitative content analysis: manual (n = 19), computer-assisted (n = 3), or a combination of the 2 (n = 2).

Intercoder reliability

Anytime quantitative content analysis is used, researchers need to demonstrate the reliability of the analysis.[48] Among the 21 studies that used manual content analysis, 7 did not report any measures of intercoder reliability. Among the 14 studies that did report intercoder reliability, Cohen κ was most often used (n = 7), followed by Krippendorff α (n = 6), and then intraclass correlation coefficient (n = 2).

Statistical tests

In addition, appropriate statistical testing is needed in this line of research. For instance, when trying to establish the factors that cause the wax and wane of public interest in EIDs on social media, researchers used a number of methods. Some only used visual inspection (eg, Househ et al[27]), which is arguably the least scientific method and should only be used as a first step in identifying the possible determinants of public interest. Some studies (eg, Mollema et al[40]) used different types of correlation tests to establish this relationship; however, it should be acknowledged that correlation is usually not enough to establish causation. One study[34] used the Granger causality test, which is a more rigorous test for the causation between 2 time series data. In fact, Neuman et al[44] pointed out that the Granger causality test is more appropriate than correlation with time lags in establishing the causal relationship between time series of media agenda and public attention.

Directions for future research

Our review of published studies also identifies a few directions for future research on EID communication on social media.

Who use social media for EID communication?

Existing studies assume that social media are an important platform for the public to seek information about EIDs and for them to share EID-related personal experiences and opinions. However, only 1 study actually examined the user profile and only in terms of sex.[33] Relying on social media for the dissemination of EID-related information without a clear idea of who is using social media for such information might even further exacerbate the digital gap between the information rich and information poor.[49] Because social media accounts often contain demographic information in users' profiles, researchers could use such information to gain a better idea of the users' profile and, more importantly, identify those subpopulations who are not accessing such useful information on social media.

How the public respond to organizations' social media strategies

A number of studies examined how different types of organizations use social media to communicate EIDs to the public; however, it is unknown whether their communication is effective. Only 2 published studies[28,33] explored how the public respond to such communication efforts, but they barely scratched the surface.

Researchers need to examine how different stakeholders evaluate and respond to the social media communication strategies used by different organizations (governmental agencies, nongovernmental organizations, and corporations). They could do so through traditional survey or experimental methods. Alternatively, they could assess the public's response by examining their responses on social media.

Small versus big data

One of the promises of social media is the creation and study of big data. Big data are typically defined as the study of large data sets using new computer analytics techniques.[50] Our systematic review shows that most of the existing studies still rely on small data (ie, the analysis of small samples of social media content through traditional manual content analysis). When used properly, sampled social media content could yield high-quality insights into EID communication on social media. However, because of the sheer amount of social media content, researchers take only very small samples from the data set. It is yet to be seen whether sampling ≤1% of social media content will yield a representative sample. Given the availability of new computer analytics techniques, such as natural language processing and deep learning, researchers could start to look at all the social media content related to an EID through a census instead of looking at a small sample.

Misinformation on social media

Our review shows that approximately 20%-30% of the YouTube videos about EIDs contain inaccurate or misleading information. However, very little is known about the misinformation about EIDs on other types of social media, such as Twitter or Facebook. When misinformation is circulated on social media to an unknowing audience, the consequences can be dire. Future research should examine the misinformation about EIDs on other social media platforms. More importantly, researchers should consider examining how social media users process the EID-related information they receive, how they evaluate the validity and accuracy of such information, and how they decide whether they will share the information with their social media contacts.

Diffusion of information

Social media are different from traditional media because they are networked.[4] In other words, information diffuses on social media through the conduit of social networks. The type of information people are exposed to on social media are determined by their Facebook friends, who they follow on Twitter, or which discussion forum they regularly visit. Future research could look into the networked nature of social media by examining how information and misinformation about EIDs diffuse on social media.

Practical implications

Our review of this body of literature also has a number of practical implications for public health professionals. First, across a number of countries and around a number of different EIDs, the pubic expressed a deeply rooted distrust toward the government (as shown in Atlani-Duault et al,[13] Ding and Zhang,[16] and Tirkkonen and Luoma-aho[25]). To successful diffuse useful information and promote prevention and timely treatment, public health professionals need to recognize this distrust in government. They could enlist alternative spokespersons as the source of their information, such as physicians, researchers, or even celebrities. Second, it appears that governmental agencies did a good job providing up-to-date information about the outbreaks to the public; however, they do not address the fear of the public enough. Given the potential of using social media to assess the public's sentiments in real life,

public health professionals could engage in 2-way communication and adapt their messages to address the feelings of their audiences.

Limitations

As with any research, this systematic literature review has its own limitations. First, studies about outbreak surveillance, which is the line of research that uses user-generated social media data to track and predict EID outbreaks, are not included in this systematic literature review. This line of research has been making rapid progress; however, using social media data to track EID trends, such as flu trends, has its challenges. In 2015, Google stopped its Web site Google Flu Trends after they grossly overestimated the flu trends in 2012 and 2013. Second, this study reviewed only published journal articles. It is possible it has left out important studies disseminated in conferences, conference proceedings, or books. Finally, as the title suggests, this article is a systematic literature analysis. It provides an overview of existing studies on EIDs and social media, but it is not a meta-analysis and does not attempt to statistically integrate the findings of existing studies.

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