Review

When Infodemic Meets Epidemic: Systematic Literature Review

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Abstract

Background: Epidemics and outbreaks present arduous challenges, requiring both individual and communal efforts. The significant medical, emotional, and financial burden associated with epidemics creates feelings of distrust, fear, and loss of control, making vulnerable populations prone to exploitation and manipulation through misinformation, rumors, and conspiracies. The use of social media sites has increased in the last decade. As a result, significant amounts of public data can be leveraged for biosurveillance. Social media sites can also provide a platform to quickly and efficiently reach a sizable percentage of the population; therefore, they have a potential role in various aspects of epidemic mitigation.

Objective: This systematic literature review aimed to provide a methodical overview of the integration of social media in 3 epidemic-related contexts: epidemic monitoring, misinformation detection, and the relationship with mental health. The aim is to understand how social media has been used efficiently in these contexts, and which gaps need further research efforts.

Methods: Three research questions, related to epidemic monitoring, misinformation, and mental health, were conceptualized for this review. In the first PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) stage, 13,522 publications were collected from several digital libraries (PubMed, IEEE Xplore, ScienceDirect, SpringerLink, MDPI, ACM, and ACL) and gray literature sources (arXiv and ProQuest), spanning from 2010 to 2022. A total of 242 (1.79%) papers were selected for inclusion and were synthesized to identify themes, methods, epidemics studied, and social media sites used.

Results: Five main themes were identified in the literature, as follows: epidemic forecasting and surveillance, public opinion understanding, fake news identification and characterization, mental health assessment, and association of social media use with psychological outcomes. Social media data were found to be an efficient tool to gauge public response, monitor discourse, identify misleading and fake news, and estimate the mental health toll of epidemics. Findings uncovered a need for more robust applications of lessons learned from epidemic "postmortem documentation." A vast gap exists between retrospective analysis of epidemic management and result integration in prospective studies.

Conclusions: Harnessing the full potential of social media in epidemic-related tasks requires streamlining the results of epidemic forecasting, public opinion understanding, and misinformation detection, all while keeping abreast of potential mental health implications. Proactive prevention has thus become vital for epidemic curtailment and containment.

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KEYWORDS

epidemics; social media; epidemic surveillance; misinformation; mental health

Introduction

Background

The global community braved the COVID-19 crisis, with multiple emerging variants, more than 6 million deaths, and 764 million cases being registered [1]. COVID-19 was dubbed "an individual and collective traumatic event," and has "directly or indirectly affected every individual in the world" [2]. Four years later, the world is still grappling with the emotional and socioeconomic aftermath of this crisis [3].

However, COVID-19 has not been the first crisis of its kind to affect global public health. Multiple epidemics have spanned the last 2 decades, causing varying degrees of instability and disease burden [4]. An epidemic is defined as "the occurrence in a community or region of cases of an illness, specific health-related behavior, or other health-related events clearly in excess of normal expectancy" [5]. When an epidemic "occurs worldwide or over a very wide area, crosses international boundaries, and affects a large number of people," it qualifies as a pandemic [5].

Epidemics are often linked to major feelings of uncertainty and loss. The 2014 Ebola outbreak caused rampant fear behaviors in West Africa [6]. The SARS outbreak has created a range of psychiatric conditions, including posttraumatic stress disorder, depressive disorders, and other anxiety spectrum disorders, such as panic, agoraphobia, and social phobia [7]. COVID-19 was associated with major stigma and psychological pressure, further aggravating feelings of guilt, shame, regret, sadness, self-pity, anger, internalized emotions, overwhelmed feelings, negative self-talk, unrealistic expectations, and perceived sense of failure [2]. During epidemics and outbreaks, mistrust of governments and health workers, misinformation, rumors, and conspiracies [8] present challenges to containment and can have a negative impact on mitigation efforts [9-11]. The particular vulnerability surrounding epidemics could render social media users highly suggestible and at risk for fake news acceptance and dissemination [12]. The substantial financial and medical burden imposed by outbreaks and epidemics, in addition to the substantial challenges arising in their progression and aftermath, further complicates the mental health toll they take on the affected population and on vulnerable communities [13].

The control strategies put in place in public health crises to contain the spread of infection are highly dependent on the transmission method and rate [14]. For instance, during COVID-19, various containment measures were adopted, including school closures, shut-downs of nonessential businesses, bans on mass gatherings, travel restrictions, border closures, and curfews [14]. These measures, although necessary for mitigation, can worsen emotional states, contribute to the exacerbation of preexisting socioeconomic inequalities in mental health [15], and lead to unhealthy coping mechanisms, such as problematic internet use, social media addiction, and emotional overeating [16-18].

During epidemics, social media platforms fulfill various functions ranging from informational support to emotional and peer support [19]. They are often a solemn companion offering a tool for connection, a space to grieve, and an instrument of outrage [19]. It is not surprising that the use of social media platforms massively increased during the COVID-19 pandemic [20], rendering them almost essential, ubiquitous, and a catalyst for change, for better and for worse [21].

Social media platforms offer significant amounts of data that can be leveraged for biosurveillance and syndromic surveillance of epidemics and outbreaks [22]. Biosurveillance provides early warning and situational awareness of events using diverse data streams [22]. Efforts directed at facilitating both the early detection and forecasting of disease outbreaks have been increasing in the past 2 decades [22]. Through the analysis of a variety of data sources, syndromic surveillance aims to discern individual and population health indicators before confirmed diagnoses are made [23] using trackable or exhibited behavioral patterns, symptoms, signs, or laboratory findings [23].

Understanding how social media shapes our experiences and preparedness during epidemics, and characterizing the roles it can fulfill, could allow for an improved apprehension of how to efficiently harness this resource for prevention efforts or alleviation of burden of disease [24].

Literature reviews have shown interest in understanding the roles social media fulfills during times of crisis, especially in the last decade [12,25-27]. Social media roles related to the facilitation of public health management, prevention of misinformation, and management of public health behavior and response were found to be of utmost priority [24], and social media topics related to surveillance and monitoring of public attitudes and perceptions, as well as mental health, misinformation, and fake news, were found to be the most well-developed research topics [28]. These 3 particular facets of social media's intersection with epidemics have not been approached in existing reviews; therefore, a gap remains for the research questions (RQs) proposed in this systematic literature review.

This Review

This review aimed to examine the "epidemic-social media" relationship and delineate its various aspects, as well as identify the methods used in harnessing social media in epidemics, with a particular focus on monitoring and surveillance, misinformation, and mental health. In light of the current state of global public health, it is vital to understand how a tool as influential as social media can shape the population's response in times of crisis and how it can be leveraged.

This systematic literature review outlines 3 RQs as follows: (1) How is social media harnessed for epidemic monitoring and management? (RQ1); (2) How is social media used for capturing and managing misinformation during epidemics? (RQ2); and (3) How is social media related to mental health during epidemics? (RQ3).

The remainder of this paper is organized as follows. Methods pertaining to the search strategy and extraction process are detailed in the Methods section. Results of the systematic review are synthesized in the Results section. Discussion of the major issues and practical implications as well as identified directions for future research are presented in the Discussion section. Conclusions are summarized in the Conclusion section.

Methods

Overview

This systematic review builds upon the preferred reporting items outlined in the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) statement [29] (Multimedia Appendix 1).

Proposed RQs

The RQs proposed in this systematic literature review examine the epidemic-social media relationship from different perspectives. The first RQ aims to identify potential uses of social media in the context of epidemic management and mitigation. The second RQ examines potential methods used in the context of social media misinformation as it relates to epidemics. Furthermore, the third RQ aims to discern potential aspects of the relationship between social media and public mental health during epidemics.

Search Strategy

A systematic literature search was undertaken at the beginning of June 2021. A collaborative planning and task allocation process was developed and updated at each stage of the study. The systematic search was conducted across multiple digital libraries—PubMed, IEEE Xplore, ACM Digital Library, ScienceDirect, MDPI, ACL, SpringerLink, arXiv, and ProQuest. Gray literature sources (arXiv and ProQuest) were used to complement the search and reduce publication bias as they provide a venue for authors to share studies with null or negative results that might otherwise not be disseminated.

The RQs were used as a guideline to identify search keywords. The search terms used included "social media" and "epidemics," with variations depending on the RQ's objectives and the database searched. For RQ1, the search results of the query ("social media" AND "epidemics") were complemented by the results of the query ("social media" AND "epidemics" AND "monitoring" AND "tracking"). The combination of these 2 queries allowed for result-filtering without overlimiting the output. The query ("social media" AND "epidemics" AND "fake news") was used for RQ2. A combination of the queries ("social media" AND "epidemics" AND "mental health" AND "support system") and ("social media" AND epidemic AND "mental health" AND addiction) was used for RQ3.

These queries were adapted to each database based on its settings. All searches used the parameters *full-text* or *all metadata* in the queries. All searches covered the time range 2010 to 2022.

Table 1 details the number of publications (without duplication) retrieved for screening from each database for each RQ.

Table 1. Output of search strategy for research questions (RQs) 1, 2, and 3.

Database	RQ1	RQ2	RQ3
IEEE Xplore	259	27	54
ScienceDirect	1180	371	240
SpringerLink	2189	367	2188
ACL	90	20	121
ACM Digital Library	672	923	1795
MDPI	178	113	70
arXiv	1544	5	0
ProQuest	226	26	127
PubMed	54	149	217

Study Selection and Data Extraction Strategy

At the initial screening stage, 3 authors assessed the titles and abstracts against the inclusion criteria. Publications included after this screening stage were then retrieved in full-text version, and subsequently screened in the eligibility stage. Three of the authors read the full-text articles independently to ascertain their relevance with regard to the search terms and the research aims. All disagreements on the included articles were resolved by consensus.

To organize the screening process, Rayyan [30], a web application facilitating the collaborative review process and screening process for systematic literature reviews, was used by the authors to import all articles initially collected and screen them following a "blind on" setting, where decisions and labels of any collaborator were not visible to others. Publications with inclusion disagreements were then identified after dropping the "blind on" setting and resolved among authors.

The inclusion and exclusion criteria specified the aims of the review and were agreed upon by all authors (Textbox 1). For a publication to be selected, it needed to address the RQs and be published within the time range. The publication was excluded if it was not a journal paper, conference proceedings paper, or peer-reviewed workshop or symposium paper. Long abstracts and posters were excluded. Publications related to the HIV or tuberculosis epidemic were excluded to preserve the homogeneity of the review. Tuberculosis is a bacterial infection with a high burden of disease, especially in developing countries, while HIV is the virus responsible for AIDS [1]. Both tuberculosis and HIV or AIDS are classified as ongoing worldwide public health issues by the World Health

Organization (WHO) and the Centers for Disease Control and Prevention [1]. Given the particularities of both tuberculosis and HIV or AIDS and the high volume of literature review publications related to them [31], the authors agreed to consider both beyond the scope of this review.

Textbox 1. Inclusion and exclusion criteria for the study selection process.

Inclusion criteria for studies

- Within the scope of one of the research questions
- Published between 2010 and 2022
- Relates to an epidemic or pandemic within the last 2 decades
- Includes the use of a social media site
- Is a journal, conference, or workshop paper

Exclusion criteria for studies

- Tuberculosis, HIV, or, noninfectious diseases
- Online forums or traditional media
- Book, e-book, letter to editor, magazine, abstracts, case reports, comments, reviews, or poster

In the data extraction stage, the final list of papers was analyzed to answer the RQs and extract pertinent information. The final stage of the PRISMA guidelines [29] was considered in this phase. The following data were extracted from selected papers: authors, publication year, epidemic studied, social media site used, theme, identified method, and key findings. All the related data were extracted independently by 2 investigators. When necessary, differences were resolved by discussing, examining, and negotiating with a third investigator.

Quality Assessment

The quality of the included studies in this review was appraised using a set checklist of quality criteria. Papers that did not fulfill at least 4 out of the 5 quality criteria were excluded. The checklist was defined as follows:

1. Are the study objectives clearly defined?
2. Are the methods clearly defined and applied?
3. Are the methods applied successfully and correctly?
4. Are accuracy values and efficiency and confidence levels reported?
5. Are limitations clearly reported and adequately represented?
6. Do the contributions outweigh the limitations of the study?

The quality criteria were formulated based on our understanding of the current state of research in this field and the research gap this systematic review is attempting to fill. The papers were assessed for their ability to answer the RQs and enrich the literature while fulfilling quality standards.

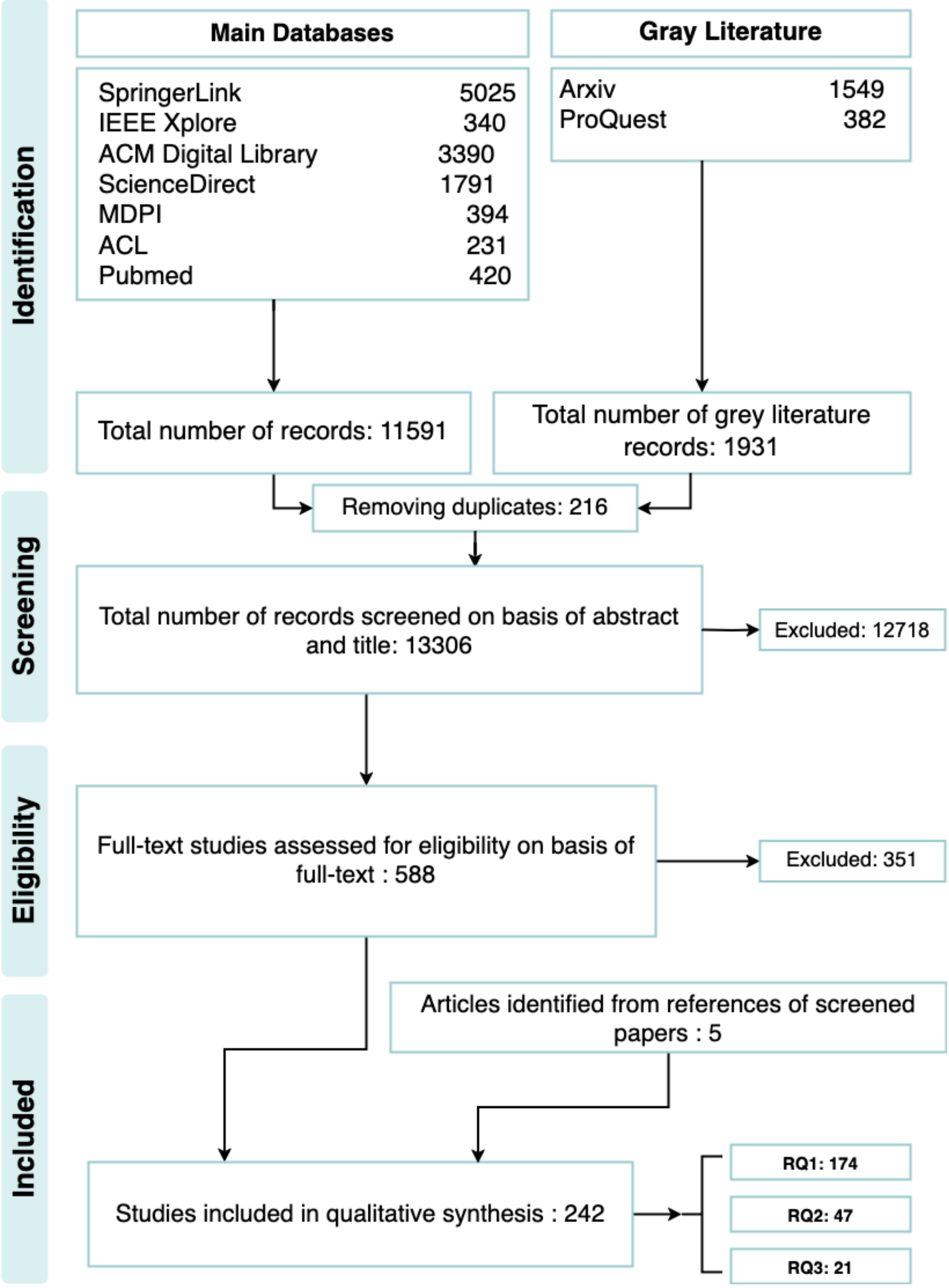
Bias was evaluated in this systematic literature review from 2 aspects. First, the risk of bias based on inclusion was limited through the use of multiple reviewers. Second, publication bias was limited by including gray literature which reports negative and null results. To enhance the quality of this review, the authors monitored the planned review tasks and ensured continuous progress monitoring. Collaborative worksheets were created to keep track of scheduled tasks and deadlines, and to note pertinent observations. Validation of the extracted data from selected papers was conducted by the authors and peer-reviewing was maintained at every stage of the systematic review process.

Results

Characteristics of the Selected Papers

The search process resulted in a total of 13,522 articles distributed over both the main and gray databases used. After the removal of duplicates, 13,306 (98.4%) titles remained. Of these, 12,718 (95.58%) studies were excluded after the title and abstract screening, as they did not fulfill the inclusion criteria. A flow diagram of the results of literature collection, screening, eligibility, and inclusion is presented in Figure 1.

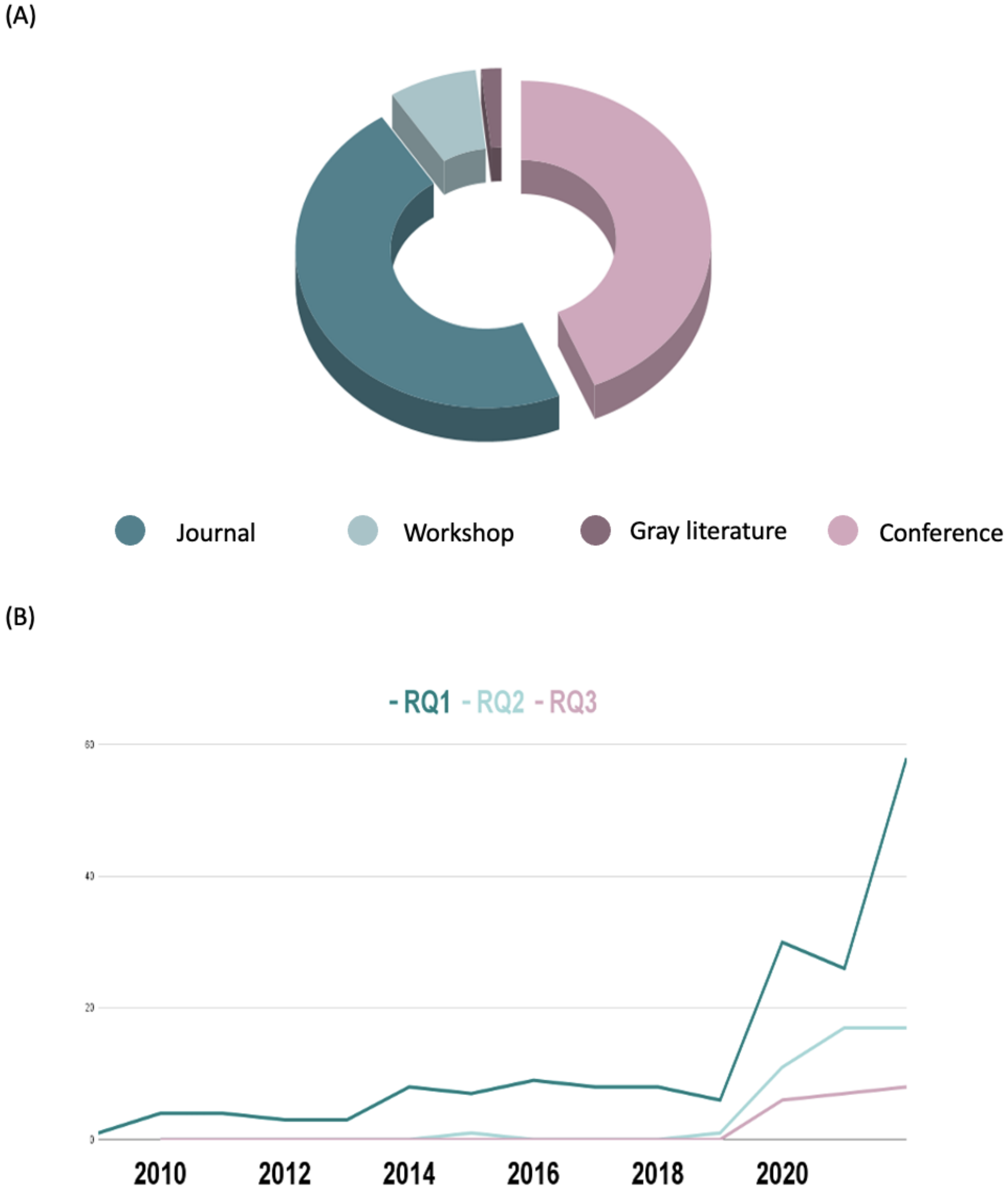
Figure 1. PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) flow diagram for the selection of articles of the literature reviewed. RQ: research question.



Of the 588 studies that were full-text screened, 351 (59.7%) did not meet the inclusion criteria. 5 (1.4%) papers were identified from reference lists of included papers. A total of 242 (67.9%) studies were selected for inclusion in this review as summarized in subsection Answers to RQs.

The papers included in the review were distributed as follows: 47.1% (114/242) were journal papers, 43.8% (106/242) were publications of conference proceedings, 7.4% (18/242) were workshop and symposium publications, while 1.7% (4/242) were gray literature (Figure 2A).

Figure 2. Distribution of selected papers by (A) type and (B) year. RQ: research question.

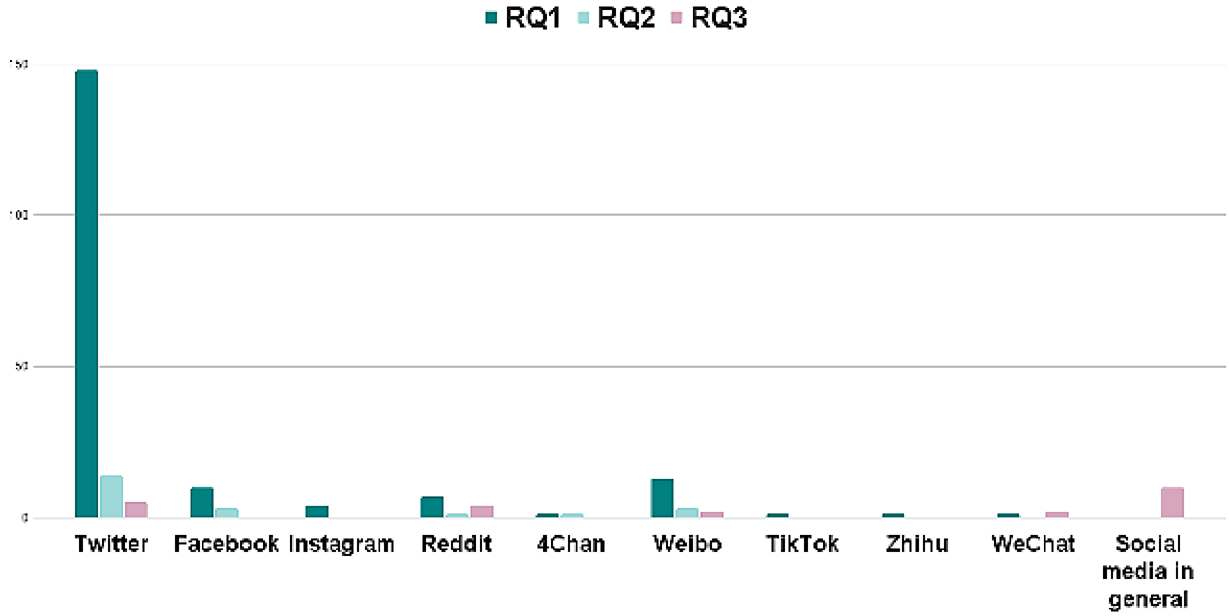


The publications spanned from 2010 to 2022. As can be seen in Figure 2B, the number of publications peaked in 2020 and continued to increase for all RQs. All the selected papers that answeredRQ3 spanned the from 2020 to 2021. A similar distribution was seen in papers that answeredRQ2, where selected papers were from 2015, 2019, 2020, and 2021. RQ1, which studies the aspects of epidemic management and mitigation using social media, included the highest number of papers and spanned the entire decade.

Social Media Platforms Used

Several social media platforms were used in the literature selected for this systematic review. X (formerly Twitter) is one of the most widely used platforms for sharing "microblogs." These short messages are called tweets and can take up to 280 characters. In contrast, Weibo, is a popular platform to share and discuss individual information and life activities as well as celebrity news in China. As can be seen in Figure 3, X followed by Weibo seems to be the platform of choice for most works aiming to study epidemic monitoring and mitigation through social media (RQ1) and epidemic-related misinformation on social media (RQ2). For epidemic and social media–related mental health aspects, most works seem to take a generalist approach rather than a platform-specific one. Compared with other social media sites, such as Facebook and Instagram, which predominantly include heterogeneous posts, X offers a more concise "microblog" format.

Figure 3. Number of selected publications using each social media platform included in the systematic literature review. RQ: research question.



Epidemics Studied

The selected literature discussed multiple epidemics (Figures 4 and 5), including vital hemorrhagic fevers and influenza-like illness (ILI).

Dengue fever and Zika fever are mosquito-borne diseases caused by the dengue virus and Zika virus, respectively, and spread by several species of female mosquitoes of the Aedes genus [1]. The disease is now endemic in more than 100 countries with potential risk in other areas [1,32]. The WHO declared the Zika outbreak of 2016 and the Ebola outbreak in 2019 as public health emergencies of international concern (PHEICs) [1].

ILI is a nonspecific respiratory illness characterized by fever, fatigue, cough, and other symptoms. Cases of ILI can be caused either by influenza strains or by other viruses, such as coronaviruses. Influenza remains a global and year-round disease burden and causes illnesses that range in severity and sometimes lead to hospitalization and death. Seasonal influenza epidemics are mainly caused by influenza A and B viruses [1]. The influenza A virus subtype strain H1N1, commonly referred to as the swine flu, disproportionately affects children and younger people. H1N1 was declared a PHEIC in 2009 and then designated a pandemic [1]. Coronaviruses include SARS, MERS (Middle East respiratory syndrome), which can be contracted through direct or indirect contact with infected animals [1], as well as COVID-19 caused by the SARS-CoV-2 virus. The latter was designated a PHEIC and a pandemic by the WHO. As of April 26, 2023, the official death toll from COVID-19 reached 6,915,268 [1].

The highest number of selected publications for all RQs related to COVID-19, followed by influenza (Figure 4). This trend is due, in part, to the volume of the COVID-19 research output [33].

Figure 4. Number of selected publications pertaining to each epidemic included in the systematic literature review. MERS: Middle East respiratory virus; RQ: research question.

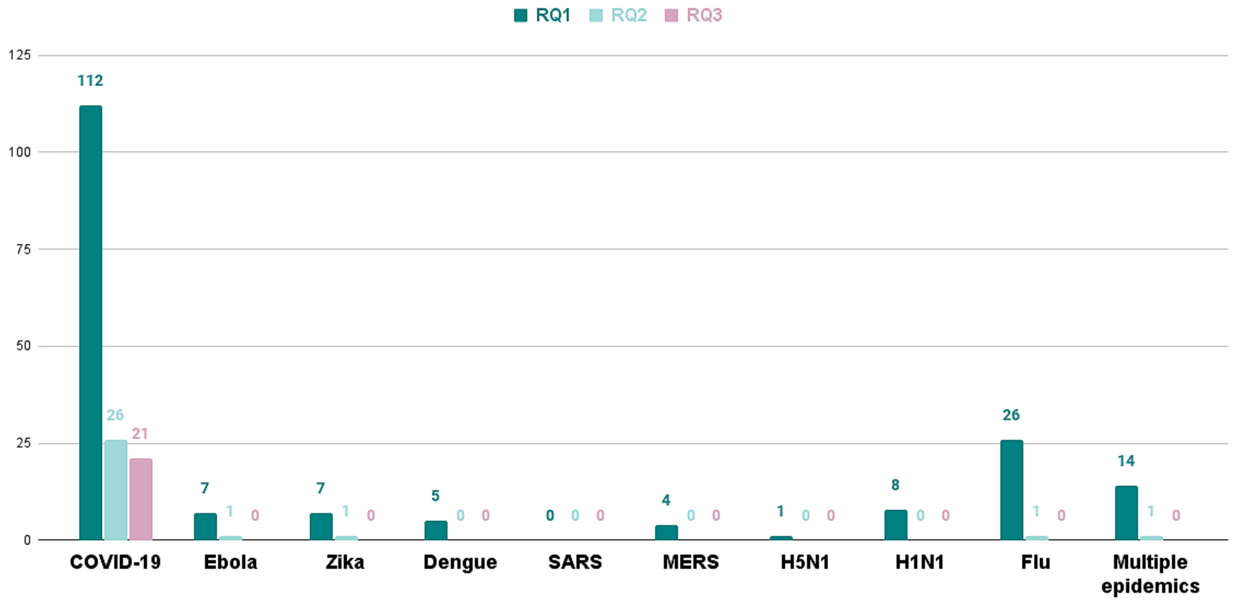
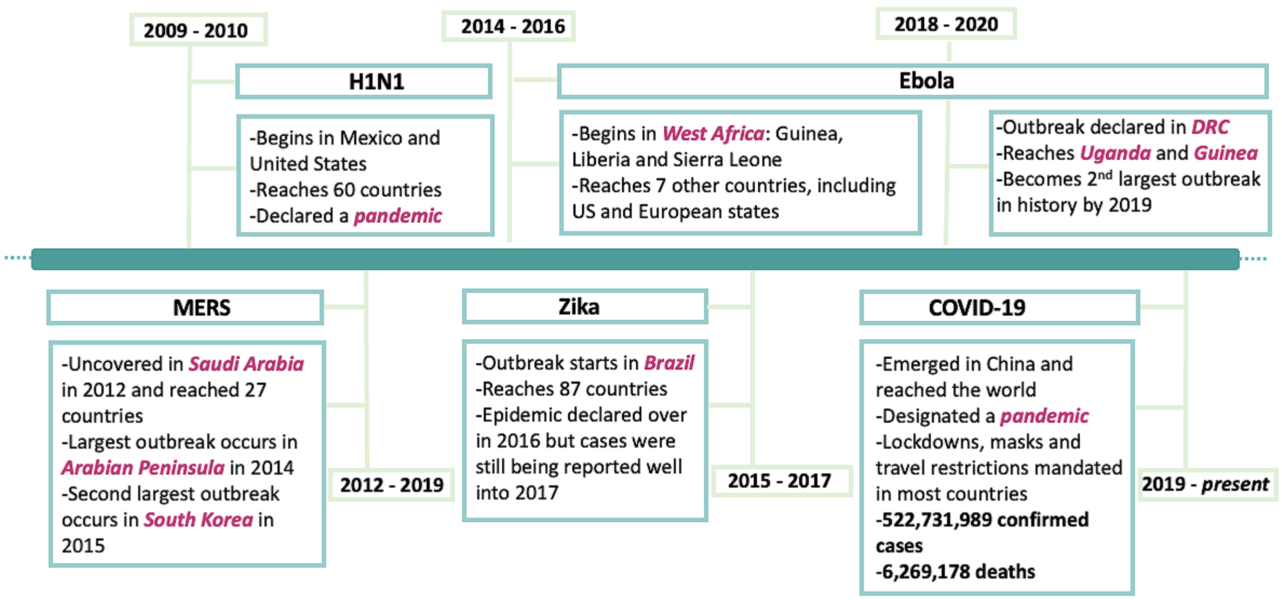


Figure 5. Timeline of the epidemics and pandemics spanning the last decade and included in the systematic literature review. SARS is pre-2009 and dengue fever has caused multiple outbreaks. Both are not illustrated in the timeline but are included in the systematic literature review. DRC: Democratic Republic of the Congo; MERS: Middle East respiratory syndrome.



Answers to RQs

Overview

A thematic analysis of the selected literature was conducted with the aim of identifying the main themes of each RQ. Themes were identified following the objectives of the paper and its results. For each theme, papers were organized by method, social media platform used, and the epidemic studied. Methods were grouped categorically. For instance, content analysis includes automated, linguistic, thematic, qualitative, or quantitative analysis, while dictionary-based classification entails a lexicon-based classification. Machine learning (ML) classification includes conventional ML models, while deep learning (DL) entails methods based on artificial neural networks with representation learning. Although it must be acknowledged that overlaps exist, the categorization used in this paper is based on the most distinctive and predominant use or theoretical approach of each method. This categorization is meant to facilitate a structured analysis and discussion of the literature by grouping papers according to their primary methodological approach, thus allowing a clearer comparison and contrast of their contributions, strengths, and limitations.

RQ1. Social Media for Epidemic Monitoring and Management

Overview

Social media platforms offer significant amounts of data, which can be potentially useful in biosurveillance and syndromic surveillance of epidemics and outbreaks.

Two main themes were identified in the selected papers that addressed how social media could be used in epidemic management, namely, (1) *epidemic surveillance and forecasting*, and (2) *public opinion understanding*.

Epidemic Surveillance and Forecasting

Several works proposed a dictionary-based classification of X for the surveillance of COVID-19 [34,35], dengue fever [36,37], Ebola [38,39], H1N1 [40,41], influenza [42-50], Zika [51,52], MERS [53], and a combination of epidemics [53-55]. Similar epidemic surveillance applications using dictionary-based classification were conducted using data from Weibo for Ebola [56] and influenza [57,58], Reddit for Zika [59], and Facebook for MERS and other epidemics [53].

Reported results indicated that epidemic surveillance can be achieved using varying strategies. For instance, social distancing–related tweets can be grouped into categories, such as implementation, purpose, social disruption, and adaptation, and used to quantify the spatiotemporal prevalence and evolution of COVID-19 social distancing on X [34]. Similarly, official social media channels of information and health organizations, such as the Centers for Disease Control and Prevention, WHO, and National Institutes of Health (NIH) can be monitored, and their X data can be classified to recognize "alarming" news and "concerning" news [35]. Dengue fever reported surveillance strategies to include systems aggregating social media data with weather and flood information [36], and using volume, location, time, and public perception as spatiotemporal dimensions [37].

Results also reported keyword-based data extraction and classification as a strategy for the creation of an Ebola monitoring platforming in China using Weibo data [56] and in Africa using X data [39], and for multiple epidemics [53-55].

Regression analysis was reported to be used for tracking and forecasting influenza [46,47,49,57] and Zika [52], and the Markov switching model was used for real-time early-stage influenza detection with emotion factors for epidemic and nonepidemic segmentation [58]. Statistical analysis was used to study the relationship between human activities collected from Sina Weibo and morbidity patterns and at-risk areas during COVID-19 in China [60].

Correlation analysis reported that X, in addition to other sources, could not provide an Ebola alert more than a week before the WHO and that X's message volume was correlated more with news article volume than with the number of Ebola cases [38].

Additional dictionary-based surveillance methods include quantitative analysis, filtering, and normalization of X data for H1N1 [40,41] and Zika [51]; mathematical modeling of influenza trends using geo-tagged X streams [42]; time series for X symptom reporting matching ILI [43]; keyword analysis for Zika risk assessment [59,61] as well as influenza risk surveillance [44] and condition aggravation [45], and upcoming influenza spike detection [50], sentiment analysis [48].

Different methodologies using conventional ML were reported to be used for dengue-related event monitoring [62] and lazy associative classification [63]; influenza detection [64-66]; influenza activity monitoring [67]; seasonal influenza trend prediction [68,69]; ILI prevalence prediction [70] and awareness or infection classification [71]; location-specific influenza state detection [58,72,73]; avian influenza outbreak detection [74]; disease-related category classification [75-77] for Ebola, MERS, and dengue fever; guideline-related category classification for ILIs [78]; supervised text classification [79]; topic classification for symptomatic manifestation and prevention of mosquito-borne diseases [80]; infectious disease analytics [81,82] and COVID-19 case forecasting [83], and X-enabled contact tracing [84] and early detection [85].

Conventional ML models used for epidemic surveillance and monitoring include support vector machine (SVM), naive Bayes (NB), and logistic regression (LR).

Several DL techniques were applied for epidemic monitoring [86-90]; fine-tuning of semisupervised model with unlabeled COVID-19 dataset [91]; disease-infected individual detection in tweets using bidirectional encoder representations from transformers (BERT)–based model and disease-infection region identification using spatial analysis [92]; classification of Zika- and Ebola-related tweets [93], COVID-19 related tweets [94], and influenza-related information [95,96]; H1N1 outbreak forecasting and individual-level disease progressing using semisupervised multilayer perceptron and a online stochastic training algorithm [97]; and correlation of X reports on H1N1 infectious disease control using gray wolf optimizer and least square method [98]. Results reported that mathematical modeling can be used to understand the influence of X on the spread of H1N1 [98,99] and information entropy to quantify the impact of social network information [100].

Results showed that social network theory and social network analysis can be used for the prediction of infected groups and early detection of contagious outbreaks in social media [101-104], and that topic modeling techniques, such as latent Dirichlet allocation (LDA) can be used for epidemic intelligence [105-110] to detect major epidemic-related events [111], monitor information spread [112], and rank epidemic-related tweets [113].

Understanding Public Opinion

Several methods were used in the selected literature to extract and analyze public opinions expressed on social media. These methods were based on content analysis of social media data, linguistic analysis, qualitative analysis, lexicon-based analysis, sentiment analysis, valence aware dictionary and sentiment reasoner–based sentiment analysis, topic modeling, conventional ML models, and DL models.

Social media content analysis was used to analyze public discourse around H1N1- [114] and Zika-related risks [61], inspect social media coverage related to influenza vaccinations [115] and COVID-19 vaccinations [116-127], measure public health concerns [128], identify stances toward policies, such as social distancing and face masks [129], identify emotional composition of online discourse before and after COVID-19 [130], and inspect the presence and escalation of negative sentiments toward China [131]. Latent semantic analysis and LDA were used to mine opinions on X related to the hashtag #IndiaFightsCorona [132]. Topic detection and sentiment analysis were performed for opinion mining, concern exploration, and public opinion analysis in the context of epidemics [133-142], and for pattern analysis [143-145]. Social media content analysis was also used for tracking information spread [146], narratives and information voids [147], monitoring engagement [148-152] and emotional response [153-161], requests for medical assistance [162], health behavior changes [163], governmental response [164,165], and physicians' opinions [166].

Public reaction tracking and investigation were performed using SVM and NB for topic and sentiment analysis [127,167-175]; SVM, NB, and random forest (RF) for social media content classification (eg, caution, advice, notifications, donations, etc) [176]; crisis analysis [177,178]; clustering for topic extraction [179]; and LR for prevention category tweet classification [180]. ML was used to analyze public discourse against masks [181], extract insights on policy response [182], and understand expressions of help-seeking during COVID-19 [183].

BERT-based models were used for public sentiment assessment of data related to COVID-19 available in X [184-186]. Multilingual COVID-19 emotion prediction was performed using a fine-tuned BERT "BERTmoticon" [187], while bias and user opinion were identified using a GPT [188]. A language model for Arabic Moroccan dialect was used for topic modeling, emotion recognition, and polarity analysis [189]. long short-term memory (LSTM), BERT, and enhanced language representation with informative entities were used to analyze the evolution of sentiments in the face of the public health crisis due to COVID-19 [190]. Bi-LSTM with an attention mechanism was used for sentiment analysis of COVID-19–related tweets [191]. Term-frequency analysis was adopted to build an emerging topic graph [192], while the k-means algorithm, LR, SVM, and NB were used to identify COVID-19–related topics [193]. An extra tree and convolutional neural network-based ensemble model was reported to have outperformed conventional ML models in a sentiment classification task [194]. French COVID-19 tweet classification was performed using FlauBERT [195], while opinion monitoring was achieved using a combination of LSTM and global vectors for word representations [196]. Convolutional neural network was used for COVID-19 personal health mention detection [197].

Findings of analyses performed in the context of Ebola, Zika, and influenza revealed that social media posts from health organizations were highly effective when incorporating visuals and that public response was more affected by these communications when they acknowledged the concerns and fear of the community [198]. In the context of Ebola, findings highlighted that online blame was directed toward the affected populations as well as figures with whom social media users had preexisting political frustrations [199].

Analysis of X discussions in relation to COVID-19 revealed the presence of negative sentiments and an association between the words "coronavirus" and "China" [200]; a gradual increase in calls for social distancing, quarantining, and working from home among social media users [201]; a growing number of anger expressions directed at individuals refusing sanitary protocols; and the frequent use of the words "family," "life," "health," and "death" [201]. Analysis of X hashtags also revealed categories, such as quarantine, panic buying, school closures, lockdowns, frustration, and hope [201], as well as mentions of mental health issues and gratitude for essential workers [201]. Other categories and themes identified or used for manual annotation of topics discussed on social media include resource provision, employment and strategies [87], statistics, prevention, hygiene, diagnosis, politics, world news [202], conspiracy, economy, mortality, origin, and outbreak [203].

Findings also indicated increased levels of connectivity and agency coordination during the early-stage response to COVID-19 [87]. Disregarding COVID-19–imposed sanitary and government recommendations was potentially linked to uncertainty in times of crisis, overwhelm by "noise" presented on social media, and varying socioeconomic factors [204].

Results revealed that social media analytics were an efficient approach to capture the attitudes and perceptions of the public during COVID-19 as mentioned in studies by Yigitcanlar et al [205] and Xia et al [206]. Fear and collectivism were identified as predictors of people's preventive intention in the context of COVID-19 [207]. "Sadness" appeared to spike after the WHO declared COVID-19 as a pandemic, while "anger" and "disgust" spiked after the death toll surpassed the hundred thousand in the United States [187].

Tables 2 and 3 summarize the methods, epidemics, and social media used in studies pertaining to epidemic forecasting and prediction and understanding of public opinion.

Table 2. Summary of methodologies used in studies addressing the first part of research question 1 (epidemic surveillance and forecasting).

Method, epidemic studied, and social media used	References
Dictionary-based classification	
COVID-19	
X (formerly Twitter)	[34,35]
Sina Weibo	[60]
Dengue fever	
X	[36,37]
Ebola	
X	[38,39]
Weibo	[56]
H1N1 or swine flu	
X	[40,41]
Influenza or flu	
X	[42-50]
Sina Weibo, Tancent Weibo	[57,58]
Zika	
X	[51,52]
Reddit	[59]
MERS[a]	
X	[53]
Facebook	[53]
Multiple epidemics	
X	[53-55]
Facebook	[53]
ML[b] **classification**	
Dengue fever	
X	[62,63]
Influenza or flu	
X	[64-73]
Sina Weibo, Tancent Weibo	[58,73]
Facebook	[68]
H1N1 or swine flu	
X	[78]
H5N1 or avian influenza	
X	[74]
MERS	
X	[75-77]
Ebola	
X	[93]
Zika	
X	[93]
COVID-19	

Method, epidemic studied, and social media used	References
X	[83-85]
Multiple epidemics	
X	[75-77,79-82]
DL[c] classification	
COVID-19	
X	[35,86,88-91,94]
Ebola	
X	[93]
Zika	
X	[93]
Influenza or flu	
X	[95]
Multiple epidemics	
X	[92]
Mathematical modeling	
COVID-19	
WeChat	[100]
H1N1 or swine flu	
X	[97-99]
Social network analysis	
COVID-19	
X	[101,102]
Influenza or flu	
Facebook	[104]
Multiple epidemics	
X	[103]
Topic modeling	
COVID-19	
X	[88,102,105,106]
Dengue fever	
X	[111]
Ebola	
X	[112]
Influenza or flu	
X	[107]
Weibo	[108]
Zika	
X	[109]
Multiple epidemics	
X	[113]

[a]MERS: Middle East respiratory syndrome.

[b]ML: machine learning.

[c]DL: deep learning.

Table 3. Summary of methodologies used in studies addressing the second part of research question 1 (understanding public opinion).

Method, epidemic studied and social media used	References
Content analysis	
COVID-19	
X	[87,123,126,141,144,146,148,151,156,157,159,160,200,201]
Instagram	[202]
Reddit	[155,157,204]
TikTok	[122]
Weibo	[151,162]
Facebook	[126,149]
Ebola	
X	[198,199]
Facebook	[199]
Instagram	[198]
Zika	
Reddit	[61]
Influenza or flu	
X	[115]
Facebook	[115]
H1N1 or swine flu	
X	[115]
Facebook	[115]
Dictionary-based classification	
COVID-19	
X	[128,129,147,153,158,165,166,203,205,206]
Facebook	[147]
Instagram	[147]
Reddit	[147]
Weibo	[129]
H1N1 or swine flu	
X	[114]
ML[a] classification	
COVID-19	
X	[127,132,164-167,177-179,181]
Weibo	[176]
Facebook	[182]
Instagram	[182]
Zika	
X	[180]
DL[b] classification	
COVID-19	
X	[118-120,130,184-189,191,194-197]
Weibo	[190]

Method, epidemic studied and social media used	References
Topic modeling	
COVID-19	
X	[116,133-135,138,143,154,163,189,192,193]
Reddit	[139]
Weibo	[136,137]
Zhihu	[183]
Social network analysis	
COVID-19	
X	[117,121,124,125,140,142,145,150,152]
Facebook	[161]

[a]ML: machine learning.

[b]DL: deep learning.

RQ2. Social Media for Misinformation Management During Epidemics

Overview

Misinformation, or "fake news," has become a social phenomenon and has received increased attention in the past few years. Although the term, "fake news" has been around since the 1890s [208], the emergence and exponential rise in popularity of social media platforms has brought the term to the "front page." Fake news can fall into multiple categories depending on the intent and form it takes [208]. For instance, fake news can be false information and rumor fabrication (eg, celebrity gossip), hoaxes (eg, doomsday 2012), conspiracy theories (Q-Anon), and satire (eg, The Onion). The intent can range from deception for the purposes of monetary or personal gain to satirizing real news.

One main theme was identified in the selected papers that addressed how social media could be used in misinformation management during epidemics, namely, misinformation detection and characterization. Three subsequent subthemes were identified based on the scope of selected literature, namely: fake news identification, fake news characterization, and information distortion and conspiracy theories.

Misinformation Detection and Characterization

Overview

The selected literature focused on the inspection of news or claims shared on social media, with the aim of classifying them based on trustworthiness. Several methods were used to analyze social media content and detect misleading information, such as expert annotation, DL models, and social network analysis. While some papers focused on technical approaches to the detection of fake news, other studies tried to identify various characteristics related to the source or propagation of fake news.

Fake News Identification

Several works performed fake news identification using DL models [209-211] with conventional ML models for comparison or as baselines. A modified 3-layer-each LSTM and gated recurrent unit were used along with 6 conventional ML classification models (decision trees, LR, k-nearest neighbors, RF, SVM, and NB) on a "Covid-19 fake news Twitter dataset" [212] to identify fake news [210]. Findings reported that the best test results were obtained by LSTM (2 layers), with an accuracy of 98.6%, a precision of 98.55%, a recall of 98.6%, and an F_1-score of 98.5% [210]. Similarly, a multilayer perceptron, LR, decision trees, RF, NB, SVM, and gradient boosting were used for COVID-19 fake news detection in tweets and concluded that RF outperformed other models with an accuracy of 78%, a recall of 100%, a precision of 85%, and an F_1-score of 83% [211]. Expert annotated tweets were used to evaluate the performance of a BERT-based misinformation detection system [213]. Findings suggest that knowledge about the domain vocabulary helps domain-adapted models in predicting the correct stance, as it did for retrieval.

Detecting misleading and fake news was also performed by several studies using methods based on pretrained transformer models, bi-LSTM networks, artificial neural networks, convolutional neural networks, deep transfer learning [214-220], and using hybrid methodologies [221-227].

A semisupervised probabilistic graphical model that aimed to jointly learn the interactions between user trustworthiness, content reliability, and post credibility for influenza posts' credibility analysis outperformed baseline models (RF and Bayesian network) with an accuracy of 71.7% on data from Sina Weibo [209]. LR was performed on a small dataset of Facebook comments to detect fake news [228]. Several ML models, including gradient boosting classifier, LR, RF classifier, and decision tree classification were used in multiple works for fake news classification on social media [229-233].

Other works seeking to curtail the misinformation of COVID-19–related news and support reliable information dissemination used manual analysis through fact-checkers as well as consensus to verify the veracity and correctness of selected tweets and social media posts [234,235]. This is illustrated in a use case analyzing Facebook and X content in both English and Amharic [234] and an Ebola study [235].

Fake News Characterization

A manual annotation of tweet sources following 5 categories (academic, government, media, health professional, and public) allowed for the creation of a gold standard dataset for training a LR model based on 6 million Arabic tweets related to infectious viruses, such as MERS and COVID-19 [236]. Rumor detection using a top-down strategy consisting of extracting posts associated with previously identified rumors reported an 84.03% accuracy for the LR classifier [236]. Higher precision was obtained at the expense of higher runtime using ML models [232]. Similarly, topic modeling based on the k-means algorithm was used to identify sources of COVID-19–related rumors [193]. An entropy-based method was used to investigate the potential control of COVID-19 rumors [237] and content analysis was used to evaluate rumor dissemination and official responses during COVID-19 [238].

Semantic correlations between textual content and attached images were mined using a pretrained convolutional neural network to learn image representations and use them to enhance textual representations and train a fake news detector [239].

Content analysis showed that fake news from multiple sources could be classified using a taxonomy of health and non–health-related types and reported that the response of the public health system was debilitated by the propagation of fake news [240]. Roots of misinformation were categorized as politically related, false medical information, celebrity and pop culture related, religious belief related, and fraud and criminality related [241]. A comparison of fake news sources between China, Iran, and the United States showed that fake science is the main "root" of misinformation in China, while counterexpertise, that is, the rejection of mainstream academic expertise, politically motivated and governmentally sourced misinformation is the most prevalent source of fake news in the United States. In Iran, discourse about COVID-19 was found to be politically manipulated by the government, while official religious figures hindered the dissemination of accurate information [241]. Statistical analysis found bias of sentiment in fake news, as well as biases of gender of the user and media use with respect to real news [242].

Bot detection using BERT was performed as a potential strategy to improve fake news detection [243]. Findings imply that the ratio of real news to fake news is very similar between human accounts and bot accounts, and bot detection could not improve the performance of the fake news detection model [243].

Findings of an information mutation study using A Lite BERT reported that misinformation propagation could potentially be exacerbated by user commentary and found a positive association between information mutation and spreading outcome [244].

The findings of a propagation analysis showed that false claims propagate faster than partially false claims and that tweets containing misinformation are more often concerned with discrediting other information on social media [245].

An investigation leveraging neural networks and quantitative content analysis that aimed to reveal the conditions that lead audiences to accept and disseminate a fake claim as it relates to the Zika virus showed that Zika tweets, including threat cues and protection cues, are positively associated with the likelihood of sharing fake news [246]. In addition, findings of a descriptive analysis showed that the quality of news sources varies considerably with regard to information on COVID-19 [247], Results of a computational analysis indicated that the COVID-19 infodemic is highly characteristic of community structure, shaped by ideological orientation, typology of fake news, and geographic areas of reference [248]. Data from X indicated that content could be labeled according to political affiliation, media source, and type of source (political, satire, mainstream media, science, conspiracy or junk science, clickbait, and fake or hoax) [248].

Information Distortion and Conspiracy Theories

Information distortion in X cascades was found to be linked to oversimplification, distortion of logical links, omission of facts, and a shift in the medical topic to political and business disputes [249]. Risk amplification by information dramatization appeared to be linked to controversial topics as well as social and cultural influences [250].

Manual content and semantic analysis and topic modeling (LDA) techniques of tweet content were conducted through an examination of key term distribution, context, and medical terminology verification [249]. In a COVID-19 5G conspiracy use case, LDA and social network analysis were used to identify several topics from dataset of tweets [251] related to "5G conspiracy" and "5G threat" and discuss topics, including 5G towers, radiation effects, network, and radiation [252,253]. Emerging COVID-19–related conspiracy theories were detected by estimating narrative networks with an underlying graphical model and using a collection of data from Reddit subreddits and 4Chan threads related to the pandemic [254]. Findings identified multiple central conspiracy theories illustrated by examples, such as incorporating the COVID-19 conspiracy into Q-Anon conspiracy, #scamdemic and #plandemic [255], 5G as the cause of COVID-19 [252,253], antivax conspiracy, Bill Gates, #filmyourhospital conspiracy [256], and Pizzagate conspiracy [254]. Table 4 summarizes the methods, epidemics, and social media used in studies pertaining to misinformation management and detection.

Table 4. Summary of methods used in papers addressing research question 2–misinformation identification and characterization.

Method, epidemic studied, and social media used	References
ML[a] classification	
COVID-19	
X	[193,210,211,221-227,229-232]
Facebook	[228,230]
Sina Weibo	[233]
Multiple epidemics	
X	[236]
DL[b] classification	
COVID-19	
X	[210,213-218,220-227,239]
Facebook	[156]
Instagram	[217]
Weibo	[219,239]
Topic modeling	
COVID-19	
X	[237,249,252,255]
Social network analysis	
COVID-19	
X	[248,252,253,256]
Reddit, 4Chan	[254]
Probabilistic graph modeling	
Influenza	
Weibo	[209]
Manual content analysis	
COVID-19	
X	[234,241,248,249]
Facebook	[234,241,247]
Weibo	[241,250]
Instagram	[241]
Ebola	
X	[235]
Quantitative content analysis	
COVID-19	
X	[213,242,245]
Weibo	[250]
Zika	
X	[246]

[a]ML: machine learning.
[b]DL: deep learning.

RQ3. Social Media's Relationship With Mental Health During Epidemics

Overview

During the implementation of restrictive measures requiring limited social contact, social media can become one of the few methods to safely engage with others, rendering it the sole support system of vulnerable populations. Mental health deterioration can manifest in expressions shared on the internet and be used to gauge the toll epidemics and subsequent containment strategies could potentially take on individuals.

Two main themes were identified in the selected papers addressing how social media can be integrated in aspects of public mental health management during epidemics, namely, (1) social media as a tool to gauge the mental health toll of epidemics, and (2) impact of social media consumption during epidemics on mental health.

Mental Health Assessment Using Social Media

Assessment of mental health state was performed using conventional ML [257-259], DL [260-262], and topic modeling techniques [263,264]. Psychological profiles of Weibo users were predicted using ML and online ecological recognition with emotional measures and cognitive indicators, such as anxiety, depression, Oxford happiness, social risk judgment, and life satisfaction [257]. LSTM was used to estimate the rate of depression in the population during the COVID-19 pandemic using Reddit data [260]. Topic modeling, expert intervention, and X data were used to evaluate the possible effects of critical factors related to COVID-19 on the mental well-being of the population in a psychological vulnerability study [263].

Findings revealed that negative emotional indicators of psychological traits increased in anxiety and depression after COVID-19 was declared an epidemic or pandemic [257,262], while life satisfaction and happiness decreased [257]. A 53% average increase in depression rate of Reddit users was noted in selected months after the pandemic [260], and negative psychological vulnerability manifested in negative emotions toward social distancing and hospitalization [263]. Financial burden was found to increase the odds of depressive nonsuicidal thoughts for individuals who suffered job loss during COVID-19 [264]. Results indicated the beginning of recovery following the immediate mental health impact of the COVID-19 pandemic [259].

Table 5 summarizes the methods, epidemics, and social media used in studies pertaining to the use of social media as a tool to gauge the mental health toll of epidemics.

Table 5. Summary of methods used in papers addressing the first part of research question 3 (mental health assessment using social media).

Method and epidemic studied	Social media used	References
ML[a] classification		
COVID-19		
	Weibo	[257]
	X	[258,259]
	Reddit	[259]
DL[b] classification		
COVID-19		
	Reddit	[260,261]
	X	[262]
Topic modeling		
COVID-19		
	X	[263,264]
	Reddit	[264]

[a]ML: machine learning.

[b]DL: deep learning.

Association of Social Media Consumption and Mental Health

Multiple papers conducted cross-sectional studies and statistical analysis to investigate the association between social media consumption and mental health complications during epidemics, particularly during COVID-19. Several studies relied on regression analysis, online surveys, the Generalized Anxiety Disorder Scale, and the Patient Health Questionnaire.

Findings revealed that frequent Sina Weibo use was associated with higher anxiety, depression, and a combination of both [265], and compulsive WeChat use was associated with social media fatigue, emotional stress, and social anxiety [266]. Frequent use of WeChat during COVID-19 was also associated with depression and secondary trauma and was found to be a significant predictor of both [19], while close contact with individuals with COVID-19, along with spending ≥2 hours daily on COVID-19–related news on WeChat was associated with probable anxiety and depression in community-based adults [267]. The association between social media consumption and anxiety and depression was found to be statistically significant

[265,268,269] and positively associated with emotional overeating and anxiety in individuals with neuroticism [18].

The association between the mental health of students receiving higher education and social media use during COVID-19 confinement was analyzed, and results indicated that students in the 18 to 24 years age group, who were not in a relationship and who had lower academic results, presented the highest levels of addiction to social media [16]. Significant positive associations were found between relatedness, need, frustration, and social media addiction, as well as between social media addiction, depressive symptoms, and loneliness [17]. Excessive social media use was also found to fully mediate the relationship between COVID-19–related life concerns and schizotypal traits [270].

Appropriate guidance of adolescents in the use of social networking sites was found to have a potential impact on the mitigation of negative emotions during the COVID-19 pandemic [271].

On the positive side, social media use was found to be rewarding for Wuhan's residents through information sharing and emotional and peer support [19]. Social media breaks were reported to have the potential to promote well-being during the COVID-19 pandemic [19]. In addition, positive mental health and mindfulness appeared to serve as protective factors, and positive mental health was found to be a mediator between the COVID-19 burden and addictive social media use [272].

Table 6 summarizes the methods, epidemics, and social media used in studies pertaining to the association of social media use with mental health issues during epidemics.

Table 6. Summary of methods used in papers addressing the second part of research question 3 (association of social media consumption with mental health).

Method, epidemic studied, and social media used	References
Statistical analysis	
COVID-19	
WeChat	[19,266]
Sina Weibo	[265]
Social media in general	[16-18,267-273]

Discussion

Principal Findings

This systematic literature review conceptualized 3 RQs to investigate if, when, and how social media can be harnessed for successful epidemic management and mitigation, effective curtailment of fake news propagation, and a refined understanding of social media's relationship with mental health during epidemics. It presented a systematic categorization and summary of methods, social media sites, and epidemics broached in the 242 selected works and identified potential research directions and practical implications related to the RQs.

Papers selected pertaining to RQ1 comprised the highest number of papers and included publications from all years of the decade, illustrating continuous and ongoing efforts by the scientific community to harness social media's potential for improved containment measures during epidemics.

COVID-19 was found to be the epidemic most studied in selected papers. This is due to the rapid increase of COVID-19–related publications since the first year of the pandemic. The frequency of publication and the volume of the academic output contributed to the creation of the COVID-19 Open Research Dataset [33]. A similar rising trend was seen in RQ2. This can be explained by the emergence of the "fake news" phenomena on social media and its particular increase in times of crisis. The selected publications answering RQ3 were published from 2020 to 2022. Papers that pertained to RQ3 were much lesser in number than those that pertained to RQ1 and RQ2. Given the mental health aspect of this particular RQ, a potential inference can be made suggesting a very recent interest in mental health as it relates to social media and epidemics. X was found to be the most used social media site in the selected literature, potentially suggesting its attractiveness to works conducting linguistic analysis and classification tasks. This can also be due to the differences in the popularity of social media sites by geographic location and key demographics. The availability of application programming interfaces to crawl data is also a major factor in choosing specific social media platforms as data sources.

General Discussion

The systematic literature review presented in this paper differs from existing reviews and aims to cover a different gap in the literature. Existing works have taken an interest in a broader range of crises, including noninfectious diseases and health risk behaviors [12], disasters in general [25], and new and reemerging infectious diseases [26]. Focus was directed toward effectively targeting vulnerable populations to test interventions and improve health outcomes [12], collective behavior [25], and generalized perspectives on emergency situations [27]. Differences other than scope include data sources, time range, and volume of literature. The review presented in this paper covered a broader time range, included gray literature, and reviewed a sizable volume of research papers.

The review's findings indicated that social media was found to be an effective way to understand the public's reactions and engagement during epidemics [205]. Monitoring topics of discussion during epidemics allowed for insights on whether aspects of epidemic management needed improvement, whether the public agrees with government decisions, and which emotions are linked to the onset of epidemics and mitigation protocols [198,204-206]. Analysis of opinions related to aspects, such as COVID-19 vaccinations were proposed and could be used to give feedback to governments and health organizations to implement better suited protocols [116,122,124-126] for mitigation, and to identify topics of misinformation, and therefore offer clarifications or conduct further awareness efforts to combat rumors and conspiracies [254]. Results also indicated that social media can be used in case forecasting [83], X-enabled contact tracing [84], early detection [85], tracking adherence to preventive guidelines, such as wearing masks and social distancing [205,206], and monitoring symptomatic self-expressions of infection [80]. Misinformation detection on social media was performed as a classification task, manually using experts and fact checkers, and using artificial intelligence techniques; however, presented several challenges. Misinformation often used language styles of academics and health professionals to deceive the public [236] and propagated faster when it included higher levels of threat due to the collective stress reaction it generated [246]. “Troll” accounts were found to play the second most prominent role is misinformation spread and present a “substantial cause for concern” [248]. Other challenges of misinformation detection related to limitations of studies due to the use of small batches of data [252], false positives [228], and a “politicization” of neutral health emergency crises [235].

Although epidemics were found to cause negative emotions and mental health issues [260,262,263], many expressions of positive emotions were noted [257], reflecting group cohesiveness rather than pure personal emotions. Group threats contributed to the manifestation of more beneficial behaviors and social solidarity [269]. Viewing heroic acts, speeches from experts, and knowledge of the disease and prevention methods were associated with more positive effects and less expressions of depression [269]. Media content, including useful information for self-protection was found to be potentially helpful to people during epidemics and may enhance active coping, prevention behaviors, and instill a sense of control [269]. The use of social media during epidemics, although linked with manifestations of anxiety and depression, appeared to benefit Wuhan residents and was perceived as an important activity during lockdown [19]. Balancing social media use to obtain ample informational as well as emotional and peer support, while avoiding the potential mental health toll, is a difficult task for users, especially without the availability of alternative and easily accessible sources of health information [19].

Using social media data for mental health assessment has its challenges and limitations. It can add a population or demographic bias to results, given that some social media sites are predominantly used by younger people or are more or less popular depending on the country [257,263]. Depending on the social media site (eg, Reddit), the user pool skews younger, and thus could be more prone to depression [260]. Moreover, some analyses are based on a weekly basis, with a relatively large granularity, which has certain influences on reflecting the changing trend of social mentality in a timely manner [257]. The qualitative nature of the results obtained and interpreted by domain experts limits the generalization of the findings and requires more corroborating results. Consequently, findings may need additional data to be strengthened [260,263]. As for works pertaining to the association of social media consumption with psychological outcomes, a causal link has not been established due to the cross-sectional nature of the contributions. Studies reflected a single point in time for participants, therefore, further longitudinal studies are necessary. In addition, the surveys were conducted on the web, and consequently, respondent bias is possible [265]. The recruitment of all participants from the same country and from one social media platform can introduce bias to studies [266,268], in addition to potential gender biases and sample representativeness [18,19], and recall bias related to self-reporting [269]. The results could not exclude the possibility of residual confounding caused by unmeasured factors.

A change can be seen in the evolution of research themes over time and through different epidemics. A sizable number of works focused on the influenza epidemic surveillance using lexicon-based and dictionary-based classifications, as well as classical ML techniques. This volume of literature could potentially be linked to the influenza prediction “wave” that preceded, paralleled, and followed the dereliction of the “Google flu trend” after its failure to predict major outbreaks [274]. Although various methods were used, ML and DL techniques were most frequently used for COVID-19 surveillance. Scientific contributions evolved with the emergence of more epidemics. COVID-19 appeared to have benefited from the digitization of literature as well as the development and improvements taking place in the fields of natural language processing, ML, DL, social network analysis, and topic modeling. The global nature of the COVID-19 crisis generated an influx of publications and contributions. The theme of misinformation management has also evolved with epidemics and with the proliferation of social media fake news, bots, troll accounts, and widely propagated conspiracy theories. COVID-19 has been the subject of multiple controversies and conspiracies, which encouraged scientific efforts to study potential curtailment methods. As for the mental health aspect, all publications pertaining to the scope of RQ3 were related to COVID-19, and it appeared that previous epidemics were not subject to social media association analysis. This could be due to the fear linked to COVID-19 and the challenging nature of sanitary measures such as global lockdowns and social distancing, which led to an increase in social media reliance. It could also be due to the decade’s zeitgeist which brought online mental health discussions and awareness front and center.

Identified Issues

One of the major issues identified was the lack of preemptive measures building on the results of previous studies and aiming to implement social media–enabled processes in real time or near real time. Lessons learned are not efficiently integrated in crisis mitigation measures nor used as building blocks for optimized proactive prevention. A synergy between government health agencies, research communities, and the public would allow for the success of social-media public health initiatives. Such collaborative efforts require effective and trustworthy interactions. This highlights an additional issue related to the relative inefficiency of social media campaigns. Populations need to be targeted for both informative purposes and for active emotional support. Understanding public opinion is useful to gauge sentiments and reactions, and therefore it is important to remedy the gap for applications integrating extracted opinions in targeted epidemic management.

Because of the medical and financial burden of epidemics, mental health concerns are often ignored by both governments and the public. As a result, the manifestation of several mental health–related symptoms becomes more prevalent as epidemics progress. In the case of the Ebola outbreak in 2014, symptoms of posttraumatic stress disorder and anxiety-depression were more prevalent even after a year of the Ebola response [199]. When limited resources are geared for epidemic containment, the health care system focuses majorly on emergency services. Therefore, individuals with substance abuse and dependency disorders may see deterioration in their mental health [13]. During community crises, event-related information is often sought in an effort to retain a sense of control in the face of fear and uncertainty and their psychological manifestations. When misleading misinformation is propagated on social media, perceptions of risk are distorted, leading to extreme public panic, stigmatization, and marginalization [13]. Psychological interventions and psychosocial support would have a direct impact on the improvement of public mental health during epidemics.

Directions for Future Research

We identified several issues and gaps in the literature related to the RQs of this systematic literature review and suggest potential paths for future research.

Given the recognized impact of epidemics on mental health and the prevalent use of social media platforms during times of crisis, it is necessary to explore the aspects of social media leading to mental health deterioration during epidemics. Potential factors range from increased consumption levels of social media, social media addiction, emotional fatigue due to overwhelm, and consumption of "sad" content. Investigating which aspects of social media use are responsible for worsening states of mental health and mental health disorders would allow a targeted approach to curbing this negative impact during times of crisis. As for health-related fake news, it is important to understand what makes citizens prone to engaging in fake news sharing. Specifically, features identifying both an individual's and a group's susceptibility to believe and share misinformation need to be determined and categorized. Levels of education, geographic and demographic profiles, cultural influences, and psychological vulnerability are potential features requiring further investigation in their association with fake news dissemination on social media and within communities.

Epidemics are rapidly changing phenomena requiring fast interventions and decision-making. Although postcrisis analysis is imperative for an improved understanding of lessons learned, proactive epidemic management is vital and would have the most impact on mitigation efforts. Integrating artificial intelligence techniques into this proactive surveillance could further optimize this process.

In addition, misinformation propagation has a significant impact on the success of interventions given that both the components of exaggerated fear and apathy linked to misinformation can hinder management efforts. However, the investigation of misinformation needs to be extended to include potential links between misinformation and mental health deterioration.

Practical Implications

This work has several potential practical implications pertaining to different entities.

Implications for governing entities include the development of an efficient misinformation correction strategy to fight incorrect information, rumors, and conspiracy theories related to epidemics; the development of clear communication channels for knowledge dissemination to build trust with the public; the development of interventions to limit the impact of epidemics on stress responses (anxiety, depression) due to distorted risk perceptions; the bolstering of public awareness efforts on sanitary measures and proactive protection; and the insurance of the supply of medical staff available to treat patients, as well as psychological support staff to assist patients and their families in navigating the ramifications of infection and loss of loved ones.

Implications for social media platforms include taking a leadership position in the management of epidemic-related fake news by implementing built-in fact-checking processes and assisting health agencies and scientific entities in disseminating factual information about the disease, its symptoms, its potential risk, and efficient sanitary measures for the public to adopt.

Implications for the public include improving community resilience during epidemics using social media groups and assisting in combating misinformation.

Limitations

The results of this review should be considered in light of several limitations. The data sources used in this review did not cover all existing scientific databases, and therefore, cannot generalize findings to the entirety of the literature. The scope of the review focused on specific aspects of the epidemic-social media relationship, and so does not provide a general overview. Although the process of data extraction and analysis was undertaken with extreme diligence, there can be potential for bias. Despite our recognition of the inherent limitations of any search strategy, we have ensured our commitment to the rigor and transparency of the systematic review process.

Conclusions

Given the collective experience of epidemics, responses by communities can often provide insight into the degree of adherence toward preventive measures as well as mitigation protocols. In an effort to control the spread of epidemics, governments, public health institutions, and health care professionals generally issue guidelines for the public through online portals, news sources, and in the past decade, social media. Online "chatter" can indicate the public's response to these guidelines, and their sentiments toward the epidemic itself or specific topics related to it, such as vaccinations, treatments, mortality rates, etc. Mitigation efforts require collaborative strategies and public involvement; therefore, gaining insight into public opinion and response can prove vital in the success or failure of such efforts.

It is evident that epidemic preparedness and mitigation protocols need to be adjusted to deal with the special challenges that accompany the technological revolution taking place, especially in light of the considerable impact of the ongoing infodemic. In addition, it is vital to have effective ways to exploit the full potential of social media without risking the toll it could potentially take on users' mental health. The systematic literature review presented in this paper covers several key aspects of the relationship between epidemics and social media, especially with respect to fake news and mental health. Methods used to answer RQs are categorized. The findings of this review could shed light on broader implications related to data quality concerns and privacy considerations in epidemic surveillance, thus highlighting the lack of works proposing ethical, legal, and technical frameworks to accompany scientific efforts. Learning from past crises and integrating a digital and social media-enabled infrastructure into public health protocols could make a difference in future preparedness levels.

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Data Availability

The datasets generated during and analyzed during this study are available in the Github repository [275].

Authors' Contributions

CA and MG conceived the study. CA and IK designed the experiments. CA, IK, and MG carried out the research. CA and IK prepared the first draft of the manuscript. MG and KB contributed to the experimental design and preparation of the manuscript. All authors were involved in the revision of the draft manuscript and have agreed to the final content.

Conflicts of Interest

None declared.

Multimedia Appendix 1

PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) checklist.
[DOCX File , 33 KB-Multimedia Appendix 1]

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Abbreviations

BERT: bidirectional encoder representations from transformers
DL: deep learning
ILI: influenza-like illness
LDA: latent Dirichlet allocation
LR: logistic regression
LSTM: long short-term memory
ML: machine learning
NB: naive Bayes
PHEIC: public health emergency of international concern
PRISMA: Preferred Reporting Items for Systematic Reviews and Meta-Analyses
RF: random forest
RQ: research question
SVM: support vector machine
WHO: World Health Organization

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