Supplementary Information

Digital public health surveillance: a systematic scoping review

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1 Supplementary Note 1: Search Strategy Details

1.1 Search Strings Formation

To form the search string for automatic database search, we applied the following non-linguistic and linguistic techniques.

Non-linguistic— We conducted a literature review and considered tentative keywords used by the existing reviews that investigated the application of Internet-based data for different aspects of public health surveillance. Also, we drew on our experience of applying social media analysis for public health surveillance and included key terms that we frequently used in our relevant studies.

Linguistic– To enrich our search strings with more context-relevant strings in the context of digital public health surveillance, we implemented the following natural language processing (NLP) techniques.

1.1.1. Data collection and preparation

We imported the `title`, `abstract`, and `discussion/conclusion` of the articles in the QGS set to separate '`.txt`' files and used this corpus as the input to our natural language processing algorithms. Due to the complexity and diversity of natural language content, this data was not immediately ready for analysis. We implemented the following data preparation steps iteratively. Each step performed in the n^{th} and final iteration is described below as well as its evolution throughout our iterations.

Step ❶ Convert text to lowercase: We used this for all three iterations. We removed case sensitivity to ensure we do not analyze a word's capitalization as a separate case than its lower-case counterpart.

Step ❷ Removing numbers and punctuations: We used this for all three iterations. This joined hyphenated words together, rather than separate them.

Step ❸ Removing stop-words: Stop-words are common words that provide no meaning on their own, such as 'the', 'this', and 'could'. In this step, we removed the default set of stop-words in the `tm_map` package for `R`. Moreover, we added a new set of stop words specific to academic publications, such as 'paper', 'research', 'propose', 'section', and 'aim'.

Step ❹ Strip Whitespace: We removed excessive whitespaces such as newlines, double spaces, and tabs.

Step ❺ Stemming: We did this for all three iterations. Stemming is the process of reducing words to their origins by removing suffixes.

The cleaned dataset was used to implement the following methods. The extracted strings using this corpus is presented in Supplementary Figure 1.

1.1.2. Lexical Association and language modelling

The traditional automatic keyword extraction methods (e.g. Term Frequency-Inverse Document Frequency (TF-IDF)[1]) use basic document features such as the frequency of terms and the document length. Using these features, relevant terms can still stay independent of other content-carrying terms in the document, which contributes to overlooking the context surrounding terms when measuring their relevance. This is a weakness shared by all *bag of words* approaches. Thus, to extract the keywords for our automatic database search process, we used `lexical association` between the terms in the cleaned corpus, which quantitatively determine the strength of association between two or more words based on their co-occurrence in a corpus [2]. The intuition behind using *lexical association* is the basic assumption that a context in which a word is used can often influence its meaning [3]. Thus, the words that are highly associated with each other occur together, more often than expected by chance, have a particular function and can be considered lexically associated terms. There is a high chance that these words (together) appear in other contextually relevant documents.

To calculate lexical association (i.e. co-occurrence knowledge), we use statistical language models (LMs), which assign probabilities to sequences of words based on their prior history. Using the *chain rule of probability*, we can decompose the probability of any sequence $w_1^n = (w_1 w_2 ... w_n)$ to:

$$P(w_1 w_2 ... w_n) = \prod_{i=1}^{n} P(w_i | w_1^{i-1}) \tag{1}$$

where $P(w|h)$ assigns a probability to term hw, considering some history h, and word w [4]. An *n-gram* model is a sequence of n words that approximates the probability of each word only to the last $n-1$ words: 'social media' and 'public health' in *'social media analysis for public health surveillance'*, are bi-grams (2-gram). Supplementary Figure 1 shows a directional graph of the bi-grams that we extracted from the QGS corpus. The directions in this graph present the order of the most frequent bi-grams. For

[1] Liu F, Liu F, Liu Y. Automatic keyword extraction for the meeting corpus using a supervised approach and bigram expansion. In 2008 IEEE Spoken Language Technology Workshop 2008 Dec 15 (pp. 181-184). IEEE.

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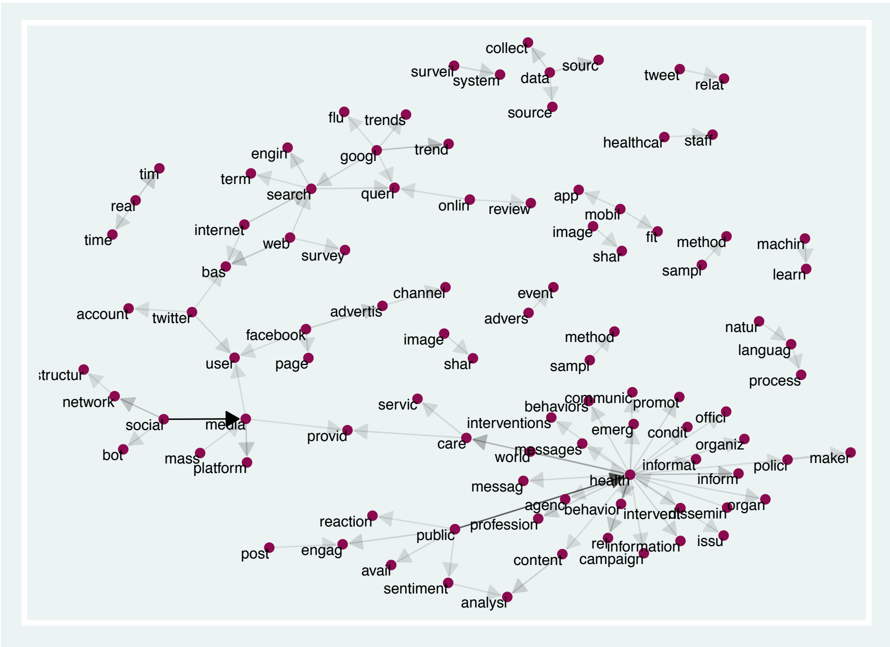
example in google→query, the word google comes before the word query, when defining the search strings.

Supplementary Table 2 lists the keywords related to each of the surveillance and digital platforms categories and can be formulated as below:

$$\texttt{Health} + t_1 \wedge (t_2 \wedge [w_1 \vee w_2 \vee \ldots \vee w_i]), \text{ where } t_1 \in C_1 \text{ and } t_2, w_i \in C_2.$$

For example, 'surveillance + health + social media' would be one of the search strings for automatic search.



Supplementary Figure 1: Directed graph of common bi-grams formed from the QGS set. These bigrams were used for defining the search strings (filters)

Supplementary Table 1: C_1: Surveillance-related keywords, C_2: Social media-related keywords. λ : empty string, |: or. The terms *infodemiology* and *digital epidemiology* were added to this list for the last round of searches.

C_1	C_2
Surveillance	Social [media, network, listening]
Public	[Facebook, Twitter, Instagram, Yelp, Flicker, Reddit, Quora, YouTube, (micro)blog, Wikipedia, Google+, Google-plus, Tumblr, MySpace, Weibo]
Crowdsource	Web | Internet [λ, forum, search, channel]
Population	Tweet
Community	Google [trends, search, query]
Monitor	Search engine
	Online [review, query, platform]

1.2 QGS

To assess the performance of our search strings in identifying Digital Public Health Surveillance (DPHS) studies in different databases, we created a Quasi Gold Standard (QGS) of 80 related papers. One author manually reviewed all the manuscripts published in the Journal of Medical Internet Research (JMIR)/Public Health and Surveillance (PHS), American Journal of Public Health (APHA), Journal of Public Health (JPH), and Journal of the American Medical Informatics Association (JAMIA) from 2017 to 2018 and selected papers based on their title, abstract, and conclusion. These papers all were used to complement the search strings of the review.

We used the number of records retrieved from database search–using our defined search strings to evaluate the effectiveness of our search process. The sensitivity of this process was defined as follows:[55]

$$\texttt{Sensitivity:}\frac{\texttt{number of QGS articles retrieved}}{\texttt{number of QGS articles indexed in the searched databases}} \quad (2)$$

The searches, using the search strings defined in Supplementary Table 2, in Global Health, Web of Science, PubMed, and Google Scholar retrieved 67 records (before applying the inclusion/exclusion criteria) of the 80 articles in the QGS set. As of these 80 articles were indexed in the searched databases, the precision of our search strings in retrieving the QGS set is 84%. Seven of these records were excluded during the `study selection` phase, which improved the sensitivity to 92%. One reason that our search process could not achieve a sensitivity of 100% is that four papers did not use any of the core terms (i.e. public health, surveillance) in their main text/title and instead, while they utilized digital data to study a public health-related theme in a population. Three papers used other terms such as `infodemiology` or `digital epidemiology` to study the application of digital data for public health surveillance. To improve the sensitivity of the search strings, we added these keywords to our search strings when updated the database search process in January 2020. However, we could not perform any statistical analysis on the updated search results as the QGS set of records was relatively small at 73 records.

Supplementary Table 2: Details of the search process [PHR: Public Health Reports]

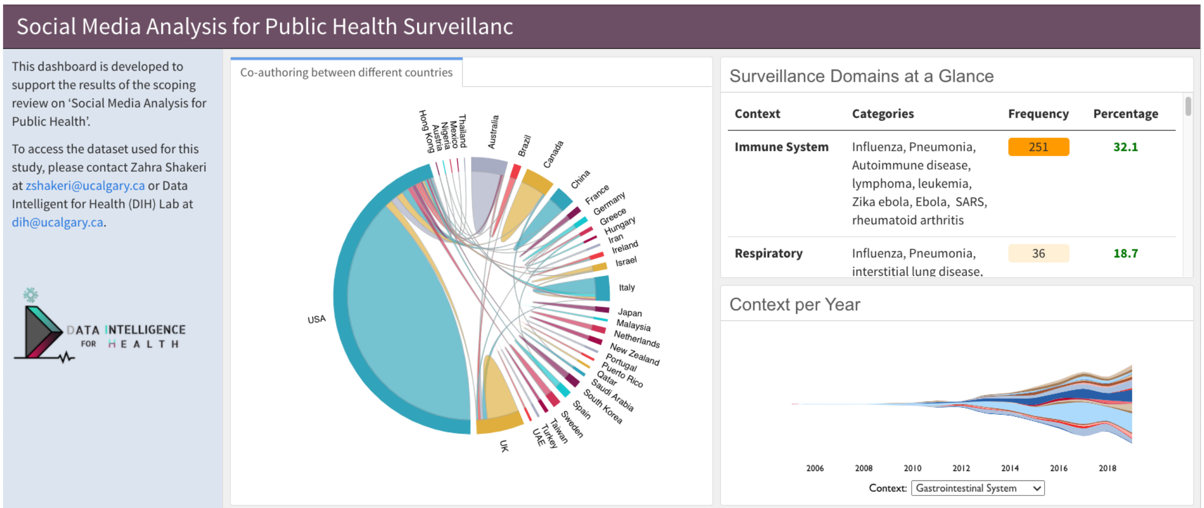
Publisher	**#QGS$_{(2017-2018)}$**	**#Retrieved**
JMIR/PHS	63	54
APHA	8	6
JPH	2	2
JAMIA	7	5
Total	80	67

1.3 Database Search

All databases were searched in April 2019, and the search was updated in September 2019 and January 2020. These searches yielded 4,249 records, of which 2,907 remained after duplicates were removed. A further 2,024 articles were excluded after a title and abstract screen; 503 for surveys, 20 were not written in English, 134 were editorials/letters/viewpoints, 31 used mobile apps to run surveys, and 1,336 were not relevant to the scope. A further 128 articles were removed after the full-text screening based on the exclusion criteria outlined in the methods section. These exclusions left 755 primary articles for the scoping review (Figure 1).

1.4 Inclusion/Exclusion Criteria

We defined the inclusion and exclusion criteria of this review based on the purpose of data generation –by the public and the purpose of data utilization – by potential studies. We detail each of these categories below:



Supplementary Figure 2: The homepage of the visual dashboard presenting the results of the included studies

Data generation purpose– We sought evidence that used data generated voluntarily by the public and is openly accessible by everyone on the Internet. By `voluntary`, we mean the data that is not generated with the primary goal of public health surveillance. Following this definition, all the content sharing and awareness media such as Wikipedia— created and maintained by a community of volunteer editors, news websites, and specific websites— created and maintained for public awareness, without the primary goal of surveillance fall under the scope of our review. In addition to the content generated by laypeople on popular social media platforms (e.g. Twitter, Facebook, Instagram, and Weibo), this definition covers implicit data generated by the public when using different Internet-based technologies. This includes search strings generated by Google Trends, access logs generated by WikiTrends, and likes/clicks generated during user interactions with different digital platforms. We did not put any constraint on the type of data and investigated ten different type combinations in this review. However we **excluded** studies that utilized the following digital data sources:

Online surveys— Studies that utilized the data generated by online surveys/poll were excluded, as this data is not generated voluntarily and might not be openly accessible to everyone. We mean surveys posted on social media platforms or are sent directly to the public by online surveys here.

Mobile App surveys— We excluded all the studies that developed an app to intentionally collect data from their users for the purpose of public health monitoring. Also, studies that used mobile apps to publish the survey link were excluded for further analysis.

Selected social media users— Studies that selected a specific cohort of users on digital platforms for their data collection, while the user was aware of this process and signed consent forms were excluded from this review.

Data utilization purpose– We included studies that used digital data to implement a surveillance system (infoveillance) directly or mined, analyzed, and aggregated information from digital resources to inform public health and public policy for public health surveillance purposes (infodemiology). All the studies that investigated the applicability and the usefulness of different types of digital data for public health surveillance were included in this review. The '`purpose`' of data utilization covers common applications such as outbreak detection, predicting seasonal diseases, exploring unhealthy advertisements, and vaccines to less common applications such as animal health, pediatric health, exploring disease burden, and the risk factors associated with different health practices. We **excluded** studies that utilized digital data for the following purposed:

Education— Studies that leveraged the content of digital media for the purpose of public health-related education (e.g. university students, public health professionals) were excluded for further analysis.

Social media for recruitment— Studies that used social media itself and digital data to recruit subjects for public health studies were excluded.

With only technical contribution— Studies that only contributed to developing a new machine learning or other technical methods for utilizing digital data in public health surveillance were excluded.

Studies were deemed eligible if they met both of the above conditions (i.e. data and purpose). Studies that did not meet any of these conditions were excluded from this review. Also, all review studies that investigated the publications on DPHS were excluded. Also, general commentary, letters, and perspective publications were excluded.

2 Supplementary Note 2: Visual Interactive Dashboard

To complement the results of this review and to add more intuition to the results with a higher level of granularity, we have developed an interactive visual dashboard that is accessible at `https://rpubs.com/zshakeri/dashboard` (Supplementary Figure 2). This dashboard contains four main visual components that are detailed below.

2.1 Chord-Diagram [Authors Collaborations]

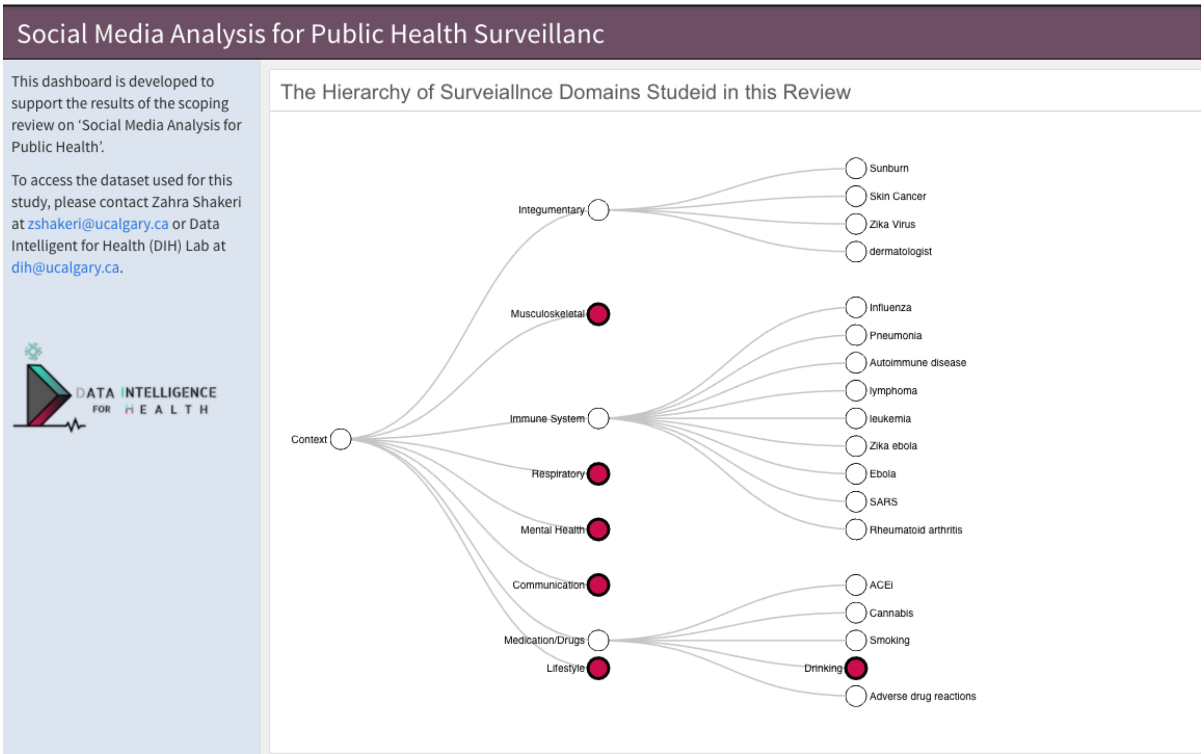
We developed a Chord diagram to show the collaboration between authors from different countries. Countries (nodes) are displayed all around a circle and connected with arcs (links). The thickness of the links shows the volume of papers that are published between the countries. Self-links visualize the sing-country publications. Users can interact with this diagram for more information about the number of publications and filter the data for further analysis.

2.2 Stream Diagram [Surveillance Topics Over Time]

A stream diagram is a variation of stacked area charts with a more flexible visual design. We used this diagram to represent the evolution of public health topics over time. Areas are usually displayed around a central axis, and edges are used to give a flowing shape. To filter the dataset based on a specific topic, users can filter the data, and the chart will be updated accordingly.

2.3 Interactive Tabular Visualization [A Big Picture of the Included Studies]

This interactive table illustrates a big picture of the included studies in this review, including the public health topics, frequency, percentage, and temporal trend. Users can interact with this table for more details on each of these variables.



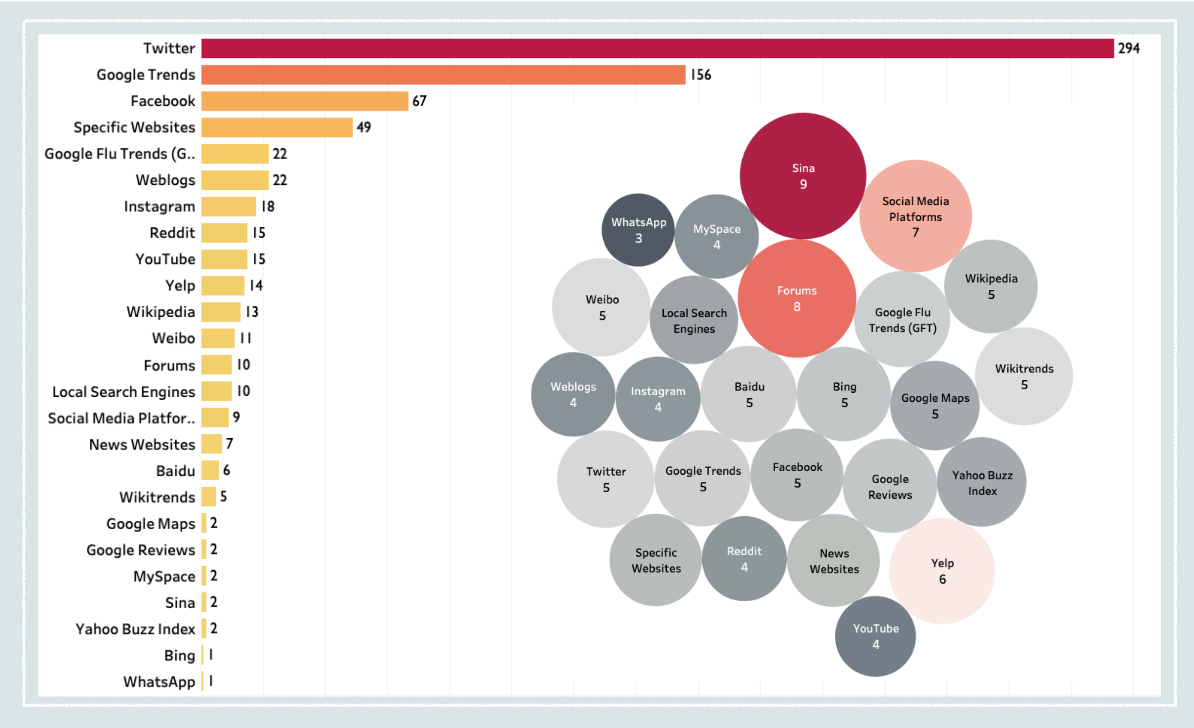
Supplementary Figure 3: Expandable tree diagram, mapped to the PHS topics/categories/sub-categories listed in Table 1.

2.4 Expandable Tree [The Hierarchy of Themes/Categories/Sub-Categories]

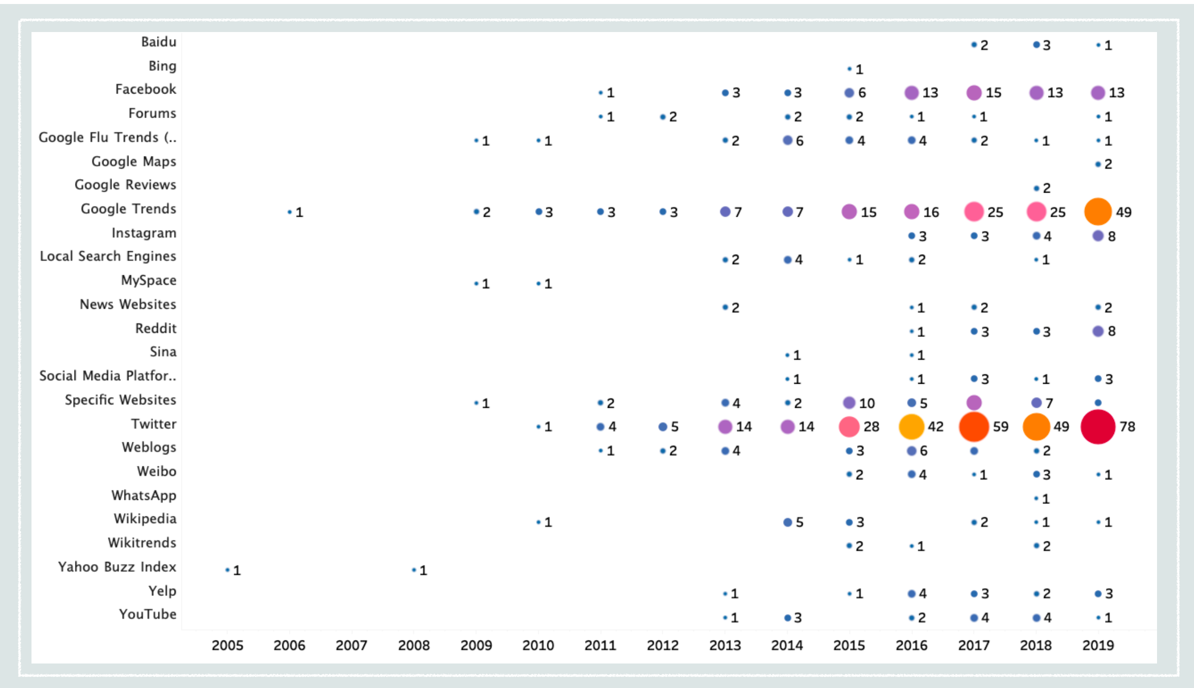
Considering the high level of details in Table 1, with a large number of categories and sub-categories, we implemented an interactive collapsible tree diagram that conclusively shows hierarchical data and can be expanded and minimized during the interactions (Supplementary Figure 3). This diagram consists of a root node connected to other nodes by branches. The first level shows the 16 public health topics listed in Table 1. The second level visualizes the 49 categories. The nodes furthest to the right of the tree present the 208 sub-categories and have no child nodes.

3 Supplementary Note 3: Digital Media Platforms

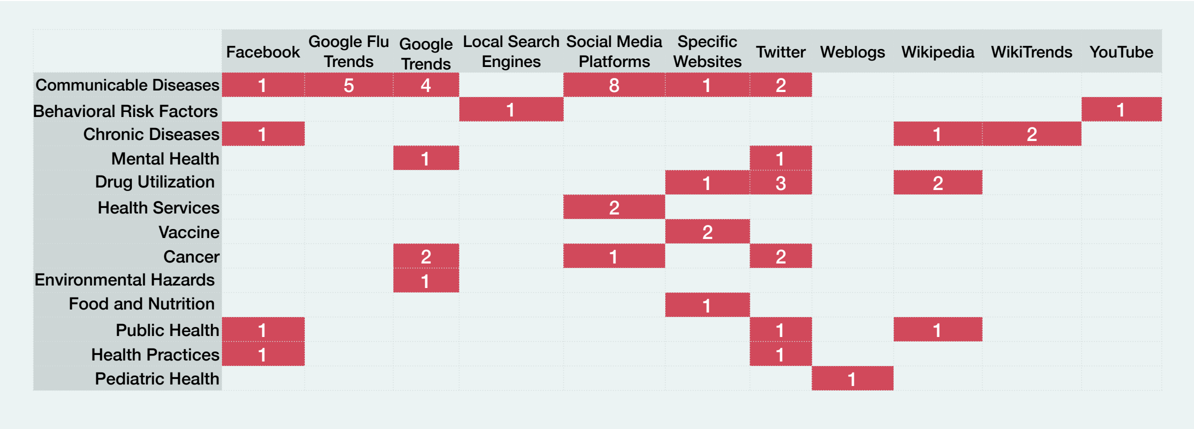
Supplementary Figure 4 represents the frequency of the digital platforms used by the included studies, and the average number of authors per platform. Bing search index, WhatsApp (with one study), Sina, MySpace, Google Reviews, and Google maps (with two studies each) were minimally represented in studies. Regarding the average # of authors per platform, the majority of the platforms follow the overall average (i.e. 5.13), with some exceptions: Sina (9), forums (8), and studies that used more than five digital platforms (social medial platforms) with an average eight authors per study. Supplementary Figure 5 shows the frequency of utilized platforms by the included studies over time. The drop in the number of Twitter studies from 2017 to 2018 could cause by Twitter's new data access policy enacted in 2018; as of July 2018, all the requests for access to Twitter's standard and premium APIs were required to go through a new process. Similarly, the number of Facebook studies spiked dramatically from 2014 to 2017 and then tapered off due to the new Facebook's data collection restrictions implemented in April 2018.



Supplementary Figure 4: The frequency of different digital platforms utilized by the included studies (bar chart), and the average number of authors per platform (bubble chart).



Supplementary Figure 5: The frequency of digital platforms used by the included studies over time.



Supplementary Figure 6: The frequency of studies that found the application of digital platforms challenging, mapped to PHS topics.

4 Supplementary Note 4: Applicability Challenges

This section describes the studies that questioned the applicability of using social media for specific purposes. Supplementary Figure 6 shows the mapping between health topics and platforms that might not be effective for them. The number in each cell shows the number of studies associated with each mapping. Interestingly, 52 (7%) studies found the application of digital platforms challenging. For example, Facebook is not an appropriate platform to study the relationship between smoking and genetics, as little information on this topic is present on this platform.[a46] Similarly, the number of views of the Italian Wikipedia articles related to multiple sclerosis (MS) and its treatment showed no promise to explore the disease prevalence,[a232] as this type of data does not reliably reflect its actual epidemiology. While several studies found Twitter as a useful tool to study public interest in and concerns about different diseases, but when it comes to disease comparison (in general), the application of Twitter is more challenging due to the lack of population demographics and word ambiguity.[a753]

The application of specific websites (e.g. news, awareness websites, or online review websites) in developing digital public health campaigns for changing public health-related behaviours was also found to be challenging, which could be due to a poor campaign design or using and inappropriate platform.[a394] The online food review websites in the United States might not be an appropriate platform to detect critical food safety violations in food establishments, as food-borne illnesses are vastly under-reported by the US public.[a516]

While Google Trends data is an accurate correlate of the reported incidence of Lyme disease and tick-borne encephalitis in Germany, but it fails to improve the performance of the predictive models.[a408,a428]

5 Supplementary References: Included Articles

In this section, we list all the included studies in this review. These numbers can be directly mapped to Tables 1 and 2 as well as the main text of the manuscript and the Supplementary Information section.

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