REVIEW

Use of unconventional data to monitor behaviors associated with influenza and dengue infections: A systematic review

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ABSTRACT

Background: Influenza and dengue are high-impact infectious diseases that continue to challenge health systems worldwide. Their control depends on identification of viral transmission patterns, but also on understanding human choices, including vaccine uptake, personal protection, and adherence to guidance. Classical reporting mechanisms, although reliable, often provide delayed or incomplete pictures of population behavior. In recent years, alternative information streams, such as online searches, social platforms, and mobile-based tools have been explored as rapid proxies to capture preventive actions and community sentiment. This systematic review synthesizes evidence on the use of unconventional data to monitor preventive behaviors for influenza and dengue, assessing their validity, opportunities, and limitations, to determine whether they can enhance conventional surveillance and provide timelier behavioral insights.
Methods: We performed a systematic review of the literature, according to PRISMA standards. Multiple databases (PubMed/MEDLINE, Scopus, EMBASE and PsycInfo) were queried. Eligible studies employed unconventional digital traces to capture prevention-related behaviors in the context of influenza or dengue. Extracted items included data source, infectious diseases explored, behavioral outcome and principal conclusions.
Results: From 5,448 records, 44 articles met inclusion criteria. 33 studies addressed influenza vaccination interest and protective measures, 9 dengue-related prevention behaviors, and 2 both diseases. Internet search activity and microblogging platforms were most frequently used. Approaches ranged from straightforward frequency tracking to advanced predictive algorithms. Several studies demonstrated that these data sources could anticipate behavioral shifts ahead of official statistics; however, validation was inconsistent and representativeness remained a recurrent concern.

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Discussion: Unconventional data sources offer valuable potential to complement established monitoring systems, providing faster signals and broader situational awareness. Nonetheless, their utility is constrained by biases in digital participation, vulnerability to misinformation, and lack of standardized evaluation. When validated and ethically applied, such data can enrich prevention monitoring and strengthen behavioral intelligence for public health decision-making.

Key words: unconventional data, preventive behaviors, influenza, dengue.

Introduction

Infectious diseases remain a persistent global health challenge, particularly in the context of urbanization, global mobility, and climate change (1). Seasonal influenza, a major contributor to annual respiratory morbidity and mortality, is estimated to cause up to 1 billion cases and 650,000 deaths worldwide each year (2). Dengue, by contrast, is a rapidly spreading arboviral infection, with transmission established in over 100 countries and nearly half the global population at risk, accounting for up to 390 million annual infections, of which 96 million have clinical manifestations (3,4). Both diseases illustrate the dual need to monitor not only pathogen circulation but also the behaviors that determine exposure, prevention, and control. Conventional epidemiological surveillance, based on clinical, laboratory, and sentinel reporting, remains the foundation of public health decision-making. Yet these systems are often constrained by time lags, underreporting, and resource demands, particularly in low and middle-income countries (5,6). To complement them, the field of digital epidemiology has emerged, leveraging unconventional data sources such as internet search queries, social media streams, wearable sensors and mobile applications (7). These sources, generated continuously and at scale, can provide near real-time insights into disease dynamics and public sentiment at a population level, potentially reducing delays inherent in traditional reporting (8). While early work in digital epidemiology focused on forecasting case counts, most famously through platforms such as Google Flu Trends, a growing body of research has shifted attention toward behavioral determinants of epidemics (9). Behaviors such as vaccine uptake, vector control practices, mask use and information-seeking can critically influence transmission trajectories (10). Importantly, the COVID-19 pandemic underscored how misinformation, trust in institutions and risk perception can shape adherence to public health measures, thereby altering outbreak dynamics independently of viral biology (11–13). Understanding and monitoring these behavioral patterns is thus as vital as tracking infections themselves.

Influenza and dengue provide complementary contexts in which to examine this question. Influenza, with its seasonal recurrences and established vaccination strategies, highlights challenges of monitoring immunization intent and coverage. Dengue, a mosquito-borne infection with strong ecological and climatic drivers, underscores the importance of surveillance of vector-control behaviors and population awareness. Together, they exemplify how unconventional data might be harnessed to strengthen preparedness and response. This systematic review synthesizes evidence on the use of unconventional data to monitor preventive behaviors for influenza and dengue. By assessing their validity, opportunities, and limitations, the review aims to inform whether such data streams can augment conventional systems, providing public health authorities with faster and richer behavioral insights. The work is conducted within the framework of the BEHAVE-MOD (Behavioral Modeling for Epidemic Decision Support) project, which seeks to develop a sustainable system for integrating real-time behavioral data into predictive models to enhance the timeliness and accuracy of epidemic responses. The review was supported by the INF-ACT Cascade Open Call for Research, Node 4 (CUP I83C22001810007).

Methods

This systematic literature review was conducted in accordance with the Preferred Reporting Items for

Systematic Reviews and Meta-Analyses (PRISMA) 2020 (14). The review protocol was developed earlier and registered in the International Prospective Register of Systematic Reviews (PROSPERO; registration number: CRD42024612121).

Search strategy

For the current systematic review, a comprehensive literature search was conducted across PubMed/MEDLINE, Scopus, EMBASE and PsycInfo on 9 November 2024. The search strategy incorporated three key elements: unconventional data (and synonyms), preventive behaviors (and synonyms) and the abovementioned infectious diseases, influenza and dengue (and synonyms). Relevant keywords, including both MeSH terms and Title/Abstract terms, were used in combination with the Boolean operators 'AND' and 'OR' and 'NOT'. The search strategy was first designed for PubMed/MEDLINE and then modified to suit Scopus, EMBASE, and PsycInfo databases. The full search strategy is detailed in Table S1. The reference lists of the included studies were manually reviewed to find any potentially relevant articles that might have been missed earlier. No time restrictions were applied.

Inclusion and exclusion criteria

Table S2 shows a detailed description of the inclusion criteria, defined according to the PICOS framework (Population, Intervention, Comparator, Outcome, Study design). Only studies involving unconventional ways to collect data on preventive behavior towards influenza and dengue were included. No restrictions were applied regarding geographic location or demographic characteristics. Only original studies written in English in international and peer-reviewed scientific journals, with available full text and without any date filter, were considered eligible.

Study selection

All identified records were first imported into the Rayyan platform for reference management and removal of duplicates (15). The screening was in two phases: first, two couples of reviewers independently and blindly assessed titles and abstracts with Rayyan to identify potential studies (AA and GER, GC and RC). Then, full texts of selected articles were retrieved and evaluated twice, in blind, for final eligibility. Any discrepancies between reviewers were discussed to reach consensus; when disagreements could not be resolved, a third reviewer was consulted. The selection process was systematically documented using a PRISMA flow diagram, detailing the number of records screened, excluded and included, along with justifications for exclusions at the full-text level.

Data extraction and synthesis

Data extraction was carried out independently and in a blinded manner using a standardized Excel spreadsheet (Microsoft Excel® for Microsoft 365 MSO, Redmond, WA, USA, 2019). The extraction template was pilot tested on a random sample of studies to ensure consistency and alignment among reviewers. Information collected included the following variables:

- Study characteristics (author name, year of publication, country where the study took place, study design, time period of monitoring);
- Population characteristics (target population);
- Objective and context data (aim of the study, infectious diseases explored);
- Unconventional data (data source, data access and amount of data collected and analyzed);
- Preventive behaviours (monitored behaviour, indicators used, main findings, comparison with conventional data);
- Outcomes (Identified benefits, challenges and limitations, practical application, authors' conclusions).

Any discrepancies during the extraction process were resolved through discussion, with the involvement of a third reviewer when necessary.

Quality assessment

The risk of bias in the included studies was independently assessed by two reviewers (GER and AA) using validated critical appraisal tools, depending on the study design. Discrepancies were resolved by consensus or by a third reviewer (RC) when necessary.

Cross-sectional studies and the randomized controlled trials (RCTs) were assessed using the Joanna Briggs Institute (JBI) Critical Appraisal Tools (16), which allow structured evaluation across multiple methodological domains. Ecological studies were assessed using the Risk Of Bias In Non-randomized Studies of Exposures (ROBINS-E) tool (17), which evaluates potential biases across domains relevant for non-randomized exposure studies. Mixed-method studies were assessed using the Mixed Methods Appraisal Tool - 2018 (MMAT) (18), which allows appraisal of studies integrating qualitative and quantitative components.

Results

Literature search

A total of 5,448 records were identified through four database searches (PubMed/MEDLINE, Scopus, EMBASE and PsycInfo). After removal of duplicates, 4,563 records remained for title and abstract screening. Of these, 50 articles were retrieved for full-text evaluation. Following full-text assessment, 11 publications were excluded due to wrong outcome (n = 11), conventional data (n = 11), and wrong publication type (n = 1). Additional 17 studies were identified through manual reference checks. At the end, 44 articles met the predefined inclusion criteria and were incorporated into the final synthesis. 33 articles focused on influenza (19–50), 9 on dengue (51–59), and 2 addressed both influenza and dengue (60,61). The study selection process is illustrated in the Supplementary Materials (Figure S1).

Aims of the included studies

The aims of the included studies were heterogeneous but could be grouped into 4 main domains. Several studies (n=17) focused on surveillance and early detection, assessing the potential of unconventional data sources to anticipate or complement traditional systems (21,22,29,30,34,38,39,43,46, 48–51,54,55,58,59). A second group examined population behaviors, perceptions, and attitudes (n=18) (19,20,23,24,26,28,31,32,35–37,40–42,44,45,52,57), particularly in relation to influenza and dengue vaccination, misinformation, and online engagement. A third set evaluated digital interventions and communication strategies (n=5) (33,42,53,60,62), such as mobile applications, targeted messaging, or incentives (33,53,60). Finally, a smaller number of studies (n=4) were oriented towards methodological validation (25,47,56,61), testing predictive models, exploring socio-spatial variations, and proposing alternative surveillance frameworks (61). The aims of the included studies are reported in Table 1.

Study design of the included studies

The study methodologies employed across the included articles were heterogeneous, as detailed in Table 1. Most studies adopted an ecological design (n = 27) (19-23,27,30,34,38-42,44-48,49,51, 54-59,61), followed by cross-sectional studies (n = 13) (24-26,28,29,31,32,35,36,43,52,60,62), mixed-methods approaches (n = 3) (37,50,53), and, in one case, a randomized controlled trial (n = 1) (33).

Country income and geographic distribution

Most included studies were conducted in high-income countries (n = 32) (19–23,26–40,42–45, 47–50,52,53,61,62). A smaller number were carried out in upper-middle-income countries (n = 4) (24,25,51,56), and lower-middle-income countries (n = 3) (55,58,60). A few involved multiple income groups or countries not classified by the World Bank (23,41,46,57,59). As Taiwan is not listed separately by the World Bank, it was considered part of China and categorized as an upper-middle-income country.

With specific reference to influenza, the majority originated from high-income countries, while dengue-related studies were more evenly distributed across different income groups. In terms of geographic distribution, influenza studies spanned 63 countries worldwide, with the United States and Canada most frequently represented, followed by several European countries. Dengue studies included 12 countries, most often the Philippines, Singapore, and Thailand. Full details are provided in Figure 1.

Table 1. Characteristics of the included studies

First Author, Year	Study Design	Aims of the study	Unconventional data	Monitored behaviour
Baltrusaitis K [2022] (21)	Ecological study	Validate healthcare-seeking behavior during influenza seasons.	Digital Crowdsourcing	Healthcare-seeking behavior of users reporting ILI symptoms
Berning P [2022] (20)	Ecological study	Evaluate the association between online search trends and vaccination rates.	Search query data	Google searches for information about influenza and COVID-19 vaccinations
Besculides M [2005] (22)	Ecological study	Test school absenteeism monitoring for early outbreak.	School attendance data	School absenteeism for early outbreak detection
Chan MPS [2020] (23)	Ecological study	Analyze how social media posts relate to vaccine attitudes and actual vaccination.	Social media	Attitudes and actual vaccination against influenza
Chang YW [2020] (24)	Cross-sectional study	Examine the association between non-English queries and epidemic outbreaks.	Search query data	Google searches for information about influenza
Cook S [2011] (49)	Ecological study	Compare the composition and performance of the Google Flu Trends model with traditional influenza surveillance systems.	Search query data	Searches for differents query: Symptoms of an influenza complication, Influenza complication, Specific influenza symptom, General influenza symptoms, Cold/flu remedy, Term for influenza, Antibiotic medication, Related disease
Dai J [2023] (25)	Cross-sectional study	Analyze sociospatial impact, spatiotemporal variations, and emotional orientations after the COVID-19 pandemic.	Social media	Sentiment expressed in the posts
Dale LP [2019] (62)	Cross-sectional study	Assess the effectiveness of an educational app and quizzes about vaccination.	App	Engagement with influenza vaccine educational content (quiz completion). Use of app features (map, location services). Visits to sponsored pharmacies. Self-reported receipt of the influenza vaccine.
Davies GR [2003] (27)	Ecological study	Determine whether over-the-counter (OTC) drug sales can predict changes in clinical conditions.	Sales data for OTC	Self-medication using OTC pharmaceuticals
Dhaliwal D [2020] (28)	Cross-sectional study	Identify messages shared by websites on social media that may influence readers and consumers.	Social media	Likes, shares, comments and discussions generated by the content
Dugas AF [2012] (29)	Cross-sectional study	Correlate Google Flu Trends, influenza cases, and crowding indices.	Search query data	Google searches for ILI symptoms
Eysenbach G [2006] (30)	Ecological study	Predict influenza epidemics using online search trend analysis.	Google Ads Data	Google searches for flu or flu symptoms

Table 1 (*continued*)

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First Author, Year	Study Design	Aims of the study	Unconventional data	Monitored behaviour
Guidry JPD [06/2020] (32)	Cross-sectional study	Examine misinformation about the flu vaccine on Pinterest.	Social media	Attitudes and representations of the flu vaccine
Guidry JPD [10/2020] (31)	Cross-sectional study	Examine how users interact with tweets about the flu vaccine during the beginning and peak of the flu season.	Social media	Health belief variables, including perceived susceptibility, severity, benefits, barriers, and self-efficacy
Huang X [2019] (26)	Cross-sectional study	Evaluate if tweets can identify real-time flu vaccination compared to traditional tracking systems.	Social media	Influenza vaccination (intended or actual receipt)
Hulth A [2011] (50)	Mixed methods study	Assess web queries based model performance for the 2009 flu pandemic.	Search query data	Submission of research queries related to influenza and flu symptoms
Lee WN [2020] (33)	Randomized Controlled Trial	Assess the impact of digital messaging and incentives on influenza vaccination rates.	App	Adherence to flu vaccination
Magruder SF [2003] (34)	Ecological study	Determine whether over-the-counter (OTC) drug sales can predict changes in clinical conditions.	Sales data for OTC	Self-medication using OTC pharmaceuticals
Meyer SB [2019] (35)	Cross-sectional study	Explore how attitudes and beliefs about influenza vaccination are shared on Web.	Website	Attitudes and beliefs about influenza vaccination
Nawa N [2016] (36)	Cross-sectional study	Categorize public concerns about flu vaccination by analyzing a large dataset of online questions.	Online community	Concerns about flu vaccinations
Nougairède A [2010] (37)	Mixed methods study	Examine the willingness of different populations to accept vaccination against influenza.	Search query data	Google searches and PubMed searches about influenza topics
Ortiz RJ [2011] (38)	Ecological study	Compare Google Flu Trends with national surveillance data.	Search query data	Public interest in information on flu symptoms
Polgreen PM [2008] (39)	Ecological study	Examine the relationship between Internet searches for influenza and the actual occurrence of influenza cases.	Online community	Searches that contain the terms “influenza” or “flu” but do not contain the terms “bird”, “avian”, “pandemic”, “vaccine”, “vaccination” and “shot”
Powell GA [2016] (40)	Ecological study	Compare the prevalence of negative sentiment and positive vaccine promotion.	Tool	Sentiments about vaccines
Prieto Santamaría L [2021] (41)	Ecological study	Analyze Twitter posts to understand public sentiments regarding measles and flu vaccines.	Social media	Sentiments about vaccines and flu
Saito S [2016] (42)	Ecological study	Assess the effect of education on the influenza epidemic curve.	Search query data	Flu vaccine coverage, search trends about flu

First Author, Year	Study Design	Aims of the study	Unconventional data	Monitored behaviour
Salathé M [2011] (19)	Ecological study	Monitoring sentiments towards the influenza vaccine during the 2009 pandemic.	Social media	Sentiments about flu vaccine
Santangelo OE [2021] (43)	Cross-sectional study	Assess alignment between internet searches for influenza and national health surveillance systems.	Search query data	Search terms in the Health category: "Influenza" (Flu) and "sintomi influenza" (Symptoms of Flu)
Signorini A [2011] (44)	Ecological study	Monitoring disease activity and public sentiment on Twitter during outbreaks.	Social media	Public sentiment towards the infection (vaccines, transmission, countermeasures, symptoms ecc) and measure actual disease activity
Sycińska-Dziarnowska M [2022] (45)	Ecological study	Assess public interest in influenza and its vaccination using Google search data.	Search query data	Searches on influenza and influenza vaccine
Valdivia A [2010] (46)	Ecological study	Correlate Google Flu Trends with sentinel physician estimates.	Search query data	Public interest in information on flu symptoms
Wagner M [2017] (47)	Ecological study	Reevaluate if statistical framework based on online user-generated content can form a valid source for influenza surveillance tasks.	Social media	Vaccination to prevent influenza transmission
Wilson N [2009] (48)	Ecological study	Explore the possible utility of Google Flu Trends in the context of an influenza pandemic.	Search query data	Google searches for ILI symptoms
Meankaew P [2022] (60)	Cross-sectional study	Provide information on the prevalence and status of infectious diseases to travellers and evaluate system usability.	App	The most requested information concerned dengue and malaria. This may reflect anxieties and vigilance regarding these diseases.
Milinovich GJ [2014] (61)	Ecological study	Provide guidance for the future development of infectious diseases digital surveillance systems.	Search query data	Search terms related to diseases or pathogens (e.g., "dengue", "influenza"), symptoms (e.g., "cough"), treatments or medications (e.g., "flu medicine", "symptoms of dengue"), general health concerns (e.g., "flu and pregnancy"), and colloquial expressions. Some queries reflecting environmental or behavioural associations were also monitored.
Dengue				
Althouse BM [2011] (51)	Ecological study	Evaluate the effectiveness of internet search data in predicting the incidence of dengue infections.	Search query data	Searches for dengue terms (nomenclature, symptoms, treatment

Table 1 (*continued*)

First Author, Year	Study Design	Aims of the study	Unconventional data	Monitored behaviour
Bravo C [2022] (52)	Cross-sectional study	Identify traveller profiles and vaccination attitudes from online forums.	Website	Attitude and behaviour toward vaccination and travel-related health information seeking activities
Carvajal P [2022] (53)	Mixed methods study	Describe outbreak mosquito-borne disease prevention information via Facebook by federal health agencies.	Social media	Trust in health agencies
Chan EH [2011] (54)	Ecological study	Evaluate early detection of dengue epidemics from web search queries.	Search query data	Searches for dengue related words
Espina K [2017] (55)	Ecological study	Integrate and accelerate surveillance data using social media.	Social media	Searches related to behaviours associated with dengue and typhoid fever
Gluskin RT [2014] (56)	Ecological study	Examine the relationship between Google Dengue Trends data and traditional surveillance data.	Search query data	Searches associated with dengue
Ho HT [2018] (58)	Ecological study	Assess the temporal relationship between Google Dengue Trends data and dengue incidence.	Search query data	Online search behavior related to dengue and its correlation with disease incidence
Jamora RDG [2023] (57)	Ecological study	Investigate whether the dengue vaccine controversy is correlated with immunization coverage.	Search query data	Web-based interest in dengvaxia and other vaccines
Strauss RA [2017] (59)	Ecological study	Evaluate the accuracy of Google Dengue Trends as an indicator of dengue spread.	Search query data	Searches for Spanish terms related to dengue (e.g., 'el dengue', 'dengue síntomas', 'síntomas dengue', 'qué es dengue', 'qué es el dengue')

Unconventional data subgrouping

Unconventional data varied across the included studies, as shown in (Table 1). The most frequently used were search query data (n = 19) (20,24,29,37,38,42,43,45,46,48–51,54,56–59,61), and social media data (n = 12) (19,23,25,26,28,31,32,41,44,47,53,56). Fewer studies relied on apps (n = 3) (33,60,62), online community data (n = 2) (36,39), OTC sales data (n = 2) (27,34), and website analytics (n = 2) (35,52). Digital crowdsourcing (21), Google Ads data (51), school attendance data (54), and dedicated tools were each reported in a single study (n = 1). Among the studies focusing on influenza, search query data emerged as the most frequently used unconventional source (n = 12) (20,24,29,37,38,42,43,45,46,48–50), followed by social media data (n = 10) (19,23,25,26,28,31,32,41,44,47). App-based data were used in 2 studies (33,62), and OTC sales data in 2 studies (27,34). Online community data were reported in 2 studies (36,39). Fewer studies relied on school attendance data (n = 1) (22), digital crowdsourcing (n = 1) (21), Google Ads data (n = 1) (19), dedicated tools (n = 1) or website analytics (n = 1) (35). Across studies investigating both influenza and dengue, 1 study used app-based data (n = 1) (60), while the other relied on search query data (n = 1) (61). Search query data represented the most

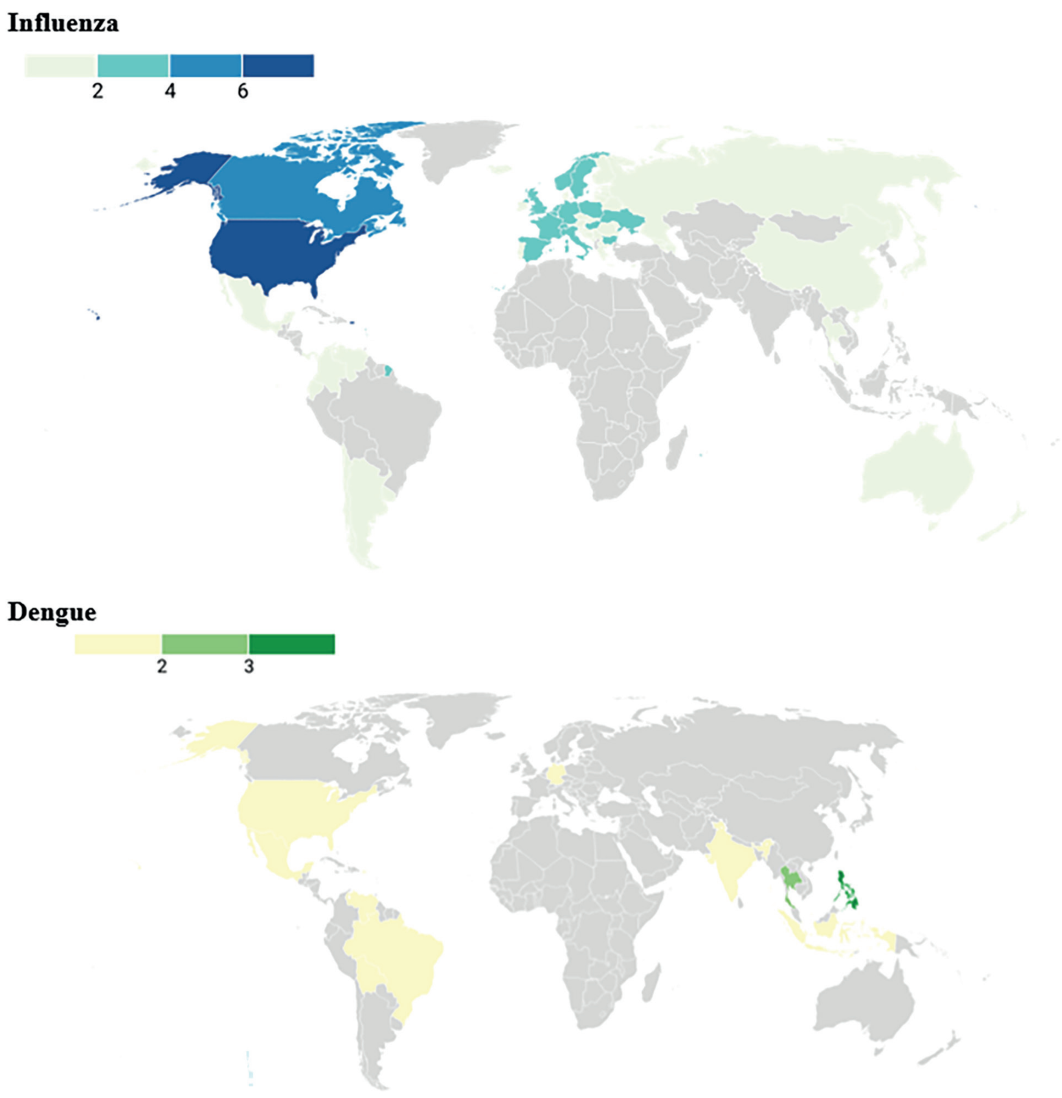

Figure 1. Geographic distribution of countries analyzed in the included studies on Influenza and Dengue.

commonly used unconventional source in studies on dengue (n = 6) (51,54,56–59), followed by social media data (n = 2) (53,55), and website analytics (n = 1) (52).

Monitored behaviour

Across the included studies, a wide range of population behaviours were monitored using unconventional data sources, as shown in (Table 1). In the studies focusing exclusively on influenza, monitored behaviours primarily involved health information-seeking through online search engines such as Google (20,24,29,30,37,38,42,43,45,46,48–50), covering topics like influenza symptoms, complications, over-the-counter treatments, and vaccination. Several studies also explored engagement with digital platforms, including interactions on social media (likes, shares, comments), sentiment expressed in user-generated content, and the use of mobile applications offering features such as geolocation and educational quizzes (19,21,23,25,28,31,32,35,36,39–41,44,47,62). Additionally, many studies assessed attitudes and beliefs related to influenza vaccination, including intention to vaccinate, perceived susceptibility and severity, perceived benefits and barriers, and self-efficacy. Preventive and care-related behaviours were also frequently monitored, such as school absenteeism (22), self-medication with OTC pharmaceuticals (27,34), and actual or intended vaccine uptake (26,33). In the 2 studies addressing both influenza and dengue, monitored behaviours focused mainly on digital searches related to symptoms (e.g., cough), treatments (e.g., flu medicine), and general health concerns (e.g., flu and pregnancy) (60,61).

Among the studies focusing solely on dengue, the monitored behaviours included online searches related to dengue symptoms, treatments, and vaccines (such as Dengvaxia) (51,54,56–59), as well as behaviours related to health information-seeking in the context of travel (52,55). Other studies examined public trust in health authorities and sentiment expressed online (53).

Data source

The most frequently exploited were Google Trends (n = 12) (20,24,42,43,45,46,54,56–59,61), followed by Twitter (n = 8) (19,23,26,31,41,44,47,55), Google Flu Trends (n = 4) (29,38,48,49), Google Search (37,51), Yahoo (36,39), and Facebook (28,53), 2 studies each. Other studies relied on a variety of less commonly used data sources, which are detailed in (Table S3). For studies focusing on influenza, the most frequently used data source was Twitter, featured in seven studies (19,23,26,31,41,44,47). This was followed by Google Trends (n = 6) (20,24,42,43,45,46), Google Flu Trends (n = 4) (29,38,48,49), and Yahoo! (n = 2) (36,39). All other sources were each used in only 1 study. Among the studies that simultaneously investigated both influenza and dengue, 2 distinct data sources were employed: 1 study relied on Google Trends (61); the other utilized ThaiEpidemics (60), a national surveillance platform providing official case data from Thailand's health authorities. Focusing solely on dengue-related studies, Google Trends was the most frequently used data source (n = 5) (54,56–59). Other sources, such as travel website forums (52), Twitter (55), Facebook (53), and Google Search (51), were each used in 1 study.

Time period of monitoring

The duration of data monitoring varied considerably across the included studies, ranging from as little as one day (31), to as long as 13 years (42). Studies focusing on influenza, (Figure 2), displayed the greatest heterogeneity. In contrast, studies investigating dengue, (Figure 3), more frequently relied on longer observation windows, typically covering multiple years. With regard to the earliest time points, the most temporally distant dataset for influenza dates back to 1992, although this refers to a single study analyzing over-the-counter (OTC) pharmaceutical sales (27). Other early datasets include school attendance records (22), and an additional study using OTC data (34), both starting in 2001. When considering more commonly used sources, such as Google search data, the earliest analyses began later in 2002. For dengue-related studies, the earliest data collection period started in 2003 (n = 2) (54,56). (Table S3) provides a detailed overview of the monitoring periods and corresponding durations across the included studies.

Data access

Most of the included studies accessed data through Application Programming Interfaces (APIs), which are standardized software interfaces that allow automated and structured retrieval of data from digital platforms. APIs facilitate the extraction of large volumes of real-time or historical data in a reproducible and scalable manner, making them particularly useful in digital epidemiology. In this review, APIs were used in 24 out of 33 studies focused on influenza (19,20,23,24,26,29–31,33,35–38,40–50), in both studies addressing influenza and dengue (60,61), and in 9 studies on dengue (51–59). Manual extraction of data from non-public sources was reported in 6 influenza studies (21,22,27,34,39,62), while 3 studies retrieved data manually from publicly available repositories or websites (25,28,31), as shown in (Table S3). No manual extraction was reported in the studies on dengue or on both dengue and influenza.

Target population

As shown in (Table S3), the target populations varied considerably. In the majority of studies, the population was specific to a given geographical area or language group (21–24,26,29,30,34,36–39,43–46,48–50,52,55–62). These geolocated or language-defined populations

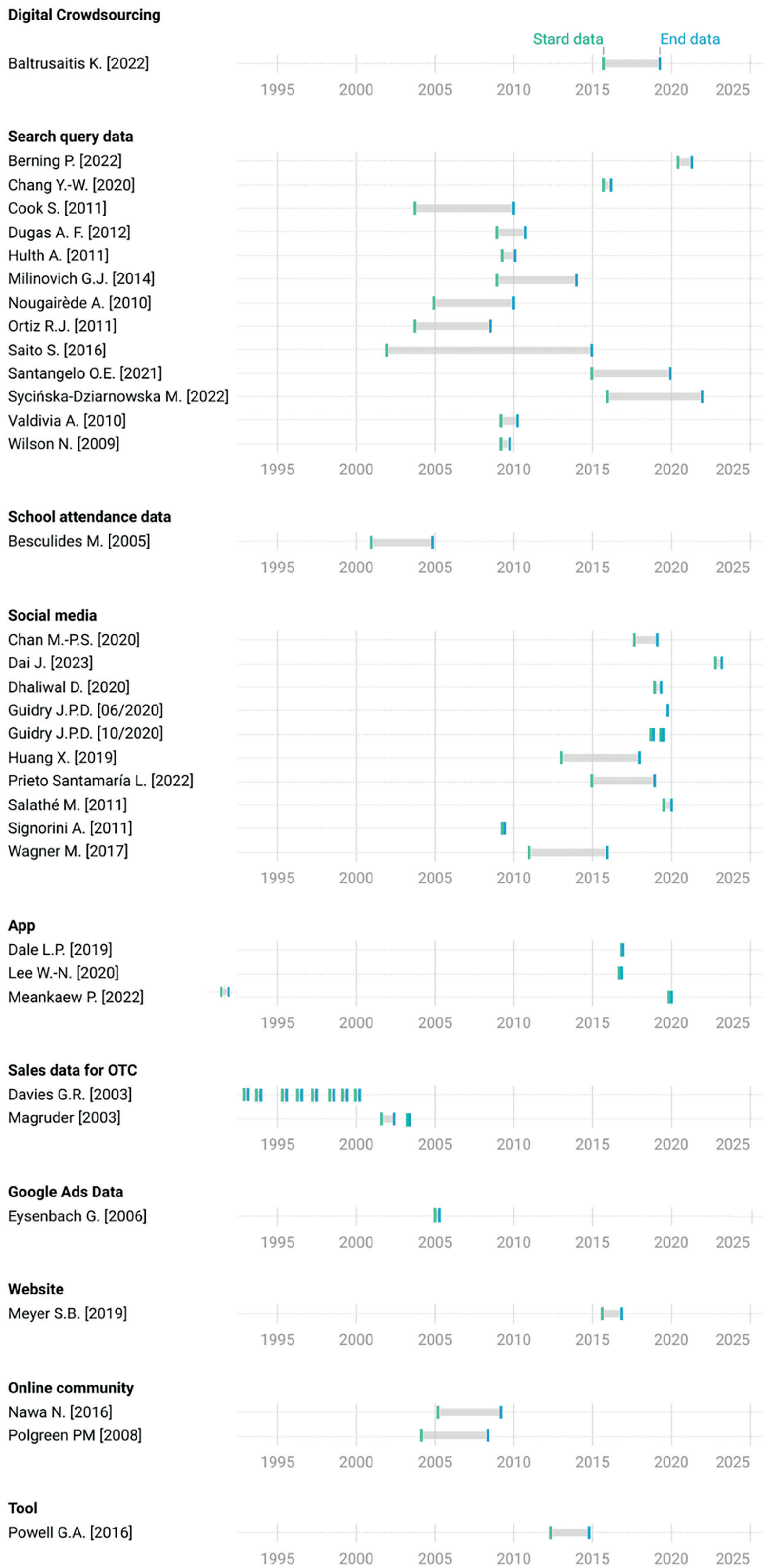

Figure 2. Time periods of monitoring across studies focusing on influenza.

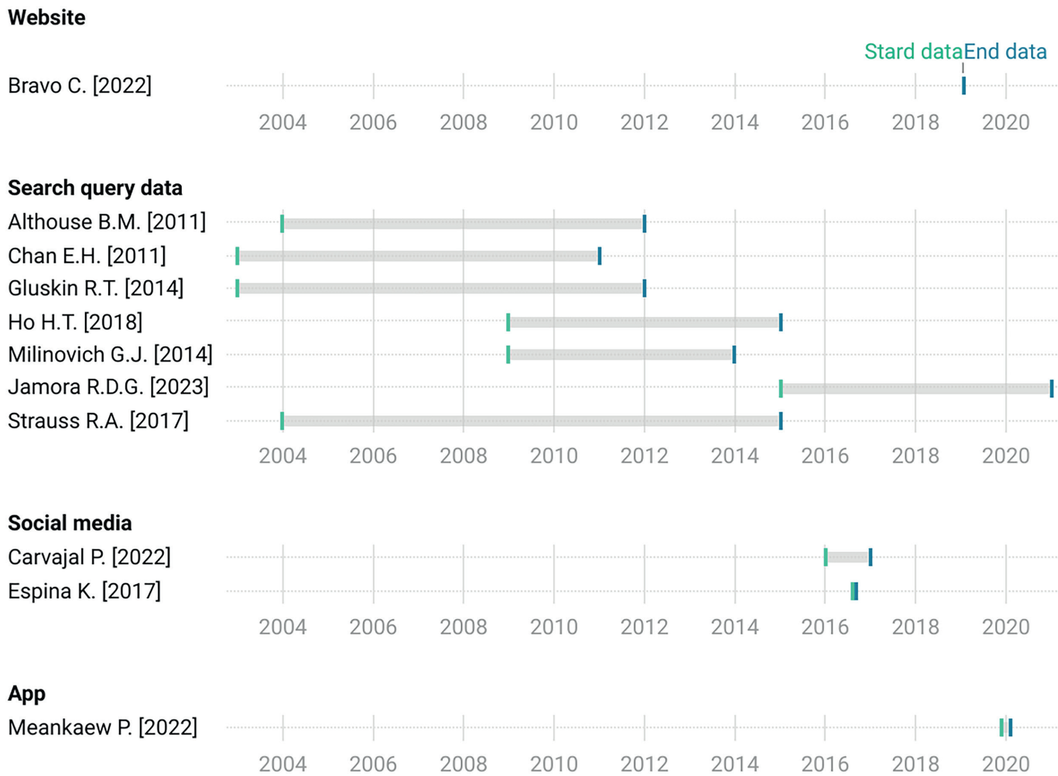

Figure 3. Time periods of monitoring across studies focusing on dengue.

allowed for a closer alignment with local epidemiological trends. In contrast, other studies relied on a broader and less specific population, such as general Google or Twitter users or followers of social media platforms, without restrictions to a particular area or demographic profile (19,20,25,27, 28,31–33,35,40–42,47,51,53,54).

Correlation analysis

Out of the 44 studies included, 26 performed correlation analyses, whereas 18 did not (Table S4). Among the studies that conducted correlation analyses, the most commonly used tests were the Pearson correlation coefficient (n = 17) (19,24,26,27,30,36,38,42,47,49,51, 53–59), and Spearman's rho (n = 4) (20,43,46,61), with 3 studies reporting R-squared values from regression models (39,50,51), and two studies employing cross-correlation tests (29,34). Additionally, 1 study applied a Bayesian approach (54). These analyses were frequently applied to time-series data on influenza or dengue incidence in relation to online search volumes or social media activity. Among the 18 studies that did not perform correlation analyses, different approaches were adopted. Specifically, 8 studies applied quantitative statistical tests, such as Chi-square tests (n=6) (21,31,33,37,60,62), Mann-Whitney U test (n=2) (31,32), Wilcoxon signed-rank (n=1) (22), Student's t-tests (n=1) (33), or logistic regression (n=1) (60). The remaining studies adopted a descriptive or qualitative approach, focusing on the analysis of the trends and sentiment of social media posts (25,28,35,40,41,45,52,53), or online discussions. Finally, 2 studies presented graphical comparisons (48), or predictive models (44), but without reporting explicit correlation coefficients.

Identified benefits, practical application and challenges

Table S5 provides a summary of the practical implications, benefits, and challenges. Across influenza studies, digital data streams, including online searches, social media, school absences, retail records, and mobile apps, offer timely, low-cost, behaviourally informative complements to traditional surveillance. Query-based tools like Google Trends enabled early influenza detection, hospital demand prediction, and vaccination monitoring, recommending integration with traditional data for better accuracy. Social media analysis added value by assessing vaccine sentiment, misinformation, and barriers, aiding targeted communication through platforms like Twitter, Facebook, and Weibo, which helped map attitudes, identify misinformation, and evaluate interventions. Alternative indicators such as school absenteeism and EPOS data provided early signals of community transmission and healthcare pressures, supporting planning and outbreak monitoring. Mobile health tools offered high engagement via push messages, geolocation, and campaign adjustments, especially for high-risk groups, though vaccine uptake remained modest.

For dengue and travel-related surveillance, Google search trends, web-scraped public perceptions, and social media monitoring showed strong predictive performance, useful in high-burden and resource-limited settings. These tools enabled early outbreak forecasting, vaccine prioritisation, traveller risk advice, and rapid misinformation detection during crises. Adding environmental and meteorological data improved predictions, highlighting the value of multi-source infodemiological systems for control. Overall, digital data sources provide actionable insights for surveillance, risk communication, and vaccination, especially when combined with traditional systems.

Influenza studies faced challenges such as sampling bias, limited representativeness, and unequal access to technology, often dominated by younger, urban, or motivated users. Many platforms lacked demographic or geographic detail, hampering subgroup analyses and equity assessments. Self-reported symptoms, volunteer participation, and user-generated content added bias and inconsistency, especially when relying on single sources. Methodological and technical issues affected reliability. Search tools were sensitive to keyword choice, media influence, seasonality, and behavioral changes, needing frequent recalibration. Google Flu Trends and similar models reflected influenza-like illness, not confirmed cases, with variable performance by region and time. Short evaluation periods, limited raw data, and non-specific indicators reduced accuracy; lack of contextual data limited validity. For social media and infodemiology, non-representative users, privacy issues, data loss, and automated analysis problems were common. Risks of misclassification, subjective interpretation, and lack of causality constrained findings. Platform features like character limits, algorithms, and transparency issues further hindered consistent monitoring. Dengue and multi-disease studies faced constraints like uneven internet access, variable case definitions, language and location issues, and crisis event impacts on search activity. Predictive accuracy was lower in low-incidence areas, and nationwide data often lacked resolution for local interventions. Small sample sizes and missing data limited analysis robustness.

Comparison with conventional data

Among studies, 24 out of 33 compared their results with conventional data sources (19–23, 26,27,29,30,34,36–39,42–50), while nine did not (25,28,31–33,35,40,41,62). The conventional sources included influenza incidence data, hospital admission records, and vaccination coverage data.

Of the 2 studies addressing both dengue and influenza, only 1 out of 2 performed a comparison with conventional data (61). Among studies focusing exclusively on dengue, 7 out of 9 compared their results with dengue surveillance data (51,54–59), while 2 did not (52,53). A summary is provided in Table S5.

Quality assessment

The risk of bias of the retrospective ecological studies was assessed using the ROBINS-E tool. Among the 19 influenza studies, 10 were rated as "Some Concerns" (19–22,27,30,40,46,47,49), 6 as "High" (34,39,41,44,45,48), and 3 as "Very High" risk of bias (23,38,42). The single study addressing both influenza and dengue was rated as "Some Concerns" (61). Of the 8 dengue studies, 4 were rated "Some Concerns" (54–56,58), 2 "High" (51,59), and 1 "Very High" (57). The methodological quality of the cross-sectional studies was evaluated using the JBI Critical Appraisal Checklist for Analytical Cross-Sectional Studies. Among the 11 influenza studies, three were judged to have a "Low" risk of bias (25,26,31), 6 a "Moderate" risk (28,29,32,35,36,43), and 2 "High" risk of bias (24,62). The study addressing both influenza and dengue (60), as well as the single study focusing exclusively on dengue (52), were rated as "Moderate" risk. In addition, 1 randomized controlled trial was included and assessed using the JBI Critical Appraisal Tool for RCTs, which indicated a "Moderate" risk of bias. Finally, 3 mixed-methods studies, 2 on influenza (37,50), and 1 on dengue (53), were assessed using the Mixed Methods Appraisal Tool, all of which were judged to have a "Low" risk of bias. Detailed results are provided in Supplementary Materials (Table S6, S7, S8 and S9).

Discussion

Main findings

This systematic review shows how unconventional data sources, such as online search trends, social media content, mobile app interactions, and sales records, can provide timely and complementary insights to traditional epidemiological surveillance systems for diseases such as influenza and dengue. Among the 44 studies analyzed, the majority reported positive correlations between digital indicators (e.g., search queries, social media engagement, mobile app usage, and over-the-counter medication sales) and conventional epidemiological measures (e.g., surveillance data, vaccination coverage, and emergency department visits). These findings show that digital data streams can improve traditional surveillance systems by enhancing their forecasting abilities. They also provide important insights into how diseases spread, especially the social and behavioral factors that affect public health prevention efforts. In other words, about one in four studies demonstrated a meaningful correlation between digital indicators and epidemiological measures, suggesting that these sources may represent a valuable tool to support public health decision-making.

Comparison with existing literature

In the context of existing literature, our findings confirm earlier evidence from the field of digital epidemiology showing that web-based data can anticipate epidemic alerts. However, unlike previous reviews, that were primarily focused on disease surveillance, our work specifically addresses preventive behaviors, such as vaccination and health information-seeking (63,64). This perspective broadens the understanding of unconventional data, not only as proxies for incidence but also as tools to interpret the social and behavioral dynamics that shape epidemic trajectories. In the context of existing literature, our findings confirm earlier evidence from digital epidemiology showing that web-based data can anticipate epidemic alerts (65). Unlike prior reviews, which primarily concentrated on disease incidence or the application of machine learning and artificial intelligence for surveillance, diagnosis, and prognosis, our research specifically focuses on preventive behaviors (63,66). This includes examining vaccination uptake and the pursuit of health information. This perspective broadens the understanding of unconventional data, positioning them not only as proxies for incidence but also as tools to interpret the social and behavioral dynamics that shape epidemic trajectories. The dual focus on influenza and dengue, two high-impact diseases with distinct epidemiological profiles, allowed us to explore a wide range of contexts and behavioral patterns.

Strengths and limitations

Nevertheless, several limitations should be acknowledged. Methodological heterogeneity among included studies, ranging from descriptive analyses to complex predictive models, prevented quantitative synthesis. The predominance of research from high-income countries limits the generalizability of findings to low- and middle-income settings (67), where digital data could be particularly valuable, but internet access remains uneven, likely due to a lack of infrastructure or socio-political challenges (68). Additionally, reliance on private platforms (e.g., Google, Twitter) raises issues of accessibility, reproducibility, and long-term sustainability (69). The evidence shows distinct patterns between the two diseases studied. For influenza, research largely focused on online information-seeking behavior, engagement with preventive interventions, and attitudes toward vaccination captured through social media. These digital traces were often strongly correlated with vaccination uptake and epidemic curves, suggesting that unconventional data can provide near real-time indicators of population behavior during seasonal epidemics. For dengue, studies emphasized search queries related to mosquito bites, symptoms, or vaccine controversies (e.g., Dengvaxia), as well as expressions of trust or mistrust toward health authorities. These findings highlight the ability of digital data to capture not only pathogen spread but also perceptions, misinformation, and institutional credibility, factors that are crucial for vector-borne diseases where community engagement drives the success of preventive measures. The broader literature in digital epidemiology and infodemiology supports these observations (70). Experiences such as Google Flu Trends and analyses during the COVID-19 pandemic have shown both the potential and the pitfalls of digital surveillance: while online signals can provide early, actionable insights, they are also vulnerable to external influences such as media coverage or political events (71). Our review synthesizes evidence across diseases with different transmission modes, demonstrating that digital approaches are versatile yet require careful validation, triangulation with traditional data, and contextual interpretation to avoid misleading conclusions (72). Timeliness is a key advantage of unconventional data. Unlike clinical or laboratory-based surveillance, which suffers from reporting delays, digital signals are generated in real time and can be continuously harvested at scale. This enables early detection of epidemic trends, dynamic monitoring of behavioral shifts, and rapid assessment of public reactions to health campaigns (73). Such behavioral insights are invaluable for public health, revealing how populations perceive risks, respond to messages, and make preventive choices.

Challenges and considerations

However, important challenges remain. Digital data are prone to selection bias: populations underrepresented online such as older adults, children, rural communities, and people with limited internet access, may be excluded. Data can be influenced by media, political debates, or celebrity statements, generating peaks unrelated to epidemiological trends. Methodological heterogeneity across platforms, search terms, algorithms, and analytical methods complicates comparability and reproducibility. Access to raw data is often restricted, creating dependencies on commercial entities and raising sustainability concerns. Finally, ethical and legal considerations, including privacy, consent, and data ownership, are paramount, particularly given the sensitivity of health-related online behavior.

Practical implications and future directions

For influenza, monitoring online vaccination discourse could help identify areas with high hesitancy and guide targeted interventions (74). For dengue, digital monitoring of public trust in health authorities could inform strategies to address misinformation and strengthen risk communication, especially after vaccine controversies. Importantly, unconventional data should complement, not replace, traditional surveillance, providing an additional layer of intelligence for situational awareness (75,76). Future research should prioritize multicenter and longitudinal studies, particularly in low- and middle-income countries, where unconventional data may offer the greatest benefit. Standardized protocols for data collection, analysis, and reporting are urgently needed to ensure comparability and reproducibility. Advances in artificial intelligence and machine learning could enhance predictive capacity, but these methods must be transparent, interpretable, and rigorously validated (77,78). Ethical frameworks must evolve alongside technological developments, balancing public health benefits with individual rights, privacy, and equitable access to digital tools. Projects such as BEHAVE-MOD offer promising examples of integrating behavioral data into sustainable, interoperable systems, linking digital signals with predictive epidemic models to support real-time decision-making. Cross-disciplinary collaboration among public health, computer science, behavioral science, and policy expertise is essential to realize this potential.

Conclusion

In conclusion, unconventional data sources hold significant promise for monitoring preventive behaviors related to influenza and dengue, with potential to complement and enhance traditional surveillance. To fully leverage this potential, attention must be given to methodological rigor, validation, ethical standards, and global equity. Addressing these challenges may allow digital epidemiology to become a cornerstone of next-generation public health surveillance, improving the timeliness, relevance, and effectiveness of interventions worldwide.

References

1. Baker RE, Mahmud AS, Miller IF, Rajeev M, Rasambainarivo F, Rice BL, et al. Infectious disease in an era of global change. Nat Rev Microbiol. 2022 Apr;20(4):193-205. doi: 10.1038/s41579-021-00639-z. Epub 2021 Oct 13.
2. Influenza (seasonal) [Internet]. [cited 2025 Sept 15]. Available from: https://www.who.int/news-room/fact-sheets/detail/influenza-(seasonal)
3. Bhatt S, Gething PW, Brady OJ, Messina JP, Farlow AW, Moyes CL, et al. The global distribution and burden of dengue. Nature. 2013 Apr 25;496(7446):504-7. doi: 10.1038/nature12060.
4. Dengue and severe dengue [Internet]. [cited 2025 Sept 15]. Available from: https://www.who.int/health-topics/dengue-and-severe-dengue
5. Funk S, Salathé M, Jansen VA. Modelling the influence of human behaviour on the spread of infectious diseases: a review. J R Soc Interface. 2010 Sep 6;7(50):1247-56. doi: 10.1098/rsif.2010.0142. Verelst F, Willem L, Beutels P. Behavioural change models for infectious disease transmission: a systematic review (2010-2015). J R Soc Interface. 2016 Dec;13(125):20160820. doi: 10.1098/rsif.2016.0820.
6. Salathé M, Bengtsson L, Bodnar TJ, Brewer DD, Brownstein JS, Buckee C, et al. Digital epidemiology. PLoS Comput Biol. 2012;8(7):e1002616. doi:10.1371/journal.pcbi.1002616. Epub 2012 Jul 26.
7. Oliver N, Lepri B, Sterly H, Lambiotte R, Deletaille S, De Nadai M, et al. Mobile phone data for informing public health actions across the COVID-19 pandemic life cycle. Sci Adv. 2020 Jun 5;6(23):eabc0764. doi: 10.1126/sciadv.abc0764.
8. Lazer D, Kennedy R, King G, Vespignani A. Big data. The parable of Google Flu: traps in big data analysis. Science. 2014 Mar 14;343(6176):1203-5. doi: 10.1126/science.1248506.
9. Pennisi F, Borlini S, Cuciniello R, D'Amelio AC, Calabretta R, Pinto A, et al. Improving Vaccine Coverage Among Older Adults and High-Risk Patients: A Systematic Review and Meta-Analysis of Hospital-Based Strategies. Healthcare (Basel). 2025 Jul 10;13(14):1667. doi: 10.3390/healthcare13141667.
10. Gentile L, Bertuccio P, Ancona A, Cucchi A, Dallagiacoma G, Godoy MA, et al. Can youtube be trusted as a source of quality and reliable information on COVID-19 vaccination in Italy? Acta Biomed. 2023 Aug 30;94(S3):e2023163. doi: 10.23750/abm.v94iS3.14558.
11. Pennisi F, Genovese C, Gianfredi V. Lessons from the COVID-19 Pandemic: Promoting Vaccination and Public Health Resilience, a Narrative Review. Vaccines (Basel). 2024 Aug 7;12(8):891. doi: 10.3390/vaccines12080891. .
12. Roozenbeek J, Schneider CR, Dryhurst S, Kerr J, Freeman ALJ, Recchia G, et al. Susceptibility to misinformation about COVID-19 around the world. R Soc Open Sci. 2020 Oct 14;7(10):201199. doi: 10.1098/rsos.201199.
13. Page MJ, McKenzie JE, Bossuyt PM, Boutron I, Hoffmann TC, Mulrow CD, et al. The PRISMA 2020 statement: an updated guideline for reporting systematic reviews. BMJ. 2021 Mar 29;372:n71. doi: 10.1136/bmj.n71.
14. Ouzzani M, Hammady H, Fedorowicz Z, Elmagarmid A. Rayyan-a web and mobile app for systematic reviews. Syst Rev. 2016 Dec 5;5(1):210. doi: 10.1186/s13643-016-0384-4.
15. Munn Z, Barker TH, Moola S, Tufanaru C, Stern C, McArthur A, et al. Methodological quality of case series studies: an introduction to the JBI critical appraisal tool. JBI Evid Synth. 2020 Oct;18(10):2127-33. doi: 10.11124/JBISRIR-D-19-00099.
16. Higgins JPT, Morgan RL, Rooney AA, Taylor KW, Thayer KA, Silva RA, et al. A tool to assess risk of bias in non-randomized follow-up studies of exposure effects (ROBINS-E). Environ Int. 2024 Apr;186:108602. doi: 10.1016/j.envint.2024.108602. Epub 2024 Mar 24.
17. Hong QN, Fàbregues S, Bartlett G, Boardman F, Cargo M, Dagenais P, et al. The Mixed Methods Appraisal Tool (MMAT) version 2018 for information professionals and researchers. Education for Information. 2018;34(4):285-91. doi: 10.3233/EFI-180221.
18. Salathé M, Khandelwal S. Assessing vaccination sentiments with online social media: implications for infectious disease dynamics and control. PLoS Comput Biol. 2011 Oct;7(10):e1002199. doi: 10.1371/journal.pcbi.1002199.
19. Berning P, Huang L, Razavi AC, Boakye E, Osuji N, Stokes AC, et al. Association of Online Search Trends With Vaccination in the United States: June 2020 Through May 2021. Front Immunol. 2022 Apr 20;13:884211. doi: 10.3389/fimmu.2022.884211. .
20. Baltrusaitis K, Reed C, Sewalk K, Brownstein JS, Crawley AW, Biggerstaff M. Healthcare-Seeking Behavior for Respiratory Illness Among Flu Near You Participants in the United States During the 2015-2016 Through 2018-2019 Influenza Seasons. J Infect Dis. 2022 Aug 24;226(2):270-7. doi: 10.1093/infdis/jiaa465.
21. Besculides M, Heffernan R, Mostashari F, Weiss D. Evaluation of school absenteeism data for early outbreak detection,

New York City. BMC Public Health. 2005 Oct 7;5:105. doi: 10.1186/1471-2458-5-105.
22. Chan MS, Jamieson KH, Albarracin D. Prospective associations of regional social media messages with attitudes and actual vaccination: A big data and survey study of the influenza vaccine in the United States. Vaccine. 2020 Sep 11;38(40):6236-47. doi: 10.1016/j.vaccine.2020.07.054.
23. Chang YW, Chiang WL, Wang WH, Lin CY, Hung LC, Tsai YC, et al. Google Trends-based non-English language query data and epidemic diseases: a cross-sectional study of the popular search behaviour in Taiwan. BMJ Open. 2020 Jul 5;10(7):e034156. doi: 10.1136/bmjopen-2019-034156. .
24. Dai J, Lyu F, Yu L, He Y. Temporal and Emotional Variations in People's Perceptions of Mass Epidemic Infectious Disease After the COVID-19 Pandemic Using Influenza A as an Example: Topic Modeling and Sentiment Analysis Based on Weibo Data. J Med Internet Res. 2023 Nov 2;25:e49300. doi: 10.2196/49300. .
25. Huang X, Smith MC, Jamison AM, Broniatowski DA, Dredze M, Quinn SC, et al. Can online self-reports assist in real-time identification of influenza vaccination uptake? A cross-sectional study of influenza vaccine-related tweets in the USA, 2013-2017. BMJ Open. 2019 Jan 15;9(1):e024018. doi: 10.1136/bmjopen-2018-024018.
26. Davies GR, Finch RG. Sales of over-the-counter remedies as an early warning system for winter bed crises. Clin Microbiol Infect. 2003 Aug;9(8):858-63. doi: 10.1046/j.1469-0691.2003.00693.x.
27. Dhaliwal D, Mannion C. Antivaccine Messages on Facebook: Preliminary Audit. JMIR Public Health Surveill. 2020 Oct 20;6(4):e18878. doi: 10.2196/18878.
28. Dugas AF, Hsieh YH, Levin SR, Pines JM, Mareiniss DP, Mohareb A, et al. Google Flu Trends: correlation with emergency department influenza rates and crowding metrics. Clin Infect Dis. 2012 Feb 15;54(4):463-9. doi: 10.1093/cid/cir883.
29. Eysenbach G. Infodemiology: tracking flu-related searches on the web for syndromic surveillance. AMIA Annu Symp Proc. 2006;2006:244-8.
30. Guidry JPD, Austin LL, O'Donnell NH, Coman IA, Lovari A, Messner M. Tweeting the #flushot: Beliefs, Barriers, and Threats During Different Periods of the 2018 to 2019 Flu Season. J Prim Care Community Health. 2020 Jan-Dec;11:2150132720932722. doi: 10.1177/2150132720932722.
31. Guidry JPD, Coman IA, Vraga EK, O'Donnell NH, Sreepada N. (S)pin the flu vaccine: Recipes for concern. Vaccine. 2020 Jul 22;38(34):5498-506. doi: 10.1016/j.vaccine.2020.06.012.
32. Lee WN, Stück D, Konty K, Rivers C, Brown CR, Zbikowski SM, et al. Large-scale influenza vaccination promotion on a mobile app platform: A randomized controlled trial. Vaccine. 2020 Apr 16;38(18):3508-14. doi: 10.1016/j.vaccine.2019.11.053. .
33. Magruder, SF. Evaluation of over-the-counter pharmaceutical sales as a possible early warning indicator of human disease. Johns Hopkins APL Technical Digest (Applied Physics Laboratory). 2003;24(4):349-53.
34. Meyer SB, Violette R, Aggarwal R, Simeoni M, MacDougall H, Waite N. Vaccine hesitancy and Web 2.0: Exploring how attitudes and beliefs about influenza vaccination are exchanged in online threaded user comments. Vaccine. 2019 Mar 22;37(13):1769-74. doi: 10.1016/j.vaccine.2019.02.028.
35. Nawa N, Kogaki S, Takahashi K, Ishida H, Baden H, Katsuragi S, et al. Analysis of public concerns about influenza vaccinations by mining a massive online question dataset in Japan. Vaccine. 2016 Jun 8;34(27):3207-13. doi: 10.1016/j.vaccine.2016.01.008. .
36. Nougairède A, Lagier JC, Ninove L, Sartor C, Badiaga S, Botelho E, et al. Likely correlation between sources of information and acceptability of A/H1N1 swine-origin influenza virus vaccine in Marseille, France. PLoS One. 2010 Jun 25;5(6):e11292. doi: 10.1371/journal.pone.0011292. .
37. Ortiz JR, Zhou H, Shay DK, Neuzil KM, Fowlkes AL, Goss CH. Monitoring influenza activity in the United States: a comparison of traditional surveillance systems with Google Flu Trends. PLoS One. 2011 Apr 27;6(4):e18687. doi: 10.1371/journal.pone.0018687.
38. Polgreen PM, Chen Y, Pennock DM, Nelson FD. Using internet searches for influenza surveillance. Clin Infect Dis. 2008 Dec 1;47(11):1443-8. doi: 10.1086/593098.
39. Powell GA, Zinszer K, Verma A, Bahk C, Madoff L, Brownstein J, et al. Media content about vaccines in the United States and Canada, 2012-2014: An analysis using data from the Vaccine Sentimeter. Vaccine. 2016 Dec 7;34(50): 6229-35. doi: 10.1016/j.vaccine.2016.10.067. .
40. Prieto Santamaría L, Tuñas JM, Fernández Peces-Barba D, Jaramillo A, Cotarelo M, Menasalvas E, et al. Influenza and Measles-MMR: two case study of the trend and impact of vaccine-related Twitter posts in Spanish during 2015-2018. Hum Vaccin Immunother. 2022 Jan 31;18(1):1-16. doi: 10.1080/21645515.2021.1877597. .
41. Saito S, Saito N, Itoga M, Ozaki H, Kimura T, Okamura Y, et al. Influence of Media on Seasonal Influenza Epidemic Curves. Int J Infect Dis. 2016 Sep;50:6-9. doi: 10.1016/j.ijid.2016.07.005.
42. Santangelo OE, Provenzano S, Gianfredi V. Infodemiology of flu: Google trends-based analysis of Italians' digital behavior and a focus on SARS-CoV-2, Italy. J Prev Med Hyg. 2021 Sep 15;62(3):E586-91. doi: 10.15167/2421-4248/jpmh2021.62.3.1704.
43. Signorini A, Segre AM, Polgreen PM. The use of Twitter to track levels of disease activity and public concern in the U.S. during the influenza A H1N1 pandemic. PLoS One. 2011 May 4;6(5):e19467. doi: 10.1371/journal.pone.0019467.
44. Sycińska-Dziarnowska M, Woźniak K, Paradowska-Stankiewicz I. Intrest in influenza and influenza like illnesses in Poland 2016-2021 based on Google Trend's data analysis. Przegl Epidemiol. 2022;76(1):11-18. doi: 10.32394/pe.76.02.

45. Valdivia A, Lopez-Alcalde J, Vicente M, Pichiule M, Ruiz M, Ordobas M. Monitoring influenza activity in Europe with Google Flu Trends: comparison with the findings of sentinel physician networks - results for 2009-10. Euro Surveill. 2010 Jul 22;15(29):19621. doi: 10.2807/ese.15.29.19621-en.
46. Wagner M, Lampos V, Yom-Tov E, Pebody R, Cox IJ. Estimating the Population Impact of a New Pediatric Influenza Vaccination Program in England Using Social Media Content. J Med Internet Res. 2017 Dec 21;19(12):e416. doi: 10.2196/jmir.8184.
47. Wilson N, Mason K, Tobias M, Peacey M, Huang QS, Baker M. Interpreting Google flu trends data for pandemic H1N1 influenza: the New Zealand experience. Euro Surveill. 2009 Nov 5;14(44):19386.
48. Cook S, Conrad C, Fowlkes AL, Mohebbi MH. Assessing Google flu trends performance in the United States during the 2009 influenza virus A (H1N1) pandemic. PLoS One. 2011;6(8):e23610. doi: 10.1371/journal.pone.0023610. Epub 2011 Aug 19.
49. Hulth A, Rydevik G. Web query-based surveillance in Sweden during the influenza A(H1N1)2009 pandemic, April 2009 to February 2010. Euro Surveill. 2011 May 5;16(18):19856.
50. Althouse BM, Ng YY, Cummings DA. Prediction of dengue incidence using search query surveillance. PLoS Negl Trop Dis. 2011 Aug;5(8):e1258. doi: 10.1371/journal.pntd.0001258.
51. Bravo C, Castells VB, Zietek-Gutsch S, Bodin PA, Molony C, Frühwein M. Using social media listening and data mining to understand travellers' perspectives on travel disease risks and vaccine-related attitudes and behaviours. J Travel Med. 2022 Mar 21;29(2):taac009. doi: 10.1093/jtm/taac009.
52. Carvajal P, Balanay JAG, Shearman S, Richards SL. Facebook and mosquito-borne disease outbreaks: An analysis of public responses to federal health agencies' posts about dengue and Zika in 2016. PLOS Glob Public Health. 2022 Sep 12;2(9):e0000977. doi: 10.1371/journal.pgph.0000977.
53. Chan EH, Sahai V, Conrad C, Brownstein JS. Using web search query data to monitor dengue epidemics: a new model for neglected tropical disease surveillance. PLoS Negl Trop Dis. 2011 May;5(5):e1206. doi: 10.1371/journal.pntd.0001206. Epub 2011 May 31. PMID: 21647308.
54. Espina K, Estuar MRJE. Infodemiology for Syndromic Surveillance of Dengue and Typhoid Fever in the Philippines. Procedia Computer Science. 2017;121:554–61. doi: 10.1016/j.procs.2017.11.073.
55. Gluskin RT, Johansson MA, Santillana M, Brownstein JS. Evaluation of Internet-Based Dengue Query Data: Google Dengue Trends. PLOS Negl Trop Dis. 2014 Feb 27;8(2):e2713. doi:10.1371/journal.pntd.0002713.
56. Jamora RDG, Lim MAR, Espiritu AI. Philippine immunization coverage and dengvaxia: An infodemiological study. Pediatr Int. 2023 Jan-Dec;65(1):e15623. doi: 10.1111/ped.15623.
57. Ho HT, Carvajal TM, Bautista JR, Capistrano JDR, Viacrusis KM, Hernandez LFT, et al. Using Google Trends to Examine the Spatio-Temporal Incidence and Behavioral Patterns of Dengue Disease: A Case Study in Metropolitan Manila, Philippines. Trop Med Infect Dis. 2018 Nov 11;3(4):118. doi: 10.3390/tropicalmed3040118.
58. Strauss R, Castro JS, Reintjes R, Torres J, Olivares JM, Herrera M, et al. Google dengue trends: An indicator of epidemic behavior. The Venezuelan case. Int J Infect Dis. 2016;53:119–20. doi:10.1016/j.ijid.2016.11.298.
59. Meankaew P, Lawpoolsri S, Piyaphanee W, Wansatid P, Chaovalit P, Lawawirojwong S, et al. Cross-platform mobile app development for disseminating public health information to travelers in Thailand: development and usability. Trop Dis Travel Med Vaccines. 2022 Jul 15;8(1):17. doi: 10.1186/s40794-022-00174-6.
60. Milinovich GJ, Avril SM, Clements AC, Brownstein JS, Tong S, Hu W. Using internet search queries for infectious disease surveillance: screening diseases for suitability. BMC Infect Dis. 2014 Dec 31;14:690. doi: 10.1186/s12879-014-0690-1.
61. Dale LP, White L, Mitchell M, Faulkner G. Smartphone app uses loyalty point incentives and push notifications to encourage influenza vaccine uptake. Vaccine. 2019 Jul 26;37(32):4594-600. doi: 10.1016/j.vaccine.2018.04.018.
62. Shakeri Hossein Abad Z, Kline A, Sultana M, Noaeen M, Nurmambetova E, Lucini F, et al. Digital public health surveillance: a systematic scoping review. NPJ Digit Med. 2021 Mar 3;4(1):41. doi: 10.1038/s41746-021-00407-6.
63. Fu Y, Han P, Wang J, Shahzad F. Digital pathways to healthcare: a systematic review for unveiling the trends and insights in online health information-seeking behavior. Front Public Health. 2025 Feb 12;13:1497025. doi: 10.3389/fpubh.2025.1497025.
64. Bansal S, Chowell G, Simonsen L, Vespignani A, Viboud C. Big Data for Infectious Disease Surveillance and Modeling. J Infect Dis. 2016 Dec 1;214(suppl_4):S375-9. doi: 10.1093/infdis/jiw400.
65. Cheah BCJ, Vicente CR, Chan KR. Machine Learning and Artificial Intelligence for Infectious Disease Surveillance, Diagnosis, and Prognosis. Viruses. 2025 Jun 23;17(7):882. doi: 10.3390/v17070882.
66. Sylla B, Ismaila O, Diallo G. 25 Years of Digital Health Toward Universal Health Coverage in Low- and Middle-Income Countries: Rapid Systematic Review. J Med Internet Res. 2025 May 29;27:e59042. doi: 10.2196/59042.
67. Monlezun DJ, Omutoko L, Oduor P, Kokonya D, Rayel J, Sotomayor C, et al. Digitalization of health care in low- and middle-income countries. Bull World Health Organ. 2025 Feb 1;103(2):148-54. doi: 10.2471/BLT.24.291643.
68. Shanahan H, Bezuidenhout L. Rethinking the A in FAIR Data: Issues of Data Access and Accessibility in Research.

Front Res Metr Anal. 2022 Jul 27;7:912456. doi: 10.3389/frma.2022.912456.
69. Cervellin G, Comelli I, Lippi G. Is Google Trends a reliable tool for digital epidemiology? Insights from different clinical settings. J Epidemiol Glob Health. 2017 Sep;7(3):185-9. doi: 10.1016/j.jegh.2017.06.001.
70. Comer L, Donelle L, Hiebert B, Smith MJ, Kothari A, Stranges S, et al. Short- and Long-Term Predicted and Witnessed Consequences of Digital Surveillance During the COVID-19 Pandemic: Scoping Review. JMIR Public Health Surveill. 2024 May 24;10:e47154. doi: 10.2196/47154.
71. Mesquita S, Perfeito L, Paolotti D, Gonçalves-Sá J. Epidemiological methods in transition: Minimizing biases in classical and digital approaches. PLOS Digit Health. 2025 Jan 13;4(1):e0000670. doi: 10.1371/journal.pdig.0000670.
72. Fallatah DI, Adekola HA. Digital Epidemiology: Harnessing Big Data For Early Detection And Monitoring Of Viral Outbreaks, Infect Prev Pract. 2024 Jun 29;6(3):100382. doi: 10.1016/j.infpip.2024.100382.
73. Yin JD. Media Data and Vaccine Hesitancy: Scoping Review. JMIR Infodemiology. 2022 Aug 10;2(2):e37300. doi: 10.2196/37300.
74. Bolt K, Gil-González D, Oliver N. Unconventional data, unprecedented insights: leveraging non-traditional data during a pandemic. Front Public Health. 2024 Mar 7;12:1350743. doi: 10.3389/fpubh.2024.1350743.
75. Green A, Wu S, Di Pasquale A, Pang T. The Role of Digital Opinion Leaders in Dengue Prevention Through Health Promotion and Public Health Collaboration: Qualitative Semistructured Interview Study. J Med Internet Res. 2025 Apr 25;27:e70997. doi: 10.2196/70997.
76. Pennisi F, Pinto A, Ricciardi GE, Signorelli C, Gianfredi V. Artificial intelligence in antimicrobial stewardship: a systematic review and meta-analysis of predictive performance and diagnostic accuracy. Eur J Clin Microbiol Infect Dis. 2025 Mar;44(3):463-513. doi: 10.1007/s10096-024-05027-y.
77. Pennisi F, Pinto A, Ricciardi GE, Signorelli C, Gianfredi V. The Role of Artificial Intelligence and Machine Learning Models in Antimicrobial Stewardship in Public Health: A Narrative Review. Antibiotics (Basel). 2025 Jan 30;14(2):134. doi: 10.3390/antibiotics14020134.