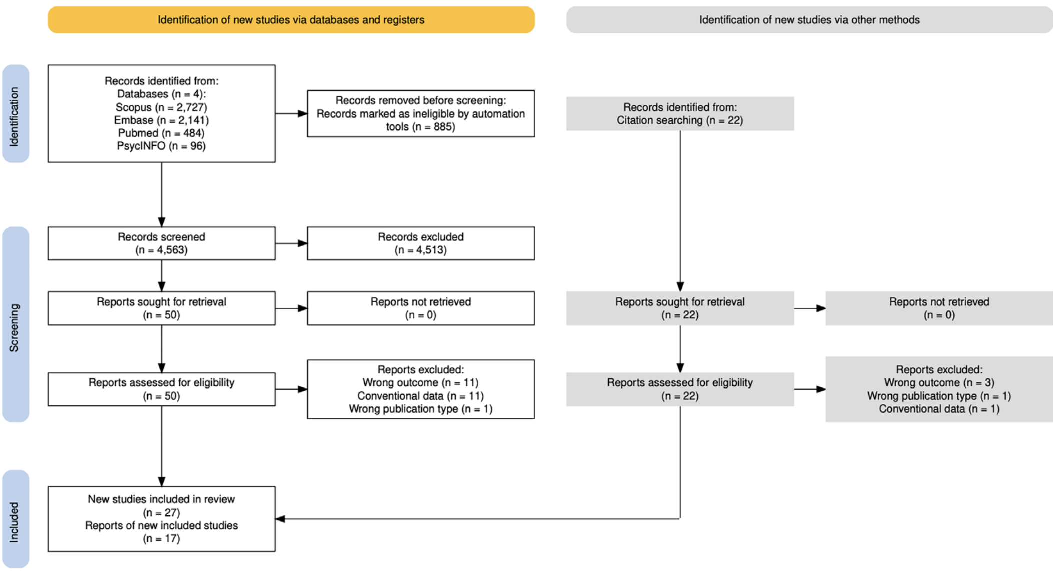

Figure S1. PRISMA study search flow diagram.

Table S1. Full search strategy

SET	Key words	Field	Component	Records retrieved (n.)
1	"Telemedicine"	**[MeSH]**	Unconventional data	
2	"Social Media"			
3	"Wearable Electronic Devices"			
4	"Digital health"			
5	"Consumer behavior"			
6	"Mobile Applications"			
7	"Unconventional data"	**[Title/Abstract]**		
8	"Unusual data"			
9	"non-conventional data"			

Table S1 (*continued*)

ANN IG. 2026; VOL. 38: 17959 DOI: 10.7416/AI.2026.17959

SET	Key words	Field	Component	Records retrieved (n.)
10	"non-standard data"			
11	"non-traditional data"			
12	"Alternative data"			
13	"big data"			
14	"atypical data"			
15	"emerging data"			
16	"innovative data"			
17	"epidemic intelligence"			
18	"internet data"			
19	"wearable device*"			
20	"Environmental sensor"			
21	"loyalty card"			
22	"Geolocation data"			
23	"credit card transaction*"			
24	"Facebook"			
25	"Tiktok"			
26	"Whatsapp"			
27	"instagram"			
28	"telegram"			
29	"youtube"			
30	"Twitter"			
31	"linkedin"			
32	"snapchat"			
33	"WeChat"			
34	"food delivery"			
35	"Twitch"			
36	"online shopping"			
37	"app"			
38	"Flutrackers"			
39	"Google trend"			
40	"digital surveillance"			
41	"WHO-EIOS"			
42	"HealthMap"			
43	"ProMED"			
44	"MedISys"			
45	"Epitweetr"			
46	"Global Outbreak Alert and Response Network"			

SET	Key words	Field	Component	Records retrieved (n.)
47	"Global Public Health Intelligence Network"			
48	"global health security initiative"			
49	"early warning"			
50	**Sets 1-49 were combined with "OR"**			233,485
51	"Preventive Health Services"	**[MeSH]**	Preventive behavior	
52	"vaccination"			
53	"vaccines"			
54	"Hand Disinfection"			
55	"Physical Distancing"			
56	"preventive behavior*"	**[Title/Abstract]**		
57	"health behavior*"			
58	"protection behavior*"			
59	"preventiv*"			
60	"health promot*"			
61	"preventive measur*"			
62	"preventive action*"			
63	"disease prevention*"			
64	"wellness behavior*"			
65	"preventive health*"			
66	"preventive intervention*"			
67	"risk reduction behavior*"			
68	"preventive service*"			
69	"self-care behavior*"			
70	"immunization"			
71	"prophylaxis"			
72	"health education"			
73	"healthy lifestyle behavior*"			
74	"mask*"			
75	"Hand Washings"			
76	"Avoiding contact"			
77	"indoor ventilation"			
78	"Social distancing"			
79	"handshake"			
80	"insect repellent*"			
81	"window net*"			
82	"hesitancy"			

Table S1 (*continued*)

SET	Key words	Field	Component	Records retrieved (n.)
83	**Sets 51-82 were combined with "OR"**			1,413,885
84	**Sets 50 and 83 were combined with "AND"**			20,199
85	"Respiratory Tract Infections"	**[MeSH]**	Respiratory (Influenza) and Vector-borne diseases (Dengue)	
86	"Influenza, Human"			
87	"Vector Borne Diseases"			
88	"mosquito-borne infection*"	**[Title/Abstract]**		
89	"arboviral infection*"			
90	"dengue"			
91	"dengue infection*"			
92	"outbreak*"			
93	**Sets 85-92 were combined with "OR"**			1,043,665
94	**Sets 84 and 93 were combined with "AND"**			3,263
95	"Comment"	**[Publication Type]**		
96	"Letter"			
97	"Editorial"			
98	"Review"			
99	"Systematic Review"			
100	"Meta-Analysis"			
101	**Sets 95-100 were combined with "OR"**			5,870,234
102	**Sets 94 and 101 were combined with "NOT"**			2,758
103	"Covid"	**[Title/Abstract]**		
104	**Sets 102 and 103 were combined with "NOT"**			484
105	**Sets 104 was limited to 9th November 2024**			

Table S2. Inclusion criteria declined according to Population, Intervention, Comparison, Outcome, and Study design (PICOS) guidelines

Inclusion Criteria	
Population (P)	General population. Only studies conducted on human subjects. No geographical or demographical limitations.
Intervention (I)	Unconventional data sources include informal networks, social media pages (e.g., Facebook and Twitter), mobile applications, internet searches, mobility data, and wearable electronic devices.
Comparison (C)	This review does not include a control group.
Outcome (O)	Monitoring preventive behavior towards influenza and dengue through unconventional data.
Study design (S)	Randomized Controlled Trials (RCTs), Prospective and retrospective cohort studies, Case-control studies, Cross-sectional studies, Qualitative studies.
Language	English
Time filter	None

Table S3. Data sources and monitoring features of the included studies

First Author, Year	Data source	Monitoring period	Duration	Data access	Target population
Influenza					
Baltrusaitis K. [2022]	FNY (Flu Near You) website, mobile application or Facebook	October 2015 - May 2019	3 years and 8 months	Manually, not public data	US users of FNY (Flu Near You)
Berning P. [2022]	Google Trends	1 June 2020 - 31 May 2021	1 year	Application Programming Interface	Google users
Besculides M. [2005]	Central database at the New York City Department of Education	2001-2004	4 years	Manually, not public data	Students enrolled in the New York City public school system
Chan M.-P.S. [2020]	Twitter	September 2017 - March 2019	1 year and 7 months	Application Programming Interface	US Twitter users
Chang Y.-W. [2020]	Google Trends	4 October 2015 - 2 April 2016	5 months and 29 days	Application Programming Interface	Taiwan Google users
Cook S. [2011]	Google Flu Trends	28 September 2003 - 31 December 2009	6 years, 3 months and 3 days	Application Programming Interface	Google search user in US
Dai J. [2023]	Weibo	1 November 2022 - 31 March 2023	5 months	Manually, public data	Weibo users
Dale L.P. [2019]	Carrot Rewards app	15 November 2016 - 15 December 2016	1 month	Manually, not public data	General population of British Columbia, Canada

Table S3 (*continued*)

First Author, Year	Data source	Monitoring period	Duration	Data access	Target population
Davies G.R. [2003]	Local electronic point-of-sale data from Boots the Chemists retail outlets and National sales data from Reckitt Benckiser's Lemsip FluForecast model.	Winter periods from 1992/1993 to 2000/2001, with detailed analysis focusing on three winters: 1998/1999, 1999/2000, and 2000/2001	Approximately 9 months	Manually, not public data	General population
Dhaliwal D. [2020]	Facebook	1 January 2019 - 30 May 2019	5 months	Manually, public data	Followers of the 4 Facebook pages
Dugas A. F. [2012]	Google Flu Trends	January 2009 - October 2010	1 year and 9 months	Application Programming Interface	Google search users in Baltimore, Maryland
Eysenbach G. [2006]	Google Adsense	3 October 2004- 21 May 2005	7 months and 18 days	Application Programming Interface	Internet users in Canada
Guidry J.P.D. [06/2020]	Pinterest	9 October 2019	1 day	Manually, public data	Pinterest users
Guidry J.P.D. [10/2020]	Twitter	1 October 2018 - 30 November 2018 1 January 2019 - 28 February 2019	4 months	Application Programming Interface	Twitter users
Huang X. [2019]	Twitter	2013-2017	5 years	Application Programming Interface	US Twitter users (18 years old), with limited representation of children and elderly
Hulth A. [2011]	Swedish medical website Vårdguiden.se	13 April 2009 - 14 February 2010	10 months and 1 day	Application Programming Interface	Swedish people looking for health information online
Lee W.-N. [2020]	Mobile app (Humana)	13 September 2016 - 4 November 2016	1 month and 22 days	Application Programming Interface	Insured adults, active mobile app users with activated notifications Participants (aged 18-65)
Magruder S.F. [2003]	Johns Hopkins University Applied Physics Laboratory	Fall 2001 - Spring 2002; Winter 2002/2003	Approximately 9 months and approximately 3 months	Manually, not public data	General population living in USA National Capital Area
Meyer S.B. [2019]	Canadian Broadcasting Corporation (CBC) website	1 September 2015 - 31 October 2016	1 year and 2 months	Application Programming Interface	Active users in CBC site comments
Nawa N. [2016]	Yahoo	April 2005-March 2009	4 years	Application Programming Interface	Japanese Yahoo users

First Author, Year	Data source	Monitoring period	Duration	Data access	Target population
Nougairède A. [2010]	Google search	2005-2009	5 years	Application Programming Interface	Google france users
Ortiz R.J. [2011]	Google Flu Trends	28 September 2003 - 17 May 2008	4 years, 7 months and 19 days	Application Programming Interface	Google search users in USA
Polgreen PM [2008]	Yahoo	March 2004 - May 2008	4 years and 2 months	Manually, not public data	US Yahoo users
Powell G.A. [2016]	Vaccine Sentimeter (Tool)	June 2012 - October 2014	2 years and 4 months	Application Programming Interface	NA
Prieto Santamaría L. [2021]	Twitter	2015-2018	4 years	Application Programming Interface	Twitter users
Saito S. [2016]	Google Trends	2002-2014	13 years	Application Programming Interface	Google search users
Salathé M. [2011]	Twitter	August 2019-January 2020	6 months	Application Programming Interface	Twitter users
Santangelo O.E. [2021]	Google Trends	2015-2019	5 years	Application Programming Interface	Google search users in Italian
Signorini A. [2011]	Twitter	29 April 2009 - 1 June 2009	1 month and 3 days	Application Programming Interface	US Twitter users
Sycińska-Dziarnowska M. [2022]	Google Trends	2016-2021	6 years	Application Programming Interface	Google search users in Polish
Valdivia A. [2010]	Google Trends	23 March 2009 - 28 March 2010	1 year and 5 days	Application Programming Interface	Internet users in European countries analysed
Wagner M. [2017]	Twitter	2011-2015	5 years	Application Programming Interface	Twitter users
Wilson N. [2009]	Google Flu Trends	29 March 2009 - 4 October 2009	6 months and 5 days	Application Programming Interface	Google search users in New Zealand
Influenza and Dengue					
Meankaew P. [2022]	ThaiEpidemics	December 2019 - January 2020	2 months	Application Programming Interface	International travelers in Thailand, particularly those visiting the Travel Clinic at the Hospital for Tropical Diseases, Mahidol University, Bangkok

Table S3 (*continued*)

First Author, Year	Data source	Monitoring period	Duration	Data access	Target population
Milinovich G.J. [2014]	Google Trends	2009-2013	5 years	Application Programming Interface	Google search users in Australia
			Dengue		
Althouse B.M. [2011]	Google search	2004-2011	7 years	Application Programming Interface	Internet users in countries analysed
Bravo C. [2022]	Travel website forums	18 - 21 January 2019	4 days	Application Programming Interface	German travellers
Carvajal P. [2022]	Facebook	2016	1 year	Application Programming Interface	Facebook users
Chan E.H. [2011]	Google Trends	2003-2010	7 years	Application Programming Interface	Internet users in countries analysed
Espina K. [2017]	Twitter	10 August 2016 - 10 September 2016	1 month	Application Programming Interface	Twitter users in Philippines
Gluskin R.T. [2014]	Google Trends	2003-2011	8 years	Application Programming Interface	Internet users in Mexico
Ho H.T. [2018]	Google Trends	2009-2014	6 years	Application Programming Interface	Google search users in Metropolitan Manila
Jamora R.D.G. [2023]	Google Trends	2015-2020	6 years	Application Programming Interface	Google search users in the Philippines and other dengue-endemic countries
Strauss R.A. [2017]	Google Trends	1January 2004 - 31 December 2014	11 years	Application Programming Interface	Internet users in Venezuela

Table S4. Correlation analyses performed in the included studies

First Author, Year	Correlation tests performed?	Type of test and result
	Influenza	
Baltrusaitis K. [2022]	No	Chi-square tests to compare proportions and age-adjusted estimates against BRFSS data, but does not present correlation tests.
Berning P. [2022]	Yes	Spearman correlation: COVID-19 (December 2020 - May 2021): rho = 0.71, P<0.001; Flu (August 2019 - May 2020): rho = 0.82, P<0.001; Flu (August 2020 - April 2021): rho = 0.91, P<0.001
Besculides M. [2005]	No	Wilcoxon signed-rank test to assess whether there is a systematic divergence in the observed differences in rates of absenteeism.

First Author, Year	**Correlation tests performed?**	**Type of test and result**
Chan M.-P.S. [2020]	Yes	Bayesian correlations between Twitter topics and attitudes towards vaccines/ vaccination status: The topic "Vaccine Science Matters" (November-February) was positively correlated with attitudes (February-March), r = 0.09, BF10 = 3.22; For participants without real-time discussions on the flu vaccine, the topic "Vaccine Fraud and Children" (November-February) was negatively associated with attitudes (February-March), r = -0.18, BF10 = 4;"Vaccine Fraud and Children" (November-February) was also inversely associated with vaccination (February-March and April-May), r from -0.18 to -0.25, BF10 = 4-146.
Chang Y.-W. [2020]	Yes	Pearson correlation without delay: Common cold: r = 0.898, p<0.001 with weekly number of positive influenza tests; Fever: r = 0.773, p<0.001 with weekly number of positive influenza tests; Cough: r = 0.796, p<0.001 with the weekly number of positive influenza tests. Pearson index with 1 week delay: Common cold: r = 0.900, p<0.001 with weekly number of positive influenza tests. Pearson index with medical claims related to ILI: Common cold: r = 0.900, p<0.001 for first aid patients with ILI; Cough: r = 0.886, p<0.001 for first aid patients with ILI; Fever: r = 0.802, p<0.001 for first aid patients with ILI. Symptom terms with weaker correlation:Runny nose: r = 0.076-0.263; Sore throat: r = 0.639-0.783.
Cook S. [2011]	Yes	Pearson correlation Pre-PH1N1: Original model: r = 0.906; Updated model: r = 0.942; Total pH1N1 period: Original model: r = 0.912;Updated model: r = 0.989; pH1N1 Wave 1 (summer): Original model: r = 0.290; Updated model: r = 0.945; pH1N1 Wave 2 (winter): Original model: r = 0.916; Updated model: r = 0.985
Dai J. [2023]	No	They focus on analysis of influenza A related Weibo posts using web crawling and topic modelling (LDA) techniques to identify hot topics and word frequency, but don't perform correlation tests with epidemiological data on incidence.
Dale L.P. [2019]	No	They use Chi-square tests to compare the proportions of influenza vaccination before and after a campaign, but don't perform correlation tests (e.g. Pearson, Spearman, cross-correlation) between continuous variables.
Davies G.R. [2003]	Yes	Pearson correlation: Respiratory emergency admissions vs. EPOS local sales: Winter 1998/99: Correlation coefficient of 0.279; Winter 1999/2000: Correlation coefficient of 0.892; Winter 2000/2001: Correlation coefficient of 0.075; Respiratory emergency admissions vs. Reckitt-Benckiser national sales: Winter 1998/99: Correlation coefficient of 0.299; Winter 1999/2000: Correlation coefficient of 0.890; Winter 2000/2001: Correlation coefficient of 0.702
Dhaliwal D. [2020]	No	They describe a qualitative analysis of social media content (Facebook) and shared links to understand views on immunization, but don't perform correlation tests with health outcomes.
Dugas A. F. [2012]	Yes	Cross-correlation test Positive influenza test results: Adult ED: r = 0.876; Paediatric ED: r = 0.718. ED access related to ILI: Adult ED: r = 0.885; Pediatric ED: r = 0.652. Overcrowding ED: Adult ED: r < 0.4; Paediatric ED: r = 0.649. Patients without doctor: Adult ED: r < 0.4; Paediatric ED: r = 0.641
Eysenbach G. [2006]	Yes	Pearson correlation: Clics vs. ILI-SPR (same week): 0.73; Clics vs. ILI-SPR (next week): 0.81; Clics vs. lab test (same week): 0.85; Clics vs. lab test (next week): 0.90; Clics vs. cases (same week): 0.88; Clicks vs. cases (next week): 0.91; ILI-SPR vs. laboratory test (same week): 0.83; ILI-SPR vs. laboratory test (next week): 0.82; ILI-SPR vs. cases (same week): 0.80;ILI-SPR vs. cases (next week): 0.75

Table S4 (*continued*)

First Author, Year	Correlation tests performed?	Type of test and result
Guidry J.P.D. [06/2020]	No	They use Mann-Whitney U tests to check for differences in engagement on Pinterest between posts with and without specific dichotomous variables, but don't perform correlation tests between continuous variables.
Guidry J.P.D. [10/2020]	No	They use Mann-Whitney U test for differences in engagement on Twitter and Chi-square test for differences between tweet start and peak season, but don't present correlation tests between continuous variables.
Huang X. [2019]	Yes	Pearson correlation between Twitter estimates and CDC data on influenza vaccination in the United States. All seasons 2013-2017: 0.799; Season 2013-2014: 0.644; Season 2014-2015: 0.950; Season 2015-2016: 0.909; Season 2016-2017: 0.910; State level (geographical): 0.387; Regional level (HHS region): 0.467
Hulth A. [2011]	Yes	Correlation coefficient: Vårdguiden model vs incomplete sentinel: 0.88; Vårdguiden model vs complete sentinel: 0.90; Google Flu Trends vs incomplete sentinel: 0.85; Google Flu Trends vs complete sentinel: 0.87 R-square: Vårdguiden model vs incomplete sentinel: 0.68; Vårdguiden model vs complete sentinel: 0.75; Google Flu Trends vs incomplete sentinel: NA;Google Flu Trends vs complete sentinel: NA
Lee W.-N. [2020]	No	They use Student's t-tests and Chi-square tests to compare the effectiveness of flu vaccination messages and incentives, but no correlation tests are provided (eg. Pearson, Spearman) between time series or continuous variables.
Magruder S.F. [2003]	Yes	Cross-correlation between over-the-counter (OTC) drug sales and medical diagnoses: Chest ointment sales vs. diagnosis of bronchitis/bronchiolitis: peak correlation of 0.86 with a 7-day delay in diagnoses compared to sales. OTC flu remedy sales vs. diagnosis of acute respiratory conditions: maximum correlation of 0.89 with a 12-day advance in sales. Sales of OTC flu remedies showed a consistent advance of about 3 days over medical diagnoses.
Meyer S.B. [2019]	No	They describe a systematic search for news about influenza and vaccination to analyze media content, but don't perform correlation tests between news and health data.
Nawa N. [2016]	Yes	Pearson correlation between the number of monthly applications and the number of flu patients in Japan: Flu-related questions and flu patients: r = 0.81, P < 0.001; Flu vaccine related questions and Google Trends search volume for "flu vaccine": r = 0.69, P < 0.001
Nougairède A. [2010]	No	They use a Chi-square test to compare vaccination coverage among different categories of health professionals. Graphs are presented for visual comparison of Google queries with laboratory influenza data, but numerical correlation coefficients are not explicitly given for these relationships in the extract.
Ortiz R.J. [2011]	Yes	Pearson correlation: between Google Flu Trends, CDC ILI Surveillance, and CDC Influenza Virologic Surveillance in the United States Overall study period (September 2003 - May 2008): Google Flu Trends vs. CDC ILI Surveillance: 0.94 (95% CI 0.92, 0.96); Google Flu Trends vs. CDC Virologic Surveillance: 0.72 (95% CI 0.64, 0.79); CDC ILI Surveillance vs. CDC Virologic Surveillance: 0.85 (95% CI 0.81, 0.89). Correlation with subsequent weeks (forecast): Google Flu Trends vs. CDC Virologic (plus one week): 0.69 (95% CI 0.60, 0.76); CDC ILI Surveillance vs. CDC Virologic (plus one week): 0.79 (95% CI 0.72, 0.84); Google Flu Trends vs. CDC Virologic (plus two weeks): 0.66 (95% CI 0.56, 0.74); CDC ILI Surveillance vs. CDC Virologic (plus two weeks): 0.75 (95% CI 0.68, 0.81) 2007-08 flu season by region: Average GFT vs. CDC ILI Surveillance: 0.97 (SD 0.02). Average GFT vs. CDC Virologic Surveillance: 0.87 (SD 0.04); Average CDC ILI Surveillance vs. CDC Virologic Surveillance: 0.89 (SD 0.05). Sensitivity analysis (excluding outliers): Google Flu Trends vs. CDC Virologic: 0.67 (95% CI 0.58, 0.75); CDC ILI Surveillance vs. CDC Virologic: 0.78 (95% CI 0.71, 0.83)

First Author, Year	Correlation tests performed?	Type of test and result
Polgreen PM [2008]	Yes	Regression analysis to predict cases of influenza and mortality based on Internet research R^2 for influenza-positive cultures (with several delays): Delay 0: 0.2075; Delay 1 week: 0.2787; Delay 2 weeks: 0.3418; Delay 3 weeks: 0.3882; Delay 4 weeks: 0.4198;Delay 5 weeks: 0.4229. R^2 for influenza-related mortality (with several delays): Delay 0: 0.2075; Delay 1 week: 0.2787; Delay 2 weeks: 0.3418; Delay 3 weeks: 0.3882; Delay 4 weeks: 0.4198;Delay 5 weeks: 0.4229.
Powell G.A. [2016]	No	They focus on the analysis of sentiment (positive, neutral, negative) and areas of interest in vaccine media reports, but don't present correlation tests with disease incidence data or other health outcomes.
Prieto Santamaría L. [2021]	No	They focuse on a descriptive analysis of the trends and sentiment of tweets related to flu vaccines and measles-MMR in Spanish, but don't present correlation tests with epidemiological data or health outcomes.
Saito S. [2016]	Yes	Pearson correlation of epidemic indicators, vaccination coverage and media information volume (MIVI) /research volume index (SVI) in Japan: Estimated dose of influenza drugs vs. DOP (duration from onset to peak): r = -0.65, p = 0.03; Estimated dose of anti-flu drugs vs. DOP/DOE (duration/exposure): r = -0.70, p = 0.02; SVI (pre-epidemic period) vs. vaccination coverage: r = 0.76, p = 0.01; SVI (epidemic period) vs. DOE (duration of the epidemic): r = 0.81, p = 0.004; SVI (epidemic period) vs. PDO/DOE: r = -0.81, p = 0.004; MIVI (pre-epidemic period) vs. PDO: r = 0.85, p = 0.0005; MIVI (pre-epidemic period) vs. vaccination coverage: r = 0.63, p = 0.03; MIVI (pre-epidemic period) vs. YES (gravity): r = -0.66, p = 0.02;MIVI (epidemic period) vs. vaccination coverage: r = 0.85, p = 0.0005.
Salathé M. [2011]	Yes	Pearson correlation between estimated immunization coverage and regional/state-level data in the United States): HHS region level: r = 0.78, p = 0.017; State level: r = 0.52, p = 0.0046.
Santangelo O.E. [2021]	Yes	Spearman correlation between Google Trends (GT) search volume and epidemiological data in Italy: Influenza cases vs. GT (period 2015-2019): rho = 0.92 (for "flu") and rho = 0.87 (for "symptoms of flu") with a delay of +1 week; Influenza cases vs. GT (period 2015-2020): rho = 0.77 (for "flu") and rho = 0.82 (for "symptoms of flu") with a delay of +1 week; Influenza deaths vs. GT (period 2016-2020): rho = 0.84 (for "flu") and rho = 0.81 (for "symptoms of flu") with a delay of +1 week; New cases of SARS-CoV-2 vs. GT ("flu" search term): rho = 0.80 with a delay of +3 weeks
Signorini A. [2011]	No	They describe an SVM-based estimator and present visual comparisons between the estimated ILI values and those reported by the CDC, but don't explicitly provide numerical correlation coefficients in the steps provided to quantify the relationship between the volume of tweets and the ILI, or the performance of the SVM estimator in terms of correlation.
Sycińska-Dziarnowska M. [2022]	No	They analyze interest in influenza and flu vaccine in Poland using data from Google Trends, describing the seasonal trend of queries and changes during the COVID-19 pandemic, but do not explicitly present correlation coefficients (e.g., Pearson, Spearman) or R2 values between research terms and disease incidence.

Table S4 (*continued*)

First Author, Year	Correlation tests performed?	Type of test and result
Valdivia A. [2010]	Yes	Spearman correlation (Rho) between GFTs and Sentinel Physician Networks (SPNs) for Influenza in Europe: Belgium (ILI): Overall period: 0.7358; Pre-pandemic period: 0.6929; Pandemic period: 0.8533; France (ILI): Overall period: 0.9124; Pre-pandemic period: 0.4957; Pandemic period: 0.9678; Hungary (ILI): Overall period: 0.8959; Pre-pandemic period: 0.3931; Pandemic period: 0.7496; Netherland (ILI): Overall period: 0.8597; Pre-pandemic period: 0.7850; Pandemic period: 0.9384; Norway (ILI): Overall period: 0.8769; Pre-pandemic period: 0.8651; Pandemic period: 0.8606; Poland (ILI): Overall period: 0.7157; Pre-pandemic period: 0.5179; Pandemic period: 0.5840; Spain (ILI): Overall period: 0.7331; Pre-pandemic period: 0.6443; Pandemic period: 0.9471; Sweden (ILI): Overall period: 0.7733; Pre-pandemic period: 0.5451; Pandemic period: 0.8704; Switzerland (ILI): Overall period: 0.8501; Pre-pandemic period: 0.8700; Pandemic period: 0.8783; Bulgaria (ARI): Overall period: 0.8377; Pre-pandemic period: 0.6263; Pandemic period: 0.7260; Germany (ARI): Overall period: 0.9396; Pre-pandemic period: 0.7370; Pandemic period: 0.9029; Russian Federation (ARI): Overall period: 0.8479; Pre-pandemic period: 0.8149; Pandemic period: 0.6899; Ukraine (ARI): Overall period: 0.8144; Pre-pandemic period: 0.7875; Pandemic period: 0.5275
Wagner M. [2017]	Yes	Pearson correlation for estimating ILI rates from Twitter activity in the UK. Gaussian Process (GP regression model performance: average r = 0.84 (SD 0.08) on 10-fold cross-validation
Wilson N. [2009]	No	They present a graphical comparison of Google Flu Trends data with ILI data from general practitioner networks and health care telephone services in New Zealand, but don't provide explicit numerical correlation coefficients to quantify these relationships.
		Influenza and Dengue
Meankaew P. [2022]	No	They evaluate the usability of a mobile app for disease surveillance and user search habits, using Chi-square testing and binary logistic regression to examine the relationships between demographic variables and increased awareness, but don't present correlation tests between search queries and disease incidence.
Milinovich G.J. [2014]	Yes	Spearman's correlation between infectious disease notifications and internet search terms in Australia: flu contagious: rho = 0.775; dengue fever: rho = 0.754
		Dengue
Althouse B.M. [2011]	Yes	Linear model AIC step-down: Bangkok: r^2 = 0.943, Pearson index 0.869; Singapore: r^2 = 0.948, Pearson index 0.931 AUC (Area Under the Curve ROC) of Support Vector Machine (SVM): Bangkok: 0.960; Singapore: 0.906
Bravo C. [2022]	No	They describe web scraping techniques and Natural Language Processing (NLP) to collect and analyze comments and posts on travel website forums, but don't perform correlation tests with health outcomes.
Carvajal P. [2022]	No	They analyze social media posts from federal health agencies for themes and feelings, but do not present correlations tests with disease incidence or other health outcomes.
Chan E.H. [2011]	Yes	Pearson correlation: Bolivia: 0.94; Brazil: 0.92; India: 0.87; Indonesia: 0.90; Singapore: 0.82 Holdout Pearson index: Bolivia: 0.83; Brazil: 0.99; India: 0.94;Indonesia: 0.94; Singapore: 0.94.
Espina K. [2017]	Yes	Pearson correlation: Dengue (Provincial Level): r = 0.845 p-value < 2.2e-16; Dengue (Municipal/City Level): r = 0.677 p-value < 2.2e-16

First Author, Year	Correlation tests performed?	Type of test and result
Gluskin R.T. [2014]	Yes	Pearson correlation: National level (2003-2011): 0.91; State level: ranged from 0.01 (Baja California) to 0.88 (Chiapas). Coefficient of determination R2: Single covariate model: R2 = 0.67; Multiple covariate model: R2 = 0.81
Ho H.T. [2018]	Yes	Pearson correlation between Google Dengue Trends (GDT) and dengue incidence (DI): Observed and weekly GDT (unadjusted): r = 0.405; Log (DI) and weekly GDT (unadjusted): r = 0.394; DI and adjusted GDT (AdjGDT): r = 0.662; Log (DI) and AdjGDT: r = 0.597; DI Scaling (ScDI) and GDT (unadjusted): r = 0.747; Log (ScDI) and GDT (unadjusted): r = 0.660; ScDI and AdjGDT: r = 0.529; Log (ScDI) and AdjGDT: r = 0.470
Jamora R.D.G. [2023]	Yes	Pearson correlation between Search Volume Index (SVI) on Google Trends for the word "Dengvaxia," those of other vaccines included in the Philippines' National Immunization Program, and estimated national vaccination coverage, for the period 2015-2019. All vaccines showed negligible correlation with SVI for Dengvaxia: Bacille Calmette-Guerin (BCG): r = -0.3749; Hepatitis B vaccine at birth: r = -0.4648; First dose of DPT: r = -0.3884; Third dose of DPT: r = -0.3884. None of the correlations proved statistically significant.
Strauss R.A. [2017]	Yes	Pearson correlation: Google Dengue Trends (GDT) and official reported cases (ORC) (2004-2014): r = 0.87, p < 0.001; ORC vs. Predicted Cases (MH): r = 0.33, p < 0.001; Epidemic weeks: r = 0.86, p < 0.001; Non-epidemic weeks: r = 0.65, p < 0.001; Monthly (2004-2014): r ranged from 0.48 (March) to 0.95 (July, August) (all p< 0.001); Annual (2004-2014): r ranged from 0.54 (2006) to 0.88 (2009) (all p< 0.001); Coefficient of determination (R^2): 0.75

Table S5. Key Findings, Practical Implications, and Challenges

First Author, Year	Main findings	Comparison with conventional data	Identified benefits, Practical application and Authors' conclusions	Challenges and limitations
Influenza				
Baltrusaitis K. [2022]	Age-adjusted percentage of participants seeking healthcare for ILI ranged 22.8–35.6%, highest in <18 and 65+ age groups and among women, mainly after ILINet peak.	Yes, compared with traditional phone surveys	Flu Near You provides real-time data on healthcare-seeking behavior, allowing assessment of seasonal trends, demographic impacts, and complementing existing surveillance systems.	Self-reported volunteer data may be biased; sample not fully representative; reporting inconsistent, likely underestimating weekly symptom reports during the 2016 season.
Berning P. [2022]	Seasonal peaks in influenza-related searches occurred in September–October (2016–2020). Trends were highly correlated with actual vaccination timing for 2019–2020 and 2020–2021; COVID-19 vaccination searches preceded vaccination trends, but influenza searches did not.	Yes, compared with vaccine administration rates	Online search data can guide public health efforts, inform policy, identify areas to expand vaccination campaigns, and potentially mirror influenza vaccination rates.	Search terms were arbitrarily selected; sample biased toward younger internet users; lacks demographic/geographic details; vaccination intent unknown; data limited to Google users.

Table S5 (*continued*)

First Author, Year	**Main findings**	**Comparison with conventional data**	**Identified benefits, Practical application and Authors' conclusions**	**Challenges and limitations**
Besculides M. [2005]	Moderate increases in absenteeism were observed among children during peak influenza seasons. Spatial analysis identified 790 significant clusters of absenteeism among elementary school children, including two coinciding with a previously reported outbreak.	Yes, compared with daily ED visits (ages 5–17) for fever or ILI and weekly influenza A/B isolates from NYC reference labs	School absenteeism data are population-based, non-confidential, nearly real-time, and can provide insights into mild illness patterns in children not seeking medical care. Useful for monitoring large-scale epidemics if absence reasons are known.	Absenteeism data are often non-specific; reasons for absence usually unknown. Data collection is discontinuous due to weekends, holidays, and vacations, and many recorded days offer limited useful information.
Chan M.-P.S. [2020]	Strong associations were found between specific online topics (e.g., Vaccine Science Matters, Big Pharma, Vaccine Fraud and Children) and vaccine-related attitudes and behaviors.	Yes, compared with surveys on vaccine attitudes, actual vaccination, and real-life discussions with family and friends	Social media data enabled prospective analysis linking online content to vaccine attitudes and uptake, incorporating individual- and regional-level data to reduce ecological fallacy. Platforms like Twitter reflect local vaccination patterns and can inform public health strategies; negative associations may be mitigated by real-life discussions.	Twitter users may not represent the general population; geographic coverage is limited. Other factors, such as health insurance coverage, also influence vaccination.
Chang Y.-W. [2020]	Strong correlation observed between Google Trends query data and influenza incidence.	Yes, compared with influenza incidence	"Big data" from online searches and social media can track and predict diseases. Monitoring search activity, including local-language queries, reflects public concern and epidemic trends faster than traditional reporting.	Short evaluation period limits capture of long-term trends; only Google Trends data were used.
Cook S. [2011]	During the pH1N1 pandemic, two Google Flu Trends (GFT) models were compared: an original model (without pH1N1 data) and an updated model (including initial pH1N1 wave and summer months). Both performed well before pH1N1 (r=0.9); the updated model slightly outperformed the original. The original model underperformed during the first wave but performed well in the second.	Yes, compared with official surveillance data from the U.S. Outpatient Influenza-like Illness Surveillance Network (ILINet)	GFT provides timely and accurate estimates of influenza activity in the U.S., especially during peak seasons and following novel influenza strains. The pH1N1 pandemic enabled model improvements combining seasonal and pandemic influenza, supporting predictive accuracy. Validation against lab-confirmed influenza remains necessary.	GFT models should be updated annually to account for behavioral changes.

First Author, Year	Main findings	Comparison with conventional data	Identified benefits, Practical application and Authors' conclusions	Challenges and limitations
Dai J. [2023]	Female Weibo users showed higher engagement than males; regular users were the majority. Public discourse was grouped into 23 themes, with predominantly negative sentiment (83%).	No	Provides insights into evolving public attitudes and concerns, supporting timely responses and adaptive communication strategies for influenza A, informed by experiences from the COVID-19 pandemic.	Data not representative of the general population; spatiotemporal analysis limited by lack of pre-pandemic comparisons.
Dale L.P. [2019]	High engagement with the Flu Campaign mobile app: 38.1% completed the quiz, 41% viewed nearest pharmacy, 77.8% enabled location services; only 0.4% visited a pharmacy, with 39.6% of those receiving the influenza vaccine. HRA sub-sample showed ~5% increase in self-reported vaccination vs. previous year.	No	Demonstrated feasibility and scalability of mobile apps for public health campaigns, with high engagement, geolocation prompting, and rapid reach. Informed campaign improvements and tailored content for high-risk populations.	Low conversion from engagement to vaccination; small incentives; limited demographic data; results may not generalize to other regions or age groups; reliance on self-reported data and limited evaluation methods.
Davies G.R. [2003]	Local EPOS sales data positively correlated with emergency admissions during winters 1998/99 and 1999/2000, providing up to two weeks' advance warning of peaks.	Yes, compared with hospital admission records and national influenza surveillance.	EPOS sales offer a simple, low-cost method to forecast hospital admission peaks and enable proactive resource allocation during winter pressures.	Limited sensitivity of ICD discharge codes; short monitoring period (3 years); weekly aggregation reduces precision; model lacks other predictors (e.g., weather, historical trends).
Dhaliwal D. [2020]	Analysis of Facebook Pages identified themes promoting anti-vaccine beliefs: (1) forming online communities, (2) widespread reach of anti-vaccine messages, (3) debates on mandatory immunization and content moderation	No	Facebook data help identify common vaccine myths, popular opinions, and influential sources. Insights into online anti-vaccine communities can guide effective communication strategies and counter misinformation, leveraging trusted public figures.	Study limited by dynamic web content and post removals; template not previously validated; user accounts may not be unique; only Facebook analyzed; authors' perspective is pro-immunization.
Dugas A. F. [2012]	City-level Google Flu Trends (GFT) strongly correlated with influenza cases and ED visits for ILI, including pediatric crowding measures and low-acuity adult visits.	Yes, compared with CDC-reported ILI data, lab-confirmed influenza, and ED crowding indices.	Validates GFT as an ED surveillance tool; supports linking GFT data to ED response plans and potential predictive models for influenza activity.	Limited generalizability: single medical center, one city, two-year period.

Table S5 (*continued*)

First Author, Year	**Main findings**	**Comparison with conventional data**	**Identified benefits, Practical application and Authors' conclusions**	**Challenges and limitations**
Eysenbach G. [2006]	Number of clicks on ads strongly correlated with traditional ILI surveillance; internet clicks provided more timely predictions for the following week.	Yes, compared with ILI reports from sentinel physicians (ILI-SPR).	Internet search data offer low-cost, timely, and accurate influenza surveillance, complement traditional systems, identify public health information gaps, and support early outbreak detection through infodemiology.	Limited access to raw data; media-driven bias; seasonal fluctuations in internet use; poor geolocation accuracy; need for further validation; lack of supply-side data.
Guidry J.P.D. [06/2020]	52.5% of posts were pro-vaccine, 47.5% anti-vaccine; anti-vaccine content received higher engagement. Most posts came from individuals, only 5% from official health agencies.	No	Enables real-time monitoring of public opinion, identification of misinformation, and informs health communication strategies. Engaging healthcare institutions on visual platforms like Pinterest can improve public perception.	Analysis of visual content requires specialized skills and is hard to automate; users may be unaware of data use; limited to posts available at a given time, not representing all vaccination discussions.
Guidry J.P.D. [10/2020]	Flu vaccine tweet content and engagement differed between start and peak of flu season; perceived vaccination barriers increased from 11.3% to 25.3%.	No	Social media provide real-time insights into beliefs, experiences, and perceived barriers to vaccination. Tailored, phase-specific health communication strategies can enhance vaccination uptake and combat misinformation.	Data may not represent the general population; observational design prevents causal inference between tweet content and vaccination behavior.
Huang X. [2019]	Monthly correlation with CDC data: 0.799 (peak: 0.950); geographical correlation: 0.387 (state), 0.467 (regional); higher Twitter activity among women, consistent with CDC trends.	Yes, compared with CDC FluVaxView data.	Social media provide timely, real-time data with geographical granularity and lower costs. Twitter can complement surveillance systems, improving speed and spatial resolution.	Under-representation of children, elderly, and rural populations; demographic bias; reliability of inferred geolocation and gender.
Hulth A. [2011]	Statistical models were consistently reliable, even during the A(H1N1) 2009 pandemic.	Yes, compared with sentinel surveillance data (percentage of ILI patients among GP visits).	Fully automatic system producing estimates ahead of traditional sources; cost-effective and complements national surveillance, providing timely additional information.	Media influence on search behavior is unknown; trend changes considered reliable only if sustained ≥2 weeks.

First Author, Year	Main findings	Comparison with conventional data	Identified benefits, Practical application and Authors' conclusions	Challenges and limitations
Lee W.-N. [2020]	Group messages: 23.2% vaccinated vs 22% control (p<0.01); effectiveness decreased with repetitions; no significant difference between message types.	No	Mobile apps can deliver timely public health interventions; push messages modestly increase vaccination, especially among young populations. Simple messages can be as effective as incentivized ones; timing is crucial.	Selection bias (app users); limited generalizability; data quality depends on user claims; privacy concerns.
Magruder S.F. [2003]	High correlation (up to 90%) between OTC flu remedy sales and physician diagnoses of acute respiratory conditions; OTC sales preceded visits by ~3 days.	Yes, compared with clinical diagnosis records.	OTC sales provide early warning (~3 days) for respiratory conditions; electronic records are readily available and predictive; can strengthen syndromic surveillance.	Seasonal and regional variability in trends; physician visits drop during holidays; OTC product groupings need refinement for better predictive accuracy.
Meyer S.B. [2019]	Comments were highly polarized, with rhetorical tactics reinforcing "echo chambers" and weak relation to article content.	No	Provides access to spontaneous, unmediated interactions in large volumes; allows observation of natural social dynamics without intervention	Self-selection bias (only motivated users); lack of demographic data; inability to track temporal changes; privacy risks.
Nawa N. [2016]	Most frequent concerns: vaccination schedule (29%), safety (25%), effectiveness (18%); efficacy questions increased during epidemics; pregnancy/lactation questions concentrated pre-epidemic.	Yes, compared with national influenza outbreak surveillance data.	Enables timely detection of seasonal trends and insights into real public concerns; supports targeted, timely communication through official platforms.	Possible selection bias (active online users); difficulty identifying duplicates; variable response quality; sample may not represent general population (no stratification by age, gender, education).
Nougairède A. [2010]	Google search trends for influenza correlated with influenza incidence.	Yes, compared with positive influenza lab samples.	Highlights the potential of integrating public health communication with real-time online data; emphasizes involving trusted sources like general practitioners to improve vaccine uptake.	Subjective classification of information sources; limited vaccine uptake in France due to exclusion of GPs, negative misinformation, top-down government approach, and perception of mild pandemic.
Ortiz R.J. [2011]	Google Flu Trends strongly correlated with ILI rates, but correlation with lab-confirmed influenza was lower.	Yes, compared with CDC ILI Surveillance and CDC Influenza Virologic Surveillance.	Provides timely data and complements traditional ILI surveillance, supporting early public health actions.	GFT estimates ILI, not actual influenza; accuracy depends on widespread search engine use and consistent behavior; affected by media trends, keyword choices, and regional cultural differences.

Table S5 (*continued*)

First Author, Year	**Main findings**	**Comparison with conventional data**	**Identified benefits, Practical application and Authors' conclusions**	**Challenges and limitations**
Polgreen PM [2008]	Influenza-related search-term activity precedes increases in lab-confirmed influenza cases and influenza/pneumonia deaths, reflecting influenza epidemiology.	Yes, compared with US clinical laboratory surveillance and Cities Mortality Reporting System.	Provides standardized, easily collected pre- and post-diagnostic data; enables early trend detection (lead time of weeks); cost-effective supplement to traditional surveillance; applicable to multiple diseases.	Limited to four years of data; search volumes influenced by media/public figures; IP-based locations may be inaccurate; privacy concerns with individual-level data; limited access to raw search logs.
Powell G.A. [2016]	Most media reports were positive or neutral; negative content mainly from blogs/non-traditional sites. HPV and Hepatitis B vaccines had more negative coverage; influenza vaccines rarely negative, with coverage peaking during seasonal vaccination campaigns.	No	Supports timely engagement with media to enhance vaccine communication; helps assess visibility and reach of key public health messages; informs strategies to improve vaccination uptake.	Reliability of article coding not formally assessed; manual classification discontinued due to funding, limiting updated analyses.
Prieto Santamaría L. [2021]	Peaks in influenza-related tweets observed in March–May and Oct–Dec, with seasonal differences between hemispheres aligned with vaccination campaigns.	No	Twitter data can capture public opinion and message patterns, supporting public health in addressing doubts, misinformation, and vaccine hesitancy.	Lack of geolocation for many tweets; difficulty in sentiment analysis due to writing variability; Twitter's character limit reduces contextual accuracy.
Saito S. [2016]	Meteorological, demographic, and behavioral factors influence influenza spread. Media-driven education, vaccination, and reduced social activity flatten epidemic curves.	Yes, with vaccine coverage and seasonal flu severity	Media-based health education improves vaccination uptake and adherence to protective measures, reducing epidemic peaks.	Analysis limited to media information, search trends, and vaccine coverage; did not account for population immunity or quality of media information.
Salathé M. [2011]	Twitter-derived vaccination sentiment strongly aligned with CDC survey-based vaccination rates by region. Clusters of negative sentiment increased outbreak risk.	Yes, with CDC-estimated vaccination rates	Social media provides real-time, cost-effective insights into vaccine attitudes, useful for identifying target areas and evaluating interventions.	Observational study design limits causality; social media users not representative; sentiment analysis accuracy limited; confounding factors (e.g., vaccine supply) not excluded.
Santangelo O.E. [2021]	Strong correlation between influenza cases/deaths (ISS data) and Google Trends searches for flu and related symptoms. Correlation strengthened with a 1-week lag. Similar correlation found with SARS-CoV-2 cases.	Yes, with weekly incidence from Italian National Institute of Health reports	Google Trends can capture emerging public interest in infectious diseases, supporting hypothesis generation on knowledge, attitudes, and practices. Potentially useful for surveillance of both known and novel diseases.	Limited to states and selected metropolitan areas; poor coverage in rural/low-access regions; anonymous data prevent subgroup analysis and limit assessment of disparities.

First Author, Year	**Main findings**	**Comparison with conventional data**	**Identified benefits, Practical application and Authors' conclusions**	**Challenges and limitations**
Signorini A. [2011]	Twitter-derived ILI estimates closely tracked reported disease levels; provided forecasts days to weeks earlier than traditional data.	Yes, with CDC Influenza Reporting Regions data	Real-time, cost-effective supplement to traditional surveillance; can estimate disease activity 1–2 weeks earlier; useful for monitoring public concerns and evaluating health messaging.	Non-uniform Twitter use across time/regions; only one year of data analyzed; demographic bias (users not representative of general population).
Sycińska-Dziarnowska M.[2022]	Correlation between Google searches on infectious diseases and national surveillance data; peaks in influenza-related searches (Feb 2017–2020) matched epidemiological incidence.	Yes, with National Institute of Public Health data on influenza and ILI.	Query data from search engines can track public interest in health topics and complement surveillance systems.	During COVID-19, variations in flu-related searches were influenced by pandemic events; peak searches (March 2020) linked to WHO pandemic announcement.
Valdivia A. [2010]	Good correlation between Google Flu Trends and Sentinel Physicians Networks in most countries.	Yes, with Sentinel physician networks (SPNs).	Estimates may be available 1–2 weeks earlier than conventional surveillance; useful complement to traditional monitoring systems, with potential accuracy improvements as internet use grows.	Correlation varies over time; possible mismatches in timing and magnitude of peaks; seasonal discrepancies; dependence on population's search habits.
Wagner M. [2017]	Reduction in ILI rates of 14% (2013/14) and 17% (2014/15) in primary school-age vaccine pilot areas; no significant impact in secondary school cohorts.	Yes, with ILI rates from the Royal College of General Practitioners.	User-generated content (e.g., Twitter) enables timely syndromic surveillance, complementing traditional systems and capturing individuals who do not seek healthcare; useful for evaluating public health interventions.	Requires methodological refinement to reduce noise and bias; ILI estimates not directly linked to confirmed cases; data influenced by user demographics (mainly 15–44 years, urban/suburban).
Wilson N. [2009]	Google Flu Trends aligned closely with two national surveillance systems but less with Healthline data.	Yes, with ILI data from Sentinel GP system, HealthStat, and Healthline.	Free and timely tool showing rise and peak of ILI; provides daily and weekly downloadable data; useful in countries with weak surveillance, complementary in well-established systems.	Did not detect outbreaks earlier than traditional systems; occasional false peaks; requires calibration with robust surveillance systems; search behavior influenced by media; disparities in internet access may reduce representativeness.
Influenza e Dengue				
Meankaew P. [2022]	92.3% of e-survey participants reported that ThaiEpidemics improved their awareness of disease prevalence/status in Thailand, independent of age, education, or continent.	No	ThaiEpidemics provides real-time disease information for travelers, raises awareness of health issues, and is open-source, allowing adaptation to other contexts.	Security/privacy concerns limited adoption; small sample size (n=83); data timeliness is crucial and may affect reliability; potential high resource usage on devices.

Table S5 (*continued*)

First Author, Year	**Main findings**	**Comparison with conventional data**	**Identified benefits, Practical application and Authors' conclusions**	**Challenges and limitations**
Milinovich G.J. [2014]	Correlation exists between Google search trends for infectious diseases and national surveillance notifications.	Yes, compared with national monthly case numbers.	Google Trends can provide early signals of outbreaks, supporting early detection and forecasting. Integrating multiple search terms and other data sources (e.g., meteorological) can improve accuracy.	Monthly data may limit timeliness; results may be influenced by media coverage; linguistic and geographic variations reduce applicability across regions or countries.
Dengue				
Althouse B.M. [2011]	Internet search terms accurately predict dengue incidence and high-transmission periods.	Yes, vs dengue surveillance data (Singapore weekly, Thailand monthly)	Yes, vs dengue surveillance data (Singapore weekly, Thailand monthly)	Yes, vs dengue surveillance data (Singapore weekly, Thailand monthly)
Bravo C. [2022]	Young people showed the highest levels of anxiety about dengue compared to other age groups, regardless of travel destination.	No	Web scraping enables access to large datasets on health-related opinions and perceptions, helping to identify misinformation, reluctance to adopt best practices, and areas where reliable guidance is needed. Findings can support healthcare professionals in counselling and reducing the risk of infection among travellers.	Limited to individuals with internet access and active on social media; dataset had a high level of missing information, not clearly specified.
Carvajal P. [2022]	Negative perception toward agency posts; comment sections spread misinformation. CERC analysis: focus on risk/warnings, little reassurance.	No	Social media (e.g., Facebook) can track perception, misinformation, and support timely, balanced health communication (monitoring disinfo within 24h, linking to hotspots).	Limited to 4 U.S. agencies on Facebook; only 2016 Zika epidemic; possible loss of nuance in sentiment analysis; no demographic data.
Chan E.H. [2011]	Strong correlation between expected and observed dengue case counts (0.82–0.99), except Bolivia 2007 (overestimate) and India 2005 (underestimate).	Yes, official data (Ministries of Health, WHO).	Near real-time availability, useful complement to dengue surveillance in several countries.	Limited internet access in rural areas, variability in national case definitions, risk of self-diagnosis, privacy concerns.
Espina K. [2017]	Infodemiological tweets add value to spatio-temporal syndromic surveillance.	Yes, vs dengue and typhoid surveillance data	Supports timely public policies; regression model can estimate incidences.	Limited real-time data access; interoperability issues; linguistic/geocoding gaps; weaker typhoid correlations; study limited to Western Visayas, needs regional expansion.

First Author, Year	Main findings	Comparison with conventional data	Identified benefits, Practical application and Authors' conclusions	Challenges and limitations
Gluskin R.T. [2014]	Captured ~83% of variability in national dengue data; accuracy higher in high-incidence, favorable climate states.	Yes, vs monthly dengue surveillance (Secretariat of Health); climate (SEMARNAT); socio-demographic data (INEGI).	Provides timely insights for predictive models; climate-based model extends utility to states without GDT; useful even with low internet penetration.	Accuracy varies by state; weaker indicator in low-incidence areas; less reliable for local transmission.
Ho H.T. [2018]	GDT follows seasonal dengue trends; moderate correlation (r=0.405 with DI, r=0.394 with LogDI); GDT leads incidence by 1–2 weeks, with peaks preceding outbreaks.	Yes, vs dengue incidence data (Philippine Dept. of Health, National Epidemiology Center).	GDT complements traditional surveillance; can help predict outbreaks; combining with meteorological, environmental, social, entomological factors improves utility.	Weak spatial correlation at city level; limited by internet penetration; media influence may bias search activity; effective mainly in high-incidence areas.
Jamora R.D.G. [2023]	Philippines showed highest SVI for Dengvaxia, closely following global trends; Pearson correlation very high for Philippines (r=0.9649), high for Singapore (r=0.7388), negligible for Malaysia and India; other countries had insufficient SVI.	Yes, vs WHO/UNICEF national immunization coverage.	Highlights potential of web-search data for infodemiology research and monitoring public interest in vaccines.	No significant correlation between SVI and actual immunization coverage; limited to Google searches, excludes social media; reflects only users with internet access and search skills.
Strauss R.A. [2017]	High correlation between official surveillance data and Google Dengue Trends (GDT), especially during high-incidence periods (May–October).	Yes, vs Venezuelan Ministry of Health weekly bulletins.	Useful for prioritizing and monitoring dengue vaccine deployment and effectiveness; supports early interventions and control measures in low-resource or high-burden regions.	Uneven internet access reduces accuracy in rural areas; susceptible to panic-driven search spikes; nationwide data limits guidance for local interventions.

Table S6. Quality assessment using the ROBINS-E tool

ROBINS-E	D1	D2	D3	D4	D5	D6	D7	Overall
Influenza								
Baltrusaitis K. [2022]	Low	Some concerns	Low	Low	Low	Low	Low	**Some concerns**
Berning P. [2022]	Some concerns	Low	Low	Low	Low	Low	Low	**Some concerns**
Besculides M. [2005]	Some concerns	Some concerns	Low	Low	Low	Low	Some concerns	**Some concerns**
Chan M.-P.S. [2020]								**Very High**
Cook S. [2011]	Some concerns	Low	Low	Low	Some concerns	Low	Some concerns	**Some concerns**
Davies G.R. [2003]	Some concerns	Some concerns	Low	Low	Low	Low	Low	**Some concerns**
Eysenbach G. [2006]	Some concerns	Some concerns	Some concerns	Low	Low	Low	Some concerns	**Some concerns**
Magruder S.F. [2003]	High	Low	Low	Some concerns	Some concerns	Low	High	**High**
Ortiz R.J. [2011]								**Very High**
Polgreen PM [2008]	High	Some concerns	Low	Low	Low	Low	High	**High**
Powell G.A. [2016]	Some concerns	Some concerns	Low	Low	Low	Some concerns	Some concerns	**Some concerns**
Prieto Santamaría L. [2021]	High	Some concerns	Some concerns	Low	Low	Low	Some concerns	**High**
Saito S. [2016]								**Very High**
Salathé M. [2011]	Some concerns	Some concerns	Low	Low	Low	Low	Some concerns	**Some concerns**
Signorini A. [2011]	High	Some concerns	Low	Low	Some concerns	Low	High	**High**
Sycińska-Dziarnowska M. [2022]	High	Low	Low	Low	Low	Low	Some concerns	**High**
Valdivia A. [2010]	Some concerns	Some concerns	Low	Low	Low	Low	Low	**Some concerns**
Wagner M. [2017]	Some concerns	Low	Low	Low	Some concerns	Low	Some concerns	**Some concerns**
Wilson N. [2009]	High	High	Low	Low	Low	Low	Some concerns	**High**
Influenza e Dengue								
Milinovich G.J. [2014]	Some concerns	Some concerns	Low	Low	Low	Low	Low	**Some concerns**
Dengue								
Althouse B.M. [2011]	High	Some concerns	Low	Low	Low	Low	High	**High**

ROBINS-E	D1	D2	D3	D4	D5	D6	D7	Overall
Chan E.H. [2011]	Some concerns	Some concerns	Low	Low	Low	Low	Some concerns	**Some concerns**
Espina K. [2017]	Some concerns	Low	Some concerns	Low	Some concerns	Some concerns	Some concerns	**Some concerns**
Gluskin R.T. [2014]	Some concerns	Some concerns	Low	Low	Low	Low	Some concerns	**Some concerns**
Ho H.T. [2018]	Some concerns	Some concerns	Low	Low	Low	Low	Some concerns	**Some concerns**
Jamora R.D.G. [2023]								**Very High**
Strauss R.A. [2017]	High	High	Low	Low	Some concerns	Low	Low	**High**

Table S7. Quality assessment using the JBI Critical Appraisal Checklist for Analytical Cross Sectional Studies

JBI CSS	D1	D2	D3	D4	D5	D6	D7	D8	Overall
Chang Y.-W. [2020]	Yes	Yes	Yes	Yes	No	No	Yes	Yes	**High**
Dai J. [2023]	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	**Low**
Dale L.P. [2019]	Yes	Yes	Yes	No	Unclear	No	No	Yes	**High**
Dhaliwal D. [2020]	Yes	Yes	Unclear	Yes	NA	NA	Unclear	Yes	**Moderate**
Dugas A. F. [2012]	Yes	Yes	Unclear	Yes	Yes	Yes	Yes	Yes	**Moderate**
Guidry J.P.D. [06/2020]	Yes	Yes	Yes	Yes	Unclear	No	Yes	Yes	**Moderate**
Guidry J.P.D. [10/2020]	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	**Low**
Huang X. [2019]	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	**Low**
Meyer S.B. [2019]	Yes	Unclear	Yes	Yes	Unclear	NA	Yes	Yes	**Moderate**
Nawa N. [2016]	Yes	Yes	Yes	Yes	Unclear	Unclear	Yes	Yes	**Moderate**
Santangelo O.E. [2021]	Yes	Yes	Yes	Yes	Yes	No	Yes	Yes	**Moderate**
Meankaew P. [2022]	Yes	Yes	Yes	No	Yes	Yes	Unclear	Yes	**Moderate**
Bravo C. [2022]	Yes	Unclear	Yes	Yes	Yes	Yes	Unclear	Yes	**Moderate**

Table S8. Quality assessment using the JBI Critical Appraisal tool for assessment of Risk of Bias for Randomized Controlled Trials

JBI RCTs	D1	D2	D3	D4	D5	D6	D7	D8	D9	D10	D11	D12	D13	Overall
Lee W.-N. [2020]	Yes	Unclear	Yes	No	No	Yes	Unclear	Yes	Yes	Yes	Yes	Yes	Yes	**Moderate**

Table S9. Quality assessment using the Mixed Methods Appraisal Tool (MMAT) - 2018

MMAT	S1	S2	1.1	1.2	1.3	1.4	1.5	4.1	4.2	4.3	4.4	4.5	5.1	5.2	5.3	5.4	5.5	Overall
Hulth A. [2011]	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	1
Nougairède A. [2010]	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No	Yes	No	Yes	Yes	Yes	Yes	Yes	Yes	0,87
Carvajal P. [2022]	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No	Yes	No	Yes	Yes	Yes	Yes	Yes	Yes	0,87