First Author, Year	Country	Design/ Method	Type of Surveillance	Data Source	Disease, Illness or Syndrome	Key Results	Quality Rating
Harder 2011*[35]	Denmark	Retrospective Secondary Analysis	Clinical Syndromic	Electronic health records reported through the DMOS	ILI/Influenza	When compared with the traditional sentinel surveillance system in Denmark, the peak in ILI incidence appeared a week earlier in the DMOS system.	Weak
McLeod 2009[20]	New Zealand	Retrospective Secondary Analysis	Clinical Syndromic	ED discharge records for all respiratory syndrome events	Respiratory syndrome/Influenza	Surveillance system may have provided early warning of a potential respiratory oubreak. Regular exceedance flags of increased illness were generated nine days prior to the initial notification received by public health.	Moderate
Mostashari 2003[21]	United States	Retrospective Secondary Analysis	Clinical Syndromic	Data on call types from 911 dispatchers	ILI/Influenza	ILI rate from 911 dispatch calls significantly increased with increased numbers of lab-confirmed influenza cases. 71 alarms occurred during the period under review, 90% of which occurred slightly before or during a period of peak influenza.	Weak
Parrella 2009[22]	Australia	Retrospective Secondary Analysis	Clinical Syndromic	ILI data from participating GPs	ILI/Influenza	ILI rates showed similar trends to FluTracking online self-reporting ILI data and National Notifiable Diseases laboratory data and consistently detected both temporal and seasonal changes in influenza incidence.	Weak
Pelat 2017*[23]	France	Retrospective Secondary Analysis	Clinical Syndromic	ICD-10 data from ED and emergency GPs; Sentinel GP ILI data	ILI/Influenza	Regional health agencies were informed of the advent of the pre-pandemic phase, then of the epidemic phase, then the post-epidemic phase using these data which enabled hospitals to progressively adapt the healthcare provision needed.	Strong

First Author, Year	Country	Design/ Method	Type of Surveillance	Data Source	Disease, Illness or Syndrome	Key Results	Quality Rating
Reich 2019[24]	UK	Retrospective Secondary Analysis	Clinical Syndromic	Ambulance service patient care records	Fever/Influenza	Data peaked with seasonal influenza and the 2016/17 outbreak was detected up to nine weeks before other surveillance programs.	Moderate
Ritzwoller 2005[25]	United States	Retrospective Secondary Analysis	Clinical Syndromic	Ambulatory ILI episodes and sentinel providers reports of patient visits for ILI	ILI/Influenza	The syndromic data showed increases in ILI at the same time as increases in lab-confirmed cases.	Moderate
Schrell 2013*[26]	Spain	Retrospective Secondary Analysis	Clinical Syndromic	ED ILI cases	ILI/Influenza	ED case number data followed similar trends when compared to sentinel GP ILI data and alerted around the same time. However, the ED data is available on a daily basis, providing a timeliness advantage compared to the sentinel GP data.	Moderate
Smith 2007[36]	UK	Retrospective Secondary Analysis	Clinical Syndromic	Reports of ILI and vomiting from participating GPs	ILI/Vomiting	Consultation rates for ILI showed similar trends to the rates reported by the Royal College of General Practitioners' (RGCP). However, the rates were lower than the RGCP. This may be due to fewer participating GPs.	Weak
Smith 2011*[27]	UK	Retrospective Secondary Analysis	Clinical Syndromic	Telephone helpline calls and GP reported ILI	ILI/Influenza	Both data sources showed peak in hotspots ahead of the national peak suggesting the potential for earlier detection using local syndromic data.	Weak
Torres 2023*[29]	Portugal	Retrospective Secondary Analysis	Clinical Syndromic	Hospitalized and ED SARI cases	SARI/Influenza/COVID-19	High correlation between SARI cases and COVID-19 incidence (r=0.78) and detected the COVID-19 epidemic peak a week earlier. However, correlation was weak between SARI cases and influenza (r=-0.20).	Moderate

First Author, Year	Country	Design/ Method	Type of Surveillance	Data Source	Disease, Illness or Syndrome	Key Results	Quality Rating
Wen 2021[30]	United States	Retrospective Secondary Analysis	Clinical Syndromic	Clinical documentation of ILI symptoms data (unclear where the data comes from)	ILI/Influenza/COVID-19	Using deep-learning to extract symptoms works for the detection of outbreaks of influenza and could have provided early warning for of a novel outbreak that did not match the symptom prevalence profile of influenza and other known ILIs	Weak
Zheng 2007*[31]	Australia	Retrospective Secondary Analysis	Clinical Syndromic	ED visits for ILI	ILI/Influenza	Short-term changes in the ED data were estimated to precede changes in lab-confirmed data by three days.	Moderate
Choi 2021*[55]	Korea	Retrospective Secondary Analysis	Drug-based surveillance	ILI-related insurance claims, defined as antipyretic and antitussive drugs	ILI	Strong significant correlation between insurance claims and sentinel clinical data (2014–2015 season, r= 0.7001, 2015–2016 season, r= 0.7774, 2016–2017 season, r = 0.8074, 2017–2018 season, r = 0.8939)	Moderate
Pesala 2019[56]	Finland	Retrospective Secondary Analysis	Drug-based surveillance	Clinician Searches for Oseltamivir	Influenza	Searches for oseltamivir started significantly earlier than influenza diagnoses by −0.80 weeks (95% CI: −1.0, 0.0) with high correlation ($\tau = 0.943$). They also found high correlation between searches for oseltamivir and laboratory reports of influenza A ($\tau = 0.889$)	Moderate
Vergu 2006*[57]	France	Retrospective Secondary Analysis	Drug-based surveillance	19 classes of medications likely to be prescribed or purchased for ILI	ILI	Found the correlation between sentinel GP data and forecast 1-3 weeks ahead based on drug sales data to be between 0.85-0.96	Moderate

First Author, Year	Country	Design/ Method	Type of Surveillance	Data Source	Disease, Illness or Syndrome	Key Results	Quality Rating
Fralick 2023[45]	Canada	Prospective Analysis	Environmental	Floor swabs for SARS-CoV-2	SARS-CoV-2	Among 10 LTCHs with an outbreak and swabs performed in the prior week, eight had positive floor swabs exceeding 10% at least 5 days before outbreak identification. For seven of these eight LTCHs, positivity of floor swabs exceeded 10% more than 10 days before the outbreak was identified.	Strong
Hrudey 2022[40]	Review	Literature Review	Environmental	Wastewater	SARS-CoV-2	Wastewater surveillance shows potential for early warnings of the emergence of a COVID-19 infection in relation to clinical testing, but its cabability is dependent on many logistical factors. Advantages include not being limited by factors such as policies governing clinical testing and its ability to detect variants of concerns.	Moderate
Hyllestad 2022[41]	Review	Systematic Review	Environmental	Wastewater	SARS-CoV-2	Wastewater-based surveillance may serve as an early warning system of 1-2 weeks, but results varied greatly between studies.	Strong
Kisand 2023[42]	Estonia	Retrospective Secondary Analysis	Environmental	Wastewater	SARS-CoV-2	The viral abundance in wastewater started to increase 1.25 weeks before the increase of positive cases. However, there was significant variation between cities that may be due to the size of the city and the centralization of the water system.	Moderate

First Author, Year	Country	Design/ Method	Type of Surveillance	Data Source	Disease, Illness or Syndrome	Key Results	Quality Rating
Mercier 2022*[44]	Canada	Retrospective Secondary Analysis	Environmental	Wastewater	Influenza A	By quantifying, typing, and subtyping the virus in municipal wastewater and primary sludge during a community outbreak, the authors forecasted a citywide flu outbreak with a 17-day lead time and provided population-level viral subtyping in near real-time.	Moderate
Zhao 2023*[43]	United States	Retrospective Secondary Analysis	Environmental	Wastewater	SARS-CoV-2	Wastewater surveillance data effectively provided early warnings for defined peaks of COVID-19 cases in Detroit. Wastewater viral signs consistently preceded the reported clinical cases.	Moderate
Araz 2014[50]	United States	Retrospective Secondary Analysis	Internet-based	Google flu trends; ED visits	ILI/Influenza/RSV	Compared Google Flu Trend data to ILI-related ED visits in Nebraska from 2008-2012 and found high correlation between these two data sources for Omaha GFT (r=0.841; 95% CI: 0.77-0.89) and Nebraska GFT (r=0.832 (95% CI: 0.78-0.87) data. Furthermore, adding GFT data to predictive models lead to better predictions of ED department visits.	Moderate
Kogan 2021*[52]	United States	Retrospective Secondary Analysis	Internet-based	Google Trends; Twitter; Smartphone-based mobility data; Clinician searches; Smart Thermometer	COVID-19	Twitter and Google trend data showed significant growth 2 to 3 weeks prior to confirmed cases and 3 to 4 weeks prior to reported deaths. Similar results were found for the other data sources included in the study.	Moderate
Samaras 2020*[53]	Greece	Retrospective Secondary Analysis	Internet-based	Google and Twitter data; sentinel primary care physician data	Influenza	Google (r=0.933) and Twitter (r=0.943) data show a high correlation with ECDC data, suggesting that online methods can be used to monitor and predict virus activity	Moderate

First Author, Year	Country	Design/ Method	Type of Surveillance	Data Source	Disease, Illness or Syndrome	Key Results	Quality Rating
Valdivia 2010[54]	Europe	Retrospective Secondary Analysis	Internet-based	Google flu trends; sentinel physician network data	ILI and ARI	In general, Google Flu Trends and sentinel physician network results showed good correlation during the 2009 influenza pandemic. However, results varied depending on the use of the internet for health-related concerns being frequently used within a country.	Moderate
Chu 2013[11]	Canada	Retrospective Secondary Analysis	Multiple	ED visits, school absenteeism, telephone helpline and antiviral prescription data	Respiratory syndrome/Influenza	Datasets varied in their timeliness when compared with lab-confirmed data and may be influenced by external factors. Telehealth data alerted 11 days prior to lab-based data while ILI data alerted 36 days prior to lab-based data. For school absenteeism, alerts from two PHUs occurred earlier, one PHU occurred on the same day, and the remaining 5 occurred 4-23 days later than alerts from laboratory data.	Moderate
Dailey 2007	Review	Literature Review	Multiple	OTC sales, emergency visits, school and work absenteeism, telephone triage in ED, and health advice calls.	ILI/Influenza	Variable timeliness depending on the data source with no strong evidence found for any data source.	Weak
de Lange 2013[51]	Netherlands	Retrospective Secondary Analysis	Multiple	Web-based Great Influenza Survey; Google Flu Trends; hospital admissions; lab-data; sentinel GP data	ILI/Influenza	Findings suggest that self-reported ILI symptoms through online web surveys were a useful additional to regular syndromic surveillance but that google flu trends showed negligible added value in combination with GP reported ILI.	Moderate

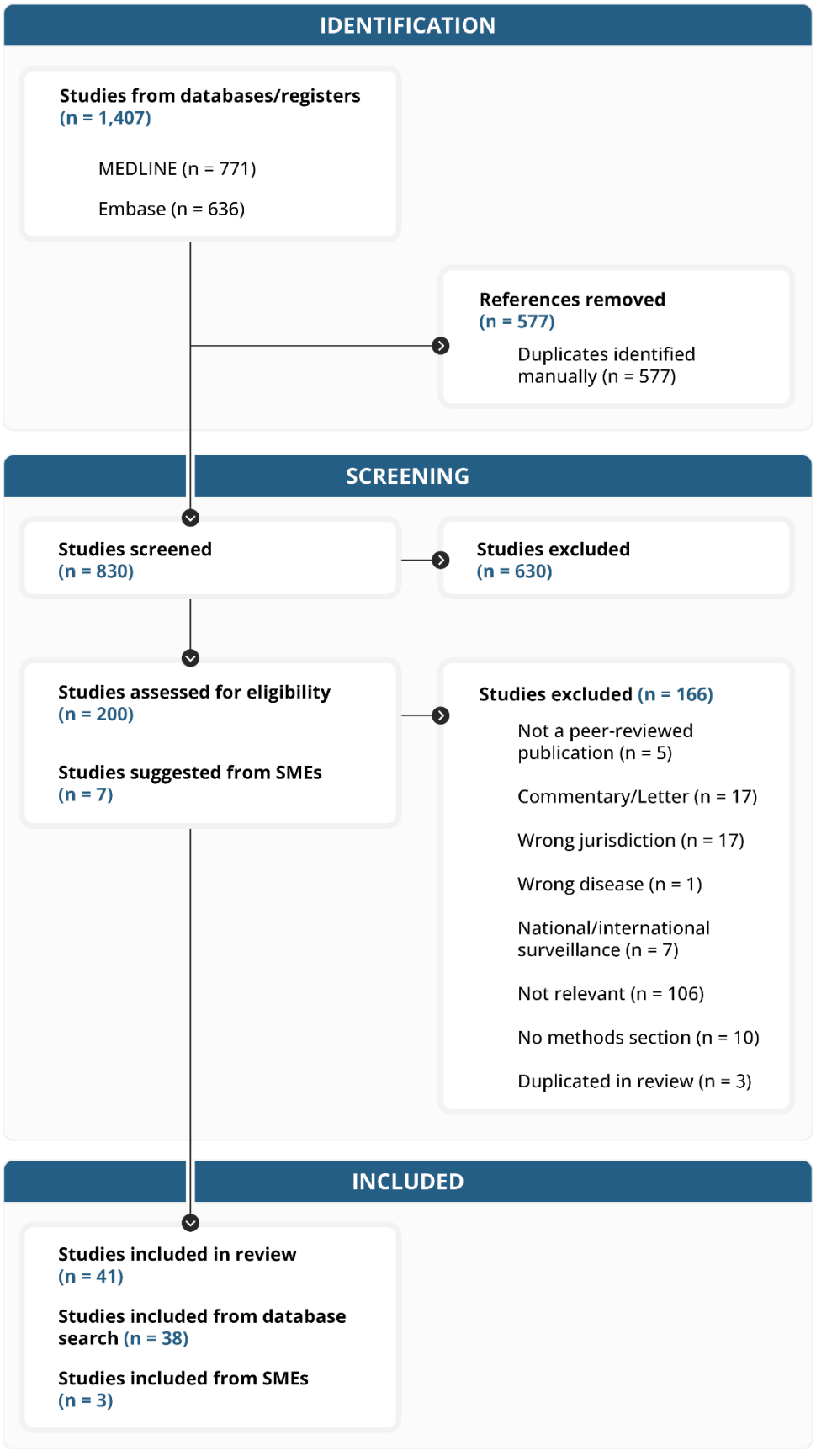
First Author, Year	Country	Design/ Method	Type of Surveillance	Data Source	Disease, Illness or Syndrome	Key Results	Quality Rating
Stoto 2012*[28]	United States	Retrospective Secondary Analysis	Multiple	Virologic surveillance and for tracking outpatient illness through sentinel healthcare providers, ED ILI cases, influenza-associated hospitalizations, pneumonia- and influenza-related mortality, population-based survey for ILI, and influenza-associated pediatric deaths, and the geographic spread of influenza and Google Flu trends	ILI/H1N1	Biases present in surveillance data for H1N1 including the overrepresentation of children and young adults and concerns/awareness of healthcare professionals resulting in increased reporting in certain areas. Even Google Flu Trends were dependent on individuals' behaviour and were susceptible to influences of media attention during a pandemic.	Moderate

First Author, Year	Country	Design/ Method	Type of Surveillance	Data Source	Disease, Illness or Syndrome	Key Results	Quality Rating
Won 2017*[38]	Multiple European Countries	Retrospective Secondary Analysis	Multiple	Reports of ILI from sentinel doctors across the EU from EISN run by ECDC, considered the ground truth in this study, Google Trends for four influenza related search-terms and Saude 24 phone calls logs, only available in Portugal.	ILI/Influenza	Included data sources more timely than traditional methods that require lab testing or centralized medical reports and were able to consistently detect and anticipate the onset of the influenza season. While the ILI dataset provided very good predictive power, the best result is a combination of different sources of data and the best model inputs depended on the country and data quality.	Moderate
Levin-Rector 2015[59]	United States	Retrospective Secondary Analysis	Targeted Laboratory-based	Lab-confirmed cases linked via addresses to buildings to locate cases in long-term care facilities	Influenza	92% of outbreaks in long-term care facilities were detected by the building analysis, and 46% were detected before other methods.	Moderate

First Author, Year	Country	Design/ Method	Type of Surveillance	Data Source	Disease, Illness or Syndrome	Key Results	Quality Rating
Meima 2023*[58]	Netherlands	Retrospective Secondary Analysis	Targeted Laboratory-based	Outbreak data among cases in elderly care facilities	SARS-CoV-2	128 elderly care facilities were registered with the MUIZ program. 89% of the facilities notified at least one outbreak during the study period with 369 notified outbreaks in total. The system provided rapid access to aggregate data providing the following advantages: it allowed for an overview of the seriousness and impact of the infection as outbreaks evolved in real time; it provided an estimate of the burden of disease within elderly care facilities and helped to identify the needs for healthcare continuity; it allowed for a high-level comparison between outbreak locations, facilitating discussion on differences in characteristics between locations that might explain differential outcomes in morbidity and mortality.	Weak

Note: * denotes studies that mention real-time or near real-time surveillance strategies; ED = emergency department, ILI = influenza-like illness, SARI = severe acute respiratory illness, ARI = acute respiratory illness.

Appendix B. PRISMA Diagram



About the Ontario Public Health Emergencies Science Advisory Committee

The Ontario Public Health Emergencies Science Advisory Committee (OPHESAC) is a group of independent, multi-disciplinary experts whose role is to enhance provincial capacity to respond to a spectrum of public health emergencies with the best available evidence. OPHESAC provides independent scientific advice to Public Health Ontario to inform the management of public health emergencies, including COVID-19. For more information about OPHESAC and its members, visit the OPHESAC webpage or contact communications@oahpp.ca.

OPHESAC Members

Dr. Upton Allen, Chair
Professor of Pediatrics
University of Toronto

Dr. Eric Kennedy
Associate Professor of Disaster & Emergency Management
York University

Dr. Na-Koshie Lamptey
Deputy Medical Officer of Health
City of Toronto

Dr. Christopher Mushquash,
Professor and Canada Research Chair,
Department of Psychology
Lakehead University

Dr. Aaron Orkin
Associate Professor of Family Medicine, Emergency Medicine, and Public Health
University of Toronto

Dr. Stephanie Premji
Associate Professor at the School of Labour Studies in the Faculty of Social Sciences
McMaster University

Dr. Lynda Redwood-Campbell
Professor of Family Medicine and Director of Global Health Postgraduate Medical Education
McMaster University

Dr. Gilla Shapiro
Psychologist
Princess Margaret Cancer Centre

Dr. Marek Smieja
Infectious Disease Physician and Microbiologist
St. Joseph's Healthcare Hamilton and Hamilton Health Sciences

Dr. Maxwell J. Smith
Bioethicist and Assistant Professor School of Health Studies
Western University

Dr. Kednapa Thavorn
Senior Scientist and Scientific Lead of Health Economics
Ottawa Hospital Research Institute

Dr. Ingrid Waldon,
Professor and HOPE Chair in Peace and Health, Global Peace and Social Justice
McMaster University

Dr. J. Scott Weese
Veterinary Internist and Professor
Ontario Veterinary College
University of Guelph

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