Rapid Review: Approaches to Respiratory Virus Surveillance

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Key Findings

- Respiratory virus surveillance in Ontario mainly relies on traditional lab-based (i.e., laboratory-tested and confirmed cases) surveillance to detect cases and outbreaks. Lab testing is vital to the detection of viruses, including influenza, severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2) and respiratory syncytial virus (RSV). However, it is often not timely.
- Additional forms of surveillance, when implemented alongside laboratory testing, can support more timely detection of cases, improve early warning and alert systems, improve outcomes of outbreaks, seasons and epidemics/pandemics, and allow healthcare facilities to better prepare for a surge in cases.
- Clinical syndromic data that focus on monitoring disease indicators that are pre-diagnostic (e.g., influenza-like illness), such as emergency department (ED) visits or outpatient visits in primary care, are data sources that can provide earlier detection of changes in patterns of respiratory viruses.
- Environmental surveillance, namely wastewater surveillance, also shows promise as an early warning mechanism of increased viral activity in the population for the surveillance of common respiratory viruses.
- Both clinical syndromic and wastewater surveillance should be used in combination with laboratory testing to provide a complete picture of the risk, transmission, severity, and impact of respiratory viruses. These systems should not be used independently.
- Recommended by the World Health Organization's (WHO) Mosaic Framework for surveillance, the optimal approach to surveillance of common respiratory viruses is implementing a system that uses multiple surveillance approaches that fit together and align to specific objectives to support the prevention, detection and control of respiratory viruses of epidemic and pandemic potential.

Background

Surveillance systems are a key component of public health practice. Public health surveillance is defined as "the ongoing, systematic collection, analysis, and interpretation of health data essential to the planning, implementation, and evaluation of public health practice, closely integrated with the timely dissemination of [this information] to those who need to know" and act upon it.[1] Surveillance systems enable these processes by contributing the data and information required to assess the burden of disease and make important public health decisions which strengthen the public health system.[2] Common seasonal (i.e., influenza, RSV) and endemic (i.e., SARS-CoV-2, the virus that causes coronavirus disease 2019 [COVID-19]) respiratory viruses are widely prevalent and include traits that make them particularly likely to be of epidemic or pandemic potential. Surveillance of these viruses is important for informing public health decision-making, which aims to protect the health of individuals and limit adverse health outcomes.[3]

A major objective of most surveillance systems for respiratory viruses is the rapid detection of outbreaks, seasonal onset, and other notable events such as anomalous patterns of disease, within a population. Recent guidelines on respiratory virus surveillance from the World Health Organization (WHO) suggest a Mosaic Framework that proposes combining multiple fit-for-purpose and complementary approaches to surveillance.[3] Respiratory virus surveillance in Ontario mainly relies on traditional lab-based (i.e., laboratory tested and confirmed cases) and health facility event-based surveillance (e.g., health workers within healthcare facilities detect and report conditions) to detect cases and outbreaks. While these are recommended as core detection strategies and are vital to the detection of viruses, they are often not timely.[4] Laboratory results are frequently subject to lags in reporting that may hinder the ability of surveillance systems to recognize a surge in cases early enough to inform public health and healthcare responses. Furthermore, representativeness of laboratory-confirmed data are contingent on testing protocols.[5] In Ontario, laboratory testing for respiratory viruses is biased towards severe cases due to testing algorithms that aim to test at the emergency department and hospital level with limited testing in the community.[6] Therefore, incorporating other forms of surveillance may improve early warning and alert capabilities, improve coverage of the burden of disease in the wider community, and allow healthcare facilities to better prepare for a surge in cases.[7,8]

While there are multiple traditional or “core” methods for the detection of respiratory viruses, such as lab-based surveillance for the detection of lab-confirmed cases and health facility event-based surveillance for the detection of outbreaks, many advances have been made to integrate novel and/or enhanced methods for rapidly detecting surges in viral activity in the population. These complementary surveillance methods include, but are not limited to, wastewater surveillance, online search engine trends, social media trends, and work and/or school absenteeism data.[9,10] Enhanced strategies such as syndromic surveillance or innovative strategies such as internet-based surveillance (e.g., social media, online search engine trends, etc.) are not well integrated into Ontario’s provincial strategy for the detection of respiratory viruses.[11] These gaps were illuminated during the 2022-23 respiratory virus season, during which Ontario experienced a substantial wave of influenza, RSV, and SARS-CoV-2, with both influenza and RSV occurring weeks ahead of their typical seasonal schedule and at higher than expected levels of transmission.[12] This contributed to a significant burden on an unprepared healthcare system; for example, the number of children and youth presenting to emergency departments (ED) with respiratory virus complaints nearly tripled over the expected seasonal average.[12] Given these issues, Ontario’s respiratory virus surveillance system, early detection mechanisms, and thus the province’s preparedness for a seasonal or an epidemic/pandemic onset of respiratory illnesses, has been questioned.[13] The addition of endemic SARS-CoV-2 infections may result in further changes to the transmission dynamics of respiratory viruses, as well as the relative and overall burden across populations and on systems to prevent, mitigate and respond to these viral infections in the years ahead.

In order to be effective, the United States Centers for Disease Control and Prevention (US CDC) guidelines for evaluating surveillance systems suggest that certain attributes should be considered in an approach to disease surveillance.[14] For the purpose of this review, we defined effectiveness of a surveillance system in terms of the seven attributes defined by the CDC: 1) simplicity; 2) flexibility; 3) acceptability; 4) sensitivity; 5) predictive value positive; 6) representativeness; and 7) timeliness. While considerable work has been done to understand traditional and novel approaches to the detection of respiratory viruses and how they compare in terms of these attributes, reviewing and synthesizing this work provides an overview of the types of detection strategies available, and their usefulness in the detection of common respiratory viruses.

Objectives and Scope

This rapid review aims to:

1. Review the published, peer-reviewed literature on traditional and novel approaches for the detection of common respiratory viruses (i.e., SARS-CoV-2, influenza and RSV) for surveillance systems.
2. Understand the effectiveness of these approaches for the detection of common respiratory viruses.

The scope of this work is focused on the population-level detection of respiratory viruses, as a first step in strengthening the surveillance of these viruses for decision-making and emergency preparedness.

This work on detection strategies does not negate the crucial need for additional work to investigate and address monitoring approaches, outcomes, equity concerns, informing interventions and other challenges that are important for respiratory virus surveillance.

Methods

The approach to produce this evidence synthesis was based on rapid review methodology to employ systematic synthesis methods while making adjustments to complete the synthesis more rapidly than traditional systematic review methods.[15]

In consultation with PHO Library Services, a systematic search strategy was developed to obtain records related to detection methods for respiratory virus surveillance. Search terms included terms related to: influenza OR SARS-CoV-2 OR COVID-19 OR RSV AND surveillance OR detection AND effectiveness. The search included published review-level and primary studies. The full search strategy is available upon request. Searches were conducted in the following databases: MEDLINE (date searched: May 5, 2023) and Embase (date searched: May 8, 2023). In addition, records suggested by subject matter experts were considered for inclusion against the eligibility criteria.

Eligibility Criteria and Screening

To be included, records identified in the search had to meet the following criteria:

1. Focused on surveillance programming or mechanisms of detection for common respiratory viruses (SARS-CoV-2, influenza, and RSV);
2. Focused on OECD countries;
3. Peer-reviewed full-text publication.

Records were excluded if they met any of the following exclusion criteria:

1. Not published in English;
2. Not a peer-reviewed full text publication;
3. Published in a journal that has been de-listed from Web of Science or Scopus due to quality concerns;
4. Commentaries or letters to the editor, or studies that did not have a methods section amenable to quality assessment;
5. Published prior to January 1, 2003;

6. Not relevant to the detection of respiratory viruses as part of public health surveillance (i.e., methodological, diagnostic, or wet lab studies, or surveillance efforts not used for detection (e.g., contact tracing));

7. National or international surveillance efforts or systems.

Screening was conducted using Covidence software. Screening at the title/abstract level was conducted in duplicate for 20% of records to ensure agreement between reviewers. The remainder of screening was conducted by single authors. The same screening method was applied at the full-text level. Screening conflicts were resolved through discussion and consensus between authors. If the two screening authors did not reach consensus through discussion, a third author was consulted to resolve the disagreement.

Data Extraction

Data extraction was conducted independently in duplicate for 10% of records to test agreement between authors before shifting to single author extraction. Extraction conflicts were resolved through discussion and consensus between authors. If the two authors did not reach consensus through discussion, a third author was consulted to resolve the disagreement.

Details including study design, jurisdiction, type of surveillance, illness(es) or syndrome(s) targeted, and key results were extracted from each included record. A summary of data extraction can be found in Appendix A. We reported key results in the main report, categorized by surveillance type.

Critical Appraisal

The quality, or risk of bias, of each included record was appraised according to the study design. For systematic reviews and rapid reviews, the Health Evidence Quality Assessment Tool was used.[16] For primary studies, the Joanna Briggs Institute Checklist for Quasi-Experimental Studies was used.[17]

Quality appraisal was conducted independently in duplicate for 20% of records to test agreement between authors. Quality appraisal conflicts were resolved through discussion and consensus between authors. If the two authors did not reach consensus through discussion, a third author was consulted to resolve the disagreement. The remainder of the records were appraised independently by single authors.

All quality appraisal tools included response options of 'Yes' or 'No'. The checklist used for quality appraisal of primary studies included response options of 'Yes', 'No', 'Unclear', or 'Not Applicable'. Consistent with the Health Evidence tool,[14] we considered studies with 80% or more answers of 'Yes' to be strong quality, >40% to <80% answers of 'Yes' to be moderate quality and 40% or fewer answers of 'Yes' to be weak quality. This rating system is intended to provide a high level overview of the body of evidence. The results of quality appraisal for each included study are provided in the table in Appendix A. More detailed results are available upon request.

Synthesis

After extraction of key results, the results were assessed and discussed by all authors to identify consistencies, inconsistencies, gaps, and any other notable patterns across key results from relevant studies. Results were synthesized narratively due to the heterogeneity in methods, interventions and outcomes across included records.

Results

The library database search returned 830 results, following the removal of duplicate records. An additional 7 records were suggested by subject matter experts. After screening titles and abstracts for eligibility, 207 full texts were screened and 41 records were included in this evidence synthesis. For more information, a PRISMA diagram can be found in Appendix B. Studies covered multiple jurisdictions including: the United States; United Kingdom; Canada; Australia; Denmark; Estonia; Finland; France; Greece; Korea; the Netherlands; New Zealand; Portugal; and Spain. Despite all seven attributes defined by the CDC being considered for inclusion, the majority of studies focused on: 1) the accuracy of the mechanism in detecting cases/outbreaks; and 2) the timeliness of the mechanism.

The following sections provide a synthesis of the identified evidence by type of surveillance.

Clinical Syndromic Surveillance

Clinical syndromic surveillance refers to an approach to public health surveillance focused on monitoring disease indicators that are pre-diagnostic (i.e., prior to laboratory confirmation) and are often based on healthcare providers reporting events related to a syndrome (e.g., influenza-like illness [ILI]).[7] Clinical syndromic surveillance data was the focus of 22 included articles. Of these, 19 retrospectively analyzed secondary surveillance data,[11,18-31] two were case studies,[32,33] and one was a literature review.[10] Eight were rated weak in quality,[21,22,27,30,33-36] 14 were rated moderate,[11,18-20,24-26,28,29,31,32,37,38] and one was rated strong.[23]

Various definitions were used in surveillance including ILI for the surveillance of influenza,[10,21-23,25-28,31,33,38] ILI for the surveillance of both influenza and SARS-CoV-2,[18,30] respiratory syndrome,[11,20] fever symptoms,[24,32] vomiting,[36] a combination of ILI and severe acute respiratory infection (SARI) definitions for the surveillance of SARS-CoV-2,[19] and a SARI definition for the surveillance of both influenza and SARS-CoV-2.[29]

Across the studies, many different clinical syndromic data sources were included. Six focused exclusively on emergency department (ED) syndromic data,[18-20,26,31,32] one incorporated ED data and all other hospitalizations for SARI,[29] and one incorporated ED data with data from emergency physicians and sentinel community general practitioners (GPs) for ILI.[23] Two studies included ILI data reported by general practitioners (GPs),[22,36] one incorporated ILI data reported by GPs with telephone helpline call data for ILI,[27] and another incorporated healthcare provider reports of ILI with episodes of ambulatory ILIs.[25] Another study focused exclusively on ambulance service patient care records for fever.[24] One study focused exclusively on data from 911 dispatchers for ILI[21] and one focused on electronic medical records reported through the Danish Medical On-Call Service (DMOS).[35] Two additional studies focused on documented clinical/healthcare provider data, but it was not clear exactly from where these data originate.[30,33] Finally, five studies included multiple data sources in different combinations, with specific information available in Appendix A.[10,11,28,37,38] While not a focus of this review, it should be noted that clinical syndromic data tend to come from two different systems of care: hospital/emergency care and primary care. Data coming from hospital/emergency care such as ED visits for ILI tend to capture severe cases, while cases in primary care such as outpatient visits for ILI at sentinel GPs may be better suited to community prevalence.[39]

Results of the studies indicate that clinical syndromic surveillance can accurately detect seasons or outbreaks, as well as provide earlier warning/alerts compared to lab-confirmed data. Many studies also mentioned that if the syndromic data did not provide an earlier warning than lab-confirmed data, it provided a timeliness advantage due to the data being capable of providing information in real or near real time.

Of the 19 included papers, only three studies had results that were inconclusive due to methodological heterogeneity across studies, bias toward children and youth in syndromic data, susceptibility to external influences such as media coverage, and SARI case definitions working well for SARS-CoV-2 but not for influenza.

Environmental Surveillance

Six of the included studies focused on environmental surveillance. Five examined wastewater surveillance for SARS-CoV-2[40-43] and influenza,[44] and one examined floor swabbing for SARS-CoV-2.[45] Three were retrospective secondary analysis studies,[42-44] one was a systematic review,[41] one was a literature review,[40] and one was a prospective study.[45] Four were rated as moderate quality,[40,42-44] and two were rated strong.[41,45] Overall, results were mostly positive on the effectiveness of wastewater surveillance for the surveillance of respiratory viruses and show promise for floor swabbing methods.

While two studies found the increases in influenza A and SARS-CoV-2 virus load in wastewater surveillance data preceded lab-confirmed cases,[43,44] another two of the five studies were unable to make strong conclusions regarding the timeliness of wastewater surveillance: one due to variation in timing across cities, and another due to variation across studies.[40,42] However, a systematic review rated strong in quality found that in 80% of their included studies, wastewater surveillance data provided earlier warning of surges in SARS-CoV-2 activity than lab-based data, providing alerts 1–3 weeks prior to laboratory alerts.[41] Despite this, they still mentioned several limitations to the approach, including being dependent on sewer system design, variation by methodology, and the inability to estimate population prevalence using wastewater surveillance.

Finally, one study leveraged floor swabbing as a mechanism of SARS-CoV-2 detection in long-term care facilities (LTCFs) that resulted in the detection of outbreaks up to 10 days earlier than laboratory confirmation.[45]

Absenteeism Surveillance

Five included articles featured absenteeism data for the surveillance of respiratory viruses; specifically, influenza surveillance. Of these, three were retrospective secondary analyses,[11,46-48] one was a systematic review and meta-analysis,[49] and one was a literature review.[10] Three studies focused on school absenteeism,[11,47,48] one study focused on work absenteeism,[46] and one included both work and school absenteeism.[10] One was rated weak in quality,[34] three were rated moderate,[11,46,48] and one was rated strong.[47] Overall, the majority of the studies were inconclusive in their results on the effectiveness of absenteeism data for the surveillance of influenza.

Four studies were inconclusive in whether absenteeism data could act as an effective strategy for the surveillance of respiratory viruses due to variation in results across reference data sets, public health units, and studies.[10,11,47,49] The systematic review and meta-analysis found a weak to moderate correlation between school absenteeism data and community-based surveillance. ILI-specific absenteeism was a better indicator of influenza activity in the community, but the ability to implement this depends on school resources and willingness to participate, making it more difficult to attain.

Only one study found that absenteeism data provided a timeliness advantage: Duchemin et al. found that sick leave records extracted from private health insurance data in France were able to detect 92% of influenza outbreaks between 2016 and 2017 and alerted an average of 2.5 weeks earlier than weekly ILI incidence from the sentinel primary care surveillance system.[46]

Internet-based Surveillance

Seven studies focused on internet-based surveillance. All studies retrospectively analyzed surveillance data, with data sources including Google,[50-54] Twitter,[52,53] and internet-based surveys.[22,37,51] The included articles assessed the results for surveillance of both ILI, [22,37,50,51,53,54] SARS-CoV-2,[52,53] and RSV.[50] All seven studies were rated moderate in quality. Overall, findings were mixed on whether internet-based surveillance data provided a timeliness advantage to other data sources.

While five studies found that Twitter and Google trend data were as accurate as clinical syndromic data and/or were more timely than clinical syndromic data,[38,50,52-54] two found that Google trend data, in particular, did not offer advantages over clinical syndromic data.[28,51] One reason mentioned for this was that the effectiveness of Google search trends as a strategy for surveillance greatly varied depending on how often it was used as a health resource in a given jurisdiction.

While studies focusing on internet-based surveys indicated alignment between survey data and clinical syndromic data, there was no indication that these data provided earlier or timelier warnings or alerts than clinical syndromic data.[22,37,51] However, survey data provide some advantages over Google trend or Twitter data as they offer additional information, such as participant characteristics, that could be used to improve understanding of affected groups.

Drug-based Surveillance

Five of the included studies focused on drug-based surveillance, all of which concentrated on influenza. The studies focused on drug-based surveillance using medication sales data, drug-based insurance claims, or clinician searches for anti-viral drugs. Four were retrospective secondary analyses[11,55-57] and one was a literature review.[10] One study was rated weak in quality[34] and four were rated moderate.[11,55-57] Overall, findings from the five studies are inconclusive in whether drug-based surveillance can be used to provide early warnings/alerts for influenza.

Three studies showed positive results with one study finding that insurance claim data was strongly correlated with clinical syndromic data over four seasons,[55] one finding that searches by physicians for oseltamivir started significantly earlier than influenza diagnoses (-0.8 weeks),[56] and a third finding that forecasted data based on medication sales was highly correlated with observed clinical syndromic data and provided a lead time of 1–3 weeks.[57] Two studies were unable to provide evidence on whether drug-based surveillance could provide early warnings. One study, conducted in Ontario, found mixed results for anti-viral prescription sales data where it was able to detect seasonal onset of influenza earlier than laboratory data in one season, but not the second season included in the study.[11] The final study was a literature review that reported that detection methodologies varied too greatly across studies to make any strong conclusions despite pharmaceutical sales data appearing to be more timely than clinical syndromic and lab-based data.[34]

Targeted Laboratory-Based Surveillance

Two studies examined novel targeted laboratory-based surveillance approaches, both implemented as a way to target long-term care facilities (LTCFs). Both were retrospective secondary analyses[58,59]. One was rated moderate in quality,[59] and one was rated weak.[58]

The studies introduce two novel approaches to the timely detection of outbreaks within LTCFs. The first utilized a registry of 128 LTCFs across the Netherlands where alerts were programmed to occur as soon as a case of SARS-CoV-2 was detected in a resident or staff member to provide warnings in near real-time, enabling early detection of possible outbreaks, providing an overview of the seriousness and impact of outbreaks, providing estimates of the burden of disease within LTCFs, and allowing for high-level comparison between outbreak locations.[58] The second introduced an approach that leveraged lab-confirmed tests of influenza linked to an individual's address to determine cases within LTCFs in New York City. Results found that 92% of outbreaks were detected in the analysis, with 46% being detected before methods traditionally used to detect outbreaks.[59]

Discussion

This rapid review aimed to review the published, peer-reviewed literature on approaches for the detection of common respiratory viruses for surveillance systems, and synthesize included studies to gain a better understanding of the effectiveness of these approaches for the surveillance of respiratory viruses. Effectiveness was defined in terms of the seven attributes outlined by the CDC as components of an effective surveillance system.[14]

Included studies focused on multiple types of surveillance including: clinical syndromic surveillance; environmental surveillance; absenteeism surveillance; internet-based surveillance; drug-based surveillance; and surveillance targeting congregate settings. Despite considering all CDC attributes for inclusion, the primary objective of the majority of included studies was to evaluate the ability of these approaches to detect outbreaks, onset of seasonal surges in community prevalence, and peaks of illness activity for SARS-CoV-2, influenza and/or RSV, and to assess their timeliness. The last objective stems from concerns regarding the timeliness of data from laboratory-confirmed cases due to lags in reporting. While laboratory testing is vital to diagnostic testing, case confirmation, and providing virologic information, its limitations may hinder its ability to inform healthcare decision-making that may need to occur early in a pandemic or seasonal surge, such as hospital resource planning.[22]

Results suggest that syndromic data, particularly clinical syndromic data including ED visits and outpatient visits in the community, can serve as complementary surveillance to laboratory-confirmed cases for the detection of abnormal and/or seasonal increases in respiratory illness activity. These data were shown to improve timely detection by detecting increased illness in the population earlier than laboratory-confirmed data and provide a timeliness advantage as syndromic data can be available faster than laboratory-confirmed case data, with several studies mentioning its ability to be provided in real or near-real time. Furthermore, clinical syndromic surveillance can provide wider coverage of the population than lab-based surveillance, particularly when both acute and primary care sectors are covered. For respiratory viruses, primary care surveillance may more likely be a first point of contact, making it a key source of surveillance for respiratory illness.[60] While complementary to data arising on confirmed cases from laboratory networks, this form of surveillance cannot be used on its own due to a lack of pathogen-specific information, thus limiting its ability to inform on the relative contributions of specific viruses.

Environmental surveillance, particularly wastewater surveillance for detecting the level of SARS-CoV-2 and influenza activity, may contribute to filling the gaps in syndromic and lab-based surveillance.[61] Evidence indicated that it shows promise as an early warning indicator of virus activity in the community while also allowing coverage of a large geographical area and population proportion, and providing the virologic information lacking in syndromic data sources.[41] Nevertheless, there are still limitations to wastewater surveillance.[40] Composition and coverage of the population of wastewater surveillance is dependent on the design of the sewer system, potentially missing substantial areas and population groups that are served by septic tanks or otherwise not connected to the sewer system. While wastewater surveillance tends to be free from biases that might be present due to differences in help-seeking behaviour, it is limited in its ability to estimate population prevalence and provide details on groups that are affected. Furthermore, virus shedding into wastewater does not always equal infectiousness as shedding can continue long after an individual has recovered.[62] Finally, optimal frequency of wastewater testing and reporting of wastewater surveillance is currently not well known, thus it is unclear what the limitations are for informing public health using wastewater surveillance. Therefore, more research is still needed to understand how to best optimize wastewater surveillance for the early detection and ongoing monitoring of respiratory viruses.

While limited, studies focusing on novel targeted laboratory-based surveillance drew attention to the importance of surveillance, particularly in LTCFs, where respiratory illness outbreaks can occur in a vulnerable population. The studies suggest potential improvements to targeted surveillance of LTCFs that could be adapted to fit other congregate living settings where outbreaks may be more likely to occur.

Limitations

This rapid review is not without limitations. Only peer-reviewed literature published in select journals was examined, therefore other relevant records may have been missed. Single author screening occurred for 80% of the title and abstract and full-text level of screening. However, we aimed to mitigate bias by completing duplicate screening for 20% of titles before moving on to single author screening.

Furthermore, this review is limited in scope. The scope of the review was to focus on the detection of respiratory viruses in the population for surveillance purposes, as a first step in strengthening the surveillance of these viruses for decision-making and emergency preparedness. However, other aspects of surveillance including monitoring approaches, outcomes, equity concerns, and informing interventions, are critical for actionable respiratory virus surveillance. Given the studies that were identified through our search strategy, this review was only able to address passive surveillance mechanisms (versus active surveillance) and does not provide information on the coverage and representativeness of the surveillance systems (e.g., populations included or excluded from surveillance programs, sentinel networks, etc.), nor context specific considerations. This means that although the surveillance system did or did not work in a specific context, does not mean it would not work in another. We have tried to combat this issue by limiting our review to studies conducted in OECD countries to improve comparability.

Conclusion

In summary, while laboratory-based surveillance of respiratory viruses is essential for many reasons, including the confirmation of cases, virological and genomic testing, and the detection of novel strains or viruses, it is considered a lagging indicator due to delays in reporting and biases in population coverage by reflecting only those who have access to testing. Results of this rapid review suggest that complementary data sources such as clinical syndromic and wastewater surveillance have the potential to improve the timely detection of increased illness in the population and collectively broaden the population represented in the data. Actionable data require clear communication and timely provision of findings to those that need it to inform decisions for public health and healthcare.[63] This, in turn, can strengthen preparedness for and responsiveness to changing pathogen trends in the community. Promising future surveillance methods that would benefit from further study include environmental swabbing and setting-specific approaches.

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Appendix A. Study Characteristics and Key Results

Table 1. Study Characteristics and Key Results

First Author, Year	Country	Design/ Method	Type of Surveillance	Data Source	Disease, Illness or Syndrome	Key Results	Quality Rating
Duchemin 2021[46]	France	Retrospective Secondary Analysis	Absenteeism	Sick leave records from private health insurance data	ILI/Influenza	92% of reported influenza outbreaks were detected using sick leave data between 2016 and 2017, and on average 2.5 weeks earlier than the sentinel primary care system.	Moderate
Kara 2012[47]	UK	Retrospective Secondary Analysis	Absenteeism	Absenteeism data from 373 state schools	H1N1/Influenza	Absenteeism data peaked with reference data concomitantly. However, a significant correlation was only observed between absenteeism data and GP data for ILI ($r=0.42$, $p=.002$). Absenteeism data did not predict peaks in disease earlier than any of the reference datasets.	Strong
Tsang 2023[49]	Review	Systematic Review and Meta-Analysis	Absenteeism	Published literature on school absenteeism	ILI/Influenza	The pooled estimate of correlation between school absenteeism and community surveillance without lag, with 1-week lag, and with 2-week lag were 0.44 (95% CI 0.34, 0.53), 0.29 (95% CI 0.15, 0.42), and 0.21 (95% CI 0.11, 0.31), respectively. The correlation between influenza activity in the community and ILI-specific absenteeism was higher than that between influenza activity in community all-cause absenteeism. Among the 19 studies that used qualitative approaches, 15 (79%) concluded that school absenteeism was in concordance with, coincided with, or was associated with community surveillance.	Moderate

First Author, Year	Country	Design/ Method	Type of Surveillance	Data Source	Disease, Illness or Syndrome	Key Results	Quality Rating
Baltrusaitis 2018[37]	United States	Retrospective Secondary Analysis	Clinical Syndromic	Electronic health records of ILI visits aggregated at the state level; Flu Near You crowd-sourced weekly survey	ILI/Influenza	In general, geographic areas that reached a certain threshold of reports (250 crowd-sourced participants or 20,000 visit counts for electronic health record data) reflected the results present in the traditional data sources and government led influenza case estimates. Correlations between data sources decreased with increases in spatial resolution.	Moderate
Bordonaro 2016[32]	United States	Case Study	Clinical Syndromic	Fever data collected via temperature monitoring in ED	H1N1/Influenza/Fever	Significant increase in fevers occurring during the H1N1 pandemic (+0.7%, p<.001) and the influenza season (+1.4%, p<.001) and peak fever rates corresponded with the periods of regionally elevated influenza activity.	Moderate
Boyle 2022[18]	Australia	Retrospective Secondary Analysis	Clinical Syndromic	ED data for ILI, influenza and COVID-19	ILI/Influenza/COVID-19	ED presentation data indicated outbreaks coinciding with the first wave of the COVID-19 pandemic and the 2017 and 2019 influenza seasons.	Moderate
Bruzda 2021[19]	United States	Retrospective Secondary Analysis	Clinical Syndromic	ICD-10 codes entered by medical students in ED	ILI/SARI/COVID-19	ILI counts that exceeded alert thresholds were consistent with the COVID-19 pandemic timeline and the first alert would have occurred nine days prior to the first lab-confirmed case in the U.S. Earlier alerts would have been provided for the onset of the COVID-19 pandemic using this data.	Moderate
Colon-Gonzalez 2018[33]	UK	Case Study	Clinical Syndromic	ILI healthcare consultations from four different databases	ILI/Influenza	Influenza outbreaks were consistently detected by all syndromic surveillance systems included in the study with probability of detection increasing and time to detection decreasing as the size of the outbreak increased.	Weak

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

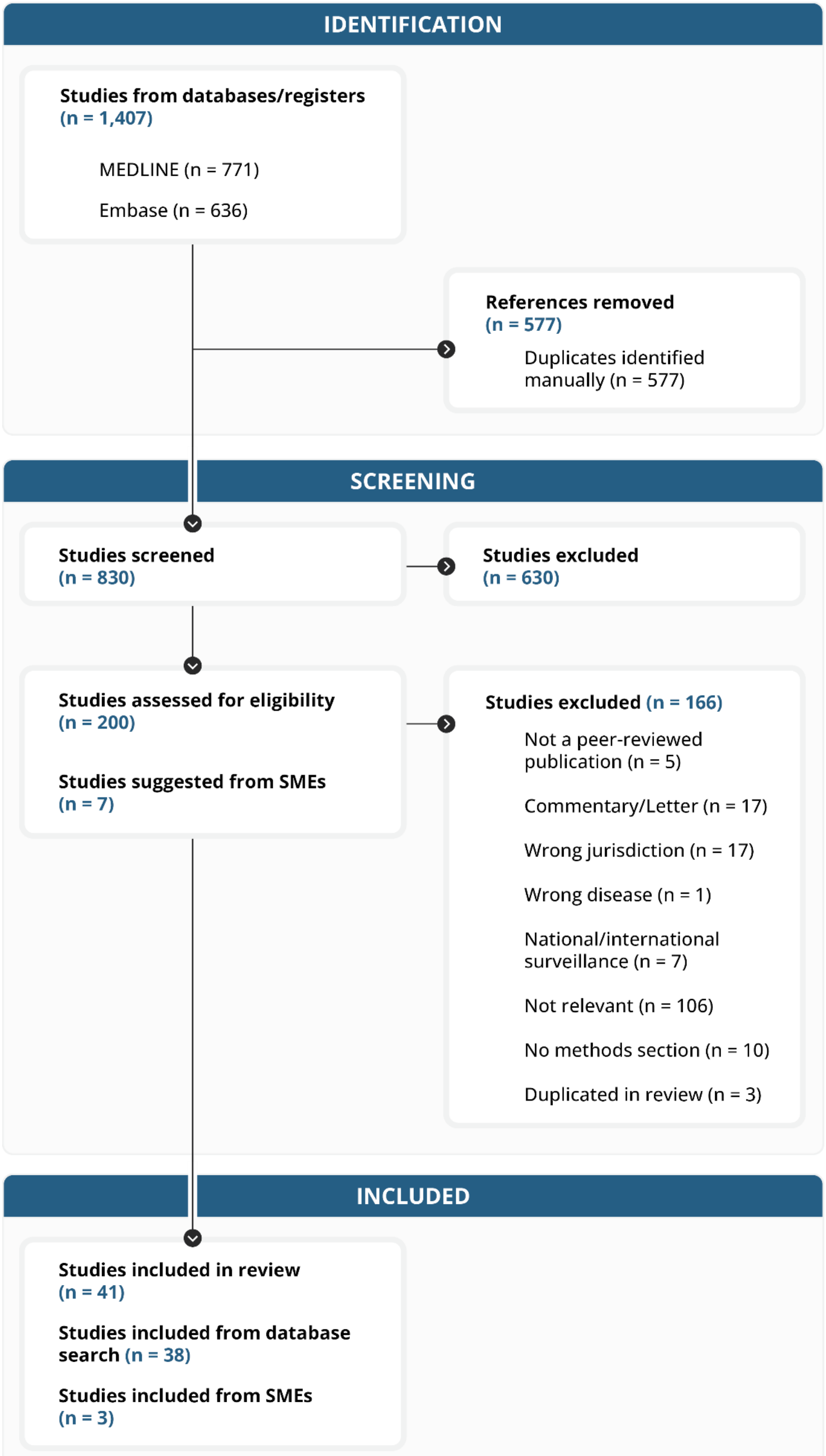
First Author, Year	Country	Design/ Method	Type of Surveillance	Data Source	Disease, Illness or Syndrome	Key Results	Quality Rating
Stoto 2012*[28]	United States	Retrospective Secondary Analysis	Multiple	Virologic surveillance and for tracking outpatient illness through sentinel healthcare providers, 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.

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