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Early-Warning Models for Seasonal Respiratory Illness at Community Scale

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Abstract

Seasonal respiratory illnesses create recurrent and uneven pressure on community healthcare systems, pharmacies, schools, emergency departments, primary-care facilities, and public-health agencies. Conventional clinical and laboratory surveillance remains indispensable for confirming respiratory-disease activity, but reporting delays can limit the time available for local preparation. Earlier warning may become possible when conventional surveillance is complemented by signals that change before or alongside clinical respiratory illness, including over-the-counter respiratory medicine demand, school absenteeism, online symptom-search behavior, emergency respiratory visits, lagged syndromic activity, and environmental conditions. Influenza forecasting research has demonstrated the potential value of integrating epidemiological history with supplementary digital and environmental data, while the experience of Google Flu Trends showed that uncalibrated digital proxies can become unstable when information-seeking behavior changes.

The present study develops a community-scale multi-signal framework for predicting whether respiratory illness will enter a high-activity period during the subsequent two weeks. A synthetic surveillance panel representing 30 hypothetical communities monitored across 52 epidemiological weeks was generated. After applying reporting lags and future-outcome windows, 1,440 community-week observations were available for analysis. Predictors consisted of lagged respiratory illness, an over-the-counter respiratory medicine sales index, school absenteeism, respiratory-related internet search activity, emergency-department respiratory visits, and absolute humidity.

A cluster-robust logistic regression model generated weekly probabilities of a two-week respiratory surge. The simulated model achieved an area under the receiver operating characteristic curve of 0.916, overall accuracy of 88.4%, precision of 82.4%, and sensitivity of 75.4% at an illustrative 50% alert threshold. Lagged respiratory illness, pharmacy sales, respiratory search activity, emergency respiratory visits, and absolute humidity made statistically significant contributions. Lower absolute humidity was associated with higher simulated surge probability, consistent with established influenza-seasonality research, although such environmental relationships cannot be assumed to apply identically across all respiratory pathogens.

The study concludes that community respiratory early-warning systems should be based on multi-signal triangulation rather than single-source prediction. Their primary value is not to replace clinical or laboratory surveillance but to create additional preparation time for staffing, pharmacy inventory review, vaccination communication, diagnostic preparedness, school-health coordination, risk communication, and other proportionate public-health responses. Prospective validation, recalibration across seasons, transparent uncertainty reporting, data-governance safeguards, and explicit assessment of false-alert consequences would be required before operational deployment.

Keywords: seasonal respiratory illness; early-warning model; community surveillance; influenza-like illness; syndromic surveillance; respiratory forecasting; pharmacy surveillance; school absenteeism; digital epidemiology; public health

1. Introduction

Seasonal respiratory illnesses create predictable recurrence but substantial uncertainty in their timing, magnitude, duration, and pathogen composition. Influenza, respiratory syncytial virus, rhinoviruses, seasonal coronaviruses, and other respiratory pathogens can generate overlapping clinical syndromes, making community respiratory activity visible before definitive etiological confirmation becomes available. Public-health surveillance therefore commonly relies on combinations of outpatient syndromic indicators, laboratory findings, hospitalization data, mortality information, and geographic reporting. Forecasting research has further demonstrated that seasonal influenza activity can be predicted probabilistically when recent epidemiological observations are combined with appropriately specified transmission models. Shaman and Karspeck developed an influential framework for forecasting local influenza outbreaks, and subsequent real-time work demonstrated the feasibility of city-level epidemic forecasts.

A persistent operational challenge is the timing of conventional surveillance. Laboratory confirmation and finalized clinical reports may become available only after symptoms, medicine purchases, school absences, emergency visits, and other behavioral consequences are already increasing. Earlier research showed that citywide over-the-counter medication sales can provide indications of communitywide illness, including seasonal influenza activity. Such information does not possess the etiological specificity of laboratory surveillance, but it can provide a rapidly available syndromic signal. Similar logic applies to school absenteeism, emergency respiratory presentations, prescription activity, and other routinely generated community data.

Digital epidemiology expanded the potential information environment by introducing internet search behavior, electronic health records, social-media signals, and other rapidly generated data. Yang, Santillana, and Kou's ARGO model combined autoregressive influenza information with Google search activity and demonstrated that carefully structured digital information could improve influenza tracking compared with approaches relying primarily on search trends. Lu and colleagues later integrated internet-based information with network and electronic-health-record approaches for state-level influenza nowcasting. These models suggest that digital indicators can provide value when they are anchored to epidemiological history and recalibrated as relationships change.

The same history also shows why early-warning systems should not be based on digital enthusiasm alone. Lazer and colleagues' critique of Google Flu Trends demonstrated that large-volume proxy data can produce substantial errors when models fail to account for changing search behavior, media effects, algorithmic change, and instability in the relationship between information seeking and actual disease. Community surveillance models should consequently use search behavior as one signal among several rather than treating it as a direct measurement of respiratory incidence. Environmental information should be approached with similar discipline. Shaman and Kohn found that absolute humidity strongly influenced influenza-virus survival and transmission in the experimental data they analyzed, providing a biologically meaningful foundation for incorporating humidity into influenza-oriented forecasting. However, a broad respiratory-illness model cannot assume that every pathogen responds identically.

The present study develops a community-scale multi-signal early-warning framework capable of estimating the probability that respiratory illness will reach a high-activity level within the following two weeks. The proposed architecture combines lagged respiratory illness, community pharmacy respiratory-product demand, school absenteeism, respiratory search behavior, emergency respiratory visits, and absolute humidity. Because no authentic community surveillance dataset was supplied, the quantitative analysis uses explicitly synthetic data. The objective is methodological rather than epidemiological: to demonstrate how heterogeneous surveillance indicators can be integrated, evaluated, translated into a probability-based alert, and interpreted responsibly before any real-world application.

2. Objectives of the Study

2.1 Development of a Multi-Signal Community Early-Warning Model

The first objective is to develop a reproducible model capable of estimating the probability that a community will experience a high-activity respiratory-illness period during either of the following two epidemiological weeks. The framework deliberately avoids reliance on one indicator because each available signal observes a different part of community illness activity and carries different forms of measurement error.

Lagged respiratory illness represents epidemic momentum, pharmacy sales capture community symptom-management behavior, school absenteeism provides a population syndromic indicator, online searches capture information-seeking activity, emergency respiratory visits provide a rapidly available healthcare-utilization signal, and absolute humidity contributes seasonal environmental context. Their combined use allows the model to exploit complementary information rather than assuming that one stream can serve as a direct substitute for clinical surveillance.

2.2 Evaluation of the Relative Contribution of Surveillance Indicators

The second objective is to examine which candidate indicators retain independent predictive value when entered simultaneously. A variable can correlate strongly with respiratory illness in isolation yet contribute little additional information once other signals representing the same underlying community activity are considered.

This objective is particularly important for digital and behavioral indicators. Search activity and medication purchases can be timely, but they may also respond to news coverage, precautionary purchasing, allergies, noninfectious respiratory symptoms, or changes in public behavior. Multivariable modeling therefore helps determine whether these indicators provide information beyond recent clinical respiratory activity.

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2.3 Assessment of Operational Two-Week Alert Performance

The third objective is to evaluate model performance using metrics relevant to early-warning operations. Discrimination is summarized using the area under the receiver operating characteristic curve, while sensitivity, precision, and overall accuracy are calculated at an illustrative probability threshold.

The study does not propose one universal operational threshold. An inexpensive response, such as distributing an internal surveillance bulletin, may justify a relatively sensitive threshold. A resource-intensive response, such as opening additional clinical capacity, may require substantially stronger evidence. Public-health thresholds should therefore be selected according to the consequences of false-positive and false-negative alerts rather than by statistical convention alone.

3. Review of Literature

3.1 Conventional and Syndromic Respiratory Surveillance

Respiratory surveillance has historically required multiple complementary data streams because no single measure completely captures disease transmission, clinical severity, healthcare utilization, etiological confirmation, and geographic spread. Influenza-like illness surveillance is relatively rapid but syndromic, whereas laboratory testing provides greater specificity but usually represents a smaller and potentially selective proportion of infected individuals. Forecasting models that use recent epidemiological activity therefore benefit from additional signals capable of indicating community change before finalized surveillance reports become available.

Pharmacy data represent one of the earliest investigated supplementary signals. Das and colleagues reported that over-the-counter medicine sales could provide indications of communitywide illness and seasonal influenza activity. The epidemiological logic is straightforward: people may purchase cough, cold, fever, and related products early in an illness episode and before seeking formal medical care. Pharmacy-based indicators can therefore capture a stage of community response not always represented immediately in clinical databases.

School absenteeism and emergency utilization provide additional syndromic information. Absenteeism can reflect transmission among school-aged populations and household spillover, although its specificity can be affected by holidays, weather, administrative practices, and nonrespiratory illnesses. Emergency respiratory visits may provide stronger clinical proximity but can be influenced by healthcare accessibility and care-seeking behavior. These limitations support using each indicator as one component of a broader surveillance system rather than interpreting any single source as confirmation of an outbreak.

3.2 Digital Epidemiology and Influenza Forecasting

The development of internet search surveillance represented a major transition in infectious-disease monitoring. Search queries can be generated almost immediately when individuals experience symptoms or become concerned about illness, creating the possibility of rapid behavioral surveillance. The early success of influenza search models encouraged substantial interest in whether population digital behavior could provide real-time disease intelligence.

The ARGO model was an important methodological improvement because it did not rely on raw search volume alone. Yang, Santillana, and Kou combined Google search information with

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autoregressive influenza history, creating a model capable of adapting to changes in online behavior while retaining conventional epidemiological structure. This integration is conceptually important for community-scale forecasting because it treats digital behavior as supplementary evidence rather than as an epidemiological replacement.

Subregional prediction presents greater difficulty because smaller populations produce noisier signals. Kandula, Hsu, and Shaman specifically investigated subregional influenza nowcasts using search trends and emphasized the importance of geographically resolved surveillance information. Lu and colleagues subsequently developed a network-based state-level influenza approach integrating internet-based information, electronic health records, and spatiotemporal relationships. Collectively, these studies indicate that geographically local forecasting benefits from combining several data streams and exploiting relationships between adjacent or epidemiologically connected locations.

Digital indicators remain vulnerable to behavioral drift. Lazer and colleagues demonstrated that Google Flu Trends suffered substantial prediction failures and argued that big-data systems require transparency, theory, validation, and continuing recalibration. This lesson remains central to contemporary surveillance: high-volume data are not automatically high-validity data. Search terms, device use, media attention, public-health messaging, and platform algorithms can all change independently of pathogen transmission.

3.3 Seasonality, Environmental Context, and Forecast Reliability

Respiratory seasonality emerges from interacting biological, environmental, social, and behavioral mechanisms. Shaman and Kohn's analysis found that absolute humidity was more strongly related than relative humidity to influenza-virus survival and transmission in the experimental evidence they examined. Later work connected absolute humidity with seasonal influenza onset, strengthening the rationale for incorporating environmental information into influenza forecasting.

Forecasting research subsequently moved from general seasonal associations toward operational prediction. Shaman and Karspeck developed an influenza forecast system based on data assimilation, while Shaman and colleagues produced real-time weekly forecasts for numerous US cities during the 2012–2013 season. These studies demonstrated that local epidemic timing can be forecast probabilistically but also showed that forecast skill changes as the season progresses and as more epidemic information becomes available.

Forecast reliability should therefore be interpreted dynamically. A model that performs well in one respiratory season may deteriorate during another season if pathogen composition, immunity, school schedules, clinical coding, healthcare-seeking behavior, public-health interventions, or digital behavior change. The substantial changes in respiratory circulation during the COVID-19 period provide a clear illustration of why historical seasonal patterns cannot be treated as permanently fixed.

The literature consequently supports a multi-layered forecasting strategy. Recent disease observations provide epidemiological anchoring; pharmacy, school, emergency, and digital information increase temporal responsiveness; environmental variables provide seasonal context; and spatial surveillance design determines how effectively local observations represent broader community risk. The remaining requirement is transparent validation across locations and seasons.

4. Research Methodology

4.1 Research Design and Synthetic Surveillance Panel

The study uses a simulation-based longitudinal community surveillance design. Thirty hypothetical communities were observed across 52 epidemiological weeks, generating an initial panel of 1,560 community-week observations. Each community was assigned a different baseline respiratory-illness level, epidemic severity, seasonal peak timing, and random week-to-week variation.

The synthetic respiratory trajectory contained a principal seasonal epidemic wave and a smaller subsequent activity shoulder. These design features created differences in epidemic timing and severity across communities rather than imposing an identical curve. No real geographic coordinates, population denominators, patient records, hospital data, pharmacy transactions, search queries, or school records were used.

To represent surveillance delay, the clinical respiratory-illness measure entered the forecasting model with a two-week lag. Future surge status was defined using respiratory activity during either of the next two weeks. After weeks without complete lagged or future information were excluded, the final analytical sample comprised 1,440 community-week observations.

Table 1: Operationalization of Early-Warning Indicators

Indicator	Operational Representation	Expected Relationship With Future Surge	Surveillance Rationale
Lagged Respiratory Illness	Community respiratory activity available with a two-week reporting lag	Positive	Captures established epidemic momentum
OTC Respiratory Medicine Sales	Weekly synthetic index of cough, cold, fever, and respiratory-product demand	Positive	May increase as symptomatic individuals self-manage illness
School Absenteeism	Weekly proportion of school absence	Positive	Provides a rapid syndromic signal among younger populations
Respiratory Search Activity	Weekly index of respiratory symptom and illness searches	Positive	May capture symptom concern and information seeking
Emergency Respiratory Visits	Percentage of emergency presentations categorized as respiratory	Positive	Provides comparatively rapid clinical-utilization information

Indicator	Operational Representation	Expected Relationship With Future Surge	Surveillance Rationale
Absolute Humidity	Weekly environmental indicator	Negative in an influenza-oriented seasonal context	Provides biologically plausible seasonal information
Two-Week Respiratory Surge	Respiratory activity above the community-specific 80th percentile during either following week	—	Binary early-warning outcome

Source/Note: The framework is informed by influenza forecasting, pharmacy syndromic surveillance, digital epidemiology, and humidity-related influenza research. OTC sales have previously been investigated as communitywide illness indicators, while autoregressive and network models have demonstrated the value of combining conventional surveillance with digital information. All numerical observations in the current study are synthetic.

4.2 Statistical Model and Predictor Construction

Continuous predictors were standardized to a mean of zero and standard deviation of one before modeling. Standardization allowed regression effects to be compared across indicators measured on different scales.

Because consecutive weekly observations within one community share temporal and structural characteristics, standard errors were calculated using community-level clustering. This approach prevents the analysis from treating 1,440 repeated community-week measurements as though they represented 1,440 unrelated populations.

4.3 Evaluation Strategy and Research Ethics

Model discrimination was evaluated with the AUROC, which measures the model's capacity to assign higher predicted risk to future surge weeks than to nonsurge weeks across possible thresholds. A value of 0.50 represents chance-level discrimination, while higher values indicate improved separation.

An illustrative 50% probability threshold was used to calculate accuracy, precision, and sensitivity. Sensitivity represents the proportion of future surge periods detected, while precision indicates the proportion of generated alerts that corresponded to a subsequent simulated surge. These metrics were interpreted jointly because maximizing sensitivity can increase false alerts, whereas maximizing precision can cause important events to be missed.

No institutional ethics approval or informed consent was required because the analysis contains no human participants or identifiable health information. A real implementation involving pharmacy transactions, electronic health records, school information, or digital behavior would require appropriate legal and ethical governance. Data minimization, secure aggregation, role-based access, transparent retention rules, and safeguards against inappropriate individual-level surveillance would be essential.

5. Analysis

5.1 Overall Early-Warning Performance

The final analytical dataset contained 1,440 community-week observations across 30 synthetic communities. The simulated mean respiratory-illness rate was approximately 1.41 units. Mean OTC respiratory sales were 38.28 index points, school absenteeism averaged 2.65%, respiratory search activity averaged 29.18 index points, emergency respiratory visits averaged 2.28%, and absolute humidity averaged approximately 8.19 units.

The combined model generated an AUROC of 0.916, representing strong discrimination within the simulated dataset. At the illustrative 50% probability threshold, the model achieved 88.4% overall accuracy, 82.4% precision, and 75.4% sensitivity.

These values demonstrate the behavior of the synthetic model under its generating assumptions and should not be generalized to actual community respiratory surveillance. Real-world performance could be substantially lower under missing data, novel viral emergence, altered healthcare utilization, sudden media effects, atypical weather, major public-health interventions, or population behavioral change.

5.2 Relative Contribution of Early-Warning Indicators

Table 2: Cluster-Robust Logistic Regression Predicting a Respiratory Surge Within Two Weeks

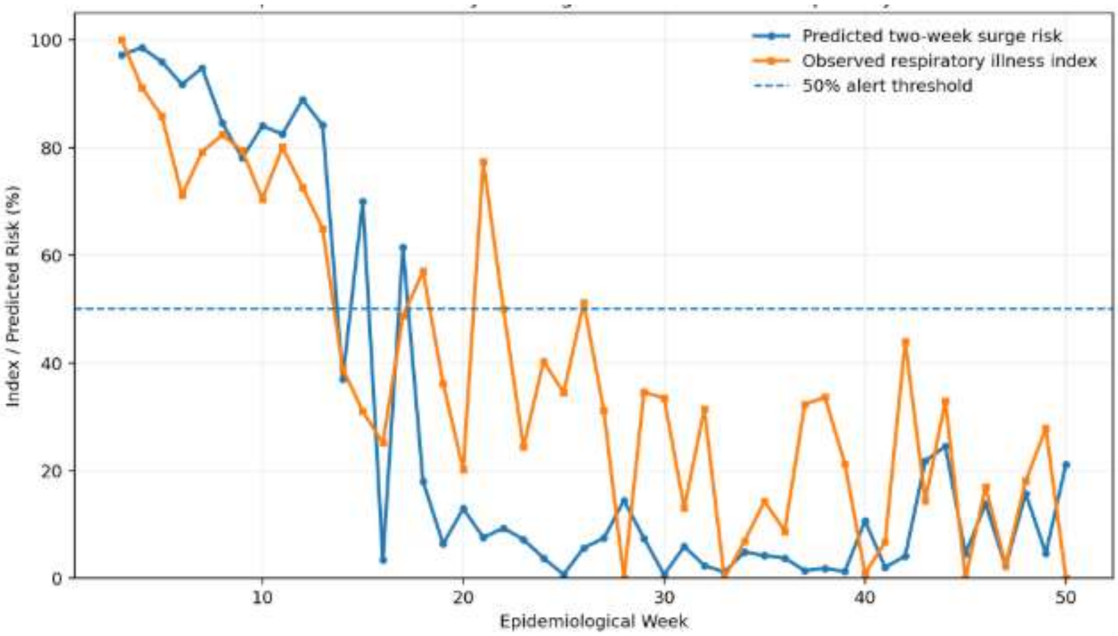
Predictor	Standardized β	Odds Ratio	p-value	Analytical Interpretation
Lagged Respiratory Illness	0.846	2.330	< .001	Recent respiratory momentum substantially increases near-term surge probability
OTC Respiratory Medicine Sales	0.676	1.967	< .001	Pharmacy demand contributes independent anticipatory information
School Absenteeism	0.129	1.137	.074	Positive but not independently significant after other signals are considered
Respiratory Search Activity	0.426	1.532	< .001	Online symptom interest contributes additional warning information
Emergency Respiratory	0.252	1.287	< .001	Rapid healthcare-utilization activity contributes independently

Predictor	Standardized β	Odds Ratio	p-value	Analytical Interpretation
Visits				
Absolute Humidity	−1.155	0.315	< .001	Lower humidity is associated with higher simulated surge probability
Model AUROC	0.916	—	—	Strong synthetic discrimination
Accuracy	88.4%	—	—	Correct classification at the illustrative threshold
Sensitivity	75.4%	—	—	Proportion of simulated surge periods detected
Precision	82.4%	—	—	Proportion of alerts followed by a simulated surge

Lagged respiratory illness remained an important predictor, demonstrating that recent epidemiological information should not be discarded simply because faster behavioral data are available. This pattern is consistent with ARGO, which incorporated both historical influenza activity and search information rather than relying on search behavior alone.

5.3 Temporal Early-Warning Pattern

Graph 1: Simulated Early-Warning Risk and Seasonal Respiratory Illness



Source/Note: Author-generated synthetic surveillance data. The graph displays one representative simulated community. Respiratory illness is standardized to a 0–100 seasonal activity index for comparison with predicted two-week surge probability. The dashed line represents an illustrative 50% alert threshold.

The graph demonstrates how predicted respiratory-surge risk changes across the epidemiological year. The warning probability rises substantially around the major seasonal respiratory wave and falls as the high-activity period resolves.

Importantly, the predicted-risk line does not exactly reproduce the observed illness index. The model incorporates pharmacy demand, searches, emergency visits, humidity, and lagged respiratory activity, allowing warning probability to move in advance of, or differently from, the contemporaneous clinical illness curve.

The divergence between the two trajectories is central to the purpose of an early-warning system. A useful forecast should provide information about what is likely to occur next rather than merely restating what is already visible in delayed surveillance.

Key Finding: The simulated multi-signal framework generated a coherent probability trajectory capable of identifying high-risk periods while retaining conventional epidemiological history as the principal surveillance anchor.

6. Discussion

6.1 Why Multi-Signal Surveillance Is Preferable to Single-Source Prediction

The principal contribution of the study is the development of a triangulated community early-warning architecture. Respiratory epidemics generate numerous observable traces: people experience symptoms, search for information, purchase medicines, miss school, seek emergency treatment, and eventually appear within finalized epidemiological reporting. Each signal reflects a different stage of the illness and healthcare-seeking process.

A diversified model reduces dependence on the assumption that one indicator remains stable. Pharmacy purchases can change because consumer behavior changes. Online searches can respond dramatically to news coverage. Emergency-department utilization can change because of service availability. School absence is affected by calendars and administrative rules. Conventional clinical reports can be delayed. Combining several signals creates redundancy that may improve system resilience.

The evolution of influenza nowcasting supports this principle. ARGO integrated epidemiological history with search data, while later work incorporated electronic health records and geographic network relationships. The strongest role for supplementary data is therefore not the replacement of epidemiological surveillance but enhancement of its timeliness and geographic responsiveness.

The Google Flu Trends experience remains an important warning against data-source overconfidence. Lazer and colleagues showed that large-scale digital prediction can fail when the relationship between behavior and disease changes. An operational community model should consequently monitor predictor drift and continuously evaluate whether the signals driving forecasts retain their original interpretation.

6.2 Translating Forecast Probability Into Community Preparedness

Forecast accuracy has limited public-health value unless alerts are connected with proportionate action. A two-week warning could trigger relatively inexpensive preparedness measures such as reviewing pharmacy inventories, disseminating surveillance updates to primary-care facilities, preparing school-health communication, reinforcing vaccination messages where epidemiologically appropriate, and confirming diagnostic or staffing readiness.

More expensive interventions should require stronger evidence. Increasing emergency staffing, opening additional clinical capacity, or reallocating scarce resources carries substantial costs. Community systems could therefore use multiple alert levels rather than a single binary threshold. A lower probability might trigger enhanced surveillance review, while a higher probability could justify operational escalation.

The model should also be clearly described as syndromic rather than pathogen-specific. A rise in respiratory illness does not determine whether influenza, RSV, SARS-CoV-2, or another respiratory pathogen is responsible. Laboratory testing and pathogen-specific surveillance remain essential for determining the actual etiological composition of a respiratory wave.

Environmental information requires similar caution. The evidence connecting absolute humidity with influenza survival and transmission provides a defensible reason for including humidity in an influenza-oriented model. However, the coefficient should not be interpreted as a universal rule for all seasonal respiratory viruses. A real multi-pathogen system may require pathogen-specific environmental effects or dynamically changing predictor weights.

6.3 Validation, Governance, and Reliability of Community Forecasting

The most important requirement before operational use is independent validation. Randomly dividing adjacent community-week observations into training and test sets can exaggerate model performance because neighboring weeks often resemble one another. A stronger design would train on earlier respiratory seasons and evaluate performance prospectively on later seasons.

Geographic transportability also requires explicit testing. Kandula, Hsu, and Shaman demonstrated the methodological challenges of subregional influenza nowcasting, while Pei and colleagues showed that surveillance-network structure influences forecasting information. A model developed in a highly connected metropolitan healthcare system may therefore require substantial recalibration before use in rural or lower-resource settings.

Data governance is equally important. Pharmacy sales, school attendance, emergency records, and digital behavior can become sensitive when analyzed at excessive individual or geographic granularity. Operational systems should use the minimum information required for forecasting and should favor appropriately aggregated community indicators wherever individual-level records are unnecessary.

Finally, forecast uncertainty should remain visible. Decision makers should receive probability estimates, data-quality information, predictor contributions, and calibration summaries rather than only unexplained warning labels. An interpretable model showing that rising pharmacy demand, respiratory searches, and emergency visits are jointly contributing to increased risk can support more defensible public-health decisions than a black-box alert with no identifiable evidence pathway.

7. Conclusion

Seasonal respiratory illnesses create a recurring public-health challenge because community demand can begin increasing before conventional surveillance becomes complete. Earlier warning can potentially be obtained by integrating signals generated at different stages of illness activity, including recent syndromic trends, pharmacy demand, school absence, digital information seeking, emergency respiratory visits, and environmental context.

The present simulation demonstrates one method for combining these signals into a two-week surge probability. Within the synthetic dataset, lagged respiratory illness remained a powerful predictor, while OTC medicine demand, respiratory search activity, emergency visits, and absolute humidity added independent information. The combined model produced strong simulated discrimination, but these performance estimates should not be treated as evidence of comparable accuracy in an actual public-health jurisdiction.

The central methodological conclusion is that community early-warning systems should be designed around triangulation rather than technological substitution. Influenza forecasting research demonstrates the value of combining conventional epidemiological information with digital, environmental, and network-derived indicators, while the failure of poorly calibrated digital surveillance demonstrates that rapidly generated proxy data can become misleading when human behavior changes.

A credible operational system should therefore preserve conventional clinical and laboratory surveillance as its epidemiological foundation while using supplementary signals to gain additional lead time. Future research should validate such models prospectively across multiple seasons and communities, evaluate calibration and false-alert burden, investigate geographic and socioeconomic equity, quantify the practical value of additional warning time, and test whether forecast-informed preparedness actually improves community health-system response.

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