

# Automated Surveillance To Detect An Influenza Epidemic: Which Respiratory Syndrome Should We Monitor?

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## BACKGROUND AND OBJECTIVE

Syndromic surveillance systems (SSS) seek early detection of infectious diseases outbreaks by focusing on pre-diagnostic symptoms. We do not yet know which respiratory syndrome should be monitored for a SSS to discover an influenza epidemic as soon as possible. This work compares the delay and workload required to detect an influenza epidemic using a SSS that targets either (1) all cases of acute respiratory infections (ARI) or (2) only those ARI cases that are febrile and satisfy CDC's definition for an influenza-like illness (ILI)

## METHODS

Using an explicit definition of ARI and ILI, we reviewed the electronic medical record (EMR) of 15,377 outpatient encounters at the Veterans Administration (VA) system. Found ARI and ILI cases served as a reference to develop case-detection algorithms (CDAs) that utilized combinations of structured EMR data and text analyses of clinical notes. We recreated historical background casecount time series by applying the most successful CDAs to historical EMR data. We injected factitious influenza cases to CDA-specific backgrounds using an age-structured modeled influenza epidemic and then used a modified CUSUM statistic daily for 50 days to detect the outbreak. This injection/prospective-surveillance cycle was repeated each week of the study year. To distinguish between true- and background-positive alarms, the daily statistics were performed on paired background+injection vs. background-only time series. We computed two benchmarks: 1) the average "Detection Delay", from the time of each injection to the first true-positive alarm; 2) the "Workload", defined as the yearly number of cases included in all the background-positive alarms. We compared these benchmarks for simulated SSS optimized to target either ARI, or febrile ILI cases.

## RESULTS

Statistical performance of illustrative CDAs targeting either ARI or (febrile) ILI is shown in the Table. For ARI, the CDAs that minimized both Detection Delay and Workload were those that maximized specificity and positive predictive value (PPV) and yet retained a sensitivity of 69-100% (Models 4 and 6). Com

Case Detection Parameters	Model Number						
	1	2	3	4	5	6	7
ICD-9 Codes	[Shaded]						
OR Cough Remedies		[Shaded]	[Shaded]		[Shaded]		
OR Text		[Shaded]					
AND Text				[Shaded]			[Shaded]
AND Temperature > 37.8°C						[Shaded]	[Shaded]
Target Syndrome							
ILI	[Shaded]						
Febrile ILI						[Shaded]	[Shaded]
Statistical Performance							
Sensitivity	79	97	99	69	75	75	71
Specificity	97	90	89	99	99	99.8	100
Positive Predictive Value	31	16	14	54	49	36.7	68
Area under the ROC	88	94	94	84	87	87	85

pared to the "respiratory" ICD-9 codeset used by CDC's "BioSense" SSS, the best ARI CDA decreased Detection Delay from 38 to 30 days, and Workload from 2397 to 483 cases/year (Figure). The best (febrile) ILI-targeted CDA further reduced Delay to 22 days and Workload to 121 cases/year (Model 7).

## RESULTS

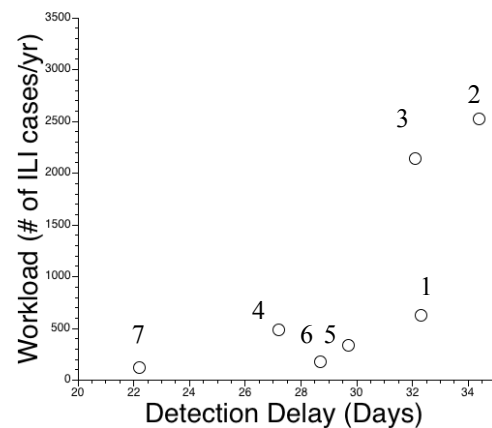


Figure. Detection delay (x-axis) and surveillance workload (y-axis) for the each of the CDA numbered in the Table

## CONCLUSIONS

Case detection methods that take advantage of information from the full EMR and that focus only on those ILI cases that are febrile can lower both the delay and the workload required to detect an influenza epidemic in the community.