ORIGINAL ARTICLE

Accuracy of Electronic Surveillance of Catheter-Associated Urinary Tract Infection at an Academic Medical Center

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OBJECTIVE. To develop and validate a methodology for electronic surveillance of catheter-associated urinary tract infections (CAUTIs).

DESIGN. Diagnostic accuracy study.

SETTING. A 425-bed university hospital.

SUBJECTS. A total of 1,695 unique inpatient encounters from November 2009 through November 2010 with a high clinical suspicion of CAUTI.

METHODS. An algorithm was developed to identify incident CAUTIs from electronic health records (EHRs) on the basis of the Centers for Disease Control and Prevention (CDC) surveillance definition. CAUTIs identified by electronic surveillance were compared with the reference standard of manual surveillance by infection preventionists. To determine diagnostic accuracy, we created 2 × 2 tables, one unadjusted and one adjusted for misclassification using chart review and case adjudication. Unadjusted and adjusted test statistics (percent agreement, sensitivity, specificity, positive predictive value [PPV], negative predictive value [NPV], and κ) were calculated.

RESULTS. Electronic surveillance identified 64 CAUTIs compared with manual surveillance, which identified 19 CAUTIs for 97% agreement, 79% sensitivity, 97% sensitivity, 23% PPV, 100% NPV, and κ of .33. Compared with the reference standard adjusted for misclassification, which identified 55 CAUTIs, electronic surveillance had 98% agreement, 80% sensitivity, 99% specificity, 69% PPV, 99% NPV, and κ of .71.

CONCLUSION. The electronic surveillance methodology had a high NPV and a low PPV compared with the reference standard, indicating a role of the electronic algorithm in screening data sets to exclude cases. However, the PPV markedly improved compared with the reference standard adjusted for misclassification, suggesting a future role in surveillance with improvements in EHRs.

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Catheter-associated urinary tract infections (CAUTIs) represent 40% of all nosocomial infections in US hospitals.[1,2] CAUTIs result in as many as 13,000 deaths each year, with costs to the US healthcare system of approximately $424 million annually.[3,4] It is estimated that 17%–69% of CAUTIs are preventable with the implementation of recommended strategies—the majority of which address the evidence-based use of indwelling urinary catheters (IUCs).[5] Since 2008, interest in CAUTI prevention has intensified, sparked by financial incentives and public reporting initiatives.[6]

Surveillance is a cornerstone of CAUTI prevention efforts, but it relies on resource-intense chart abstraction by specially trained personnel.[7] Even so, this "manual surveillance" is not a gold standard, as the extent of active case finding and the application of the surveillance definitions is variable across facilities and practitioners.[8] Electronic health record (EHR)–enabled surveillance has gained interest for its potential as a fast and reliable method for comparing infection rates across hospitals.[9] However, concerns about the feasibility of electronic surveillance remain. Since 2010, the surveillance definitions of CAUTI require documentation of fever or symptoms referable to the lower urinary tract.[7] Deficiencies in the documentation of subjective symptoms may affect the performance of electronic surveillance. In addition, the accurate documentation of IUCs is a requirement for fully automated surveillance. Anecdotally, IUC documentation is poor, but recent experience with integrated EHRs is more encouraging.[10]

The objective of this study was to develop an electronic methodology for surveillance of CAUTIs using electronic clinical, laboratory, and administrative data from the University of Colorado Hospital (UCH) and modified Centers for Disease Control and Prevention (CDC) National Healthcare Safety Network (NHSN) definitions.[7] We sought to validate this methodology against the reference standard, manual surveillance. Acknowledging the limitations of manual surveillance, medical record review and adjudication allowed for adjustment of the reference standard manual surveillance re-

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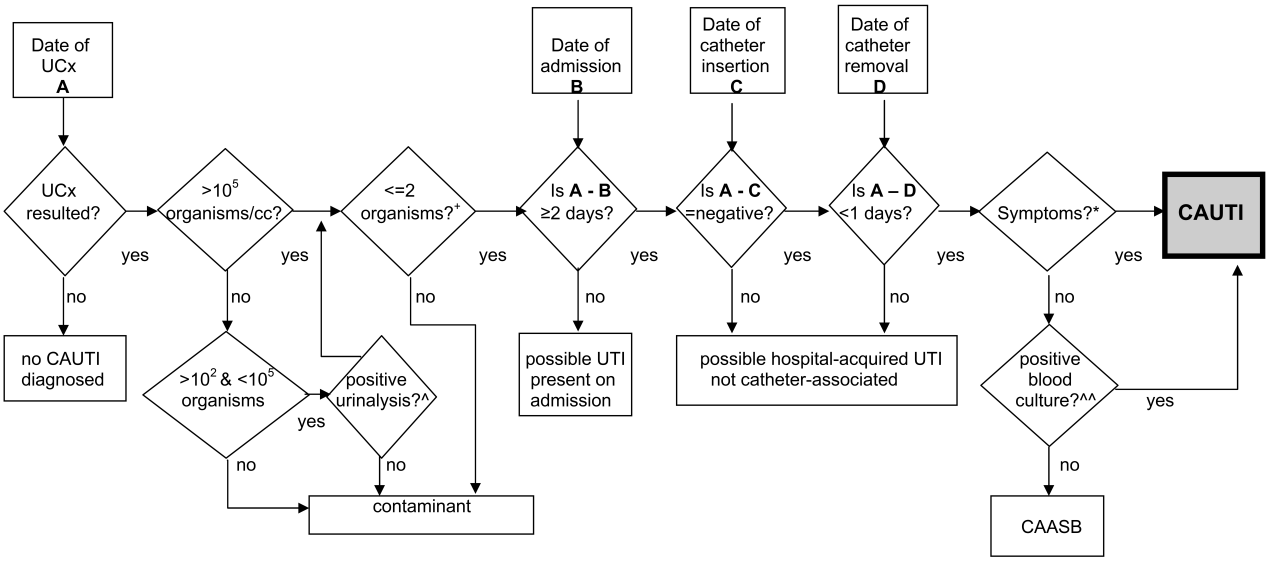

FIGURE 1. Logic diagram for catheter-associated urinary tract infection (CAUTI) diagnostic algorithm. [+]Any mixed gram-positive organism counts as 2 organisms and excludes the culture. [^]Positive urinalysis is (1) positive dipstick for leukocyte esterase and/or nitrite, (2) pyuria (urine specimen with more than or equal to 10 white blood cells/mm^3 or more than or equal to 3 white blood cells/high-power field of unspun urine), or (3) organisms seen on Gram stain of unspun urine. [*]For this algorithm only temperature more than 38.0°C (not determined: suprapubic tenderness, costovertebral angle pain, or tenderness all without another recognized cause). [^^]Positive blood culture contains matching organism of urine culture. CAASB, catheter-associated asymptomatic bacteriuria; UCx, urine culture; USB, urinary source bacteremia; UTI, urinary tract infection.

sults for misclassification, an approach adapted from other authors assessing diagnostic accuracy against a manual surveillance reference standard.[11]

METHODS

This study was conducted at the UCH Anschutz Inpatient Pavilion in Aurora, Colorado, a 425-bed urban tertiary care hospital and the major teaching affiliate of the University of Colorado School of Medicine. Eligible subjects included inpatients greater than 18 years of age between November 15, 2009, and November 14, 2010, with a high clinical suspicion of CAUTI. Patients were considered to have had a high clinical suspicion of CAUTI if they had both an indwelling catheter documented and a urine culture during the hospitalization of interest. Excluded patients were those less than 18 years of age and those admitted to labor and delivery or psychiatry units. Hospitalizations of the same patient more than once during the study period were counted as independent episodes. If more than 1 urine culture was present during an episode of hospitalization, only the earliest available culture was included. Four high clinical suspicion cases were excluded because of administrative data missing from the EHR (ie, date of admission). At the time of the study, UCH maintained clinical nursing data using McKesson Horizon Clinicals (formerly Pathways Care Manager), administrative data on IDX Centricity Web, and laboratory data on Cerner Classic PathNet. Physician orders and notes were maintained in paper charts. The study was reviewed by the Colorado Multiple Institutional Review Board and determined to be in compliance with federal standards regarding handling of protected health information. HIPAA authorization and informed consent were not required.

Electronic Surveillance Algorithm

An algorithm was developed on the basis of the CDC/NHSN's laboratory-based surveillance definition of CAUTI from January 2010 utilizing clinical, laboratory, and administrative data and was informed by the theoretical framework of Hota et al.[12] At that time, CAUTI was defined by the CDC/NHSN as meeting all of the following criteria: (1) a UTI (a positive urine culture from a patient with either fever or symptoms referable to the urinary tract or from a patient with a positive blood culture matching the urine culture), (2) diagnosed from a culture sent more than 48 hours after admission to the hospital, and (3) diagnosed in a patient who has had an IUC in place or removed within 48 hours before the culture.[7] The logic for the algorithm was incorporated into Structured Query Language code in Microsoft Access (Figure 1). The algorithm differed from the CDC's definition in the following ways: (1) subjective symptoms referable to the urinary tract were not incorporated and (2) 2 calendar days was used for attribution of a positive culture to a catheter and hospital in lieu of 48 hours. An iterative process of refinement and audit was used to arrive at the final algorithm.

Several queries were written to extract clinical nursing documentation and demographic data daily from Care Manager

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(McKesson). Laboratory results were extracted monthly from Cerner. All reports were posted to a shared server and subsequently imported into an Access database that was designed with logic to manage and analyze the information as specified by the algorithm. Electronic documentation of IUCs was validated against the charge nurse report as reported elsewhere.[13]

Manual Surveillance Algorithm (Reference Standard)

Infection preventionists (IPs) have performed standard NHSN-style surveillance housewide at UCH since January 2009, utilizing the definition for CAUTI as described above during the study period. During the time period of the study, IPs reviewed printed reports from Cerner of all urine culture results each 24-hour period. For each encounter with a urine culture meeting the CDC/NHSN criteria for urine culture positivity, an IP reviewed the EHR for admission dates, dates of catheter insertion, temperatures, and additional test results (urinalyses and blood cultures) and applied the surveillance definition to identify CAUTIs. Concurrent review of paper charts was periodically performed for cases requiring more clinical context for diagnosis, such as evidence of lower urinary tract symptoms. Final adjudication of difficult cases was done by the hospital epidemiologist, if necessary.

Medical Record Review with Adjudication

Because manual surveillance is not a gold standard but a reference standard, we attempted to adjust for manual surveillance misclassification[11] by performing retrospective medical record review and case adjudication of selected cases as described in the section on analysis below. Medical record review was conducted by research nurses with master's degrees who were trained to review paper charts and an electronic repository of laboratory data. The necessary data elements were abstracted into REDCap (Research Electronic Data Capture), a secure web-based application designed to support data capture for research studies.[14] A sample of charts was reviewed by both reviewers until there was less than 10% discrepancy between reviewers in key data fields. A random sample of 10% of reviewed charts was rereviewed by the PI throughout the medical record review period to ensure consistency. When chart review was complete, a panel of 3 IPs was assembled to adjudicate cases according to the 2010 CDC definition. Disagreement among the IP panelists was discussed until consensus was achieved. The research nurses and IP panelists were blinded to the results of the manual and electronic surveillance and to the purpose of the adjudication process.

Analysis: Determination of Diagnostic Accuracy of Electronic Surveillance

A 2 × 2 table was constructed to determine the diagnostic accuracy of electronic surveillance versus manual surveillance (reference standard; Table 1, pt. A). To adjust for potential misclassification, we performed medical record review of all true positives (count a), all false positives (count b), and all false negatives (count c). Because the number of true negatives (count d) was large, only a randomly selected 10% sample of true negatives was reviewed (count m). We then reclassified cases as necessary on the basis of the medical record review and produced the adjusted 2 × 2 table (Table 1, pt. B). Those cases misclassified as true positive (a_1) were removed from count a and added to count b. Those cases misclassified as false positive (b_1) were removed from count b and added to count a. Those cases misclassified as false negative (c_1) were removed from count c and added to count d. Cases misclassified as true negative (count d_1) were used to estimate the proportion of count d that were false negatives (d_1/m); these were removed from count d and added to count c.

TABLE 1. Unadjusted and Adjusted 2 × 2 Tables

	Manual surveillance +	Manual surveillance −
A. Unadjusted 2 × 2 table		
Electronic surveillance +	a	b
Electronic surveillance −	c	d
B. Adjusted 2 × 2 table		
Electronic surveillance +	$a + b_1 - a_1$	$b + a_1 - b_1$
Electronic surveillance −	$c - c_1 + \left(\frac{d_1}{m}d\right)$	$d + c_1 - \left(\frac{d_1}{m}d\right)$

NOTE. A 2 × 2 table was constructed to determine the diagnostic accuracy of electronic surveillance versus manual surveillance (reference standard; pt. A). To adjust for potential misclassification, we performed medical record review and case adjudication of all true positives (count a), all false positives (count b), and all false negatives (count c). Because the number of true negatives (count d) was large, only a randomly selected 10% sample of true negatives was reviewed (count m). An adjusted 2 × 2 table was constructed (pt. B), corrected for cases determined to be misclassified as true positive (a_1), misclassified as false positive (b_1), misclassified as false negative (c_1), and misclassified as true negative (count d_1). See details in the text.

Estimates of percent agreement, sensitivity, specificity, positive predictive value (PPV), negative predictive value (NPV), and Cohen's κ were calculated. Percent agreement assessed the proportion of all cases where the reference standard and electronic surveillance agree. Sensitivity assessed the probability that electronic surveillance diagnosed a CAUTI, given that the reference standard diagnosed a CAUTI. Specificity assessed the probability that electronic surveillance did not diagnose a CAUTI, given that the reference standard did not diagnose a CAUTI. The PPV was the probability that the reference standard diagnosed a CAUTI, given that the electronic surveillance diagnosed a CAUTI. The NPV was the probability that the reference standard did not diagnose a CAUTI, given that the electronic surveillance did diagnose a

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TABLE 2. Characteristics of High Clinical Suspicion Population

Characteristic (unique inpatient encounters n = 1,695)	Value
Age,[a] mean ± SD, years	57.8 ± 16.3
Sex, %	
Female	42.5
Male	49.0
Unknown	8.5
Race, %	
American Indian/Alaska Native	0.6
Asian	1.5
Black or African American	8.2
White	44.5
Unknown	45.1
Ethnicity, %	
Not Hispanic/Latino	32.1
Hispanic/Latino	8.7
Unknown	59.2
Length of stay, mean ± SD, days	14.2 ± 16.5
Average catheter duration, mean ± SD, days	8.8 ± 10.9

NOTE. SD, standard deviation.
[a] Less than or equal to 2.5% missing data.

CAUTI. Cohen's κ (percent agreement that corrects for the possibility of agreement occurring by chance) was determined for electronic surveillance compared with the reference standard as a measure of consistency. For all test statistics, 95% confidence intervals (CIs) were calculated. These calculations were repeated for comparison of electronic surveillance to manual surveillance adjusted for misclassification. SAS (ver. 9.3; SAS Institute) was used for all calculations. The earlier medical record review allowed for the identification of the reason for discordance remaining between manual surveillance and electronic surveillance following adjustment for misclassification.

Sensitivity Analyses

Sensitivity analyses were performed to assess the impact of our assumptions about medical record review and case adjudication. First, we explored the possible scenario that all positives determined by manual surveillance were correctly classified ($a_1 = 0$, $c_1 = 0$), given that manual surveillance was concurrent and may have been able to access data that the medical record review could not (scenario 1). Second, we identified missing urinalysis data from the medical record review, which prevented completion of the diagnostic algorithm in the adjudication of false-positive cases. We therefore explored the scenario that all of the cases with insufficient data were truly CAUTI (scenario 2).

RESULTS

Study Population

During the study period, our query identified 1,695 high clinical suspicion episodes that met inclusion criteria from 1,586 unique patients. The characteristics of the study population are summarized in Table 2.

Diagnostic Accuracy

An unadjusted 2 × 2 table was constructed comparing electronic surveillance with manual surveillance (Table 3, pt. A). Electronic surveillance diagnosed a total of 64 CAUTIs; 15 of these cases were true positives diagnosed with CAUTI by manual surveillance (a), and 49 of these cases were false positives not diagnosed with CAUTI by manual surveillance (b). Electronic surveillance identified a total of 1,631 negative cases. Among these, 4 were false-negative cases diagnosed as CAUTI by manual surveillance (c). There were 1,627 true negatives (d) that were diagnosed as CAUTI by neither method. After medical record review and adjudication, there were 2 cases misclassified as true positive (a_1), 31 misclassified as false positive (b_1), and 3 misclassified as false negative (c_1). Among the 168 cases that comprised the 10% sample of true negatives (m), 1 case was determined to be positive (d_1). The 2 × 2 table adjusted for misclassification appears in Table 3, part B.

On the basis of Table 3, test statistics of electronic surveillance were calculated (Table 4). Compared with manual surveillance, the electronic algorithm had 97% agreement (95% CI, 96%–98%), 79% sensitivity (95% CI, 61%–97%),

TABLE 3. Unadjusted and Adjusted 2 × 2 Tables

	Manual surveillance +	Manual surveillance −	Total
A. Unadjusted 2 × 2 table			
Electronic surveillance +	15	49	64
Electronic surveillance −	4	1,627	1,631
Total	19	1,676	1,695
B. Adjusted 2 × 2 table			
Electronic surveillance +	44	20[a]	64
Electronic surveillance −	11[b]	1,620	1,631
Total	55	1,640	1,695

[a] False positives were attributed to positive urinalyses results in cultures with low colony counts identified in the electronic surveillance data set but not identified by manual surveillance (n = 8), an elevated temperature identified in the electronic surveillance data set but not identified by manual surveillance (n = 4), or a suprapubic catheter, condom catheter, or nephrostomy tube misidentified as an indwelling urinary catheter in the electronic surveillance data set (n = 8). In the case of the 8 discordant urinalyses and the 4 discordant temperatures, the paper charts were incomplete and did not allow for confirmation of the urinalysis or temperatures contained in the electronic health record.
[b] False negatives either were attributed to a discrepancy in catheter insertion and removal dates obtained by the 2 methods (n = 1) or were extrapolated as misclassified due to the correction employed to account for the 10% sample reviewed (n = 10).

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TABLE 4. Test Statistics and Sensitivity Analysis

Scenario	% agreement (95% CI)	Sensitivity, % (95% CI)	Specificity, % (95% CI)	Positive predictive value, % (95% CI)	Negative predictive value, % (95% CI)	κ (95% CI)
Unadjusted	97 (96–98)	79 (61–97)	97 (96–98)	23 (12–32)	100 (100–100)	.33 (.21–.46)
Adjusted for all misclassification	98 (97–99)	80 (70–91)	99 (98–99)	69 (56–80)	99 (98–100)	.71 (.61–.80)
Scenario 1:[a] adjusted for negatives only ($a_1 = 0$, $c_1 = 0$)	98 (97–99)	77 (66–88)	99 (98–99)	72 (57–79)	99 (99–100)	.71 (.62–.80)
Scenario 2:[b] adjusted for missing data in paper chart (gold standard)	99 (98–99)	84 (74–91)	100 (99–100)	88 (82–97)	99 (99–100)	.85 (.78–.91)

NOTE. a_1 = cases misclassified as true positive; c_1 = cases misclassified as false negative; CI, confidence interval.

[a] Assumes all positives by manual surveillance are correctly classified.

[b] Assumes all cases with missing data are misclassified.

97% specificity (95% CI, 96%–98%), 23% PPV (95% CI, 12%–32%), 100% NPV (95% CI, 100%–100%), and κ of .33 (95% CI, .21–.46; Table 4). After adjustment for misclassification, the electronic algorithm's PPV rose to 69% (95% CI, 56%–80%), and κ rose to .71 (95% CI, .61–.80).

Discordant Cases

We examined discordant cases remaining after adjustment for misclassification. There were 20 electronic surveillance cases that remained false positive because of positive urinalyses results in cultures with low colony counts identified in the electronic surveillance data set but not identified by manual surveillance ($n = 8$), an elevated temperature identified in the electronic surveillance data set but not identified by manual surveillance ($n = 4$), or a suprapubic catheter, condom catheter, or nephrostomy tube misidentified as an IUC in the electronic surveillance data set ($n = 8$). In the case of the 8 discordant urinalyses and the 4 discordant temperatures, the paper charts were incomplete and did not allow for confirmation of the urinalysis or temperatures contained in the EHR. In addition, 11 electronic surveillance cases remained classified as false negative either because there was a discrepancy in catheter insertion and removal dates obtained by the 2 methods ($n = 1$) or because they were extrapolated as misclassified due to the correction employed to account for the 10% sample ($n = 10$).

Sensitivity Analysis

Sensitivity analysis explored the scenario that (1) all manual surveillance positives were correctly classified and (2) all false positives were truly positive. The results of the 2 scenarios are shown in Table 4. In scenario 1, we recalculated the test characteristics assigning $a_1 = 0$ and $c_1 = 0$. In scenario 2, there were 20 screen-negative cases that were confirmed by medical record review with adjudication as negative but were identified as CAUTI by electronic surveillance. Upon review of these cases, we determined that the paper medical record was missing laboratory or temperature data that had been available electronically ($n = 12$). In this scenario, we added an additional 12 cases to b_1.

DISCUSSION

CAUTI is an ideal condition for automated surveillance because of a widely accepted surveillance definition employing clinical and laboratory data, which can be documented in discrete fields in the EHR. Choudhuri et al[15] reported the validation of an electronic surveillance tool for CAUTI on small samples that did not attempt to look at misclassification. In contrast, this article reports on an algorithm for CAUTI surveillance that was validated in a large sample at an urban tertiary care center prior to the implementation of an integrated EHR. Compared with manual surveillance, electronic surveillance had a poor PPV but a high NPV, which would make it an efficient screening tool to exclude cases prior to manual review. Compared with manual surveillance adjusted for misclassification, the PPV rose markedly. A sensitivity analysis based on the impact of missing data suggested that the test characteristics may be significantly improved in the era of the integrated EHR, which would allow for comprehensive data pulls and complete capture of nursing data elements in discrete fields, including IUC insertion and removal dates and catheter type.

Manual surveillance, the industry standard, is recognized as imperfect because of challenges of applying NHSN definitions. A study of 18 IPs reviewing the same central line–associated bloodstream infection (CLABSI) cases using NHSN definitions had an overall interrater reliability (κ) of .42.[8] Thus, one benefit of electronic surveillance is the ability to apply a standard definition to cases across clinical sites without requiring subjective interpretations of the surveillance definition. Lin et al[9] highlighted this benefit by comparing CLABSI rates determined by manual surveillance to those determined by electronic surveillance at the same 4 hospitals and found the rankings to be markedly different depending on the methodology. Similar problems are expected with CAUTI surveillance, although the degree to which this is a problem is not known.

Anecdotally, providers are relying on electronic tools to assist with case finding, but the validation of these tools for use as formal surveillance is unknown.[16] There is reason be

concerned with over- or underidentification of hospital-acquired infections on the basis of algorithms that cannot account for subtle clinical findings or data elements not captured in discrete EHR data fields. The CAUTI algorithm described in this article did not identify lower urinary tract symptoms, relying exclusively on fever to identify symptomatic infections. While natural language processing holds promise for identifying such information from clinician notes,[17] its success is reliant on their identification and documentation. In practice, such symptoms in patients with CAUTI may be either poorly documented or uncommon. Of 240 charts reviewed in this study, no cases were incorrectly categorized because of a failure of electronic surveillance to identify clinical symptoms identified by other methodologies. While an electronic definition may not be able to capture the subtleties of every CAUTI case, the use of standard electronic algorithms will reassure providers that rankings and benchmarking are based on identical definitions.

This study has several limitations inherent to its design. First, this single-center study was performed at an academic medical center, and its findings may not be generalizable to other settings. Second, while manual surveillance adjusted for misclassification using chart review and case adjudication has good face validity for use as a research tool, this approach is not a validated "gold standard" for CAUTI surveillance. There is no data to suggest that this resource-intensive process should be used in routine clinical application. Third, medical record review and case adjudication was limited by missing data elements related to its retrospective nature. We performed a sensitivity analysis to account for this, but because we did not review all 1,695 charts, our estimates may not accurately represent the performance of electronic surveillance. Nonetheless, the sensitivity analysis suggests that the base-case test characteristics are a low-end estimate of the diagnostic accuracy of this algorithm. Finally, IUC insertion and removal dates were extrapolated from daily nursing assessments, which did not record insertion and removal dates or the type of catheter used. We have previously reported on the accuracy of daily catheter documentation at UCH during the study period.[13] We found that most discrepancies resulting in disagreement with manual surveillance in our data set were related to catheter type (indwelling, straight catheter, etc), not insertion and removal dates. The limitations of our data set are likely to be improved with next-generation EHRs.[18]

In summary, electronic surveillance demonstrated acceptable test characteristics only when compared with manual surveillance adjusted for misclassification. In its current form, electronic surveillance might allow for elimination of negative cases for a large surveillance program or serve as a source of data to trend events over time. However, improvements to the PPV of electronic surveillance may be achieved with the adoption of integrated EHRs. Future work should include multisite validation at hospitals with integrated EHRs.

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