A COMPARISON BETWEEN THE EFFECTIVENESS OF MANUAL WARD SURVEILLANCE AND ELECTRONIC SURVEILLANCE OF HEALTHCARE-ASSOCIATED INFECTIONS

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Abstract

Healthcare-associated infections (HAIs) are a serious threat to patients, especially in intensive care units (ICUs), making HAI surveillance a labor-intensive and time-consuming necessity. In this paper we compared the efficiency and performance of manual surveillance (MS) to those of electronic surveillance (ES). In a six-week study, 102 patients admitted to two ICUs were observed and thirty HAI episodes were confirmed by a consensus group. Results showed that the sensitivity and specificity of ES were superior over those of MS while reducing time spent on HAI detection by almost 85%.

Keywords – ***Healthcare-associate infections, Infection control, Automated surveillance, Computer-assisted monitoring.***

1. Introduction

Studies showed that yearly more than 4 million people suffer from healthcare-associated infections (HAIs) in Europe, resulting in nearly 150,000 fatalities [1]. Patients admitted to intensive care units (ICUs) are more likely to develop an HAI than elsewhere in a hospital; infection rates for ICUs vary between 14% and 35%, whereas infection rates for other wards are about 6–10% [2-4]. Infection rates can be reduced by hospital infection control programs [5,6], but these programs are both labor-intensive and time-consuming [7].

Since 2004, the Hospitals in Europe Link for Infection Control through Surveillance (HELICS) reporting and prevention program has been adopted by hospitals across Europe, and was integrated in the European Centre for Disease Prevention and Control surveillance activities in 2008 [8]. Within this program, definitions and rules for the detection of the most common HAIs have been established [9], which in turn enables the creation of rule-based clinical detection and monitoring systems (CMSs) to automate the surveillance of HAIs, lessening the work burden on healthcare personnel.

In this study we established the performances of manual ward surveillance (MS) of HAIs and electronic surveillance with MONI-ICU (ES), a rule-based infection control CMS for monitoring of

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HAIs in adult patient ICUs [10-12], and compared them with each other. To determine the performance of both surveillance methods, MS and ES were performed in parallel at two ICUs over a period of three months, and their results were compared to an established clinical reference standard. Comparisons focussed on surveillance quality and efficiency.

2. Methods

This study was performed at the Vienna General Hospital (VGH), a 2135-bed tertiary care and teaching hospital. Two ICUs were selected for this study, one at the Department of Gastroenterology and Hepatology and the other at the Department of Internal Medicine. All patients admitted to these ICUs who stayed for a period longer than 48 hours between November 13, 2006 and February 7, 2007 were selected and subsequently evaluated according to HELICS-defined rules for HAIs.

2. 1. Study design

This study concerned itself with the detection of ICU-acquired infections, which are infections that occur later than 48 hours after the patient has been admitted to an ICU [9]. The following types of HELICS-defined ICU-acquired infections were included in this study:

- Blood stream infection (BSI),
- Pneumonia (PN),
- Central venous catheter-related infection (CRI),
- Urinary tract infection (UTI).

2.1. 1. Manual surveillance

MS of HAIs was performed by an infection preventionist (IP) from the *Division of Hospital Hygiene (DHH)* at the VGH. During the study period, the IP visited each ICU at least twice a week to confer with the attending ICU physicians and to review patient charts and PDMS data as well as hardcopies of microbiology and radiology results.

2.1. 2. Electronic surveillance

MONI-ICU receives clinical, laboratory and nursing data from the Philips CareVue patient data management systems (PDMSs) in operation at the ICU wards. For patients' microbiology data, it is connected with the laboratory information system (LIS) of the Department of Microbiology of the VGH. Administrative data from the VGH's hospital information system is used to correctly combine and match data with patients.

MONI-ICU uses a knowledge base (KB) in which the HAI rules and linguistic concepts defined by the HELICS-group are implemented in Arden Syntax [13] extended with fuzzy set theory and logic. The KB consists of a collection of medical logic modules (MLMs), each of which calculates the fuzzy score of an intermediate linguistic concept. These linguistic concepts are then evaluated according to the HELICS-defined rules, which have been translated into logical rules that combine data with fuzzy implication, conjunction and disjunction operators, yielding a score between 0 and 100 for each type of HAI, whereby 0 means no indication of HAI, 100 means that an HAI has been established for certain, and everything in between means that there are signs indicative for infection, but that not all HELICS prerequisites have been fully met. Table 1 shows the main fuzzy linguistic and laboratory-based concepts in MONI-ICU.

Table 1: Overview of fuzzy and laboratory-based infection parameters

	BSI	PN	UTI	CRI
General infection parameters	Fever, increased CRP, leukopenia, leukocytosis			
Specific infection parameter	Shock, hypotension	Decreased gas exchange, respiratory device present ≤ 48 hours	Urinary catheter present ≤ 48 hours	Shock, hypotension, catheter present ≤ 48 hours
Laboratory results	Microbiology: blood cultures	Microbiology: blood cultures, BAL, DPA, PB cultures	Microbiology: Urine cultures, catheter cultures	Microbiology: blood cultures, catheter cultures

Note: BSI, blood stream infection; PN, pneumonia; UTI, urinary tract infection; CRI, central venous catheter-related infection; CRP, C-reactive protein; BAL, bronchoalveolar lavage; DPA, distal protected aspirate; PB, protected brush.

For each day in the study period, laboratory and nursing data was downloaded from the PDMSs of both ICUs and microbiology data was downloaded from the LIS of the Department of Microbiology of the VGH. After data transfer was complete, the MLMs were executed by the Arden Syntax rule-engine in three phases: First, the raw data are pre-processed and filtered; second, all intermediate (fuzzy) concepts are calculated in their respective MLMs; third, HAI detection results are calculated for each of the HAI types defined in the HELICS rules. Adhering to the de facto standard for epidemiological reporting, patients were determined to have an HAI episode only when the score for an HAI rule was 100%, thus excluding fuzzy results.

2.1. 3. Clinical reference standard

The clinical reference standard was constructed by two senior IPs of the Division of Hospital Hygiene. Both infection control specialists scrutinized and used the data sources and results from both surveillance methods, and repeated the MS process using all available data. In case their findings contradicted the outcome of one of the surveillance methods, the available data would be studied until an explanation was found, after which a consensus was established. In preparation of this study, a review of the reference standard was done involving both infection control specialists and a data analyst to improve data quality.

2. 2. Outcome measures

Both surveillance methods were analyzed on the basis of patient events, which are defined as either the detection of an HAI episode or the lack of such an episode during an entire patient's stay. Performance measures used in the comparison of both surveillance methods are sensitivity, specificity, positive predictive value (PPV), negative predictive value (NPV), overall accuracy and Cohen's kappa measure of agreement (kappa) [14]. Where possible, the Wilson score interval incorporating continuity corrections was calculated to determine 95% confidence interval indications [15, 16].

2. 3. Methods for data analysis

Formulas for sensitivity, specificity, PPV, NPV, accuracy, kappa and confidence intervals were calculated in Microsoft Excel 2007. Confidence interval calculation was done under the assumption of a normal distribution of data elements.

3. Results

During the study period 130 patient admissions were recorded, 102 of which were longer than 48 hours, comprising 923 patient days. After data quality control, 93 admissions comprising 800 patient days were deemed eligible for analysis. The clinical reference standard was based on the analysis of this data. Of these 93 admissions, 75 admissions were without HAIs and a total of 30 HAI episodes occurred in the remaining 18 admissions; three episodes of BSI, five episodes of PN, 18 episodes of CRI and four episodes of UTI were detected.

Table 2: Performance of manual ward surveillance and electronic surveillance

	Manual surveillance	Electronic surveillance
Sensitivity, %	40.0 (23.2–59.3)	86.7 (68.4–95.6)
Specificity, %	93.6 (85.0–97.6)	98.7 (91.9–99.9)
PPV, %	70.6 (44.0–88.6)	96.3 (79.1–99.8)
NPV, %	80.2 (70.3–87.6)	94.9 (86.9–98.4)
Accuracy, %	78.7 (69.6–85.6)	95.3 (88.8–98.3)
kappa	.388	.880

Note: Data in parentheses are 95% confidence intervals; PPV, positive predictive value; NPV, negative predictive value; kappa, Cohen's kappa measure of agreement.

Table 2 shows performance indications for both surveillance methods. MS failed to detect 18 out of 30 HAI episodes and detected five false positives. As a result, sensitivity was 40%, specificity 93.6%, PPV 70.6%, NPV 80.2%, accuracy 78.7%, and kappa .39. ES missed four out of 30 HAI episodes and generated one false positive. As a result, sensitivity was 86.7%, specificity 98.7%, PPV 96.3%, NPV 94.9%, accuracy 95.3%, and kappa .88. Finally, MS took 82.5 personnel hours for data collection and analysis. In contrast, manual evaluation of results generated by MONI-ICU only took 12.5 personnel hours, a reduction of almost 85%.

4. Conclusion

The study showed that ES performed significantly better than MS while saving almost 85% of the personnel resources. It detected twice as many HAI episodes correctly, while generating five times less false positives. As a result, sensitivity and kappa scores were more than twice as high for ES as they were for MS; there were also significant differences in PPV, NPV and accuracy.

Weaknesses of MS have several causes, such as time constraints and human factors such as stress and fatigue, which can all negatively influence decision making. The subjectivity of HELICS-rules is also an important factor contributing to a lower performance of MS; although standard rules for HAI detection have been defined, the interpretation of those rules can differ from person-to-person, or even from time-to-time for the same person. The strength of ES is that it performs its surveillance on a daily basis and has an unambiguous, clearly defined medical knowledge base. The weakness of ES lies in its dependency on a relatively restricted number of data sources; MS has access to more data sources, increasing data redundancy as well as diversity.

There have been several other European hospitals that have implemented ES for HAIs but they have all used the CDC definitions or modifications of those, not HELICS rules [17, 18]. Furthermore, none of the systems encountered used fuzzy set theory and logic to introduce degrees of compatibility in the detection process, but rather tried to provide a binary, black and white classification of an HAI episode, which results in a loss of (intermediate) information.

The results of this study could have an impact on infection control and information infrastructure in the VGH and on the development of future MONI-ICU versions. This study has shown that ES provides higher quality surveillance than MS does, but also that it is not perfect yet, and that efforts must be made to improve the quality of HAI detection, both in the development of the KB and the development of data connections to diverse information systems of the VGH. Several of these improvements have already been made.

5. Conflict of Interest

Klaus-Peter Adlassnig is also co-founder, CEO and scientific head of Medexter Healthcare, established to broadly disseminate decision support systems with clinically proven usefulness.

6. References

[1] Healthcare-associated infections. In Annual Epidemiological Report on Communicable Diseases in Europe 2008: 16-38. [Accessed November 8, 2011] Available from: http://ecdc.europa.eu/en/publications/Publications/0812_SUR_Annual_Epidemiological_Report_2008.pdf.

[2] Chandrasekar PH, Kruse JA and Mathews MF. Nosocomial infection among patients in different types of intensive care units at a city hospital. Crit Care Med. 1986;14(5):508-510

[3] Chen YY, Wang FD, Liu CY and Chou P. Incidence rate and variable cost of nosocomial infections in different types of intensive care units. Infect Control Hosp Epidemiol. 2009;30(1):39-46

[4] Donowitz LG, Wenzel RP and Hoyt JW. High risk of hospital-acquired infection in the ICU patient. Crit Care Med. 1982;10(6):355-357

[5] Delgado-Rodriguez M, Gomez-Ortega A, Sillero-Arenas M, Martinez-Gallego G, Medina-Cuadros M and Llorca J. Efficacy of surveillance in nosocomial infection control in a surgical service. Am J Infect Control. 2001;29(5):289-294

[6] Haley RW, Culver DH, White JW, Morgan WM, Emori TG, Munn VP and Hooton TM. The efficacy of infection surveillance and control programs in preventing nosocomial infections in US hospitals. Am J Epidemiol. 1985;121(2):182-205

[7] Klompas M and Yokoe DS. Automated surveillance of health care-associated infections. Clin Infect Dis. 2009;48(9):1268-1275

[8] ECDC. Healthcare-associated Infections Surveillance Network (HAI-Net). In 2011. [Accessed Jan 23, 2012] Available from: http://ecdc.europa.eu/en/activities/surveillance/HAI/Pages/default.aspx.

[9] Surveillance of Nosocomial Infections in Intensive Care Units – Protocol Version 6.1. In 2004. [Accessed August 23, 2011] Available from: http://helics.univ-lyon1.fr.

[10] Adlassnig K-P, Blacky A and Koller W. Fuzzy-based nosocomial infection control. In: M. Nikravesh, J. Kacprzyk and L. Zadeh, editors. Forging New Frontiers: Fuzzy Pioneers II. 1st edition. Berlin: Springer; 2008:343-349.

[11] Adlassnig K-P, Blacky A and Koller W. Artificial-intelligence-based hospital-acquired infection control. Stud Health Technol Inform. 2009;149:103-110

[12] Blacky A, Mandl H, Adlassnig K-P and Koller W. Fully automated surveillance of healthcare-associated infections with MONI-ICU – A breakthrough in clinical infection surveillance. Applied Clinical Informatics. 2011;2(3):365-372

[13] The Arden Syntax for Medical Logic Systems Version 2.7. Ann Arbor, MI, 2008: Health Level Seven Inc.

[14] Cohen J. A coefficient of agreement for nominal scales. Educ Psychol Meas. 1960;20(1):37-46

[15] Wilson EB. Probable inference, the law of succession, and statistical inference. J Am Stat Assoc. 1927;22:209-212

[16] Newcombe RG. Two-sided confidence intervals for the single proportion: Comparison of seven methods. Stat Med. 1998;17(8):857-872

[17] Bouam S, Girou E, Brun-Buisson C, Karadimas H and Lepage E. An intranet-based automated system for the surveillance of nosocomial infections: prospective validation compared with physicians` self-reports. Infect Control Hosp Epidemiol. 2003;24(1):51-55

[18] Leth RA and Møller JK. Surveillance of hospital-acquired infections based on electronic hospital registries. J Hosp Infect. 2006;62(1):71-79

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