THE EFFECTIVENESS OF MICROBIOLOGY DATA IN THE ELECTRONIC DETECTION OF HEALTHCARE-ASSOCIATED INFECTIONS – A SYSTEMATIC REVIEW

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Abstract

To make healthcare-associated infection (HAI) programs cost-effective, many healthcare institutes use electronic HAI detection systems. Microbiology plays a central role in the detection of HAIs, and thus many HAI detection systems incorporate microbiology results. In this study we analyzed eight systems that applied microbiology data to detect HAIs. Results showed that systems based solely on microbiology have a sensitivity of 72-98% and a specificity of 60-100%. Adding additional data sources resulted in a higher sensitivity, but a substantially lower specificity.

***Keywords** – Infection Control, Cross Infection, Microbiology, Automatic Data Processing, Review.*

1. Introduction

As healthcare-associated infections (HAIs) have become an increasing threat to patient health and recovery, national and international healthcare authorities have implemented infection surveillance and control programs to assess and counter this threat. The results of the SENIC project show that infection surveillance and control programs in hospitals can reduce the amount of infections by as much as 32% [1,2]. However, implementing an infection surveillance and control program requires a relatively high initial investment, and places a heavy continuous burden on hospital personnel resources [3]. Moreover, despite its proven effectiveness, surveillance results are prone to considerable variation [4]. Because of these drawbacks and the increased availability of electronic hospital records, implementation of electronic HAI surveillance programs has become increasingly popular.

Microbiology results play a central role in the infection control and surveillance programs, as they are a part of the detection rules for most types of HAIs [5,6]. As a result, many electronic HAI surveillance systems are either based on or incorporate electronic microbiology results to detect various infections. In this paper we assess how effective electronic HAI detection systems based on microbiology results are, and what the effect of adding other electronic data sources is. We performed a structured search for Medline-indexed publications which discuss electronic HAI

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detection systems based either solely or partially on microbiology results. To give an indication of the effectiveness of microbiology data, we analysed performance statistics such as sensitivity and specificity for each of the discussed systems.

2. Methods

2. 1. Search strategies and information sources

A systematic search of publications that evaluate the routine application of electronic surveillance of HAIs was conducted. Searches were done both electronically and manually; the PubMed service was used to search for publications indexed in Medline between 1st of January, 2001 and 31st of March, 2012, and manual searches were performed by scanning the bibliographies of all relevant publications found. The electronic search comprised a conjunction of three queries, each query comprising the terms *surveillance*, *electronic* or *infection*, or synonyms. All searches were limited by the filters "human" and "abstract", and the publication language was restricted to English.

2. 2. Eligibility criteria and study selection

Titles and abstracts were evaluated independently by all three authors of the present article to confirm article appropriateness. Any disagreement between the authors was settled by a majority wins consensus. Relevant complete articles were retrieved and a reviewed independently to assess if they met the predetermined criteria.

Only articles that described a system that uses electronically available microbiology data to perform surveillance or detection of HAIs were included. If a system used additional data sources, only those studies were selected which also considered system configurations using only microbiology data. Reviews and publications addressing modifications to earlier published systems were excluded. There were no restrictions to what HAI types could be monitored. Furthermore, to provide a basis for uniform comparison, at least sensitivity and specificity of the system had to be stated.

2. 3. Data collection and extraction

Data from each article were abstracted to a standardized Excel worksheet. JSB reviewed all articles, while CS and WS reviewed half. Data collected included patient characteristics and hospital setting, the types of infections that were detected by the system, and performance measures. For each article, data elements not confirmed by all reviewers were discussed until a consensus was reached.

3. Results

Aforementioned search strategy generated 410 results; 379 publications were found in the electronic search, and 31 in bibliographies of relevant articles. Sixty-four articles were determined to be relevant enough, of which 55 were available as full text paper. Eight publications satisfied the predetermined criteria and were included in the review.

3. 1. Electronic systems solely based on microbiology data

Four electronic HAI detection systems used *only* microbiology data. Sensitivity was fairly high, ranging between 60-100%, depending on the infection site. Specificity was overall very high, ranging between 69-99.9%. An overview of these systems is shown in the upper half of *Table 1*.

Bouam et al. discussed a system which used a knowledge base to analyze test results from the microbiology laboratory and combined them antibiotic susceptibility patterns. The system achieved an overall sensitivity of 91% (80-95%, depending on infection site) and specificity of 91% (75-100%). Missed cases were attributed to the lack of electronically available clinical data and inappropriate interpretations of antibiotic susceptibility patterns [7].

In Brossette et al., a similar approach was taken, both for hospital-wide and for intensive care unit (ICU) only surveillance; through a series of filtering and exclusion steps, the system isolated positive microbiology results. In the hospital-wide setting, the system achieved a sensitivity of 86% (60-100%), and a specificity of 98%; In an ICU setting, the system sensitivity improved to 100%, whereas specificity improved only slightly. Missed cases were primarily HAIs without culture or with culture-negative results [8].

Bellini et al. described a system which combined positive blood and catheter culture results, and used a four-step filtering algorithm to classify events as contaminations, duplications, community-acquired infections, blood stream infections or catheter-related infections (CRIs). Depending on the infection type, sensitivity ranged between 78-98%, and specificity was 69-93%. While no specific reasons for the missed cases were given, the authors did argue that improvements could be made by incorporating data on quantitative blood cultures and the timing of blood sampling [9].

Finally, Chalfine et al. discussed a semi-automated system that detects surgical site infections resulting from gastrointestinal surgery. For each patient, the system searches for positive microbiology results for surgical-site specimens, and generates a questionnaire for the surgeon responsible for the patient to manually establish the infection. Sensitivity for the system was 84%, while specificity was nearly perfect. Missed cases were attributed to the lack of specimens submitted for microbiology analysis, or errors in specimen indications [10].

3. 2. Electronic systems based on multiple data sources

Four systems combined electronic microbiology data with one or more other electronic data sources, such as administrative, biochemical, and pharmaceutical data, and compared the effectiveness of the optimal configuration with a configuration using only microbiology data. In general, sensitivity of these systems was higher, ranging between 81-100% depending on infection site and system configurations. As a trade-off, specificity was generally lower, ranging from 40-83%. The lower half of *Table 1* shows an overview of all systems combining microbiology data with other data sources.

In Trick et al. a system was discussed which used microbiology and pharmacy data to detect CRIs. The systems used a knowledge base in which rules for positive blood cultures from blood and central venous catheter cultures were combined with electronic records documenting vancomycin administration in order to classify events as contaminations, secondary infections, community-acquired infections, or CRIs. The system had an overall sensitivity of 81%, and a specificity of

72%. This approach was more sensitive than using microbiology data alone, which resulted in a sensitivity of 72%, though slightly increasing the specificity to 74% [11].

In Leth et al., the authors described a system that combines data from several electronic sources such as administrative discharge code and pharmaceutical data, and microbiology, biochemistry, and radiology results. Through combinations of antibiotic treatments, positive microbiology and abnormal biochemistry results, the system achieved a sensitivity of 94%, with a specificity of 40%. In contrast, an approach using only positive microbiology results yielded a sensitivity of almost 80%, and a specificity of 60-70% [12].

In Pokorny et al., positive microbiology results were combined with discharge codes and antibiotic administration records. The most satisfactory and balanced result yielded 94% sensitivity and 83% specificity. However, the best sensitivity was achieved by a disjunction of all positive results from all electronic sources; which yielded a sensitivity of 100%, but lowered specificity to 54%. The use of microbiology results alone resulted in a sensitivity of 86%, and a specificity of 81% [13]. Bouzbid et al. studied the same electronic data sources and found the best sensitivity in a disjunction of positive microbiology results and antibiotic administration, which resulted in 99% sensitivity vs. 57% specificity. When using only positive microbiology results, the sensitivity dropped to 94%, while specificity increased to 77% [14].

Table 1: Effectiveness of electronic HAI detection systems

Study	Study setting and size	Sen.	Spec.	Sen (Mibi)	Spec (Mibi)
Bouam et al. [7]	Teaching hospital, 548 microbiology samples.	-	-	91%	91%
Brossette et al. [8]	One teaching hospital and two community hospitals, 907 patients in total.	-	-	86%	98%
Bellini et al. [9]	University hospital, 669 positive blood cultures.	-	-	78-98%	69-93%
Chalfine et al. [10	Tertiary care hospital, 776 patients.	-	-	84.3%	99.9%
Trick et al. [11]	Teaching & community hospital, 127 patients in total.	81%	72%	72%	74%
Leth et al. [12]	Teaching hospital, 1129 patients.	94%	40%	80%	60-70%
Pokorny et al. [13]	Acute care and teaching hospital, 1043 patients.	94%	83%	86%	81%
Bouzbid et al. [14]	University hospital, 1499 patients.	99%	57%	94%	77%

Note: Sen. and Spec. indicate the sensitivity and specificity using the optimal combination of all available electronic data sources. Sen. (Mibi) and Spec. (Mibi) indicate the sensitivity and specificity of the system configuration using only microbiology data.

4. Discussion

In this study we analysed the performance of electronic HAI detection systems which were either solely based on or incorporated microbiology results. We found that systems based on only microbiology data alone have a fairly high and balanced performance, with sensitivities of 78-91% and specificities of 69-99.9%; similar sensitivities were achieved by systems that were designed to use multiple data sources, but were limited to using only microbiology data for research purposes. However, these systems showed lower specificity scores, despite the fact that they were configured to use solely microbiology data. The utilization of additional data sources such as discharge codes and pharmaceutical data, as well as biochemistry and radiology results increased the sensitivity of these systems somewhat, but decreased their specificity substantially.

Several studies suggest that the percentage of culture-negative infections is 5-16%, depending on infection site [15,16]. This corresponds well with the sensitivities of the systems based on or configured for the utilization of only microbiology data. Most studies also indicate that the lack of cultures and culture-negative infections are the main causes of missed infections. Other causes mentioned are data errors and inaccuracies, and errors of interpretation in data such as antibiograms.

The addition of one or multiple other types of patient data resulted in a moderate improvement of sensitivity, but as a drawback decreased specificity substantially. Most systems combined the results of multiple data sources through logical conjunction. While this method can certainly detect more HAI cases, especially those that are culture-negative, it also generates many false-positives. For example, inclusion of discharge codes could enable the detection of culture-negative HAIs, but their use can be very subjective and inaccurate [17,18]. Similarly, the use of pharmaceutical records of patient antibiotic use could lead to an increase of false positives, especially in surgical wards, where antibiotic use as prophylaxis is very common.

Despite the shortcomings of electronic surveillance based on microbiology data, its performance is usually on a par with or better than manual surveillance. In three of the eight studies a comparison was made between the performance of electronic and manual surveillance. In [7,11], sensitivities are significantly better for electronic surveillance, whereas specificity is comparable; in [8], sensitivities are comparable, whereas manual surveillance achieves a slightly higher specificity. Time saving is also recorded in several studies. In [7], personnel time spent on surveillance was reduced from 7 minutes 43 seconds per ward per week to 54 seconds per ward per week; in [8], personnel time required went from 17 minutes per admission to less than a second per admission; in [10,14], time savings are reported of 60-63%.

5. References

[1] 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

[2] Hughes JM. Study on the efficacy of nosocomial infection control (SENIC Project): results and implications for the future. Chemotherapy. 1988;34(6):553-561

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

[4] Glenister HM, Taylor LJ, Bartlett CL, Cooke EM, Sedgwick JA and Mackintosh CA. An evaluation of surveillance methods for detecting infections in hospital inpatients. J Hosp Infect. 1993;23(3):229-242

[5] HAIICU Protocol v1.01 STANDARD and LIGHT. In 2010. [Accessed Nov 12, 2012] Available from: http://www.ecdc.europa.eu/en/aboutus/calls/Procurement%20Related%20Documents/5_ECDC_HAIICU_protocol_v1_1.pdf.

[6] Horan TC, Andrus M and Dudeck MA. CDC/NHSN surveillance definition of health care-associated infection and criteria for specific types of infections in the acute care setting. Am J Infect Control. 2008;36(5):309-332

[7] 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

[8] Brossette SE, Hacek DM, Gavin PJ, Kamdar MA, Gadbois KD, Fisher AG and Peterson LR. A laboratory-based, hospital-wide, electronic marker for nosocomial infection: the future of infection control surveillance? Am J Clin Pathol. 2006;125(1):34-39

[9] Bellini C, Petignat C, Francioli P, Wenger A, Bille J, Klopotov A, Vallet Y, Patthey R and Zanetti G. Comparison of automated strategies for surveillance of nosocomial bacteremia. Infect Control Hosp Epidemiol. 2007;28(9):1030-1035

[10] Chalfine A, Cauet D, Lin WC, Gonot J, Calvo-Verjat N, Dazza FE, Billuart O, Kitzis MD, Bleriot JP, Pibarot ML and Carlet J. Highly sensitive and efficient computer-assisted system for routine surveillance for surgical site infection. Infect Control Hosp Epidemiol. 2006;27(8):794-801

[11] Trick WE, Zagorski BM, Tokars JI, Vernon MO, Welbel SF, Wisniewski MF, Richards C and Weinstein RA. Computer algorithms to detect bloodstream infections. Emerg Infect Dis. 2004;10(9):1612-1620

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

[13] Pokorny L, Rovira A, Martin-Baranera M, Gimeno C, Alonso-Tarres C and Vilarasau J. Automatic detection of patients with nosocomial infection by a computer-based surveillance system: a validation study in a general hospital. Infect Control Hosp Epidemiol. 2006;27(5):500-503

[14] Bouzbid S, Gicquel Q, Gerbier S, Chomarat M, Pradat E, Fabry J, Lepape A and Metzger MH. Automated detection of nosocomial infections: evaluation of different strategies in an intensive care unit 2000-2006. J Hosp Infect. 2011;79(1):38-43

[15] Giacometti A, Cirioni O, Schimizzi AM, Del Prete MS, Barchiesi F, D'Errico MM, Petrelli E and Scalise G. Epidemiology and microbiology of surgical wound infections. J Clin Microbiol. 2000;38(2):918-922

[16] Horan TC, White JW, Jarvis WR, Emori TG, Culver DH, Munn VP, Thornsberry C, Olson DR and Hughes JM. Nosocomial infection surveillance, 1984. MMWR CDC Surveill Summ. 1986;35(1):17SS-29SS

[17] Madsen KM, Schonheyder HC, Kristensen B, Nielsen GL and Sorensen HT. Can hospital discharge diagnosis be used for surveillance of bacteremia? A data quality study of a Danish hospital discharge registry. Infect Control Hosp Epidemiol. 1998;19(3):175-180

[18] Moro ML and Morsillo F. Can hospital discharge diagnoses be used for surveillance of surgical-site infections? J Hosp Infect. 2004;56(3):239-241

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