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

De Bruin JS¹, Blacky A², Adlassnig K-P¹,³ and Koller W²

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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HAI s 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 focused 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 HAI s.

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

2.1.1. Manual surveillance

MS of HAI s 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

<table>
<thead>
<tr>
<th>General infection parameters</th>
<th>BSI</th>
<th>PN</th>
<th>UTI</th>
<th>CRI</th>
</tr>
</thead>
<tbody>
<tr>
<td>Fever, increased CRP, leukopenia, leukocytosis</td>
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</table>

<table>
<thead>
<tr>
<th>Specific infection parameter</th>
<th>Shock, hypotension</th>
<th>Decreased gas exchange, respiratory device present ≤ 48 hours</th>
<th>Urinary catheter present ≤ 48 hours</th>
<th>Shock, hypotension, catheter present ≤ 48 hours</th>
</tr>
</thead>
<tbody>
<tr>
<td>Laboratory results</td>
<td>Microbiology: blood cultures</td>
<td>Microbiology: blood cultures, BAL, DPA, PB cultures</td>
<td>Microbiology: Urine cultures, catheter cultures</td>
<td>Microbiology: blood cultures, catheter cultures</td>
</tr>
</tbody>
</table>

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

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

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


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