Automated surveillance systems for healthcare-associated infections: results from a European survey and experiences from real-life utilization

Verberk, J.d.m.; Aghdassi, S.j.s.; Abbas, Mohamed; Nauclér, P.; Gubbels, S.; Maldonado, N.; Palacios-Baena, Z.r.; Johansson, A.f.; Gastmeier, P.; Behnke, M.; van Rooden, S.m.; van Mourik, M.s.m.

How to cite

VERBERK, J.d.m. et al. Automated surveillance systems for healthcare-associated infections: results from a European survey and experiences from real-life utilization. In: The Journal of hospital infection, 2022, vol. 122, p. 35–43. doi: 10.1016/j.jhin.2021.12.021

This publication URL: https://archive-ouverte.unige.ch/unige:166801
Publication DOI: 10.1016/j.jhin.2021.12.021

Journal of Hospital Infection 122 (2022) 35–43

Available online at www.sciencedirect.com

Journal of Hospital Infection

journal homepage: www.elsevier.com/locate/jhin

Automated surveillance systems for healthcare-associated infections: results from a European survey and experiences from real-life utilization

J.D.M. Verberk [a,b,c,*,†], S.J.S. Aghdassi [d,e,†], M. Abbas [f], P. Nauclér [g,h], S. Gubbels [i], N. Maldonado [j], Z.R. Palacios-Baena [j], A.F. Johansson [k], P. Gastmeier [d], M. Behnke [d], S.M. van Rooden [b,c], M.S.M. van Mourik [a]

[a] *Department of Medical Microbiology and Infection Prevention, University Medical Centre Utrecht, Utrecht, the Netherlands*
[b] *Julius Centre for Health Sciences and Primary Care, University Medical Centre Utrecht, Utrecht, the Netherlands*
[c] *Department of Epidemiology and Surveillance, Centre for Infectious Diseases Control, National Institute for Public Health and the Environment, Bilthoven, the Netherlands*
[d] *Institute of Hygiene and Environmental Medicine, Charité—Universitätsmedizin Berlin, Corporate Member of Freie Universität Berlin and Humboldt—Universität zu Berlin, Berlin, Germany*
[e] *Berlin Institute of Health at Charité—Universitätsmedizin Berlin, BIH Biomedical Innovation Academy, BIH Charité Digital Clinician Scientist Program, Charitéplatz 1,10117 Berlin, Germany*
[f] *Infection Control Programme, Geneva University Hospitals and Faculty of Medicine, Geneva, Switzerland*
[g] *Department of Medicine Solna, Division of Infectious Disease, Karolinska Institutet, Stockholm, Sweden*
[h] *Department of Infectious Diseases, Karolinska University Hospital, Stockholm, Sweden*
[i] *Department of Infectious Disease Preparedness, Statens Serum Institut, Copenhagen, Denmark*
[j] *Unit of Infectious Diseases, Clinical Microbiology and Preventive Medicine, Hospital Universitario Virgen Macarena, Institute of Biomedicine of Seville (IBIS), Sevilla, Spain*
[k] *Department of Clinical Microbiology and the Laboratory for Molecular Infection Medicine (MIMS), Umeå University, Umeå, Sweden*

ARTICLE INFO

Article history:
Received 8 November 2021
Accepted 4 December 2021
Available online 12 January 2022

Keywords:
Surveillance
Automation
Healthcare-associated infection

SUMMARY

Background: As most automated surveillance (AS) methods to detect healthcare-associated infections (HAIs) have been developed and implemented in research settings, information about the feasibility of large-scale implementation is scarce.
Aim: To describe key aspects of the design of AS systems and implementation in European institutions and hospitals.
Methods: An online survey was distributed via e-mail in February/March 2019 among (i) PRAISE (Providing a Roadmap for Automated Infection Surveillance in Europe) network members; (ii) corresponding authors of peer-reviewed European publications on existing AS systems; and (iii) the mailing list of national infection prevention and control focal points of the European Centre for Disease Prevention and Control. Three AS systems from

* Corresponding author. Address: Department of Medical Microbiology and Infection Control, UMC Utrecht, P.O. Box 85500, 3508 GA Utrecht, the Netherlands. Tel.: +31 0 30 27 43891.
E-mail address: j.d.m.verberk-2@umcutrecht.nl (J.D.M. Verberk).
† Authors of equal contribution.

https://doi.org/10.1016/j.jhin.2021.12.021

the survey were selected, based on quintessential features, for in-depth review focusing on implementation in practice.

Findings: Through the survey and the review of three selected AS systems, notable differences regarding the methods, algorithms, data sources, and targeted HAIs were identified. The majority of AS systems used a classification algorithm for semi-automated surveillance and targeted HAIs were mostly surgical site infections, urinary tract infections, sepsis, or other bloodstream infections. AS systems yielded a reduction of workload for hospital staff. Principal barriers of implementation were strict data security regulations as well as creating and maintaining an information technology infrastructure.

Conclusion: AS in Europe is characterized by heterogeneity in methods and surveillance targets. To allow for comparisons and encourage homogenization, future publications on AS systems should provide detailed information on source data, methods, and the state of implementation.

Introduction

Healthcare-associated infections (HAIs) are a worldwide concern due to their implications on morbidity, mortality, and costs [1—3]. In Europe, annually, around 3.2 million people are affected by HAIs [4]. Surveillance of HAIs is listed as a core component of effective infection prevention and control (IPC) programmes by the World Health Organization, and has been demonstrated to effectively reduce HAI occurrence [5—9]. Despite the adoption of electronic health records (EHRs), the majority of surveillance activities still relies on manual patient chart review by infection control staff, a process that is often paper-based and resource-intensive [10,11]. This conventional surveillance is prone to human error as well as low inter-rater reliability [12—14]. The opportunities arising from improved information technology (IT) infrastructures in many hospitals have incentivized the development of automated surveillance (AS) systems to overcome the limitations of traditional manual surveillance [15,16].

Surveillance of HAIs can be automated to various degrees, but generally two methods can be distinguished: semi-automated surveillance and fully automated surveillance [15,17]. In semi-automated surveillance, an algorithm classifies patients as having a high or low probability for certain HAIs. Whereas 'high-probability' patients require manual confirmation to classify them as having an HAI or not, low-probability patients are assumed not to have HAIs and no manual assessment is performed. The algorithms used in semi-automated surveillance can be classification algorithms or decision trees, comprising a set of indicators derived from structured data from hospital information systems [18—21]. The selection of indicators incorporated in the algorithms is based on previous experience and clinical knowledge, statistical methods, or machine learning techniques [18,19,22—24]. For fully automated surveillance, algorithms perform HAI ascertainment without human interference. Algorithms for fully automated surveillance have been developed using (clinical) indicators by various techniques such as statistical models or machine learning, or by using data that represent infection criteria (rule-based algorithms) [25—33]. For incorporating unstructured data in the algorithm, text-mining techniques can be used [27,34—36]. Overall, most published AS methods reduce the workload and some showed even higher sensitivity compared to manual surveillance [20,37—39].

Though many AS methods and algorithms show promising results, the majority has been developed and implemented in (single-centre) research settings and information about the feasibility of large-scale implementation is scarce. Research showed that only 25% of the systems are actually used in clinical routine [39—41]. The PRAISE network (Providing a Roadmap for Automated Infection Surveillance in Europe) was established to support the transition to large-scale implementation. This network involved 30 experts from 10 countries, representing different types of institution, such as hospitals and public health institutes. The PRAISE network recently developed a roadmap to bring AS from the research setting to large-scale implementation [17]. As part of this project, the network investigated and evaluated AS systems that are currently implemented and in use by means of a survey.

The aim of this study was to describe key aspects of AS systems and implementation thereof in European institutions and hospitals based on survey results. Furthermore, we selected AS systems that were included in the survey and for further elaboration on their distinctive features and real-life implementation challenges.

Methods

The PRAISE network developed a survey with the main aim to map the current state of AS systems for HAIs in Europe, including existing systems as well as pre-implementation research, and to illustrate key aspects of AS systems (including types of HAI under surveillance, degree of automation, underlying algorithms), and identify barriers and limitations. Furthermore, the survey aimed to describe extraction and utilization of raw data (e.g. migration of patient-related data into a data warehouse), and learn about implementation, maintenance, and evaluation of AS systems. As a secondary objective, the survey aimed to identify existing AS systems to be selected for a more in-depth investigation through follow-up interviews and complementary literature searches.

In February and March 2019, the survey was distributed among network members via e-mail (purposive sampling). Invitations were also sent to corresponding authors of peer-reviewed publications on AS in Europe published between 2010 and 2019. To achieve maximum dissemination, survey invitees were encouraged to share the survey link with other suitable

persons (snowball sampling). Furthermore, the questionnaire was distributed via the mailing list of national IPC focal points of the European Centre for Disease Prevention and Control (ECDC). The survey language was English and contained both multiple choice and free text questions. Data were entered online and data entry was possible from February 13th, 2019 until July 22nd, 2019. A reminder was sent to all invitees in May 2019. The survey comprised a maximum of 29 questions that explored different aspects of AS (Appendix 1). Nineteen questions were directly targeted to learn about specifications of existing AS systems; additional questions collected context information.

Only responses from European institutions who fully completed the survey were included. Where more than one response per institution was received ('duplicates'), responses were merged. Free text answers were grouped into thematic groups at the discretion of the study team in order to increase the intelligibility of the content. From the responses received, three AS systems were selected by the authors, based on quintessential characteristics, to be described in greater detail and to further illustrate the possibilities and variability of AS systems.

Results

A total of 25 responses were transmitted to the PRAISE network. Three responses were excluded due to incompleteness ($N = 1$) and country of origin outside of Europe ($N = 2$). In three cases, two responses were attributable to the same institution and therefore merged, leaving 19 responses for further analysis. The data were from 11 countries (Netherlands, $N = 5$; France, $N = 4$; Sweden, $N = 2$; Austria, Belgium, Denmark, Finland, Germany, Norway, Switzerland, Wales, all $N = 1$). Eight responses pertained to a surveillance network, and 11 pertained to a hospital (tertiary care university centres, $N = 9$; non-university teaching hospitals, $N = 2$).

Twelve (63%) survey participants reported that AS was in use at their hospital or surveillance network at the time of the survey (surveillance network, $N = 5$; hospital, $N = 7$: six university hospital, one non-university hospital). Seven (37%) participants stated that AS had been considered but was not implemented at the time of the survey (surveillance network, $N = 3$; hospital, $N = 4$: three university hospital, one non-university hospital). Reasons for non-implementation reported by surveillance networks were a lack of data harmonization and willingness of the participating hospitals. Hospitals reported the lack of digitalization of patient data and insufficient IT infrastructure along with low prioritization by hospital management and data security concerns.

Automated surveillance systems

Existing AS systems mostly targeted surgical site infections (SSIs), urinary tract infections (UTIs), central line-associated or -related bloodstream infections, and sepsis or other bloodstream infections (Figure 1). Whereas four (surveillance network, $N = 2$; hospital, $N = 2$) institutions reported employing a fully automated surveillance method, seven (surveillance network, $N = 3$; hospital, $N = 4$) reported conducting semi-automated surveillance. Information on this aspect was not provided by one institution. Classification models ($N = 8$) were the most prevalent algorithm type. A machine learning system or regression model was reported by one participant each. Two participants were unable to provide specifics on underlying algorithms. Specifics on the source data included in the AS system are illustrated in Figure 2. Five AS systems (all from hospitals) reported migration of most or all data sources into a clinical data warehouse, and seven AS systems (surveillance network, $N = 5$; hospital, $N = 2$) relied on collecting data from multiple separate data sources.

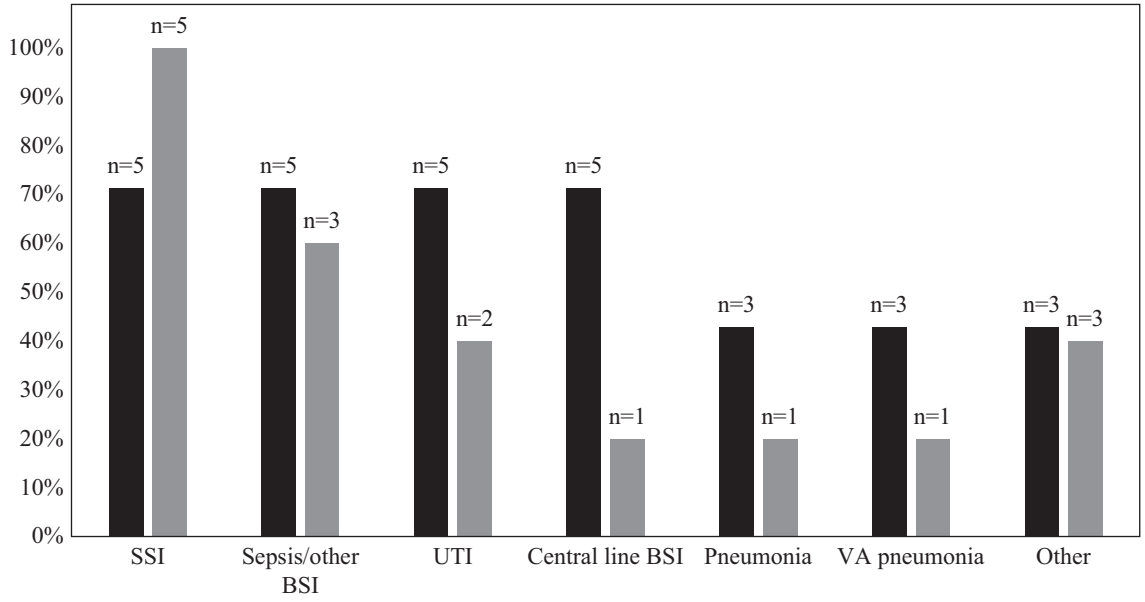

Figure 1. Healthcare-associated infections under surveillance in existing automated surveillance systems at the surveillance network (grey bars, $N = 5$) and hospital level (black bars, $N = 7$). BSI, bloodstream infection; SSI, surgical site infection; UTI, urinary tract infection; VA, ventilator-associated.

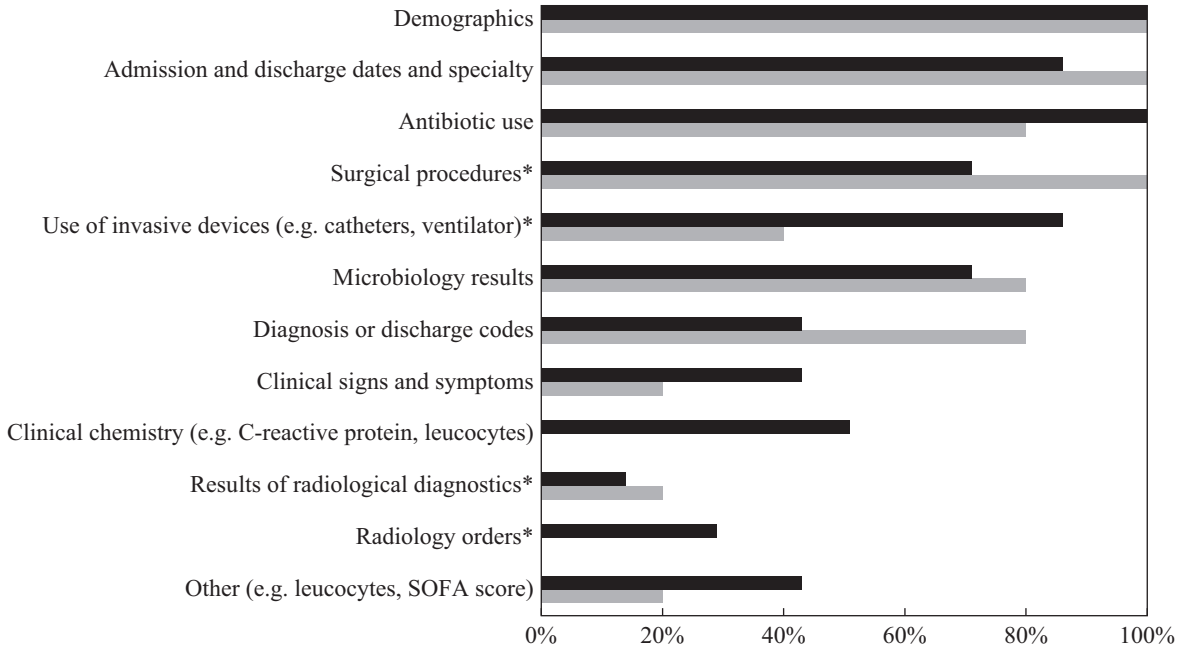

Figure 2. Source data types included in existing automated surveillance systems at the surveillance network (grey bars, $N = 5$) and hospital (black bars, $N = 7$) level. *Note that relevance of these data sources depends on the targeted infection (e.g. use of invasive devices is not applicable to surgical site infection surveillance). SOFA, sequential organ failure assessment.

Experience of implementing AS

Table I summarizes experienced advantages of the AS system, key determinants of successful implementation and barriers, as well as potential improvements. Most noticeably, time efficiency and reduction of workload for hospital staff were cited as the most important advantages of AS. Conversely, creation and maintenance of sophisticated IT infrastructures as well as strict data security regulations were reported as the most significant barriers for successful AS implementation.

In-depth view of three existing AS systems

There is a large variety in the methods, algorithms, data sources and targeted HAIs used for AS, complicating head-to-head comparisons. Additionally, information publicly available regarding surveillance systems is not exhaustive, and usually has a technical focus, whereas the process of actual implementation, architecture, maintenance, and workflow are generally not systematically published [42]. For these reasons, three successfully implemented AS systems are described in greater detail, focusing on the aspects that are not described in scientific reports [18,20,29,30,42,43]. A concise overview of these systems is provided in Table II.

Danish Hospital-Associated Infections Database (HAIBA)

Increased attention to HAIs and the increasing threat of antimicrobial resistance has led to the vision of establishing the Healthcare-Associated Infections Database (HAIBA) in Denmark. HAIBA was developed on request of the Danish Ministry of Health by the Statens Serum Institute in collaboration with the Danish Regions, departments of clinical microbiology, infection control units, and clinical societies. The first edition of HAIBA was launched in March 2015, and soon became the main tool for monitoring of HAIs in Denmark, replacing the prevalence surveys [44–46]. HAIBA's data are publicly available on http://www.esundhed.dk, and sent to regional servers, where they are integrated on hospital intranet pages and in hospital management systems.

Data, algorithms, and method of validation

All patients that have been in contact with the Danish healthcare system, both in outpatient and inpatient settings, are included in the HAIBA surveillance system. HAIBA generates incidence data by fully automated surveillance for the following: hospital-onset bacteraemia (i.e. positive blood cultures more than 48 h after admission), UTIs, *Clostridioides difficile* infections, and deep SSIs after total hip and knee replacement [29,43,44]. The algorithms are rule-based and use data from existing data sources: (i) the Danish Microbiology Database, a real-time database including all microbiological testing; (ii) the National Patient Registry, containing administrative data on admissions and ambulatory contacts with the secondary and tertiary healthcare system, diagnosis codes (Danish adaptation of the ICD-10 classification), and operation codes (Nordic Classification of Surgical Procedures); and (iii) the civil registration registry. Data from these registries are linked by a personal health identification number, and are updated, extracted and evaluated by algorithms every night; as a result of the COVID-19 pandemic and competing server capacity, the update frequency has been reduced to weekly. The algorithms were validated by comparing with results from

Table I
Reported experiences of users of semi- and or fully automated surveillance systems at the surveillance network ($N = 5$) and hospital ($N = 7$) level

Topic	Surveillance network	Hospital
Key advantages of automated surveillance systems over manual surveillance systems	— Time efficiency/reduction of workload — Re-allocation of saved IPC resources — Greater uniformity and validity of data across different hospitals — High acceptance by staff in participating hospitals	— Time efficiency/reduction of workload — Re-allocation of saved IPC resources — Better involvement of non-IPC staff — Inclusion of larger amounts of data (e.g. more procedures, more types of HAIs) to generate a more comprehensive overview — Higher structural uniformity of collected data — Real-time data view
Key determinants of successful implementation of automated surveillance systems	— Legal regulations (mandatory participation) — Flexibility for participating hospitals with regard to software selection — Clearly defined responsibilities — Frequent exchange with regional/hospital partners — Availability of high-quality data	— Support from hospital management — Functioning cooperation with an IT department — Existence of a data warehouse — Exclusion of unnecessary details — Involvement of frontline healthcare workers into the daily workflow
Barriers of successful implementation of automated surveillance systems	— Strict data protection regulations — Heterogeneity of data sources and data quality — Lack of adequate IT infrastructures	— Strict data protection regulations — Difficult accessibility and low quality of data sources — Lack of quality control of source data — Lack of prioritization within hospital
Possible further improvements of implemented automated surveillance systems	— Further integration of data sources — More freedom concerning data protection regulations (e.g. access to non-anonymized data)	— Harmonization with existing (international) HAI definitions — More comprehensive data reporting — Flexibility concerning included data (e.g. in case of outbreaks) — Reduction of manual work processes

IPC, infection prevention and control; IT, information technology; HAI, healthcare-associated infection.

prevalence surveys and manual evaluation of medical records for discrepant cases.

The Danish Health Data Authority maintains the servers. The surveillance system is maintained at Statens Serum Institute, encompassing IT infrastructure (i.e. servers, connections with data sources), applications (i.e. visualization software), adjustment of data model and algorithms to new features in data sources (i.e. new variables, changes in data models, new classification systems such as ICD-10).

Next steps

A change in the Danish law is expected to facilitate data sharing between regions on the level of individual patients. This will further increase the possibilities for applying surveillance data for specific IPC use cases.

Semi-automated SSI surveillance

From 2010 onwards, the University Medical Centre Utrecht (UMCU) has been developing AS of HAIs using internal funds. After an implementation period of two years to prepare the infrastructure, a semi-automated surveillance system was launched in 2015 for surveillance of SSI after orthopaedic and cardiac surgery.

Data, algorithms, and method of validation

Patients are automatically included in the surveillance, based on procedure codes for targeted surgical procedures. After a 120-day follow-up period, algorithms are applied to identify patients with a high probability of having developed an SSI in the 90 days following surgery. Manual chart review verifying an SSI is performed for these patients only. Surveillance results are documented in the EHR, and used for feedback to clinicians, both in yearly reports and via an interactive online dashboard.

The source data required for inclusion of patients in the surveillance, application of the algorithm, and some risk factors are extracted from a clinical data warehouse that is maintained by the hospital's IT department. Classification algorithms are applied to administrative data (information about admissions and discharges), antibiotic prescriptions, surgical procedures and results of microbiological testing.

Table II
System features and lessons learned from automated surveillance systems HAIBA, semi-automated SSI surveillance (UMCU), and HAI-proactive

	HAI-Proactive	UMCU	HAIBA
Country	Sweden	The Netherlands	Denmark
Year of implementation	Currently being implemented	2015	2015
Administration level	Regional	Local (institutional)	National
Type of system	Fully automated rule-based algorithm	Semi-automated classification tree	Fully automated rule-based algorithm
HAI targets	Hospital-onset sepsis, UTI	Deep-Incisional SSI (after THA, TKA, cardiac, spinal, IO surgeries)	HOB, UTI, CDI, deep-incisional SSI (after THA and TKA)
Data sources	Structured/unstructured EHR data	Structured EHR data	Structured data from national registries
Data type included	Microbiology, antibiotics, clinical	Administrative, microbiology, antibiotics	Administrative, microbiology
Sensitivity	>85% compared to manual surveillance	>95% compared to manual surveillance	36% compared to PPS
Reporting	Manual to healthcare providers	Online dashboard within institution	Automated output reports
Lessons learned	– Unstructured free text data is useful for finding symptoms. – Legislation and data protect ion regulation can be very time consuming elements in the development and implementation of systems.	– Distinction primary and non-primary procedures not always feasible. – Collection of risk factor data is limited to those variables documented systematically in the EHR.	– Develop a system in close colla boration with the end users. This ensures algorithms and outputs are meaningful and increases trust in the system. – Changes in the data sources can have a major impact.

HO, hospital-onset; UTI, urinary tract infection; SSI, surgical site infection; EHR, electronic health records; THA, total hip arthroplasty; TKA, total knee arthroplasty; IO, intra-ocular; HOB, hospital-onset bloodstream infection; CDI, *Clostridioides difficile* infection; PPS, point prevalence survey.

Algorithms are run bi-monthly by a local data manager. Maintenance is performed yearly by the infection control department and includes updates of procedure codes, validation of the algorithm and evaluation of IT infrastructure.

Next steps

Development of new algorithms and HAI outcomes is ongoing, in close collaboration with clinical departments. Experiences are being transferred to the national surveillance network 'PREZIES' that is currently preparing a strategy to implement the semi-automated algorithm for SSIs after orthopaedic surgery nationally [20].

HAI-Proactive

The national innovation project 'HAI-Proactive', supported by the Swedish Innovation Agency (VINNOVA), aims to develop fully automated surveillance tools for HAIs. The project, headed by Karolinska University Hospital (KUH) and Region Stockholm, is organized in three phases: (i) collaboration building between healthcare providers, academic institutions, and industry (2015); (ii) prototype development (2016–2018); and (iii) implementation (2018–2021).

Data, algorithms, and method of validation

To date, two rule-based algorithms for healthcare-associated sepsis and UTIs have been developed locally, using data from a testbed that consists of EHR data from KUH from 2008 to 2014 [30,31]. Both algorithms include all patients aged >18 years who have been admitted to the hospital for >24 h. The sepsis algorithm was developed using retrospective data to identify patients fulfilling the Sepsis-3 clinical criteria, based on structured data from antibiotics, microbiological test results, and sequential organ failure (SOFA) scores [30]. The algorithm accounts for baseline values and dynamic changes in the SOFA score. The algorithm for UTIs is designed to perform surveillance of microbiologically confirmed UTIs according to ECDC definitions [31]. It is a rule-based algorithm that utilizes microbiological culture results and information on symptoms both from structured and unstructured (text) data from EHRs. Performance of algorithms is assessed in validation sets of care episodes that have been annotated by infectious disease physicians.

Next steps

Currently, the project works towards implementation of the surveillance algorithms within a centrally organized data warehouse that receives comprehensive EHR data from multiple hospitals in Region Stockholm and Region Västerbotten, Sweden. Data are planned to be extracted daily by the IT department, to which algorithms are applied to continuously monitor patients for sepsis or UTI cases. Aggregated results will be reported back to local care providers for epidemiological surveillance. Future targets are to develop algorithms for other HAIs and to utilize data for HAI risk prediction as well as increasing the amount of incorporated primary healthcare data.

Discussion

The current landscape of AS of HAIs in Europe is promising in terms of innovation and research, but at the same time heterogeneous with regards to methods, algorithms, data sources, and targeted HAIs. Overall, AS systems based on classification algorithms for semi-automated surveillance were found to be most prevalent. Workload reduction and time efficiency were identified as primary benefits of AS over the conventional approach. Moreover, we described three examples of successfully operating systems in more detail. Sharing more detailed information on the development and implementation can support others who intend to start, implement, or use AS surveillance.

Although it is encouraging that some AS systems are operational and in use, AS in Europe is to a certain extent still in its infancy, because many institutions face multiple barriers impeding successful implementation. Main barriers perceived and reported by institutions already using AS systems and those that do not include a lack of harmonized IT infrastructure and strict data protection regulations. This finding underscores the need for standardization and interoperability of medical data across different institutions to support the reuse of EHR data for the development of more efficient and less resource-intensive surveillance methods. Furthermore, whereas data security and privacy regulations are a cornerstone in the practice of medicine, our findings illustrate the need to clarify or even adapt certain regulations that could potentially discourage important developments benefiting patient safety as well as the need to broadly implement technical solutions that facilitate use of personal (health) data under the current regulations.

Heterogeneity in AS systems is in itself not a limiting factor, however, it hampers comparisons. There are several systematic reviews trying to compare systems, however, they all concluded that certain performance characteristics were missing and methodological differences impede head-to-head comparisons [39–41,47,48]. For institutions interested in establishing AS, it is difficult to choose an approach that suits their needs. To facilitate more widespread development of AS and the ability to compare surveillance systems, essential specifications in future publications on surveillance systems should be described (Box 1). First, it would be helpful if all systems clearly explain what population they include in their surveillance, and the data sources and data cleaning steps utilized for population selection and algorithm application. Second, it is important that both the algorithm and the definitions of targeted HAIs are described in detail, as in some AS systems existing HAI definitions are adapted [17]. Third, performance characteristics should be reported, such as sensitivity, specificity, positive predictive value, negative predictive value, time savings, or reduction in the number of charts to review. Fourth, it should be clearly described how the system was validated (i.e. against which reference standard, in what time period, and in how many patients), so others can assess their validation method. Last, authors should be explicit about which phase the proposed AS method is in at the time of writing (development phase, implementation phase, or in actual use in the clinic or surveillance network). To encourage implementation, it will be helpful if logistics and organizational matters are systematically reported in scientific publications or reports, such as maintenance needs, specifics on algorithm application (e.g. frequency), and barriers and facilitators of implementation (Box 1).

The main limitation of the current study is that no systematic review of AS systems was performed, and therefore we do not know whether all AS systems that have been developed and implemented in Europe are included in the survey responses. However, as the actual state of implementation often remains unclear in research papers targeted by systematic reviews, we have chosen to broaden our scope by opting for a survey, using snowball sampling. We have also actively invited researchers of published papers to complete the survey.

In conclusion, creating and maintaining IT infrastructures and data security restrictions represent the most relevant challenges and barriers for AS implementation. Existing AS systems in Europe encompass a variety of data sources, algorithms, and HAI targets, thereby reducing comparability across systems. In order to facilitate comparisons and stimulate exchange of experiences and surveillance methodology, it should be encouraged to describe AS systems with a standardized minimum set of information.

Box 1
Items for reporting automated surveillance systems in (scientific) publications

- Describe data sources needed for patient selection and algorithms
- Describe inclusion criteria of the patient population under surveillance and clarify how they are selected (manual, partially or fully automated including details)
- Describe what healthcare-associated infection definitions are targeted by the algorithm, and how they are adapted for automating purposes
- Describe the algorithm and algorithm performance (in terms of sensitivity, specificity, positive predictive value, negative predictive value, time savings and/or reduction in records to review)
- Describe the method of validation (reference standard used, sample size)
- Clarify the phase of the automated surveillance system (development phase, implementation phase or in actual use)
- If implemented, describe the workflow and maintenance of the surveillance system
- If implemented, describe barriers/facilitators of implementation

Acknowledgements

We wish to thank all members of the PRAISE network and respondents to the survey. We would like to express special gratitude for the insights on the three selected automated surveillance systems provided by colleagues from Karolinska University Hospital (Sweden), University Medical Centre Utrecht (the Netherlands) and Statens Serum Institute (Denmark).

Dr Aghdassi is participant in the Charité Digital Clinician Scientist Program funded by the DFG, the Charité Universitätsmedizin – Berlin, and the Berlin Institute of Health at Charité (BIH).

Conflict of interest statement
None declared.

Funding sources
The PRAISE network has been supported under 7th transnational call within the Joint Programming Initiative on Antimicrobial Resistance (JPIAMR), Network Call on Surveillance (2018) and was thereby funded by ZonMw (grant number 549007001).

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jhin.2021.12.021.

References

[1] Lambert ML, Suetens C, Savey A, Palomar M, Hiesmayr M, Morales I, et al. Clinical outcomes of health-care-associated infections and antimicrobial resistance in patients admitted to European intensive-care units: a cohort study. Lancet Infect Dis 2011;11:30—8. https://doi.org/10.1016/S1473-3099(10)70258-9.

[2] Koek MBG, van der Kooi TII, Stigter FCA, de Boer PT, de Gier B, Hopmans TEM, et al. Burden of surgical site infections in the Netherlands: cost analyses and disability-adjusted life years. J Hosp Infect 2019;103:293—302. https://doi.org/10.1016/j.jhin.2019.07.010.

[3] Manoukian S, Stewart S, Graves N, Mason H, Robertson C, Kennedy S, et al. Bed-days and costs associated with the inpatient burden of healthcare-associated infection in the UK. J Hosp Infect 2021;114:43—50. https://doi.org/10.1016/j.jhin.2020.12.027.

[4] European Centre for Disease Prevention and Control. Point prevalence survey of healthcare-associated infections and antimicrobial use in European acute care hospitals. Stockholm: ECDC; 2013.

[5] Storr J, Twyman A, Zingg W, Damani N, Kilpatrick C, Reilly J, et al. Core components for effective infection prevention and control programmes: new WHO evidence-based recommendations. Antimicrob Resist Infect Control 2017;6:6. https://doi.org/10.1186/s13756-016-0149-9.

[6] Brandt C, Sohr D, Behnke M, Daschner F, Rüden H, Gastmeier P. Reduction of surgical site infection rates associated with active surveillance. Infect Control Hosp Epidemiol 2006;27:1347—51. https://doi.org/10.1086/509843.

[7] Haley RW, Culver DH, White JW, Morgan WM, Emori TG, Munn VP, et al. The efficacy of infection surveillance and control programs in preventing nosocomial infections in US hospitals. Am J Epidemiol 1985;121:182—205. https://doi.org/10.1093/oxfordjournals.aje.a113990.

[8] Abbas M, de Kraker MEA, Aghayev E, Astagneau P, Aupee M, Behnke M, et al. Impact of participation in a surgical site infection surveillance network: results from a large international cohort study. J Hosp Infect 2019;102:267—76. https://doi.org/10.1016/j.jhin.2018.12.003.

[9] Gastmeier P, Geffers C, Brandt C, Zuschneid I, Sohr D, Schwab F, et al. Effectiveness of a nationwide nosocomial infection surveillance system for reducing nosocomial infections. J Hosp Infect 2006;64:16—22. https://doi.org/10.1016/j.jhin.2006.04.017.

[10] Evans RS. Electronic health records: then, now, and in the future. Yearb Med Inform 2016;(Suppl 1):S48—61. https://doi.org/10.15265/IYS-2016-s006.

[11] Mitchell BG, Hall L, Halton K, MacBeth D, Gardner A. Time spent by infection control professionals undertaking healthcare associated infection surveillance: a multi-centred cross sectional study. Infect Dis Health 2016;21:36—40. https://doi.org/10.1016/j.idh.2016.03.003.

[12] Birgand G, Lepelletier D, Baron G, Barrett S, Breier AC, Buke C, et al. Agreement among healthcare professionals in ten European countries in diagnosing case-vignettes of surgical-site infections. PLoS One 2013;8:e68618. https://doi.org/10.1371/journal.pone.0068618.

[13] Ehrenkranz NJ, Shultz JM, Richter EL. Recorded criteria as a "gold standard" for sensitivity and specificity estimates of surveillance of nosocomial infection: a novel method to measure job performance. Infect Control Hosp Epidemiol 1995;16:697—702. https://doi.org/10.1086/647043.

[14] Adams J, Mauldin T, Yates K, Zumwalt C, Ashe T, Cervantes D, et al. Factors related to the accurate application of NHSN surveillance definitions for CAUTI and CLABSI in Texas hospitals: a cross-sectional survey. Am J Infect Control 2022;50:111—13. https://doi.org/10.1016/j.ajic.2021.07.007.

[15] Wright M-O. Automated surveillance and infection control: toward a better tomorrow. Am J Infect Control 2008;36:S1—6. https://doi.org/10.1016/j.ajic.2007.09.003.

[16] van Mourik MSM, Perencevich EN, Gastmeier P, Bonten MJM. Designing surveillance of healthcare-associated infections in the era of automation and reporting mandates. Clin Infect Dis 2018;66:970—6. https://doi.org/10.1093/cid/cix835.

[17] van Mourik MSM, van Rooden SM, Abbas M, Aspevall O, Astagneau P, Bonten MJM, et al. PRAISE: providing a roadmap for automated infection surveillance in Europe. Clin Microbiol Infect 2021;27(Suppl 1):S3—19. https://doi.org/10.1016/j.cmi.2021.02.028.

[18] Sips ME, Bonten MJM, van Mourik MSM. Semiautomated surveillance of deep surgical site infections after primary total hip or knee arthroplasty. Infect Control Hosp Epidemiol 2017;38:732—5. https://doi.org/10.1017/ice.2017.37.

[19] van Rooden SM, Tacconelli E, Pujol M, Gomila A, Kluytmans J, Romme J, et al. A framework to develop semiautomated surveillance of surgical site infections: an international multicenter study. Infect Control Hosp Epidemiol 2020;41:194—201. https://doi.org/10.1017/ice.2019.321.

[20] Verberk JDM, van Rooden SM, Koek MBG, Hetem DJ, Smilde AE, Bril WS, et al. Validation of an algorithm for semiautomated surveillance to detect deep surgical site infections after primary total hip or knee arthroplasty — a multicenter study. Infect Control Hosp Epidemiol 2021;42:69—74. https://doi.org/10.1017/ice.2020.377.

[21] Cho SY, Chung DR, Choi JR, Kim DM, Kim SH, Huh K, et al. Validation of semiautomated surgical site infection surveillance using electronic screening algorithms in 38 surgery categories. Infect Control Hosp Epidemiol 2018;39:931—5. https://doi.org/10.1017/ice.2018.116.

[22] Sips ME, Bonten MJM, van Mourik MSM. Automated surveillance of healthcare-associated infections: state of the art. Curr Opin Infect Dis 2017;30:425—31. https://doi.org/10.1097/QCO.0000000000000376.

[23] Mulder T, Kluytmans-van den Bergh MFQ, van Mourik MSM, Romme J, Crolla RMPH, Bonten MJM, et al. A diagnostic algorithm for the surveillance of deep surgical site infections after colorectal surgery. Infect Control Hosp Epidemiol 2019;40:574—8. https://doi.org/10.1017/ice.2019.36.

[24] van Mourik MS, Troelstra A, Berkelbach van der Sprenkel JW, van der Jagt-Zwetsloot MC, Nelson JH, Vos P, et al. Validation of an automated surveillance approach for drain-related meningitis: a multicenter study. Infect Control Hosp Epidemiol 2015;36:65—75. https://doi.org/10.1017/ice.2014.5.

[25] Apte M, Landers T, Furuya Y, Hyman S, Larson E. Comparison of two computer algorithms to identify surgical site infections. Surg Infect (Larchmt) 2011;12:459—64. https://doi.org/10.1089/sur.2010.109.

[26] Hota B, Lin M, Doherty JA, Borlawsky T, Woeltje K, Stevenson K, et al. Formulation of a model for automating infection surveillance: algorithmic detection of central-line associated bloodstream infection. J Am Med Inform Assoc 2010;17:42—8. https://doi.org/10.1197/jamia.M3196.

[27] Thirukumaran CP, Zaman A, Rubery PT, Calabria C, Li Y, Ricciardi BF, et al. Natural language processing for the identification of surgical site infections in orthopaedics. J Bone Joint Surg Am 2019;101:2167—74. https://doi.org/10.2106/JBJS.19.00661.
[28] Suzuki H, Clore GS, Perencevich EN, Hockett-Sherlock SM, Goto M, Nair R, et al. Development of a fully automated surgical site infection detection algorithm for use in cardiac and orthopedic surgery research. Infect Control Hosp Epidemiol 2021;42:1215—20. https://doi.org/10.1017/ice.2020.1387.
[29] Gubbels S, Nielsen J, Voldstedlund M, Kristensen B, Schønheyder HC, Ellermann-Eriksen S, et al. National automated surveillance of hospital-acquired bacteremia in Denmark using a computer algorithm. Infect Control Hosp Epidemiol 2017;38:559—66. https://doi.org/10.1017/ice.2017.1.
[30] Valik JK, Ward L, Tanushi H, Müllersdorf K, Ternhag A, Aufwerber E, et al. Validation of automated sepsis surveillance based on the Sepsis-3 clinical criteria against physician record review in a general hospital population: observational study using electronic health records data. BMJ Qual Saf 2020;29:735—45. https://doi.org/10.1136/bmjqs-2019-010123.
[31] van der Werff SD, Thiman E, Tanushi H, Valik JK, Henriksson A, Ul Alam M, et al. The accuracy of fully automated algorithms for surveillance of healthcare-associated urinary tract infections in hospitalized patients. J Hosp Infect 2021;110:139—47. https://doi.org/10.1016/j.jhin.2021.01.023.
[32] de Bruin JS, Adlassnig K-P, Blacky A, Koller W. Detecting borderline infection in an automated monitoring system for healthcare-associated infection using fuzzy logic. Artif Intel Med 2016;69:33—41. https://doi.org/10.1016/j.artmed.2016.04.005.
[33] Ehrentraut C, Ekholm M, Tanushi H, Tiedemann J, Dalianis H. Detecting hospital-acquired infections: a document classification approach using support vector machines and gradient tree boosting. Health Inform J 2018;24:24—42. https://doi.org/10.1177/1460458216656471.
[34] Bi Q, Goodman KE, Kaminsky J, Lessler J. What is machine learning? A primer for the epidemiologist. Am J Epidemiol 2019;188:2222—39. https://doi.org/10.1093/aje/kwz189.
[35] Branch-Elliman W, Strymish J, Kudesia V, Rosen AK, Gupta K. Natural language processing for real-time catheter-associated urinary tract infection surveillance: results of a pilot implementation trial. Infect Control Hosp Epidemiol 2015;36:1004—10. https://doi.org/10.1017/ice.2015.122.
[36] Koleck TA, Dreisbach C, Bourne PE, Bakken S. Natural language processing of symptoms documented in free-text narratives of electronic health records: a systematic review. J Am Med Inform Assoc 2019;26:364—79. https://doi.org/10.1093/jamia/ocy173.
[37] Trick WE. Decision making during healthcare-associated infection surveillance: a rationale for automation. Clin Infect Dis 2013;57:434—40. https://doi.org/10.1093/cid/cit249.
[38] Lin MY, Woeltje KF, Khan YM, Hota B, Doherty JA, Borlawsky TB, et al. Multicenter evaluation of computer automated versus traditional surveillance of hospital-acquired bloodstream infections. Infect Control Hosp Epidemiol 2014;35:1483—90. https://doi.org/10.1086/678602.
[39] de Bruin JS, Seeling W, Schuh C. Data use and effectiveness in electronic surveillance of healthcare associated infections in the 21st century: a systematic review. J Am Med Inform Assoc 2014;21:942—51. https://doi.org/10.1136/amiajnl-2013-002089.
[40] Cato KD, Cohen B, Larson E. Data elements and validation methods used for electronic surveillance of health care-associated infections: a systematic review. Am J Infect Control 2015;43:600—5. https://doi.org/10.1016/j.ajic.2015.02.006.
[41] Scardoni A, Balzarini F, Signorelli C, Cabitza F, Odone A. Artificial intelligence-based tools to control healthcare associated infections: a systematic review of the literature. J Infect Public Health 2020;13:1061—77. https://doi.org/10.1016/j.jiph.2020.06.006.
[42] Gómez-Vallejo HJ, Uriel-Latorre B, Sande-Meijide M, Villamarín-Bello B, Pavón R, Fdez-Riverola F, et al. A case-based reasoning system for aiding detection and classification of nosocomial infections. Decision Support Syst 2016;84:104—16. https://doi.org/10.1016/j.dss.2016.02.005.
[43] Condell O, Gubbels S, Nielsen J, Espenhain L, Frimodt-Møller N, Engberg J, et al. Automated surveillance system for hospital-acquired urinary tract infections in Denmark. J Hosp Infect 2016;93:290—6. https://doi.org/10.1016/j.jhin.2016.04.001.
[44] Chaine M, Gubbels S, Voldstedlund M, Kristensen B, Nielsen J, Andersen LP, et al. Description and validation of a new automated surveillance system for *Clostridium difficile* in Denmark. Epidemiol Infect 2017;145:2594—602. https://doi.org/10.1017/S0950268817001315.
[45] Healthcare-Associated Infections Database (HAIBA). Available at: https://miba.ssi.dk/haiba [last accessed October 2021].
[46] HAIBA on eSundhed. Available at: https://www.esundhed.dk/Emner/Patienter-og-sygehuse/HAIBA [last accessed October 2021].
[47] Streefkerk HRA, Verkooijen RP, Bramer WM, Verbrugh HA. Electronically assisted surveillance systems of healthcare-associated infections: a systematic review. Euro Surveill 2020;25(2). https://doi.org/10.2807/1560-7917.ES.2020.25.2.1900321.
[48] Russo PL, Shaban RZ, Macbeth D, Carter A, Mitchell BG. Impact of electronic healthcare-associated infection surveillance software on infection prevention resources: a systematic review of the literature. J Hosp Infect 2018;99:1—7. https://doi.org/10.1016/j.jhin.2017.09.002.