Fuzziness in Healthcare-Associated Infection Monitoring and Surveillance

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Abstract—**Automated identification, monitoring, and reporting of healthcare-associated infections in intensive care units by connecting intensive-care medical information, laboratory information, and Arden-Syntax-based clinical decision support systems was proven feasible and operable. Raw clinical and laboratory data of patients are transferred to the system's data warehouse. Ontologies listing all of the applied terms and a structured knowledge base with procedural and rule-based formalizations of the involved concepts and their relationships between them are part of the system. The inherent linguistic uncertainty of clinical terms is modeled by fuzzy sets. Degrees of compatibility (fuzzy degrees of membership) between data and the respective clinical terms under consideration are propagated by fuzzy logic. Uncertainty—when it is a part of clinical propositions—is modeled by truth values, and propagated by fuzzy logic as well. This large-scale system is known as Moni-ICU and runs as a routine clinical application at Vienna General Hospital, Austria.**

Keywords—fuzzy sets; fuzzy logic; linguistic and propositional uncertainty; healthcare-associated infections; infection control; infection reporting; quality benchmarking

I. INTRODUCTION

Surveillance of healthcare-associated infections (HAIs) is a key parameter of good clinical practice, especially in intensive care medicine. Assessment of HAIs is a time-consuming task for highly trained experts who, in clinical settings, are neither available nor affordable in sufficient numbers for continuous surveillance. Many published surveillance studies have been performed with additionally budgeted (scientific) staff or with information technology tools specifically developed for such studies, and often not installed for regular use afterwards. Healthcare institutions are increasingly called upon by healthcare authorities to install and use HAI surveillance regularly as a part of quality management. However, this sound demand is often overruled by financial constraints or simply by the unavailability of a suitable workforce at the local or regional level. For some time now, we have succeeded in bridging these gaps by establishing a fully automated computer-based system for early recognition, continuous monitoring, and extended reporting of HAIs. The foremost challenge was to obtain reliable surveillance data from intensive care units (ICUs) and laboratory information systems of the hospital, without the need to employ additional documentation staff and statisticians. No less challenging was the development of a clinical knowledge base with which the required clinical interpretations and logical inferences could be made in fully automated fashion. The inherent unsharpness of clinical terms could be retained, and evaluations based on it are propagated throughout the clinical inference network. Thus, linguistic uncertainty became a part of the system. Moreover, some clinical situations require graded propositions of their potential presence or absence. Here, the introduction of propositional uncertainty became necessary.

The purpose of this report is to describe an operational clinical system that makes extended use of fuzzy sets and fuzzy logic, and to argue that these methodologies are highly beneficial—if not obligatory—in the development of "intelligent" information technology systems in clinical medicine.

Most of the underlying theoretical concepts can be found in [1–7]. The extended application of those concepts in a differential diagnostic consultation system for clinical rheumatology, and some of the achieved results can be found in [8–10].

II. METHODS

A. Moni-ICU—Monitoring of ICU-Associated Infections

This large-scale system is known as Moni-ICU [11–14] and runs as a routine clinical application at Vienna General Hospital, a tertiary care hospital with 2,134 beds and the main teaching hospital of the Medical University of Vienna, Austria. Moni stands for monitoring of nosocomial infections. Moni-ICU has been established for electronic fully-automated monitoring, surveillance, and reporting of HAIs at the hospital's ICUs with adult patients.

B. Data Sources

Data sources for Moni-ICU are the intensive-care information systems at the ICUs for administrative and clinical data. Required data from the central laboratory information system are also transferred to the intensive-care information systems. All data are stored in the respective database of the

intensive-care information system, displayed for patient care on bedside monitors, and—in slightly filtered form—sent through a communication interface to the data warehouse of Moni-ICU. In addition, the microbiology laboratory information system provides microbiological test results. Again, a communication interface was set up to receive the data in Moni-ICU's data warehouse. The data warehouse, with its uniform data representation, is then the starting point of all further processing.

C. Output

The primary output is displayed on the cockpit surveillance screen to determine which patient at which ICU ward developed an HAI, continued to have one, or recovered from one. Further output is generated automatically for internal, national, and international reporting and quality benchmarking, and for mandatory legal reporting [15].

D. Surveillance Criteria

Moni-ICU's processing of the included surveillance criteria for HAIs is based on the published textual criteria definitions as issued by the Centers for Disease Control and Prevention, National Healthcare Safety Network (CDC/NHSN) [16], Atlanta, USA, the European Center for Disease Prevention and Control (ECDC) [17], Stockholm, Sweden, and the German National Reference Center for Surveillance of Nosocomial Infections [18], Berlin, Germany. The published criteria of the various relevant forms of septicemias, pneumonias, urinary tract infections, and central-venous-catheter-associated infections were decomposed according to their meaning, rearranged according to formal points of view, and fully structured, including all the necessary calculations, operands, and operators, by a small team of clinical informaticians and experienced clinicians. The development of the clinical knowledge base of Moni-ICU consisted of mapping the raw medical data of patients (observed clinical data entered into the intensive-care information system, measured physiological or pathophysiological parameters, and obtained numerical laboratory test results)—all of which were already a part of the data warehouse—into relevant clinical concepts (clinical signs, interpretations of laboratory test results). In many cases, the mapping is performed by predefined fuzzy sets which are not only able to map data into concepts on a yes-or-no basis, but also to preserve possible borderline results. Some examples of such fuzzy sets are shown in Fig. 1. It should be mentioned that the applied fuzzy sets are parameterized and, in several cases, depend on their context.

The following can be seen in Fig. 1. Body temperature of 38 ℃ (or higher) will result in the interpretation: fever is present to 100% (1.0) or, equivalently, the degree of compatibility of the measured value of 38 ℃ (or higher) and the clinical concept of fever is 100%. Analogously, a body temperature of 37.9 ℃ results in the proposition that fever is present to 80% (0.8). These clinical concepts were then combined by rules, and the results again combined with further rules, until the top-level rules were achieved (see also [11,12], Fig. 2). During this process, logical operators (and other formal structures), such as conjunction, disjunction, or negation will be encountered. Here, their fuzzy-logical expressions are applied. In simple situations, this is the min, max, and complement operator, but—very importantly—unknown was introduced as a valid operand. Again, results at the first level are combined and the inferred results are propagated to the next level. This is done several times until the top-level concepts, here HAI surveillance definitions, are reached.

One example of such a top-level HAI concept is a symptomatic urinary tract infection, which is present to 100%, meaning that the patient's observed and measured clinical data are fully compatible with the given surveillance definition of this HAI. As mentioned earlier, the degree of compatibility might be less than 100% or, also, just 0%.

Clinical knowledge acquisition of ontologies, fuzzy sets, rules, and procedures was supported by authoring, test, and validation tools.
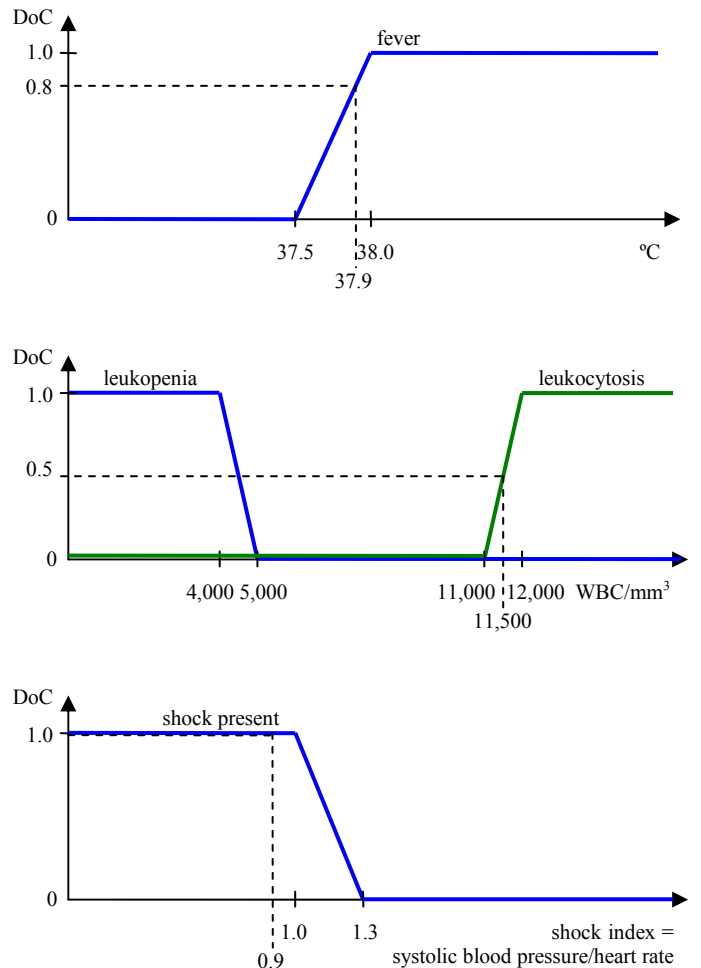

Fig. 1. Examples of fuzzy set definitions as they are applied in Moni-ICU. (DoC: degree of compatibility). Some fuzzy-set-based mappings of obtained numerical test results into linguistic clinical concepts are presented. The clinical terms are labels of fuzzy sets.
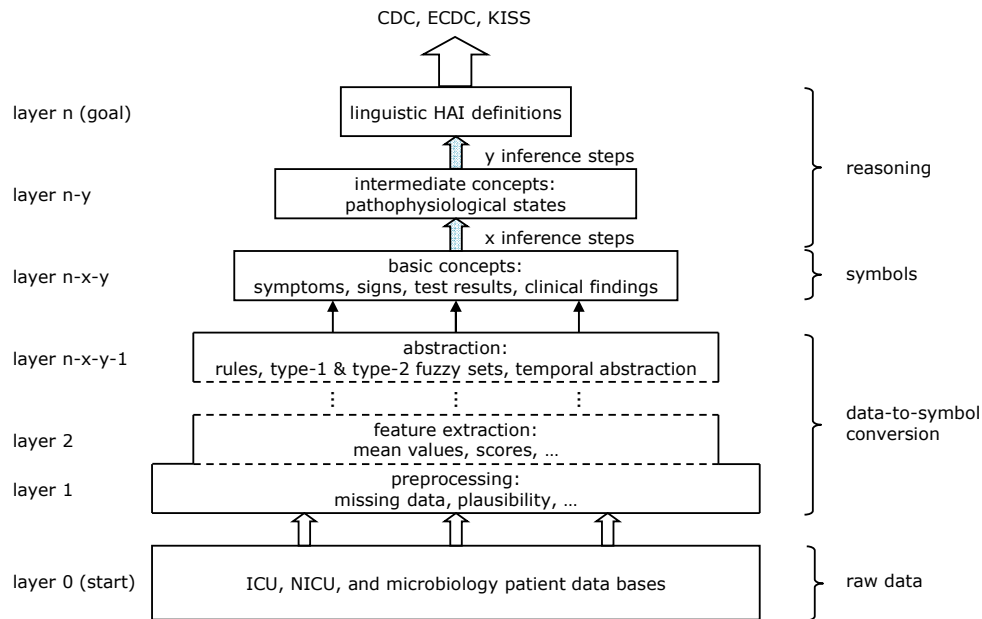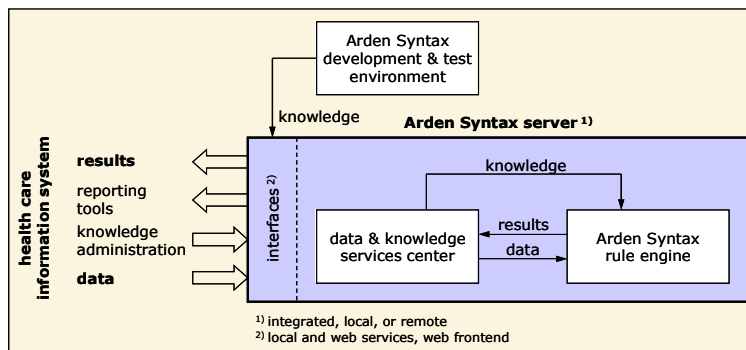
Fig. 2. Data processing layers in Moni explaining the pathway from raw data input [of electronic bedside sensors (e.g., pulse, blood pressure, body temperature), from biochemical laboratory (e.g., leukocyte count, erythrocyte sedimentation rate, C-reactive protein), from microbiology, and from routine bedside data entries by ICU staff] to the required specific outputs. HAI: healthcare-associated infection, ICU: intensive care unit, NICU: neonatal intensive care unit.

E. Arden Syntax

The resulting clinical knowledge base was brought into Arden Syntax [19] medical logic module (MLM) code. Arden Syntax is a medical knowledge representation and processing scheme for the development of clinical decision support (CDS) systems, that originated in 1989 at a meeting of several medical informaticians from the USA, the Netherlands, and Sweden at the Arden Homestead Retreat in Orange County, NY, which are conference estates owned by the Columbia University. The intention was to write computer-based clinical reminders, diagnostic and therapeutic recommendations, and crucial alerts in a clear and readable way. Besides, one of the main objectives was to make these shareable with others. Since then, the early versions of Arden Syntax have been updated, extended, and were adopted by standards organizations. The American Society for Testing and Materials (ASTM) first approved the Arden Syntax as standard E-1460-92 in 1992. Ownership was transferred to Health Level Seven (HL7)—now Health Level Seven (HL7) International—and the American National Standards Institute (ANSI) in 1999, with the approval of version 2.0 of the standard. The latest release is Arden Syntax version 2.9, which was approved by HL7 International [20] and ANSI [21] in March 2013. This newest version now includes a full fuzzification of all defined values, operators, and programming structures (see also [22,23]). It should be mentioned that the present knowledge of Moni-ICU was written in pure Arden Syntax, where fuzzy sets and fuzzy logic were fully programmed in Arden Syntax code. Fuzzy Arden Syntax, now available with version 2.9, will be applied in a further step of this development.

- Arden Syntax integrated development and test environment (IDE), including
  - Medical logic module (MLM) editor and authoring tool
  - Arden Syntax compiler (versions 2.1, 2.5, 2.6, 2.7, 2.8, and 2.9)
  - Arden Syntax engine
  - MLM test environment
  - MLM export component
- command-line Arden Syntax compiler

- web-services-based Arden Syntax server, including
  - Arden Syntax engine
  - MLM manager
  - XML-protocol-based interfaces, e.g., SOAP, REST, and HL7
  - a project-specific data and knowledge services center may be hosted
- Java libraries
  - Arden Syntax compiler
  - Arden Syntax engine

Fig. 3. Suite of Arden Syntax software—service-oriented architecture and software components.
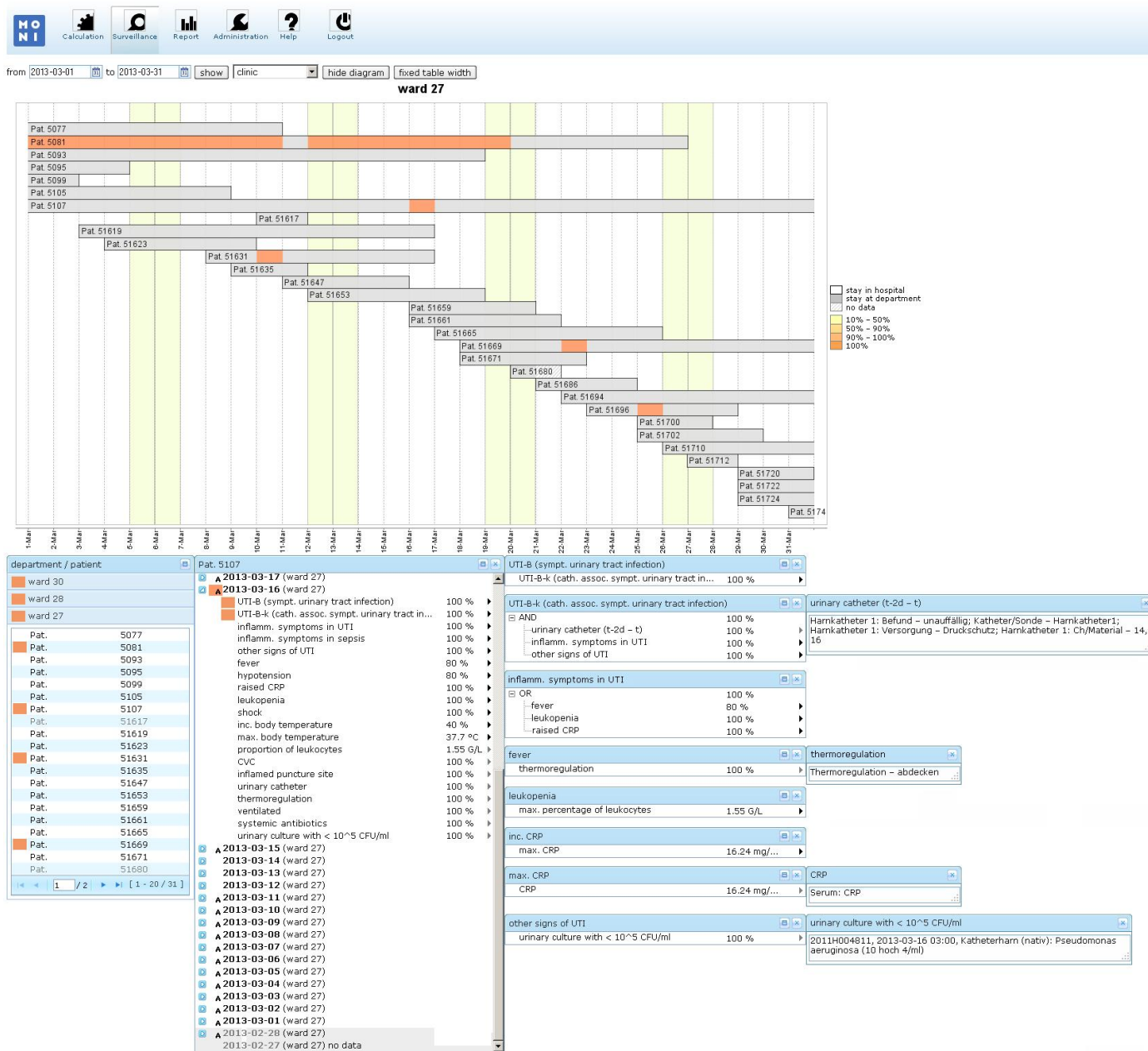
Fig. 4. Moni-ICU cockpit view (wards and patients were anonymized; wards and patients are listed on the left side of the screen; the middle part shows the days of the patient's ICU stay with one day opened; final as well as intermediate and some raw data are presented beneath the opened day; an explanation for one derived clinical concept is provided on the right hand side).

F. Processing

To summarize the processing steps, layers of raw data calculation and interpretation to intermediate and high-level clinical concept evaluation were introduced, and a package of hierarchically interwoven MLMs was established (see also [24]). Patients' medical data are measured, observed, and automatically transferred from the intensive-care medical information systems and the microbiology laboratory. The data are then passed through a step-by-step pipeline of aggregation, interpretation, and evaluation, which is eventually used to draw conclusions as to whether one or more of the included HAI surveillance criteria are fulfilled, fulfilled to a certain degree, or not fulfilled. Most of the encoded clinical entities are modeled as fuzzy sets, and fuzzy logic is used to perform the subsequent inference steps.

G. Service-Oriented Architecture

Following current software architectures and providing the Arden Syntax execution engine within a service-oriented architecture make it possible to offer interoperable CDS systems for a variety of tasks. These tasks all have in common the fact that data sources such as clinical, laboratory, or

intensive-care information systems, or the web "itself" supply the data to be processed—preferably through standardized data communication—and that the MLM-processed results be returned to the connected information systems, or reported by separate web-based applications. Fig. 3 shows the structure of the Arden-Syntax-based, service-oriented CDS system that was realized for Moni-ICU, and lists some of its software components.

III. RESULTS

A. Application and Knowledge Base

At present, this Arden Syntax application is used by ten ICUs at Vienna General Hospital with a total of 87 beds. The ICUs and the microbiology department provide about 18,000 data items every day (raw data). For each of the possible 87 patients, an Arden Syntax knowledge package containing 72 MLMs is automatically invoked, and both intermediate clinical concepts and final HAI surveillance results are computed (see again Fig. 2). The intermediate and final results are stored in Moni-ICU's data warehouse, and prepared for viewing on screen, reporting, or quality benchmarking. One example of the cockpit surveillance screen is shown in Fig. 4.

B. Clinical Studies

Studies evaluating effectiveness have shown the excellent conformance of Moni-ICU with an established clinical reference standard [25], as well as Moni-ICU's superiority in minimizing time demands on the infection control team with respect to electronically supported versus sole human surveillance [14]. The achieved results are shown in Tables I and II.

A sensitivity of about 87% was determined from Table I. There were four false-negative results: three cases of false-negative pneumonias and one case of a missed central-venous-catheter-associated infection. All of the errors occurred because of missing microbiological data from the microbiology department. Furthermore, Moni-ICU had a specificity of nearly 99%. There was one false-positive case because of concomitant leukemia present in one patient, who thus falsely showed all of the necessary signs of one of the defined HAI infections.

TABLE I.   HAI EPISODES CORRECTLY OR FALSELY IDENTIFIED OR MISSED BY MONI-ICU (FROM [25])

HAI episode	Present according to gold standard	Absent according to gold standard
Present according to Moni-ICU	26/30 86.7%	1/76 1.3%
Absent according to Moni-ICU	4/30 13.3%	75/76 98.7%

Basis: 93 ICU patient admissions; 882 patient days; 30 HAI episodes over the complete or partial duration of the patient's stay; 76 stays with no HAI episodes

TABLE II.   TIME EXPENDITURE FOR CONVENTIONAL (HUMAN) AND MONI-ICU SURVEILLANCE (FROM [14])

	Manual surveillance	Moni-ICU surveillance
Time spent	82.5 h (100%)	12.5 h (15.2%)

Conventional surveillance involved 52 ward visits and the time taken was 82.5 hours (including 7.2 hours of walking) for human data collection and analysis. Moni-ICU analysis of the same 99 admissions took 12.5 hours at the Moni cockpit, which was roughly 15% of the time taken for conventional surveillance.

IV. DISCUSSION

A. Reasons for Moni-ICU's Success

Clinical. The cockpit surveillance system, which can also be accessed away from the bedside, is considered attractive. It provides an excellent overview at a high level of clinical information. Usually, clinical information systems display patient data at the raw data level (or text files). Here, information is presented as data interpretations, abstractions, physiological or pathophysiological states, or even as being compatible with HAI surveillance definitions.

Moreover, Moni-ICU does not display results as clinical diagnoses, which would interfere with human patient care. Instead, results are presented at the level of surveillance criteria: fulfilled, fulfilled to a certain degree, or not fulfilled. This increases acceptance by the clinical community, and has also legal relevance.

Furthermore, no additional data entry is required. This is extremely important, because additional data entry usually distracts the clinician from his/her actual patient care or will interrupt the clinician's work flow. This is usually not accepted.

Methodological. Moni-ICU was designed as a knowledge-based system with detailed explanatory capabilities. It does not rely on machine learning. The applied clinical knowledge is based on consensus surveillance criteria established by infection control experts. These consensus criteria have been announced and backed by well-known medical community or governmental institutions.

When using Moni-ICU, the explanatory system clearly states what is included in the system and what is not. This feature provides full transparency of any inferred clinical result and lays the foundation for trust in the system.

Moni-ICU is based on continuous steps of abstraction and aggregation, as is the approach in human reasoning in clinical medicine (and in other areas).

And—last but not least—Moni-ICU avoids "jumps" in reasoning: a small change in input parameters yields a small change in clinical output.

Technical. Data sources, knowledge packages, rule processing, and output routines are separated, and are

combined in a flexible way. Adaptation to changes in data sources (from one intensive-care information or laboratory system to another) can be done more easily (although it is still not easy).

Administrative. The several ICUs agreed upon one single way of configuring their intensive-care medical information systems, thus providing a uniform data source from their many systems. Consequently, the same clinical item in one ICU is stored in the "same" place in the intensive-care information system, even if it is derived from another ICU. The fact that it may be different might come as a surprise, but the practice is still common in the realm of hospital information systems.

Moni-ICU was supported by the hospital administration to introduce this originally academic development into routine patient care. And—again last but not least—several lead users fostered its development over a long period of time, failing which the system would not have succeeded.

B. Survey of Similar Systems

An extensive survey of the electronic surveillance of HAIs in the 21st century was recently published by de Bruin et al. [26]. The authors compared 27 electronic HAI detection systems and discussed clinical and technical methodologies, results, and their advantages and disadvantages. Similar to a number of other systems, Moni-ICU is not only based on microbiological data, but also on patients' clinical data. The accuracy varies but Moni-ICU, with its tested sensitivity of about 87% and its specificity of about 99%, is within the excellent range. What is special and unique about Moni-ICU is its use of fuzzy set theory and fuzzy logic to model linguistic and propositional uncertainty, which is a frequently neglected but integral part of clinical medicine.

C. Clinical Benefits of Fuzzy Set Theory and Fuzzy Logic

Broad application of fuzzy set theory and fuzzy logic in Moni-ICU is not the foremost characteristic of Moni-ICU.

For an operational clinical system, data and workflow integration, automated data collection from different sources, its ease of use for clinical users or allied medical personnel, and its potential applicability for different clinical tasks (monitoring, surveillance, reporting, benchmarking, telesurveillance for infection control personnel, information source for infection specialists, and others) are, to a certain extent, mandatory and of immediate importance for clinical users.

However, broad comprehension of the immanent uncertainty of linguistic clinical terms and thus straightforward, "intelligent" processing of patients' borderline values make Moni-ICU a more fitting HAI surveillance detection system for clinical use. The usual "black and white", and partially arbitrary approach, to evaluate the presence or absence of clinical states in a patient was "engineered" away and evolved into a successful solution.

We will further evaluate the advantages of fuzziness in Moni-ICU. Clinicians will be using the system more extensively in hospital settings, which is expected to disclose further anticipated and unexpected benefits.

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