Improving Clinical Practice using Clinical Decision Support Systems with Medical Logic Modules

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Abstract - *The provisioning of clinical decision support systems (CDSS) would enable the discovery of patterns in health data which might be important for the fight against nosocomial infections, incorrect diagnosis, and improper use of medication. Since the potential of medical decision making was first realized, hundreds of articles introducing decision support systems (DSS) have been published in the last three decades. But even today, only few systems are in clinical use, and their full potential for optimizing the healthcare system is far from realized. Clinician's acceptance and utilization of CDSS depends on its workflow-oriented context sensitive accessibility and availability at the point of care, and on the integration into a hospital information system (HIS). This paper outlines technical and medical aspects of a seamless integration of two CDSS into a HIS at the General Hospital of Vienna. The medical knowledge representation and reasoning of the CDSS is realized with Arden Syntax and Medical Logic Modules (MLM). Experiences gained by the clinical use of the systems are used to analyze the little use of CDSS in today's clinical practice.*

Keywords: Hospital information systems, clinical decision support system, fuzzy based decision support, Arden syntax, and medical logic modules

1 Introduction

Over the past three decades medical treatment has made enormous progress. In modern health care environment, the amount of information available is very large, and in order to manage it computers are used in medicine in almost all areas. Clinicians and nurses are still performing time-consuming manual data analysis for making the most optimal medical decision for each individual patient [1-3]. They must choose from and interpret a huge variety of clinical data, while facing pressure to decrease uncertainty, risks to patients and costs. Computer technology can assist by generating case-specific advice for clinical decision making. The computer systems used are usually referred to as clinical decision support systems or CDSS [4, 5].

While electronic health records and databases help physicians manage this rising tide of information, patient-specific recommendations provided by clinical decision support systems can do even more by improving decision making and helping ensure patient safety. The provisioning of CDSS would enable the discovery of patterns in health data which might be important for the fight against nosocomial infections, incorrect diagnosis, unnecessary prescriptions, and improper use of medication. Current hospital information systems (HIS) are not offering an infrastructure for data-driven guidance, modeling of critical illness and infection surveillance.

Since the potential of medical decision making was first realized, hundreds of articles introducing CDSS have been published in the last three decades. But over the years' experience has shown that the expectations were not always fulfilled. Even today, only few systems, so asserted, are in clinical use. Even fewer are in use outside their site of origin, and their full potential for optimizing the healthcare system is far from realized.

The greatest barrier to routine use of decision support by clinicians has been inertia. Systems has been designed in the past for single problems that arise infrequently and have generally not been integrated into the routine data-management environment for the user [4], [14].

Clinicians' acceptance and utilization of CDSS depends on its workflow-oriented, context-sensitive accessibility and availability at the point of care, and ideally integrated into a HIS [11-13]. Commercially operated HIS often focus on administrative tasks and mostly do not provide additional knowledge based functionality. Their monolithic and closed software architecture encumbers integration of and interaction with external software modules [44 - 49].

This paper outlines technical and medical aspects of a seamless integration of two CDSS into a HIS at the General Hospital of Vienna. The medical knowledge representation and reasoning of the implemented CDSSs is realized with Arden Syntax and Medical Logic Modules (MLM).

The next section gives a brief history of CDSS with the Arden and Fuzzy Arden Syntax concept for MLMs that have been used in these applications. Further the conceptual architecture of CDSS and the integration of into the HIS will be introduced also. Finally, experiences gained by the clinical use of the implemented systems are used to analyze the little use of CDSS in today's clinical practice.

2 Decision Support Systems

A generic decision support system (DSS) receives a certain amount of data as input, processes it using a specific methodology and offers as a result some output that can help the decision-makers.

The concept of clinical decision support or DSS in general, is built on the paradigm of support. The term "decision support systems" (DSS) was coined the beginning of the 1970's to denote a computer program that could support a manager in making semi-structured or unstructured decisions.

It is not due to just data retrieval and numeric calculations either, which are the functions found in a traditional DSS. What is needed is a system which can process quantitative and qualitative data of varying levels of precision and, by reasoning, transform this data into opinions, judgments, evaluations and advice. These intelligent systems must be able to expect a tolerance for imprecision, uncertainty, and partial truth to achieve tractability, robustness, low solution cost, and better rapport with reality [15 - 17].

2.1 Clinical Decision Support Systems (CDSS)

CDSSs has been defined as ''any computer program designed to help health professionals make clinical decisions, deal with medical data about patients or with the knowledge of medicine necessary to interpret such data''.

In general computer applications should identify and reduce the rate of errors, inappropriate or inefficient actions, and adverse events. Therefore a CDSS can be broadly defined as DSS that integrate patient data with a knowledge-base and an inference mechanism to produce patient specific output in the form of care recommendations, assessments, alerts and reminders, to actively support practitioners and clinicians in clinical decision making [18, 19], [44]. A typical clinical therapeutic cycle in a simplified view is shown in Fig.1.

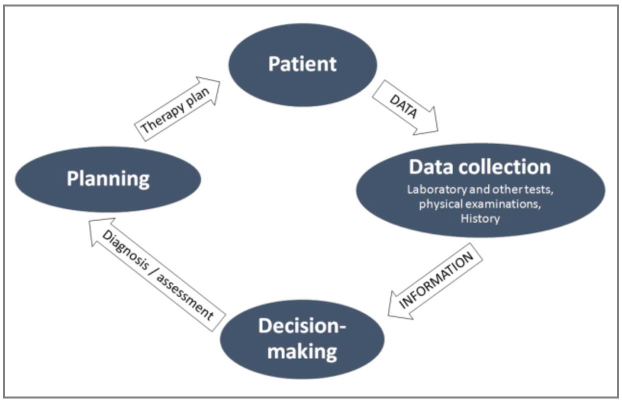

Fig. 1: The Diagnostic-Therapeutic Cycle (a simplified view)

Patient data can be input by digital entry queried from a HIS, patient data management systems (PDMS), or transmitted from other medical devices [30]. Patient data are compared against a knowledge-base and made sense of by an inference mechanism. The inference mechanism itself can be highly variable in sophistication ranging from simple 'if rules 'yes' or 'no' and 'if 'then', 'else' statements to Bayesian prediction techniques and/or with fuzzy logic [15 - 17].

Expert or knowledge-based systems are another type of CDSS capable of being programmed to perform decision making at the level of a domain expert [19]. These systems represent the most prevalent type of CDSS used in medical clinical practices today. Though CDSS can include different components, and though domain knowledge can be structured in a variety of ways, certain elements are common to all: a user interface, a knowledge base, a database, a knowledge acquisition facility, and an inference mechanism.

The two CDSSs presented in this paper [20, 21], interacts with the Arden and Fuzzy Arden Syntax concept, and the knowledge representation is realized with MLMs.

2.2 CDSS with Fuzzy Logic and Fuzzy Control

The concept of fuzzy set theory, which was developed by Zadeh (1965), makes it possible to define inexact medical entities as fuzzy sets. The Fuzzy set theory [15 - 17] derives from the fact that most natural classes and concepts are of fuzzy rather than crisp nature. By generalization of usual set theory an object cannot only be seen as an element of a set (membership value 1) or not an element of this set (membership value 0), but it can also have a membership value between 0 and 1 , (Fig. 2). Therefore fuzzy sets defined by their membership function μ which is allowed to assume any value in the interval [0, 1] instead of their characteristic function.

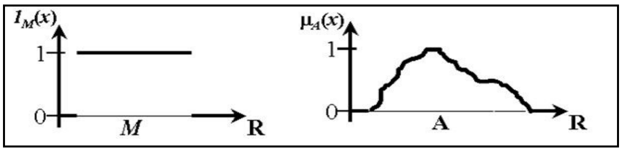

Figure 2: Characteristic function of a set *M* and membership function of a fuzzy set *A*.

A clinical fuzzy decision support system (CFDSS) is simply a DSS that is focused on using a knowledge management based on the fuzzy set theory in such a way to achieve clinical advice for patient care based on some number of items of patient data. A more far-reaching concept of modeling relationships was introduced by Sanchez 1979 [29]. Sanchez postulates the concept of "medical knowledge" based on a relationship between symptoms and diagnoses [35].

Using this composition formula as an inference rule, Assilian and Mamdani developed the concept of f*uzzy control* in the early 1970s [25].

Mamdani's development of fuzzy controllers in 1974 gave rise to the utilization of these fuzzy controllers in ever-expanding capacities [25, 26], [43]. Therefore these new intelligent CFDSS must be able to expect a tolerance for imprecision, uncertainty, and partial truth to achieve tractability, robustness, low solution cost, and better rapport with reality.

3 Applications & Clinical Results

There are many different methodologies that can be used by a CDSS in order to provide support to the health care professional. In our case the inference mechanism, i.e. a set of rules derived from the physician's (experts) and evidence-based medicine, and the knowledge base itself, are implemented for both CDSSs through medical logic modules (MLMs) based on a language such as Arden syntax [22 - 24].

3.1 Technical Aspects

3.1.1 Arden Syntax decision support sharing efforts

The Arden Syntax for Medical Logic Modules or rather for CDSSs is a language for encoding medical knowledge bases that consist of independent modules. The Arden Syntax has been used to generate clinical alerts, diagnostic interpretations, management messages, and screening for research studies and quality assurance. An Arden Syntax knowledge base consists of rules called Medical Logic Modules (MLMs), which are stored as simple ASCII files that can be written on any text editor. An MLM is a hybrid between a production rule (i.e. an "if-then" rule) and a procedural formalism. Each MLM is invoked as if it were a single-step "if-then" rule, but then it executes serially as a sequence of instructions, including queries, calculations, logic statements and write statements. One of the earliest efforts at sharing clinical decision support content was the Arden Syntax Medical Logic Module (MLM) repository. Arden Syntax now is a standard for encoding event-driven rule based clinical knowledge for use in clinical decision support systems [22 - 25]. A first draft of the standard was prepared at a meeting at the Arden Homestead, New York, in 1989. Health Level 7 (HL7) published Arden Syntax version 2.0 in the year 1999 and has been hosting the development of all newer versions of the Arden Syntax standard ever since [22]. The present, most recent version of Arden Syntax is version 2.8. [26].

3.1.2 Hospital Information System (HIS)

The communication mechanism, the host system of the CDSSs will allow showing the results to the users, as well as have input into the system.

At the General Hospital of Vienna this fully featured HIS is i.s.h.med and represents the communication mechanism of the implemented CDSSs. Additionally the HIS i.s.h.med provides a clinical workplace, a parametric medical document (PMD) and an interface via Web Service. The Arden Syntax Server represents in this scenario the reasoning and inference mechanism with MLMs, which can be realized in fuzzy and crisp nature, and processes the patient data, which is received from the HIS i.s.h.med via web services (Fig. 3).

The clinical workplace (Host System CDSS) provides a work environment for the medical users (including patient and ward lists, access to scheduled appointments, etc.). Information received from the CDSS, e.g. alerts or reminders, can be displayed in the respective list(s) on the clinical workplace.

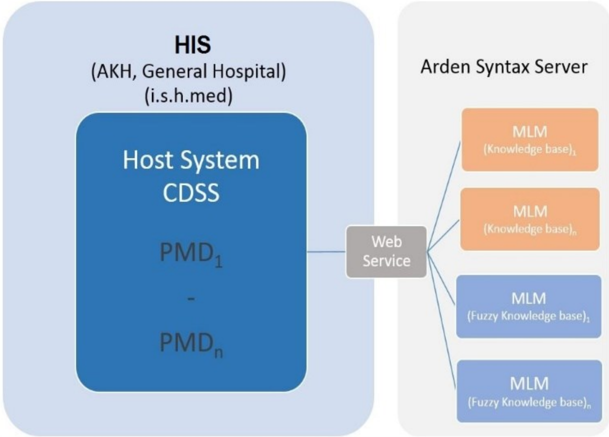

Fig. 3: CDSS integration into the HIS i.s.h.med at the General Hospital of Vienna

The PMD provides a framework for medical documentation which can be customized to the special medical needs of the respective clinical department and the PMDs are used as the user interface of the CDSSs.

The web service has two basic communication functions: First, it provides laboratory (e.g. tumor markers) and clinical data (see above) for sending to the Arden Syntax server in XML format. Second, it receives results (and explanation, if applicable) from Arden Syntax server and saves those into the i.s.h.med PMD (Fig 4).

By programming, the PMD can – on receiving results – trigger certain "events" in the software, e.g. put alerts or reminders on a patient list on the clinical workplace.

3.2 Prediction of Melanoma Metastasis Events

3.2.1 Clinical Background

Cutaneous Melanoma (CM), the most lethal form of skin cancer can be highly metastatic. The most common site of metastatic disease in melanoma is the regional lymph nodes indicating that metastatic spread usually occurs via the lymphatic system.

There is substantial evidence that cases of CM are still increasing worldwide. The increase of the incidence amounts to about 4-8% [32, 33]. According to Meves, a duplication of the incidence until 2020 is conceivable [34]. Today's incidence in Europe ranges between 12-15 /100,000 inhabitants [33]. The most widely used prognostic indicator for survival is Breslow thickness, however, this is still inaccurate for a significant number of patients [31]. CM is initially treated by surgical excision. After excision, tumors are classified according to the American Joint Committee on Cancer (AJCC) published TNM classification for CM, based on studies from Balch et al. [37, 38]. The AJCC classification [39] allows to classify CM into different categories, predicting the risk for widespread metastatic disease. The presence of metastatic disease correlates with the concentration of several tumor markers. The already routinely established tumor markers for CM are S100β, MIA and LDH. These parameters were chosen for the predictive model [40-42], and in addition for the implementation of the CDSS knowledge base.

3.2.2 Predictive probability model

The patient's pretest probability assessment is based on predictive characteristics from the literature. These include the tumor thickness according to Breslow [31], mitotic rate and ulceration which can be used to make conclusions of the tumor behavior. The final version of the seventh edition of the AJCC melanoma staging and classification [37 - 39] includes the revised TNM classification for CM.

This classification is particularly well suited for rule-based programming languages because it’s IF-THEN rule structure. The knowledge base developed in this particular CDSS calculates the present risk for metastasis in CM patients. Calculations are based on the pretest probability for metastasis in combination with the recent results from the tumor markers stated above and is shown in Fig. 4.

3.2.3 TSM-CDS Application

The knowledge base itself is a combination of multiple risk assessments.

In detail it’s a rule-based interpretation of the TNM classification according AJCC. Further the interpretation of the tumor markers S100β, melanoma inhibitory activity (MIA) and lactate dehydrogenase (LDH). And final the risk assessment of survival function (present statistical mortality risk), based on the results of the AJCC. The front end of the system is the implementation of the PMD (Fig. 4).

Fig. 4: PMD screen of the TSM-CDS application.

The CDSS supports the physicians by calculating the tumor stage. Furthermore, it offers an interpretation whether a given pattern of tumor markers is suspicious for an underlying metastatic event. As mentioned above the CDSS integrates seamless into the workflow of the HIS i.s.h.med. Specifically, results from tumor markers are automatically fed into the CDSS out of the laboratory information system (LIS). Further the clinical data are extracted from patient’s history and from the patient histopathological report. As a result these steps of data extraction feed the CDSS with all relevant data.

As mentioned the pre-test probability according to TNM was implemented in Arden Syntax, and the rules are grouped in MLMs. In this current version the knowledge base is crisp nature. In a future project there will be an extended version with fuzzy Arden Syntax and fuzzy MLMs.

The HIS- PMD itself has only a German user interface, thus the PMDs of the TNM-CDSS is also in German (Fig. 4). The values (LDH 100, MA 15, S100ß 0.5) in combination with a tumor thickness of 1 mm has as TNM result “T1aN0M0 (IA)”.

Currently, the CDSS is in clinical evaluation and calculates the probability whether not a given pattern of tumor markers is suggested for metastatic disease, but will not display this result to the user. More than 260 clinical cases have been gathered up to now. The response system is received just in the background and not shown to the physician. Instead, the user is prompted to give his or her expert opinion whether or not the given pattern is suggestive for metastatic disease.

The results in general confirm the applicability of the application to represent medical knowledge, thus rendering the TNM process transparent and comprehend-sible [42].

The system appears to be well accepted by the clinical experts. This is mainly due to the fact that the CDSS is almost seamlessly integrated into the routine HIS i.s.h.med. Initial data show that the comparison of the physicians' decisions with the CDSS resulted in 106 (49.53%) complete matches, which implies that the CDSS and the physician completely agreed. In 48 (22.43%) cases, the system calculated a lower risk for the patient, whereby in 10 (4.67%) cases the calculations resulted in a higher risk, respectively. In 50 (23.36%) cases, no decision was neither possible for the CDSS nor for the physician, due to the lack of parameters. Parameters are automatically extracted from its data sources without any hassle for the physicians in charge. The performance of the system is still under investiga-tion.

3.3 Fuzzy monitoring systems: MONI-ICU

Since 2004, the Clinical institute of Hospital Hygiene at the Vienna General Hospital has used an electronic monitoring system called MONI-ICU (acronym for monitoring of nosocomial infections in intensive care units) to automatically detect nosocomial infections, otherwise known as healthcare-associated infections (HAIs). The newest installment of this system incorporates fuzzy sets and logic to represent abstract, linguistic clinical concepts.

HAIs are infections that result from a patient’s treatment in a healthcare setting such as a hospital. Due to the relatively high presence of multidrug resistant pathogens in hospitals, HAIs can have severe consequences on a patient’s health and recovery, and this risk only increases as more pathogens develop antibiotic resistances. In order to asses and counter the threat of HAIs, the European Centre for Disease Prevention and Control has developed HAI surveillance programs [8]. While HAI incidence rates have gone down as a result of these programs, they also place a high burden on personnel and hospital resources [7, 8].

The MONI-ICU surveillance system [9, 10] has been created to decrease the burden of infection surveillance on hospitals, thereby allowing infection control specialists to concentrate on infection prevention. The system combines electronic patient data such as microbiology and biochemistry test results with clinical data from ICU patient data management systems and administrative patient data to detect a variety of HAI types such as blood stream infections, urinary tract infections, catheter-related infections and pneumonia.

As a knowledge base, the system uses a set of rules derived from the ECDC HAI surveillance definitions, which are part of the ECDC HAIICU surveillance protocol [6]. These surveillance definitions have been translated by clinical and infection control experts into a computer-readable Arden Syntax representation. Furthermore, fuzzy sets have been defined by infection control experts to represent many of the basic clinical and biochemical concepts whose values can be derived directly from raw data; fuzzy logic is then applied throughout the knowledge base to combine these basic concepts into more abstract, linguistic clinical terms, which combined with results from other data sources are used to deduce the presence or absence of HAIs, and to what extent.

Fig. 5 shows a graphical depiction of part of the knowledge base.

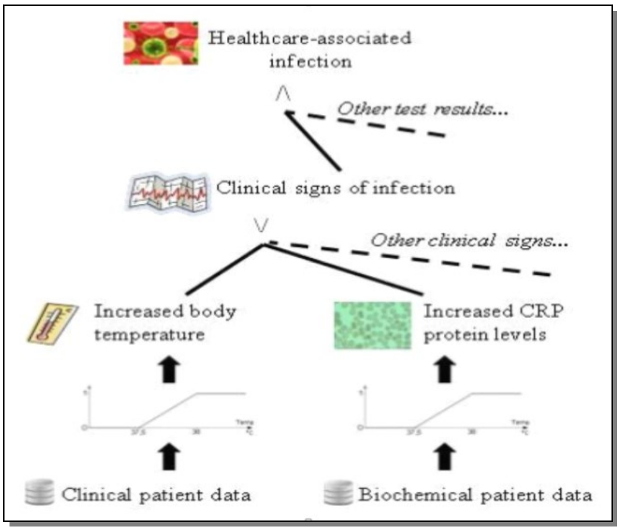

Fig. 5: The MONI-ICU knowledge base and info structure

In this figure, clinical patient data are filtered for information on body temperature, and using a fuzzy set, the raw data are transformed into a fuzzy value for the abstract clinical term increased body temperature. Similarly, biochemical data indicating a patient's C-reactive protein (CRP) value is transformed to a fuzzy value for the abstract term increased C-reactive protein levels.

Afterwards, fuzzy values for these and other clinical indications of infection are grouped into a clinical denominator called clinical signs of infection with a single fuzzy value using the standard (Gödel) triangular conorm. In turn, this fuzzy value is abstracted along with other test results (e.g. microbiology results and administrative data) using the standard (Gödel) triangular norm into a final denominator indicating the presence of HAIs. Currently, the system is in the clinical test phase, and the daily results are used by the Clinical institute of Hospital Hygiene as part of their daily afternoon briefing, and as a research platform.

Preliminary evaluation of the system indicates that it performs better than manual ward surveillance (sensitivity 87% vs. 40% for manual surveillance, specificity 99% vs. 94% for manual ward surveillance). Furthermore, the time spent on surveillance by infection control specialists has been reduced by almost 85% [9].

4 Conclusions and future work

A problem that occurs with any form of clinical knowledge representation is the need to interact with a clinical database in order to provide alerts and reminders. Database schemata, clinical vocabulary and data access methods vary widely so any encoding of clinical knowledge, such as a MLMs, must be adapted to the local institution in order to use the local clinical repository. This hinders knowledge sharing. Arden Syntax is the only standard for procedurally representing declarative clinical knowledge (contrast GLIF or PRO*forma*, for example, which are more declarative formats), so this problem is associated with Arden, but it is not unique to it. Based on the literature, current CDSS are limited in application. Roughly seventy known proprietary medical CDSS exists. Only ten out of seventy geared towards routinely use. Unfortunately there is no information available about a real daily average usage of these systems.

The concept of CDSS or DSS in general, is built on the paradigm of *support.* Again a well-designed CDSS should have the potential to assist physicians who can and do use it as often as possible in the daily routine work. In some situations physicians learns from using a CDSS about criteria, facts or process issues that need to be considered in a specific decision situation. CDSS encourage and promote "rationality" in decision making. CDSSs are intended to support not replace physicians, so the users need to consciously interact with a CDSS to use it effectively.

One large roadblock to acceptance is workflow integration. This is mainly also in our case due to the fact that the CDSS is almost seamlessly integrated into the routine HIS i.s.h.med. Often these systems are stand-alone applications, requiring the clinician to cease working on their current report system, switch to the CDSS, input the necessary data, and receive the information.

Further, a big issue is that the expectation needs to be created that the physicians are the ultimate authority and that the physicians can anytime "over rule" or choose to ignore analyses and recommendations of the CDSS. This is a feature key of the PDM concept of the HIS i.s.h.med that is used at the General Hospital.

Anticipated limitations of CDSS are that an optimal physician's treatment requires that physicians be able to have the following information, in real time, if possible: What is happening right now? What will happen in the future? What do I need to create the future I want? To answer these questions effectively, physicians requires data that are factual, factual inferential (why type questions) and predictive (what if questions). To date, the best support that a CDSS has been able to provide is data that answer factual and maybe some forms of predictive questions [3]. As mentioned above one big argument of the rare utilization at this time is that most of the CDSS have not progressed beyond the prototype stage [46]. There are no standards or universally accepted evaluation or validation methodologies to ensure that the system's knowledge base is complete and correct.

With respect to the deployment and support of CDSS, it also appears a major barrier to progress is lack of appreciation of the difficulty of the problem. On the surface, for instance in our case also, most of the CDSS does not appear to be very complicated to implement, i.e. the MLS are not highly sophisticated and so on.

The point that is often overlooked, however is that robust sustainable use of CDSS is not at all simple, even with the if … then rules MLM concept or order sets, when one considers it not with respect to a single point in time but from a long –term maintenance and update perspective. The knowledge assets underlying CDSS are time consuming and expensive to generate, and subject to change and reuse them if once created, would be highly advantageous with Arden Syntax MLM concept. We think that the lack of such capabilities is one of the primary impediments to driving widespread CDSS adoption and use.

In our case both introduced systems are used consequently in the daily routine and fulfill the questions mention above. The absence of a well-defined or universal evaluation methodology makes these questions of course difficult to answer. To date, an examination of the literature indicates that there is virtually no information available related to the cost or cost effectiveness of CDSS. Most of the CDSS, ours equally, are university-based developments, and still in prototype stage. These costs regarding the initial investment of CDDS tend to be hidden and therefore difficult to access. This frightens or hinders the industry's interest in funding and encouraging the development of CDSS in health care in general.

The physicians at the General Hospital of Vienna, and many others have a real positive outlook on the potential for CDSSs, particularly in relating to practitioner performance. However, until the use of CDSS in general is a routine as the use of the blood pressure cuff, it is important to be sensitive to resistance to using these systems.

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