Computerized Clinical Decision Support in a Hospital Information System

Christian J. Schuh, Walter Seeling
Center for Medical Statistics, Informatics and Intelligent Systems (CeMSIIS),
Medical Expert and Knowledge-Based Systems,
Medical University of Vienna, Spitalgasse 23,
A-1090 Vienna, Austria

Abstract - Since the big potential of medical decision making was first realized, hundreds of articles introducing Clinical Decision Support Systems (CDSSs) have been published in the last three decades. But even today, only few systems 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.

Clinician’s acceptance and utilization of CDSSs depends on its workflow-oriented, context-sensitive accessibility, and availability at the point of care, integrated into a Hospital Information System (HIS). Commercially available HIS often focus on administrative tasks and mostly do not provide additional knowledge based functionality. This paper works out advantages and disadvantages of several approaches and compares them against possible alternatives. Finally, experiences, gained by clinical use of two introduced systems, integrated in the HIS of the Vienna General Hospital, to analyze the little use of CDSSs in today’s clinical routine practice.

Keywords: Clinical decision support, Hospital Information Systems, Knowledge Acquisition, Medical Applications.

1 Introduction

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. It is generally assumed that every patient generates around 20,000 different data values on a daily base. Over 236 different variable categories in a medical ICU record are common and conclude that this far exceeds human intellectual capability [1]. Physicians and nurses are still performing time consuming manual data analysis for making the most optimal medical decision for each individual patient [11-13]. They must choose from and interpret a huge variety of clinical data, while facing pressure to decrease uncertainty, risks to patients and costs. The true essence of healthcare delivery is decision making - what information to gather, which tests to order, how to interpret and integrate this information into diagnostic hypotheses and what treatments to administer. Moreover, current ICU platforms are not offering an infrastructure for infection surveillance, data-driven guidance and modeling of critical illness.

The provisioning of Clinical Decision Support Systems (CDSSs) 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.

Since the potential of medical decision making was first realized, hundreds of articles introducing CDSSs 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.

Shortliffe [20] outlines, that “the greatest barrier to routine use of decision support by clinicians has been inertia; systems has been designed for single problems that arise infrequently and have generally not been integrated into the routine data-management environment for the user”.

The Clinicians’ acceptance and utilization of CDSSs depends on its workflow-oriented, context-sensitive accessibility and availability at the point of care, integrated into a Hospital Information System (HIS). Commercially HIS often focus on administrative tasks and mostly do not provide additional knowledge based functionality [33, 36]. This paper surveys on two concrete applications the capabilities as well as limitations of CDSSs. Both presented systems are established as real-time applications. They are fully integrated in the HIS, and have reached the state of extensive clinical testing at the Vienna General Hospital. Finally, experiences, gained by clinical use of the systems, are used to analyze the little use of CDSSs in today’s clinical routine practice.

2 Methods

2.1 Clinical Decision Support Systems (CDSS)

CDSS can be broadly defined as software applications 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 in clinical decision-making.

Generally CDSS are any type of application that support the decision making process. A generic 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 (physicians) decision-makers. A typical therapeutic cycle in a simplified view is shown in Fig.1.

![Diagram of Therapeutic Cycle](image)

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

In principle a DSS can be classified into the following six frameworks [22]: Text-, Database-oriented, Spreadsheet-oriented, Solver-oriented, Rule-oriented, and into a Compound DSS. A compound DSS is the most popular classification for a DSS [37, 38]. It is a hybrid system that includes two or more of the five basic structures of DSSs. Patient data can be input by digital entry, queried from a HIS, Patient Data Management Systems (PDMS) or transmitted from other medical devices. Patient data are compared against a knowledge-base and made sense of by an inference mechanism. The inference mechanism 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 [8], [21]. Expert or knowledge-based systems are another type of DSS capable of being programmed to perform decision making at the level of a domain expert [24]. These systems represent the most prevalent type of CDSS used in medical clinical practices today. Though CDSSs 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. In the next section two CDSSs integrated via web services in a HIS are presented. Both systems are established as real-time applications and have reached the state of extensive clinical testing at the Vienna General Hospital. The first one is to hyperglycemia management system for critically ill surgical patients. The second gives immune-suppressive therapy for kidney-transplant patients.

### 2.2 Maintaining Hyperglycemia

Hyperglycemia has been shown to be an independent risk factor of mortality in patients with stroke and myocardial infarction. There is increasing evidence that tight blood glucose (TBG) control improves outcomes in critically ill adults. Furthermore, strict control of hyperglycemia reduces the rates of infectious complications in surgical Intensive Care Unit (ICU) patients. The risk of mortality or significant morbidity is high among critically ill patients who are treated in the Intensive Care Unit (ICU) for more than 5 days. These patients are susceptible to sepsis, excessive inflammation and multiple organ failure, the latter often being the cause of death. Most intensive care patients, even those who did not previously suffer from diabetes, are hyperglycemic.

Hyperglycemia caused by insulin resistance in the liver and muscles is common in intensive care patients [2]. Van den Berghe showed that Tight Glycemic Control (TGC) i.e. Controlling Blood Glucose Levels (BGLs) within 80–110 mg/dl using intensive insulin therapy, provides significant improvement in mortality (8 to 4.6%) and morbidity in surgical ICU patients.

Several published clinical trials have demonstrated morbidity and mortality benefits of moderate-to-tight glycemic control in an intensive care environment [3, 4], [6], [9, 10].

**Tight Glycaemic Protocols:**

The tight management of hyperglycaemic crises requires expensive and labor-intensive procedures that are not achievable in all clinical settings. The currently implemented algorithm for achieving and maintaining hyperglycemia and the used tight glucose protocol at our hospital’s ICU is shown in Table I.

<table>
<thead>
<tr>
<th>Test</th>
<th>Result of BG measurement</th>
<th>Action</th>
</tr>
</thead>
<tbody>
<tr>
<td>Measure BG an admission to ICU</td>
<td>&gt; 220 mg/dl</td>
<td>Start insulin 2 – 4 U/h</td>
</tr>
<tr>
<td></td>
<td>220 – 110 mg/dl</td>
<td>Start insulin 1 – 2 U/h</td>
</tr>
<tr>
<td></td>
<td>&lt; 110 mg/dl</td>
<td>Don’t start insulin but continue BG monitoring every 4 h</td>
</tr>
<tr>
<td>Measure BG every 1 - 2 h until in normal range</td>
<td>&gt; 140 mg/dl</td>
<td>Increase insulin dose by 1 – 2 U/h</td>
</tr>
<tr>
<td></td>
<td>110 – 140 mg/dl</td>
<td>Increase insulin dose by 0.5 – 1 U/h</td>
</tr>
<tr>
<td>Measure BG every 4 h approaching normal range</td>
<td>60 -80 mg/dl</td>
<td>Reduce insulin by half and check more frequently</td>
</tr>
<tr>
<td></td>
<td>40 – 60 mg/dl</td>
<td>Stop insulin infusion, assure adequate baseline glucose intake and check BG with 1 h</td>
</tr>
<tr>
<td></td>
<td>&lt; 40 mg/dl</td>
<td>Stop insulin infusion, assure adequate baseline glucose intake, administer glucose per 10 g IV boluses and check BG with 1 h</td>
</tr>
</tbody>
</table>

In general protocols to assist in management of hyperglycemia are becoming more widely used and have been shown to improve outcomes for hyperglycemic patients. Several protocols for glucose control have been adapted [7], [25, 26], [28]. In a pilot study [5] was found that the majority
of patients were not achieving target BGL consistently and although the incidence of hypoglycemia was rare, the range of insulin infusion rates prescribed was often greater than patient requirements presenting a risk of overdose. This audit aims to further assess the success and safety of TGC in ICU [7]. As with any protocol, this algorithm alone does not guarantee improvement in quality of care or clinical outcome. However, in the context of the treating physician’s knowledge and experience, this approach could be expected to realize significant reductions in mortality and morbidity.

2.3 Immune-Suppressive Therapy for Kidney Transplant Patients

Many chronic kidney disease patients profit from a kidney transplantation. A necessary component after transplantation is an immunosuppressive therapy. As there is a narrow range between kidney transplant rejection and the side effects of over-immune-suppression (such as an increased vulnerability to infections), therapeutic drug monitoring is another necessary component [11].

The most frequently used immune-suppressive drugs are Calcineurin inhibitors, which inhibit the cell-mediated and humoral immune responses. One of those is Tacrolimus. Since the drug absorption rate varies, close therapeutic drug monitoring is necessary. According to Satohiro [14] the therapeutic range of Tacrolimus is located between 10-20ng/ml blood concentration to avoid rejection and infections. These Calcineurin inhibitors have many side effects, one of the most popular include reversible disturbances of liver function, cardiac toxicity, edema, blurred vision, depression, sleep disturbances and nephrotoxicity, neurotoxicity, and hyperglycemia [15, 16].

Currently the immunosuppressant dosage is determined on the basis of the actual medication level and various factors (immunological situation, time after transplant rejection reactions, laboratory values, etc.). The ultimate goal is to develop a theoretical model that maps the therapy with their influencing factors [16]. A theoretical model of the dosage determination will enable physicians to gain new insights into the treatment monitoring of immunosuppressive drugs and potentially enable automation of drug dosing.

2.3.1 Data Description

To create a immune-suppressive therapy model historical patient therapy data and laboratory parameters could be used within a period of 13 years from the General Hospital of Vienna. Data from 492 patients and 13.053 consequent examination dates were available for evaluation. These data include the measured blood levels of the administered medication and the daily medications, as well as the time of the medication measured and medication administered.

2.3.2 Data Processing and Analysis

In current clinical praxis, medication adaptations are based on preliminary medication levels and other characteristics of the patients.

Consequentially, medication adaptation and preliminary data have a strong correlation, thereby confounding each other. This makes a simple estimate of the effect of a medication adaptation almost impossible. The problem is illustrated in Figure 2 (left side), where in the x-axis (-1) means to adjust down, (0) to stay and (1) to adjust upward medication. The boxplot shows that if you lower the medication, a higher medication level could be expected. Avoid using too many capital letters. All section headings including the subsection headings should be flushed left.

Fig. 2: Confounding Effect & Validation

This could be explained by the fact that physicians only lower the medication if the medication level is already quite high, but this action generally does not completely normalize the medication level. The main problem is to obtain the pure biological response of the patients. Since only a few medication adaptations are frequent, these were divided into three categories: upward adaptations (1), down (-1) and retention of the medication (0).

3 Conclusions

3.1 Technical Aspects

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 through medical logic modules (MLMs) based on a language such as Arden syntax [18]. The Arden Syntax Server represents therefore the reasoning and inference mechanism with MLMs and processes the patient data, which is received from the HIS via web services. The communication mechanism of a CDSS will allow the system to show the results to the users as well as have input into the system. The HIS at the General Hospital of Vienna is i.s.h.med. This fully featured HIS represents the CDSS' communication mechanism. It provides a framework for medical documentation which can be easily customized in form of parametric medical documentation (PMD) to the special needs of the respective clinical departments.
### 3.2 Hyperglycemia Decision Support System

The communication mechanism of the CDSS is realized as a PMD of the HIS. The system is used for postoperative cardiac patients in an ICU at the Vienna General Hospital [29]. The advantages of the system are its easy application and generation of more specific knowledge bases with MLMs, which allow smoother treatment. The CDSS is currently being tested with a sample of prospective randomized cases currently undergoing treatment (Fig. 3).

![HDSS Application](image3)

Fig. 3: HDSS Application

The results confirm the applicability of the application to represent medical knowledge, thus rendering the glycaemic process transparent and comprehensible. A direct connection, for instance with an insulin perfusion pump, would allow smooth adaptation continuously. The hyperglycaemic control may be better if appropriate safety controls can also be put in place. Safe implementation of tight glycemic control requires appropriate monitoring to reduce the risk of this complication [39]. Several protocols for glycemic control have been adapted [5, 9, 10, 25, 27, 32]. In a pilot study could be found that the majority of patients were not achieving target BGL consistently and although the incidence of hypoglycemia was rare, the range of insulin infusion rates prescribed was often greater than patient requirements presenting a risk of overdose. This audit aims to further assess the success and safety of TGC in ICU [32].

Alerts are triggered within several time depended columns of the application. The actual values and proposals and alerts are displayed in different coloured symbols. Currently the implemented colours are red, yellow and green. These colours represent an urgent, a warning, and an information level (Fig. 4). If there is no reaction within a defined time period, i.e. column on an urgent (red) information level an acoustic alarm is activated also to force an urgent reaction.

With the control unit itself it’s possible to change the glucose level, according to the proposals of the program. If different settings to the proposed one have to be set, there is also a possibility to log this information. The logging feature allows a fine tuning of the knowledge bases off line.

![HDSS alert screen](image4)

Fig. 4: HDSS alert screen

### 3.3 Immunosuppression Therapy System

To create a knowledgebase for immunosuppression therapy the medication blood level thresholds has been estimated statistically by a regression tree. Since this is an ordinal outcome variable, the method of Conditional Inference Trees (CITs) [17] has been chosen. Classes could be formed where the statistical relationship between preliminary data and the medication adaption isn’t longer significant. The determined classification is shown in Table II.

| Table II: Classification determined from the CIT |
|---|---|---|
| Class | BL | Additional Decision Parameters |
| 1 | ≤3.8 | |
| 2 | (3.8,4.7] | TSS: ≤27153 |
| 3 | (3.8,4.7] | TSS: >27153 |
| 4 | (4.7,6.9] | TSS: ≤6490 |
| 5 | (4.7,6.9] | TSS: >6490 |
| 6 | (4.7,6.9] | TSS: >49281 |
| 7 | (6.9,9.3] | TSS: ≤4544 |
| 8 | (6.9,9.3] | TSS: >4544 |
| 9 | (9.3,10.9] | TSS: ≤34018 |
| 10 | (9.3,10.9] | TSS: >34018 |
| 11 | (10.9,13.9] | APR: ≤7.5 & PRO: 3,4 |
| 12 | (10.9,13.9] | APR: ≤7.5 & PRO: 0.1,2 |
| 13 | (10.9,13.9] | APR: >7.5 |
| 14 | >13.9 | LT: ≤2 |
| 15 | (13.9,15.2] | LT: >2 |
| 16 | >15.2 | LT: >2 |

The CIT took the following parameters into account: Tacrolimus blood level (BL) [ng/dl] now and at the last ward round [ng/dl]. The dose of the proliferation inhibitor [mg], of the additional Aprendisolon (APR) [mg] and of the last Tacrolimus (LT) [mg] administered. Further parameters are sex, age at – and time since surgery (TSS) [h]. A model validation was performed with 80% of the data for the training set and 20% for the test set. To test the model, the ensuing medication blood levels were compared to the respective medication adaption [23]. The CIT formed homogenous classes to eliminate the confounding effect. When we performed model validation for one of the calculated groups, the distribution behave largely
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.

The greatest anticipated benefit of a CDSS lies in the constituency and uniformity in applying decision criteria of a given situation. Physicians have difficulty making decisions because they cannot exhaustively consider every factor relevant to the decision, due to either limited memory or limited information.

Anticipated limitations of CDSSs 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 [30, 35, 39].

Physicians have no shortage of data available to them. Thus, physicians have found that currently available CDSSs are not able to meet their more complex information needs. As mentioned above one big argument of the rare utilization at this time is that most of the CDSSs have not progressed beyond the prototype stage. There are no standards or universally accepted evaluation or validation methodologies to ensure that the system’s knowledge base is complete and correct.

Further questions about CDSSs are: Does the use of a CDSS improve the quality of decisions produced? And are the economic or other benefits, as for instance patients comfort, attributable to the use of the CDSS?

The absence of a well-defined or universal evaluation methodology makes these questions 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 CDSSs. Most of the CDSSs are university-based developments, and still in prototype stage. These costs regarding the initial investment of CDSSs tend to be hidden and therefore difficult to access.

This frightens or hinders the industry’s interest in funding and encouraging the development of CDSSs in health care in general [19]. Still, many physicians have a real positive outlook on the potential for these systems, particularly relating to practitioner performance. However, until the use of CDSS is a routine as the use of the blood pressure cuff, it is important to be sensitive to resistance to using these systems.

4 Conclusions

When CDSS or DSS in general where initially developed, each knowledge base and inference mechanism required programming before the knowledge base content could be written. As the field evolved, researchers found that it was possible to separate the inference mechanism from the domain specific knowledge and databases. This key design feature became responsible for the commercial success of decision support systems.

Producing standard inference mechanism and knowledge bases made it possible to unplug one knowledge base and then connect a different one. Based on the literature, current computer-based clinical CDSS are limited in application. Roughly seventy known proprietary medical CDSS exists. Only ten out of seventy CDSSs geared towards routinely use. There is no information available about a real daily average usage of these systems.

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. CDSSs 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.

5 References


