Chapter 25

MEDICAL DECISION SUPPORT SYSTEMS

The Wide Realm of Possibilities

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Abstract: Need and know-how have come together to start in earnest the era of medical decision support systems. Reducing medical errors while saving costs, and discovering new medical knowledge while reducing information overload are among the conflicting needs addressed. Decision support systems span the realms of home health care to enterprise-wide systems to medical research laboratories. Limited use of electronic patient records, incomplete standards, and difficulties in encoding all aspects of the patient encounter are examples of hurdles to overcome. In the short-term we will see more intelligent alerts, earlier indicators of critical conditions discovered by data mining, and context aware displays. In the long-term we hope to see a highly integrated continuum of care with guardian angel and coaching applications helping us not only in illness, but also with our health and wellness.

Keywords: Decision support systems, medical error reduction, electronic patient record, data mining, knowledge representation

1. INTRODUCTION

Science fiction would have us believe that the manifestation of medical decision support systems requires autonomous robots or holograms that can completely replace humans. Though far more mundane than those of science fiction, medical decision support systems have existed for decades with many now in common use, and saving lives. Today’s technologies coupled with the driving forces of standardization efforts, consumer and corporate advocacy, governmental initiatives, and sociological changes in the acceptance of computers in medicine are all escalating the use of more advanced decision support systems. These systems will help answer the cry for reducing medical errors, reducing medical costs, detecting diseases earlier, and achieving preventive medicine.

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But what are these existing systems, and what might they be in 5 years, in 10 years? In this chapter you will be introduced to the wide scope of medical decision support applications and the driving forces behind them. We will paint our vision of the future paired with the hurdles in front of us and the technologies to get us there.

Broadly speaking decision support systems are any systems that help in the decision making process. Key in this definition is the word *help*. These systems do not necessarily make decisions, but more times than not just *help* in the decision making process. Accomplishing this can be done in numerous ways as will be demonstrated through examples in the following sections. Similarly, a key word missing in the above definition is *electronic*, or *computer*. There are many non-computer-based decision support systems (i.e., reference books like the *Physicians' Desk Refernce*[1], using colleagues for second opinions). However, we will restrict ourselves to computer-based decision support systems in this chapter.

Our focus in this chapter will be on medical decision support systems outside the domains of medical imaging and bioinformatics, as these have their own dedicated chapters. Core to this chapter will be Clinical Decision Support Systems (CDSS), applications used in a clinical setting by medical professionals to help them make decisions. However, clinical decision support systems alone would be too limiting, so we also include applications for non-professionals, systems used outside of formal clinical environments, and systems to enhance health care research.

2. DRIVERS

Many drivers are indirectly responsible for the increasing prevalence of and the push for decision support systems, but perhaps the biggest influence has come from two IOM books: *To Err is Human*[2], and *Crossing the Quality Chasm*[3]. Almost single handedly these books have raised the awareness of the number of lives lost per year due to medical errors: 96,000 per year in the United States alone. Far more are injured or suffer an adverse experience due to medical errors. Reducing medical errors has become the number one driver in healthcare today. Unfortunately, the number two driver is close behind and can be seen as conflicting: reducing medical costs. Other drivers that indirectly help promote the use of decision support systems are improving the quality of life, advancing medical science, combating the shortages of physicians and nurses, and making the use of medical knowledge and technology more widespread and timely. As we drill down into these drivers we see directly the influencing factors behind the growing interest in decision support.

2.1 Data overload

Advancing medical technologies are giving us access to more data about patients than ever before. Just as in imaging, where we produce more images than doctors can look at, patient-monitoring equipment provides innumerable real-time physiological data as more parameters can be monitored, and newly developed tests mean more lab values to sort through. All this in a world where information technology allows us to store unlimited amounts of data indefinitely. Meanwhile there is a real or perceived need to run more tests for fear of lawsuits. Data availability does not necessarily lead to better outcomes though, especially when coupled with the need to reduce costs, which can mean less staff available, less training among staff members, or just less time to spend per patient.

Data need to be turned into information. Data are not information unless they are necessary for the current medical decision and are understandable in the time available for the decision. Decision support systems can help with visualization. In imaging this could mean producing a fly through of 4-D data sets or highlighting suspicious areas. For monitoring data this could mean showing trends instead of raw data, and highlighting values outside of expected results.

2.2 High complexity

Devices can be too complex to operate, processes can be too complex to follow, not to mention how complex diagnosing and therapy planning have become with all the new medical knowledge and therapy options. Coupled with complexity is the need for more and better training of users. With the push to reduce costs, systems that allow users with less training to do their job to the level of highly trained individuals will be highly sought after. One solution to help reduce training time is for vendors to have a common interface look, feel, and functionality across their product lines as Philips has done with Vequion. Decision support technologies can also play a role by automating complex workflows, and helping navigate through complex diagnostic and therapeutic decision trees.

2.3 Ubiquitous availability

Where someone lives, works, and vacations can have a direct influence on the quality of medical care they receive. Rural communities as well as impoverished communities often lack world-class medical facilities. Telemedicine offers a partial solution, but can actually increase the number of medical personnel needed per patient case, as you need both local and remote staff. Decision support systems that help bring the expertise directly to locations without experts in a certain area can do so without putting undue burden on the experts. Such systems can be made available to serve people at all levels of the healthcare delivery chain, including radiologists working outside their subspecialty, primary care physicians working with rare conditions, technicians setting up for non-standard imaging exams, and even potential patients in deciding if they need to see a healthcare professional and which one.

3. DEFINITION BY EXAMPLES

The primary goals of clinical decision support systems are focused on assistance with diagnosis and patient safety. In diagnosis, clinical information is used to enhance decisions. Clinical decision support systems vary greatly in their complexity, function and application. Initially these systems differed from clinical practice guidelines and critical pathways in that they required the input of patient-specific clinical variables and as a result provided patient-specific recommendations. Paper-based guidelines and pathways, in contrast, provide more general suggestions for care and treatment. However, electronic clinical guidelines and electronic critical pathways as part of the clinical decision support system can combine general suggestions with patient-specific clinical information, as will be shown among the examples below.

3.1 Help making difficult decisions

You've just received a patient in the Emergency Department (ED) who is exhibiting signs of hemiparesis and aphasia. You suspect stroke. If this patient has had an ischemic stroke and the onset was within the past three hours, thrombolitics may lead to improvement and even a full recovery. However, if this patient has suffered a hemorrhagic stroke, the same treatment may cause death. What do you do?

Although stated simply in the scenario above the decision is not just a critical one, but also difficult because of the number of factors that must be weighed. Knowledge exists to make the best decision for/with the patient, but today in the United States there are a paucity of hospitals with this knowledge[4]. Decision support systems that lead the ED staff through the recommended battery of questions and tests could make the positive outcomes obtained in certified/designated stroke centers more wide spread[5].

3.2 Help making simple yet repetitive decisions

Performing simple arithmetic calculations and looking up values in tables are certainly skills that nurses and doctors have, but over time errors will be made. Computers on the other hand will perform the same all the time. As a patient do you want a nurse responsible for 10 patients calculating a medication dose based on your body weight in kilograms after obtaining your weight in pounds? How about a first year resident after being woken up at 2:30 in the morning?

Among the most common forms of decision support systems are drug-dosing calculators. These computer-based programs calculate appropriate doses of medications after clinicians input key data.

Physiologic calculations are also provided in advanced bedside monitors and information systems. These calculations utilize existing information and proven formulas to eliminate errors and save valuable clinician time.

The potential exists for more advanced automation via closed loop and/or clinician-directed closed loop systems. These systems would monitor the patient's variance from a target and apply or ask for therapy to bring the patient back. Glucose levels could be an early target for these types of systems. Specific examples of closed loop therapy have already been applied. For example, Kouchoukos and Sheppard[6] built a computer-based system in 1967 that was used in the observation and treatment of patients following cardiac surgical procedures. The system performed automatic control of blood infusion and vasodilating agents by closed loop feedback control techniques. Excessive blood loss was detected via hourly evaluation of chest tube drainage patterns following surgery. The infusion rate of pharmacologic agents was calculated according to a specified dosage. According to literature, the use of the system contributed to the reduction of patient time spent in the unit to 24 hours or less for the majority of the patients.

3.3 Help reducing time, errors, and variance of practice

For years clerical staff have set up radiologists' workspaces for reading films. Current and previous films are pre-fetched and arranged on rotating light boxes, alternators, to speed up the process by which they read films. Everything the radiologists will need to make decisions about the films is within their reach and in the order they will need it. On the other hand, clinical decisions by doctors in the various intensive care units, for example, require looking through many pages of a paper-based *medical record or screens of a an electronic medical record. Why can't the efficiency afforded radiologists be more widespread?*

Clinical guidelines, critical pathways, bundles, standing orders, and other varieties of recommendations are all knowledge sources for what to do in various situations[7]. If a computer system can use these in the way a clerical staff uses knowledge of how radiologists practice, then given the decision an intensivist in the Medical ICU has to make next about a patient, the computer system should be able to anticipate the information required to make the decision. If so, the system can then pre-fetch and arrange the information in such a way as to help speed up the decision making process. As time is related to cost, money can be saved.

Additionally, because all the recommended information required to make a decision is pre-fetched and displayed in an easy-to-view manner, errors of omission will be reduced. Likewise, such a system can be set up so that all staff using the system will be making their decision starting from the same set of information, thereby reducing the variance in practice among staff members.

3.4 Help in combining imaging and non-imaging information for diagnoses

A 53-years old marketing executive just had a state-of-the-art thoracic CT scan. She was a heavy smoker for 20 years, but quit 8 years ago. The radiologist is looking at her CT scan on a workstation accompanied by a CAD (Computer-Aided Detection) system, which can help identify suspicious lesions. Several of the lung nodules have a diameter of 1 mm. Can the radiologist determine that these nodules are malignant or benign without ordering a biopsy or repeating a CT scan in half a year?

Diagnosis is one of the most difficult tasks clinicians face everyday, it carries with it many serious implications, such as prognosis, treatment options, and often life or death. Early stage cancer diagnosis in asymptomatic patients is an especially a challenging task even for experienced physicians. About 1.4 million new cancer cases (excluding basal and squamous cell skin cancer) are expected to be diagnosed in the USA alone in 2005 and cancer is the second leading cause of the death in the USA[8].

Early detection and diagnosis of suspicious lesions allow for earlier intervention, which lead to better prognosis for the patients. While recent advances in imaging modalities (e.g. 128-slice CT scanners), molecular imaging, and genomics make possible the diagnosis of cancer at an earlier stage than ever before; it also creates a huge amount of data (images, lab reports, findings) that have to be interpreted by radiologists and/or oncologists. Computer Aided Diagnosis (CADx) can facilitate fast and accurate diagnosis and can increase workflow[9]. However, it is important to emphasize, that these system should provide only a second opinion to the clinicians, which they can use to help form a diagnosis or improve their confidence.

While some CAD systems that help to localize abnormalities (e.g. tumors) have already received FDA approvals and started to be 'must-haves' with imaging equipment (e.g. CAD for breast cancer), CADx systems are still mostly in research and development stages. CADx systems, more so than CAD systems, require state-of-the-art thin slice CT scans to perform well. Multiple 3D characterizations of lesions are derived from thin slice CT scans by the CADx systems. This information combined with patient information (e.g. age, sex, family history, cancer history, etc.), findings from molecular imaging, and findings from molecular diagnostics may all be used to build CADx systems that clinicians will use and trust. Desired output of CADx systems include a likelihood estimate of malignancy, or pointers to similar cases with known diagnoses[10].

3.5 Help in staying aware of critical changes

The alarm from the ECG monitor for the patient in MICU room 3 has just gone off for the sixth time in only two hours into your shift. Mr. James has been particularly restless today, and in the previous five times the alarm was caused by artifacts generated by his excessive movement. When the alarm goes off for the sixth time you happen to be on the phone with another patient's cardiologist, one that you have been trying to get a hold of for the past 45 minutes. Do you finish your conversation with the cardiologist or go check out the alarm?

Studies have shown that upwards of 96% of patient monitoring alarms are not significant[11]. Recent studies have shown that utilizing multiple hemodynamic signals can be an effective way to screen out many of these false alarms[12]. These so called intelligent alarms can positively impact patient safety and improve the overall clinical workflow.

An example of advanced alarming is an Advanced Event Surveillance (AES) application[13]. This application provides a way for clinicians to correlate parameter information in a way that it is easier to interpret changes in a patient's condition. AES allows the clinician to combine their choice of parameters and set a deviation threshold, combined with delay times. For example: Heart rate 10% change in 60 seconds *or* 6 bpm for 60 seconds.

The resultant type of notification can be selected depending on the severity of condition.

In clinical practice AES can be used by clinicians to enter protocol requirements. An example of this is sepsis. All four physiologic parameters (HR, RR, BP and temperature) recommended by current practice guidelines are routinely available in critical care monitoring. The laboratory parameters of CO2, WBC and serum lactate that are also part of early identification can be measured easily, quickly and with minimal expense. When used together, this information may provide early recognition of sepsis.

3.6 Help reducing the education and experience required

When seventy-two year old Emily Madison had called into the living room five minutes ago to tell her seventy-six year old husband, Andrew, that dinner was ready, all she heard back was a muffled groan. She just assumed that it was because his beloved Yankees were losing again, and yelled back "just Tivo it and come eat." Now, when she walks in she finds him slumped in his chair and unresponsive. What can she do?

Perhaps the poster child for how decision support can put advanced capabilities into the hands of untrained or minimally trained people is the Automated External Defibrillator (AED) such as the Philips HeartStart Home Defibrillator[14]. AEDs for home use are now available in the United States on-line and in stores without a prescription. Although some training is recommended, most people can operate the HeartStart Home Defibrillator without previous training. From the time the unit is opened, very simple pictures and voice prompts lead the user through each step of its use. Decisions that 15 years ago had to be made by highly trained physicians, nurses, and paramedics, are now made by the AED. The current day user does not have to differentiate between atrial fibrillation and ventricular fibrillation, ventricular tachycardia and asystole, or even know what 200 watts/second is. All this knowledge is built into the AED.

3.7 Help in knowledge discovery

Thousands of patient cases from various ICU facilities at multiple hospitals have been collected into one database. Contained within this database are all the reasons for admissions, monitored data (ECG, SpO2, arterial blood pressure, etc.), medication administrations, lab results, nurses' notes, final outcomes, and more. In this wealth of data, is there new knowledge to be discovered?

Data mining, the analysis of data sets for the purpose of discovering new knowledge, helps in that the knowledge discovered can be used in making subsequent clinical decisions. An example of this is work from Philips Research that uses data mining of large ICU/CCU data sets to help determine the proper parameters for a predictive index of patient instability[15]. Figure 5-1 shows a subset of the types of data that new knowledge will hopefully be drawn from. Methods currently exist for predicting mortality at the time of hospital admission; however, they are not adequate predictors of patient deterioration during the course of stay.

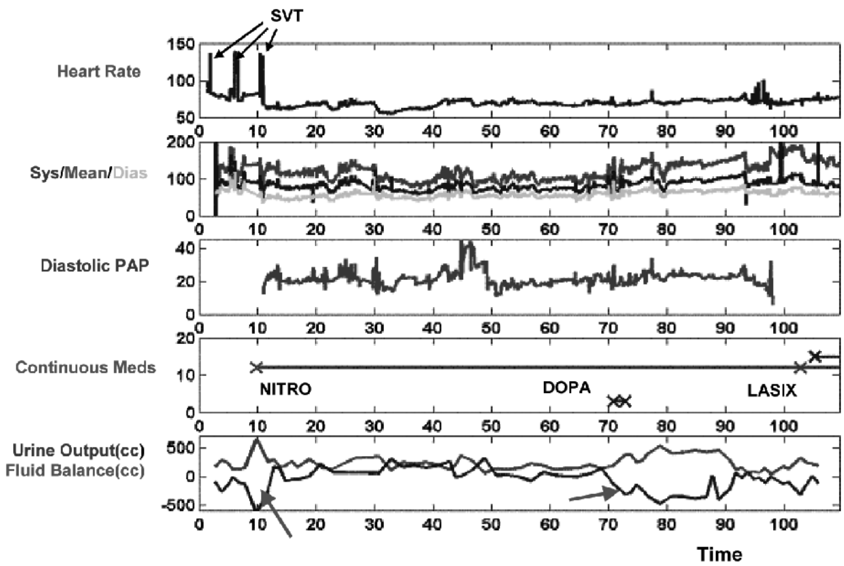

Figure 25-1. Sample of some ICU parameters used in data mining for knowledge discovery.

Two common pathways for a patient's condition to deteriorate in the ICU are single-organ system failure (SOSF) and multi-organ system failure (MOSF). SOSF and MOSF have multiple causes, but all frequently indicate that the patient's condition is worsening, which usually results in a poor outcome. Early identification of SOSF or MOSF by identifying the initial signs of patient deterioration could lead to earlier interventions and in turn, better outcomes. But what are these signs? This is where data mining comes in.

Working with a large database of ICU/CCU patient cases collected from a consortium of Boston area hospitals, universities, and companies, Philips Research performed data mining on the database to discover similarities among patient cases where the patients ended up having SOSF or MOSF. Key to this whole process is that the outcomes of the patients were known.

After applicable verification resulting early indicators can be set up as part of an existing real-time patient monitoring system.

4. TECHNOLOGIES

Implementing the capabilities described above in the scenarios requires multiple technologies, which can be grouped into two main categories: knowledge discovery, and knowledge representation and interpretation. Far too many technologies exist to cover in this chapter, however we present the goals behind using a class of decision support technology along with a brief mention of some of the algorithms themselves.

4.1 Knowledge discovery from data (KDD)

Knowledge discovery from data, also known as data mining, attempts to find potentially useful relations from data sets, with the goal that discovered knowledge can eventually be used to help predict some medical event. Discovered relationships may or may not be easily understood by humans. Acceptance of new knowledge discovered by some of the various methods discussed below is greater and quicker when the causality between the signs discovered and outcomes observed is easily explained. In other words, there is an explainable mapping from patients' phenotypes to their outcomes. Technologies involved in knowledge discovery for data mining include some combination of databases, statistical analysis, modeling techniques and machine learning. Data mining can be further categorized into algorithm types and specific algorithms as shown in Figure 5-2. The three most common algorithm types are:

Classification and regression: Classification is learning a function that maps (classifies) a data item into one of several pre-defined classes, for example mapping a patient's signs and symptoms onto a specific disease. Regression is learning a function that maps a data item to a real-valued prediction variable, for example determining the predictive value of an antigen from a blood test (like PSA) to the probability of having a disease (prostate cancer).

Clustering: Clustering breaks a set of data records into groups of similar content in such a way that the groups are as dissimilar as possible. Clustering is helpful when the user does not know the nature or structure of the data, and is looking to gain insight into the distribution of the data. It is often used as a pre-processing step for classification algorithms.

Dependency modeling: Dependency modeling attempts to find significant dependencies among variables. A simple example would be, if

82% of the time a patient has a specific blood test come back high, a specific test from urinalysis comes back low. The goal is to find much more complex dependencies than the example, like patient acuity indices.

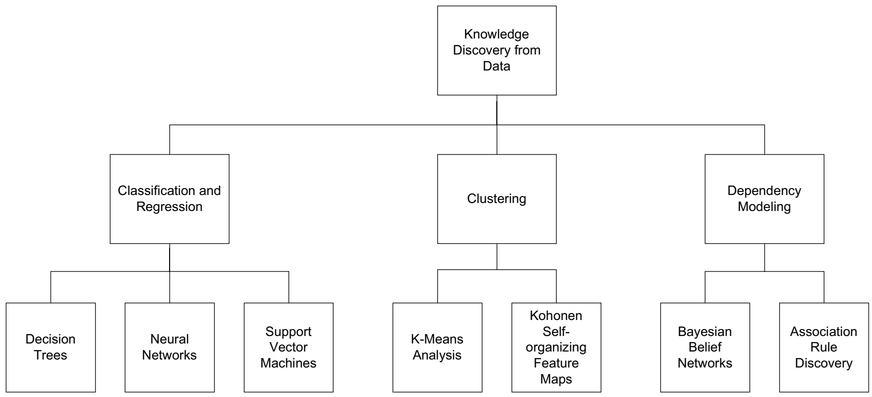

Figure 25-2. Various data mining technologies and representative algorithms.

4.2 Knowledge representation and interpretation

Knowledge representation is about encoding knowledge in an information system in such a way that it can be used later by decision support applications. This goes far beyond storing and retrieving information in/from a database or a data structure in that there is a need for algorithms to interpret the information; it must be understandable to both humans and machines.

Beyond the question of how do you best represent knowledge, is the question of what knowledge do you want to represent, and what do you want to be able to do with it. Four such areas alluded to in Section 3 are:

Differential diagnoses. Determining which of two or more diseases with similar signs and symptoms is currently afflicting the patient is a process that can be aided by algorithms. The type of algorithm to use is dependent on the knowledge known about the patient and the possible diseases. If the causal logic to go from signs and symptoms to diagnosis has been well articulated as a set of rules, then a case-based reasoning system could be the best approach. When the sensitivities and specificities of various tests used to diagnose are well known then a Bayesian Network could offer the best results. When many previous cases with known outcomes are available to learn from, a neural net approach may offer the best results.

Most existing work for CADx follows the same methodology as supervised learning: starting with a collection of data with ground truth, a classifier is trained with the data using a set of features (computed e.g. from diagnostic images) that are believed to have enough discriminant power to distinguish between malignant and benign lesions. Challenges include extracting the features that can discriminate between categories, finding the most relevant features from a feature pool, combining heterogeneous information (e.g. image-based features with patient data), and finding similarity metrics for example-based approaches.

Clinical guidelines. Clinical guidelines along with critical pathways recommend procedural steps and options for next steps based on a patient's condition. Adherence to these guidelines and pathways is generally seen as a way to have more consistent treatment of patients among practitioners and to reduce medical errors. Executable clinical guidelines attempt to follow the course of a patient's care for the purpose of being able to alert users to an action they are about to take that is not the recommended one, advise on what step is next, and to anticipate the care provider's needs for information, order sets, and resources.

Workflow. Closely related to executable clinical guidelines is workflow automation. Whereas clinical guidelines focus on the clinical needs of the patient, workflow focuses on the interaction among care providers, management, and patients. Workflow automation systems allow designers and users to specify actions to automatically take place upon the completion of various tasks. For example, if we look at a patient who has just shown up for an outpatient diagnostic cardiac catheterization, they will first check in at the reception desk. After the receptionist completes this task, notification of the patient's arrival should automatically be sent to the nurse charged with this patient. The nurse may be automatically presented with a task list that specifies steps to take with the patient, like getting a release form signed, drawing blood, obtaining vitals, etc. Any one of these actions, or all of them together may trigger notification of other people that will be involved with the patient to start certain tasks, and so on.

Modeling. Modeling can be used in various ways. One way, not mentioned above, is to help with a differential diagnosis. With a model of a physiological system, patient parameters can be entered into the model to help determine the root cause of why specific parameters are abnormal, like low cardiac output or hypotension. Another use of a physiological model can be to ask 'what if' scenarios. Again the patient's parameters are input to the model, but now we ask "what will happen to this patient if we give him a vasodilator?" or "what will happen to this patient if we reduce the oxygen percentage on her ventilator to 28%?"

5. IMPEDIMENTS

Medical decision support systems have been around since the 1960's, but the vision from the 60's of what these systems would be doing here in the 21st century is not[16]. Why is this? The following sections present some of the bigger contributing causes.

5.1 Electronic patient record

Access to clinical data in electronic form is essential for creating computer-based decision support systems. Unfortunately this is not the norm. Less than 20% of hospitals are completely digital[17]. Although this situation is a currently a major impediment for decision support systems that require integration of data from all aspects of a patient's care, there are still plenty of opportunities for decision support systems that run on standalone systems or minimally integrated systems, like departmental information systems, lab systems, image review workstations, treatment planning systems, order entry systems, and monitoring systems.

5.2 Standards

Standards like DICOM and HL7 have made great progress in providing standards for many aspects of data capture, storage, and exchange[18,19]. Other standards exist for specialty areas. But even if standards existed for all aspects of clinical care, impediments would still exist:

- Legacy systems may not support standards or the current versions of standards.
- Not all vendors provide solutions that support standards.
- There are multiple standards, sometimes overlapping.
- Standards are continually evolving making today's state-of-the-art systems, tomorrow's legacy systems.
- The granularity of data supported by standards is often too course grained for the requirements of decision support systems. This issue is closely related to the coding of data.

5.3 Coding

Coding is the translation and classification of data, typically from a human readable form to a form that can be processed by a computer. Many coding schemes exist; many overlap, and there are even coding systems that convert from one coding scheme to another. Coding systems suffer from all the impediments of standards, plus more. At first glance it may seem that coding systems excel at coding quantified data like heart rate, blood pressure, ejection fraction, etc., but upon further inspection there are still difficulties. Taking ejection fraction as an example, coding the numbers is easy, but we may need to know by which method was the ejection fraction established (ultrasound, MR, or in a hemodynamic lab), and who or what performed the segmentation? This information may not matter for a specific patient's care, but may matter for a data mining application evaluating the predictive capabilities of ejection fraction as an indicator for a specific condition. Beyond the capabilities of the coding system itself are the difficulties of automating the coding process. Perhaps the most difficult task for automated coding systems is the coding of free text. Without extremely advanced natural language processing capabilities any automated coding system will fail to differentiate the clinical significance of the following two patients' chief complaints: "I get chest pains when I take my dog out for a walk," and "I sometimes get chest pain watching TV."

5.4 Human computer interaction

Like most computer applications, the application's human computer interaction can make or break its acceptance. Many early-day decision support systems failed because of their user interfaces, even though they produced clinically correct and relevant results. Some of the most successful systems of today work almost completely behind the scenes, only becoming apparent upon alert situations. Some of the key issues in designing the human computer interaction of decision support systems are:

- Little to no training should be required to use the system. Designers need to keep in mind that many potential users of a system will not have time to receive training on your (and every other) system in the department. Many nurses work on a per diem basis or are 'floaters' filling in where needed. These people may end up working in a different department each day of the week. Likewise, doctors on rotations, doctors on call, and doctors with practice privileges in multiple hospitals face a similar situation.
- A system must strike the proper balance of being helpful without being annoying. An analogy from the computer world for many is their acceptance of the automatic spell checker with the red underlining of misspelled words, versus their loathing of the 'paperclip guy.'
- A system should improve or fit in as much as possible with normal workflow. A system that requires extra work and/or extra time to use, even if it improves clinical outcomes, will likely be rejected

5.5 Social acceptance

Beyond acceptance of the human computer interface discussed above are other acceptance issues. Key among these is trust. Healthcare professionals will not use decision support systems they don't trust. Trust may come from a number of sources:

- Knowledge of how a systems works, for example knowing and agreeing with the rules a rule-based system uses. (Note that neural network solutions don't meet this requirement and have met reluctance because of it).
- Evidence from clinical trials.
- Positive experience from using the system (the system appears to have both high sensitivity and specificity).
- Recommendations from colleagues and/or professional organizations.

5.6 Costs

Like all other purchases in a professional health care setting, there must be a positive Return on Investment (ROI). With decision support systems the anticipated ROI will be indirect. It is unlikely there will be decision support systems whose use can be directly charged for. A notable exception to this is that the use of certain computer aided detection systems for screening is reimbursable when used as second readers. The return will come from when time saved, errors reduced, training requirements eased, and staffing levels reduced get translated into money.

6. VISION OF THE FUTURE

Our vision of the future for decision support systems is tightly coupled with our vision of the future for electronic patient records. We envision a day when the so-called 'lust to dust' electronic patient records are a reality. Not only would these electronic records store data for the duration of one's life, but they would cover all aspects of your life that contribute to your health and well-being, providing true continuity of care.

Such an electronic patient record capability enables countless decision support possibilities. With proper access to large populations of complete electronic patient records by the medical research community, knowledge discovery through data mining could produce new knowledge at a never-before seen pace. Among the knowledge to be discovered would be early indicators of diseases and conditions. And if genomic data is part of the electronic patient record, personalized medicine will become the norm.

With the electronic patient record being a longitudinal record, guardian angel software could regularly look over the record for early indicators, be they single events, combinations of values, or trends over time. The electronic patient record need not stop with being just a keeper of medical records. Together with new sensors embedded in our everyday clothing and workout clothes, it could also obtain health and wellness data, and fitness data. This further enables applications playing the role of a diet advisor or a fitness coach.

Overall we see decision support adding to the already overwhelming amount of medical knowledge, but still making it easier to practice medicine. Saving time. Saving money. Saving lives. Sense and simplicity.

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