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Clinical Decision Support at Intermountain Healthcare

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Decision support technologies are becoming increasingly available to medical practitioners. A variety of programs designed to assist with drug dosing, health maintenance, diagnosis, and other clinically relevant healthcare decisions have been developed for the medical workplace. Increasing ease of access to personal computers is partially responsible for this growth. More important, however, is the growing dependency on computers to maintain part or all of the medical record. This has led to a growing interest in and, in some cases, dependency on, automated medical decision making to support the delivery of economical, quality care.

The Electronic Health Record (EHR) is the primary driver for the growing use of computerized decision tools. The growth in use and sophistication of the EHR has provided a backdrop against which clinical decision support systems (CDSS) appear as a logical consequence.

The EHR itself may be seen as a response to the increasing complexity and volume of both the clinical data associated with an individual patient and the medical knowledge necessary to assimilate and respond to this data. Recent evidence emphasizes the cost of failures to properly integrate the patient's findings with the fruits of medical science. In 1999, the Institute of Medicine estimated that between 44,000 and 98,000 Americans die each year because of medical errors.[1] Computer-based systems have been proposed as a remedy for a large subset of these errors.[2–5]

CDSS are often described as a cure for these and other failings in traditional care delivery. Much of the literature that has sparked this awareness comes from research done on an older generation of medical information systems. These systems reside on large mainframe computing hardware. Many of them have been designed to serve hospitals and have supported the patient care given there.[6–7] The applications and algorithms that were piloted in these systems have provided the background for the modern decision support technologies, which we see developing and evolving in client/server environments, on personal computers, and on systems based in Internet technologies.

Contributors to the science of applying computer systems to clinical practice include the several sites where hospital-based, medical decision support has been implemented and studied. Among the leaders in these efforts have been groups at the Regenstrief Institute in Indianapolis,[8] Columbia-Presbyterian Medical Center in New York,[9] Beth Israel Hospital in Boston,[10] and the HELP System at the LDS Hospital in Salt Lake City.[11] Successful efforts to incorporate decision support into order entry systems at the Brigham and Women's Hospital in Boston[12] and Vanderbilt University Medical Center in Nashville[13] are helping to define the direction that healthcare computing will follow in the future. In this chapter, we will review the experience gained in 25 years of CDSS delivered through the HELP System.

While a great deal can be learned from these hospital-based information systems, a new generation of medical computing environments is evolving. The creators of these environments are not satisfied to provide service for hospitalized patients alone. Instead, their intended scope is the entire healthcare record, covering patients served in both the inpatient and outpatient setting. The systems produced strive to provide a truly longitudinal and comprehensive medical record.

As new systems develop, the infrastructure necessary to provide CDSS is being newly engineered. This provides an opportunity to review the lessons learned in the older systems mentioned above, and to give those lessons form by incorporating them in new healthcare computing implementations. Below, we describe the architecture that we have chosen to incorporate into our newest CDSS as well as the effects of a growing focus on the delivery of new types of medical knowledge.

In this chapter, we focus on the experience of Intermountain Healthcare (IHC), a provider of integrated medical services in the Intermountain West, as an example of two phenomena readily recognized in a variety of healthcare organizations, as they adopt or extend systems designed to replace the paper-based medical record with an electronic one. These phenomena are the continued value of decision support applications in the hospital setting and the growing effort to project and expand the use of these technologies across the entire gamut of clinical care, supporting both new and old CDSS agendas in the inpatient and outpatient setting.

To illustrate decision support in the inpatient setting, we will describe a set of classic applications evolved in the HELP Hospital Information System (HIS) located at the LDS Hospital in Salt Lake City. Teams from IHC, the Department of Medical Informatics of the University of Utah, and commercial partners developed these applications. As a part of our description of decision support, we will discuss the data used and the mechanism through which suggested decisions are communicated to the user. Most CDSS in hospitals depend on simple algorithms to inform and remind users of important clinical data or of medical facts, which may change the decisions they have made or will make. Examples of these include decision

support tools that critique medication orders, and the system for identifying life-threatening laboratory results that are described below.

Below, we also discuss the adaptation of classical CDSS architecture to serve within an enterprise EHR. Rather than focusing on examples, we will endeavor, in this section, to describe the constituents of an environment appropriate for the creation of robust, enterprise CDSS.

An enterprise CDSS implies an enterprise model for knowledge management. This is particularly relevant in light of several new types of decision support being integrated into clinical computing environments.

A key example of these new decision support models is the CDSS associated with Computer-based Physician Order Entry (CPOE). CPOE differs dramatically from the classical decision support environments. These were generally constructed around a vision of the physician's workflow that differed little from the behaviors supported by a wholly paper medical record. CPOE requires an approach to design and delivery that reflects a careful remodeling of the way in which physicians manage a key part of their medical responsibilities, the overall direction of patient care.

The Help System

The overall setting for the CDSS examples described here is the HELP Hospital Information System (HIS). This system is a culmination of more than 25 years of development and testing.[11] It currently operates on high availability hardware supplied by the HP NonStop Enterprise Division. Software components of the HELP system have also been installed in many of the 20 hospitals operated by Intermountain Healthcare (IHC). At the LDS Hospital, IHC's central, tertiary care facility, the information system communicates with users and developers through approximately 2,000 terminals and more than 200 printers. The system is interfaced with a variety of other computer systems, including a billing system, a laboratory system, a medical records system, a digital radiology system, and a collection of local area networks (LANs) used by a variety of departments for local research and departmental management functions.

The HELP System consists of an integrated clinical database, a frame-based medical decision support system, programs to support hospital and departmental clinical and administrative functions, and the software tools needed to maintain and expand these components. The integrated clinical database contains a variety of patient data (Table 8.1) kept online during the patient's stay to allow review by health-care professionals at terminals throughout the hospital. These terminals allow the entry of pertinent clinical data into the HELP system by personnel who are involved in patient care. In addition, automated systems capture clinical information directly from monitors and other instruments in the hospitals' ICUs.

TABLE 8.1. Clinical data routinely captured by the HELP hospital information system (partial list).

Chemistry	Hematology
Medications	X-ray Findings
Allergies	Dietary Information
Blood Gases	Surgical Procedures
Electrocardiograms	ICU Monitoring
Intake/Output	Pulmonary Function
Demographic Information	Microbiology
Cardiac Catheterization Data	Respiratory Therapy Notes
Biopsy Results	Nursing Data
Select Physical Examination	Pathology Department Data
Admit/Discharge Information	History and Physical Exam Reports
Consult Reports	Procedure Reports

Use of the HELP system as a medical expert system has been a major focus of research since the system's inception. The result has been a set of embedded expert system development tools. The HELP System contains a decision support subsystem based on a modular representation of medical decision logic in frames.[14] These modules are used to: (1) define the data used in making the target medical decision; and (2) encode the logic that converts the raw data into the proposed decision. Decisions encoded in these modules resemble small computer programs written in a Pascal-like language. They are each designed to represent a single simple decision capable of activation in a number of ways. The language supports either simple or multiple outputs from a frame. This flexibility can be used to create more complex modules capable of deriving several distinct decisions from the same data.

This set of tools has led to the successful development of expert systems in blood gas interpretation,[15] intensive care settings,[16] and medication monitoring,[17] to name a few. The HELP System hardware and software environment has provided the setting for the implementation and testing of most of the decision support examples described below.

The history of decision support in the HELP System extends more than 25 years into the past. This classic hospital information system includes two types of CDSS systems. The first type focuses on narrowly circumscribed medical conditions. The logic is typically simple and the data requirements modest. The Critical Laboratory Alerting System described below is an example of this type.

The second type of CDSS is much less common. This type of tool attempts to discriminate among a group of important *diagnostic* entities using raw medical data. Diagnostic systems often attempt the challenging task of managing large degrees of uncertainty using pattern matching algorithms. Several of these systems have been, or are being, tested in the HELP

environment. Below, we describe experience with three of the experimental diagnostic applications.

Categories of Decision Support Technologies

Independent of the environment in which they are used, two elements of medical decision support applications are critical to their success. These are: (1) the mechanism by which the systems acquire the data used in their decision algorithms; and (2) the interface through which they interact with clinicians to report their results. These considerations have led us to describe different categorizations of decision support.[18] Although somewhat arbitrary, this categorization captures the idea that different models of computerized assistance may be needed for different types of clinical problems.

The four categories are:

1. Processes which respond to clinical data by issuing an alert;
2. Programs activated in response to recorded decisions to alter care (typically new orders); these applications work by critiquing the decision and proposing alternative suggestions as appropriate;
3. Applications that respond to a request by the decision maker by suggesting a set of diagnostic or therapeutic maneuvers fitted to the patient's needs;
4. Retrospective quality assurance applications where clinical data are abstracted from patient records and summary decisions about the quality of care are made and fed back to caregivers.

We will describe the first three types in this chapter.

Alerting Systems

Alerting processes are programs that function continuously, monitoring select clinical data as it is stored in the patient's electronic record. They are designed to test specific types of data against predefined criteria. If the data meet the criteria, these systems alert medical personnel. The timing and character of the messages vary with the alerting goals.

A typical example is a subsystem implemented within the HELP System that monitors common laboratory results and detects and alerts for potentially life-threatening abnormalities in the data acquired. This type of application is notable for the simplicity of its decision logic as well as for the magnitude of its potential impact.

The HELP System captures results from the clinical laboratory through an interface to a dedicated laboratory information system (LIS). The results are collected and returned to the HELP System for storage in the clinical record as soon as they are collected and validated in the LIS.

Laboratory results are reviewed by personnel engaged in patient care both through terminals connected to the HELP System and through a variety of special and general-purpose printouts, such as rounds reports generated by the HELP System. The "times" when the data are reviewed have only a loose relationship to the "times" when these data become available. Instead, the principal determinant of the review time is typically the work schedules of the physicians and nurses involved with the patient. The physician, for instance, may visit the hospital twice a day for rounds and review patient data only during those times unless some aspect of the patient's condition prompts a more aggressive approach.

Under these circumstances, abnormalities in laboratory results, especially those that are unexpected, may not receive the timely attention they deserve. In particular, unexpected laboratory abnormalities may go unseen for hours until a nurse or physician reviews them during their routine activities. Or, as some authors have noted, they may be missed entirely.[19,20]

As a response to this disparity, Karen Bradshaw-Tate and her associates have described an experiment with a Computerized Laboratory Alerting System (CLAS) designed to bring potentially life-threatening conditions to the attention of caregivers.[21–24] This system was constructed by reducing a set of 60 alerts developed during a previous pilot system[25] to the 10 most important (Table 8.2).

Six medical experts from the disciplines of surgery, cardiology, internal medicine, and critical care participated in the development of these alerts and the system used to deliver them. The alerts chosen were translated into computer logic and tested to determine that the logic functioned properly. Data from previously admitted patients were used to refine and test the logic.

Once the logic was deemed acceptable, an experiment was designed to evaluate the effect of the system on several intermediate outcome

TABLE 8.2. Alerts for which computerized alerting logic was created.

Alerting Condition	Criteria
Hyponatremia (NAL)	$Na^+ < 120$ mEq/l
Falling Sodium (NAF)	Na^+ fallen 15+ mEq/l in 24 h and $Na^+ < 130$ mEq/l
Hypernatremia (NAH)	$Na^+ > 155$ mEq/l
Hypokalemia (KL)	$K^+ < 2.7$ mEq/l
Falling Potassium (KLF)	K^+ fallen 1+ mEq/l in 24 h and $K^+ < 3.2$ mEq/l
Hypokalemia, patient on digoxin (KLD)	$K^+ < 3.3$ mEq/l and patient on digoxin
Hyperkalemia (KH)	$K^+ > 6.0$ mEq/l
Metabolic Acidosis (CO_2L)	$CO_2 < 15$ and BUN < 50
	or $CO_2 < 18$ and BUN < 50
	or $CO_2 < 18$ (BUN unknown)
	or CO_2 fallen 10+ in 24 hr. and $CO_2 < 25$
Hypoglycemia (GL)	Glucose < 45 mg%
Hyperglycemia (GH)	Glucose > 500 mg%

measures. Two approaches were tested for delivering the alerts. The first of these techniques was tested on a single nursing division to determine its acceptability. A flashing yellow light was installed in the division, and whenever an alert was generated for a patient in that division, the light was activated. It continued to flash until the alert was reviewed and acknowledged on a computer terminal.

The second approach was less intrusive to the nursing staff. Whenever anyone accessed the program used to review a patient's laboratory results, any unacknowledged alerts for that patient were immediately displayed along with the data that had triggered them.

The results of this type of intervention were tested in three ways. First, appropriateness of treatment was evaluated. The alerting system was shown to result in a significant increase in appropriate therapy for conditions involving abnormalities of Na^+, K^+, and glucose. Second, time spent in the life-threatening condition with and without the alerting system was examined. Finally, the hospital length of stay was examined. A significant improvement in this parameter was also noted for the patients with abnormalities of Na^+, K^+, or glucose.

This type of decision support intervention is becoming increasingly common as hospital information systems evolve.[26] In the inpatient environment where the severity of illness is steadily increasing, the possiblility of better alerting has the potential to improve quality of patient care.

Interestingly, the system for alerting on critical laboratory values has been re-implemented in recent years. The IHC laboratory that processes the inpatient laboratory values also serves a variety of locations into which the HELP System does not reach, notably a large number of outpatient clinics. Based upon the value of this type of intervention, Laboratory Services has instituted the process of having personnel telephone ordering physicians or other caregivers whenever critical laboratory values are detected. Thus, the limitations of a model that was restricted to select inpatient locations have been circumvented.

The developing enterprise information system, parts of which are described below, will provide yet another way to avoid the limitations of an inpatient system. This system can reach the caregivers associated with outpatients as well as inpatients, and it invites a re-implementation of the computerized version of this system in a way that provides comprehensive coverage. The evolving capability to move alerting to an outpatient setting is illustrated by the example that follows.

A recent alerting application designed to work in the outpatient setting is among the first to take advantage of a new, enterprise CDSS infrastructure. This application automates a part of the Chronic Anticoagulation Clinic's (CAC) anticoagulation protocol. This clinic manages patients that are taking anticoagulation drugs (principally Coumadin) for extended periods of time. The objective is to maintain each patient's International Normalized Ratio (INR) within a range specified for the patient. A key component is a

rule-based system that monitors coagulation studies for compliance with these goals and presents alerts to the clinical user through a computerized in-box. Alerts for dangerously altered INRs are also sent to the clinic nurse practitioner's pager so that immediate action can be taken.

The CAC protocol has been working since June 2003, and since then the clinic has come to rely completely on the alerts generated by the protocol. They replace a paper-based process and couple the prescribing practice of the physicians (captured in the enterprise EHR) with the clotting test results captured in the clinical laboratory that reflect the effectiveness of this therapeutic intervention.

Critiquing Systems

In the alerting example described above, the computer system responded to abnormalities in the data as they entered into the database by prompting those caring for the patient to intervene. In contrast, critiquing processes begin functioning when an order for a medical intervention is entered into the information system. Such methods typically respond by evaluating an order and either pointing out disparities between the order and an internal definition of proper care or by proposing an alternative therapeutic approach. Below, we describe a critiquing subsystem that specifically targets orders for blood products.

Over the years, it has become apparent that the transfusion of blood products is an important, often life-saving, therapy and that these same blood products must be ordered and administered with care. Not only are there significant reasons for anxiety concerning diseases that can be transmitted during transfusions, but also the limited supply and short shelf life of blood products make them a scarce resource to be used sparingly. In 1987, the Joint Commission for the Accreditation of Healthcare Organizations (JCAHO) began to require healthcare institutions to develop criteria for the use of blood products and to carefully monitor compliance with these criteria.

At the LDS Hospital, the response to these requirements was to develop a computer system designed specifically to manage the ordering of transfusions and to assist in ensuring compliance with criteria for proper use of blood products.[27–30] A central premise of the system design was that all orders would be entered into the computer and that physicians or nurses would enter all blood orders.

Embedded in the blood-ordering program is a critiquing tool designed to ascertain the reason for every transfusion and to compare the reason against strict criteria. The approach used provides information specific to the type of transfusion planned. For instance, when an order is made for packed red blood cells, the criteria in Table 8.3 are used to critique the order.

TABLE 8.3. Simplified criteria for ordering red blood cells.

Hemoglobin < 12 g/dl or hematocrit < 35% if age ≥ 35 years
Hemoglobin < 10 g/dl or hematocrit < 30% if age < 35 years
Oxygen saturation (SaO_2) < 95%
Active bleeding
Blood loss > 500 ml
Systolic blood pressure < 100 mm Hg or heart rate > 100 bpm
Adult respiratory distress syndrome (ARDS)

The process of entering an order into this system includes several points at which information bearing on the propriety of giving blood products is displayed. As a first step, the physician is shown the blood products ordered in the last 24 hours. This is followed by a display of the applicable laboratory data. Then the user chooses the specific blood products required along with the number of units and the priority (stat, routine, etc.). At this point, the user is asked to document the reason for the order. A list of reasons, specific to the blood product chosen, is displayed, and the user chooses the appropriate rationale for the intervention. The computer then applies the stored criteria and determines whether the order meets the hospital's guidelines.

If the guidelines are met, the order is logged and the blood bank and nursing division are informed electronically and via computer printout. If the criteria are not met, the user is presented with a message stating the applicable criteria and relevant patient data. The physician or nurse may optionally decide to place or cancel the order. If the order is made, he or she is required to enter the reasons for the decision to override the system.

The criteria used are the result of a consensus effort by the LDS Hospital medical staff. The criteria were developed using primarily published guidelines but with some adaptations for local conditions (altitude of 4,500 feet). The criteria have undergone several modifications based on experience as well as new definitions of standards for these therapies.

One way of measuring the effectiveness of the system's various critiquing messages is to examine the frequency with which the process of ordering blood products is terminated as a result of the feedback. During one six-month period, the ordering program was entered and then exited without an order 677 times. This was 12.9% of the total uses. We estimate that one-half of these exits represent decisions not to order blood products based on feedback from the program.

The program relies heavily on the integrated clinical database in the HELP System. It accesses data from: (1) the admitting department; (2) the clinical laboratory; (3) surgical scheduling; (4) the blood bank; and (5) the orders entered by nurses and physicians.

The blood-ordering program described above contains processes that support computerized critiquing. The program responds to interventions chosen by the physician by analyzing the order and, if appropriate, suggesting reasons to alter the therapeutic plan.

The process used by the blood-ordering program is different than that used in the alerting application in that it involves a dialogue with the user. As a result, the critique can provide a series of informational responses designed to assure that the user is fully aware of the status of the patient as well as of accepted guidelines governing blood product usage.

Historically, physician use of generalized computerized order entry programs has been limited. However, modern order entry programs are being designed to encourage their use by physicians. A part of this encouragement is based on the ability of these programs to critique orders. Physicians often appreciate the ability of an automated ordering system to give feedback on proper dosing and accepted care protocols as they make their interventional decisions. Opportunities for a constructive interaction between the computer and the clinician are clearly growing, and applications that critique medical decisions can contribute to this growth.

Suggestion Systems

The third category of computer applications designed to support medical decision making is potentially the most interactive. This group of processes is designed to react to requests (either direct or implied) for assistance. These processes respond by making concrete suggestions concerning which actions should be taken next.

Unlike alerts, action oriented messages from these systems are expected. Clinicians would typically call up a computer screen, enter requested data, and wait for suggestions from these systems before instituting a new therapy. Unlike critiquing systems, the physician need not commit to an order before the program applies its stored medical logic. Instead, the program conducts an interactive session with the user during which a suggestion concerning a specific therapeutic decision is sought. The system then reviews relevant data, including data that has been requested from the user, and formulates a suggestion for an intervention based on the medical knowledge stored in its knowledge base.

The example below is, in many ways, typical of suggestion systems. It functions in the realm of ventilator therapy and has been implemented in increasingly more sophisticated forms in intensive care settings at the LDS Hospital since 1987.

As a tertiary care setting, LDS Hospital sees a large number of patients with respiratory failure. One of the more difficult of these problems is that of Adult Respiratory Distress Syndrome (ARDS). This disease can complicate a number of other conditions, including trauma, infectious disease,

and shock. The usual therapy includes respiratory support while the underlying pulmonary injury heals. Unfortunately, overall mortality for ARDS had remained at about 50% for many years. For the subset of ARDS patients who manifest severe hypoxemia, the mortality had been approximately 90%.

The study of computer protocols for delivering care to ARDS patients was a side effect of research into the effectiveness of a new therapeutic intervention of this difficult disease. In the early 1980s, research began to suggest that external membrane devices that bypassed the lungs to remove carbon dioxide (CO_2) directly from a patient's body might improve survival in the most severely ill ARDS patients. Physicians at the LDS Hospital wanted to study this new approach in a rigorously controlled clinical trial. They chose to do an experiment with a test group that received the external lung treatment and a control group that did not receive the treatment. However, the researchers were aware that the management of ARDS differed from patient to patient, depending on the course the disease followed, and the training and previous experience of the physicians and staff caring for the patient. For this reason, they decided to standardize care by strict adherence to predetermined treatment protocols.

At first, they developed a set of paper protocols. As the protocols became more complex, it became clear that they would be difficult to follow manually. Therefore, it was decided to computerize them. The result was a set of computerized rules that were designed to direct, in detail, the management of patients in both the test and control branches of a study of extracorporeal CO_2 removal ($ECCO_2R$).[31–33] While the rules were designed initially for this research, they were soon made general enough that they could be used in the management of other patients requiring ventilator support.

The protocols were created by a group of physicians, nurses, respiratory therapists, and specialists in medical informatics. The initial study period was to be 18 months. Subsequent development concentrated on first eliminating errors in protocol logic, second on extending the scope of these tools, and finally on reworking behavioral patterns in the intensive care setting so that the protocols could be effectively implemented.

The protocol system devised was used successfully during the $ECCO_2R$ study. The study was terminated after 40 patients were treated, 21 with $ECCO_2R$ and 19 with conventional therapy. At that time, there were eight survivors in the conventional therapy group (42%) and seven in the $ECCO_2R$ group (33%).[33] The study group concluded that there was no significant difference between $ECCO_2R$ and conventional treatment of severe ARDS. However, the 42% survival in the control group was unexpected. Reported survivals in these severely ill patients were less than 15%. The results led the researchers to suspect that the quality and uniformity of care provided through the use of computerized protocols had resulted in an important improvement in patient outcomes.

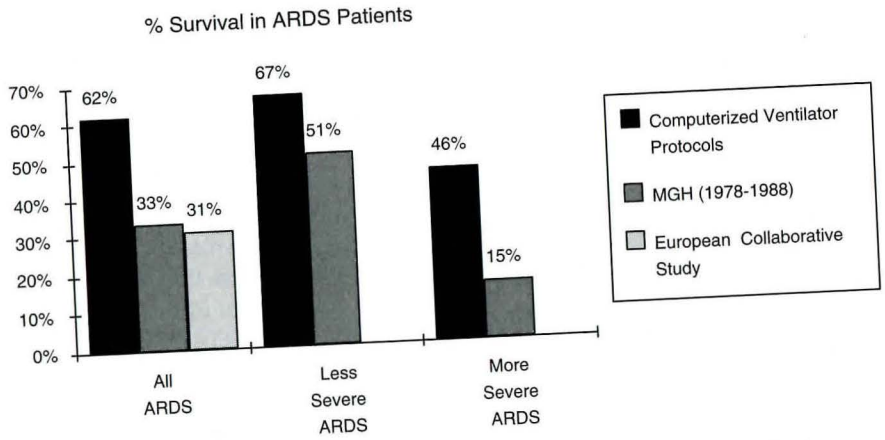

FIGURE 8.1. Comparative results for groups managing ARDS patients.

As a consequence, development and study of these protocols has continued. Figure 8.1 summarizes the results of their use in 111 LDS Hospital patients, and compares these results to those of two other groups Massachusetts General Hospital (MGH) and a group in Europe (the European Collaborative Study) interested in the problem of treating ARDS. It is becoming increasingly clear that the standardization of complex ventilator care decisions possible with computers has a pronounced benefit for patients.

It should be noted that here we have focused the definition of systems for suggesting therapeutic interventions quite narrowly. We have limited our example to a system that responds with a suggestion when the clinician has explicitly or implicitly requested one. Such a computerized decision support process is an area in which we are continuing to explore better ways to interact with clinicians and better ways to capture and encode protocol knowledge.

Diagnostic Decision Support in the Help System

The examples above have stressed different approaches to the activation of medical decision support logic and to the delivery of the resulting decisions to the computer user. Below, we change our focus. One of the greatest challenges for a computerized medical decision system is to participate usefully in the diagnostic process. Diagnostic decision support systems (DDSS) differ from the CDSS described above. Typical decision support systems can draw attention to specific data elements and/or derive therapeutic suggestions from these elements. Such applications offer assistance in the basic

recognition processes and can categorize patients by pathophysiologic condition. On the other hand, the diagnostic process is a preliminary step to suggesting therapeutic interventions. Computerized diagnostic decisions are generally involved with different goals, interfaces, and decision algorithms than the applications previously described.

Two types of diagnostic applications are described. They differ in the degree with which the developers have solved the problem of providing a clinically useful service. The first type represents a group of applications that, using a set of raw clinical data, attempt to standardize various diagnostic categorizations that impact discrete therapeutic decisions. Three HELP System examples are discussed.

The second group of diagnostic processes described comes from the family of applications that attempt to simulate the more extensive and flexible diagnostic behavior of physicians. Those discussed here represent preliminary research whose clinical applicability remains to be determined. The status of these applications in terms of preliminary data and experience limited to a research and development environment are described.

Proven Diagnostic Applications

A number of applications residing in the HELP system can, through the use of various diagnostic strategies, affect patient care. Below we describe three of these applications. The first is an application that evaluates patient data to detect adverse drug events. The second is a tool that recognizes nosocomial infections. The third is a computerized assistant that informs and advises physicians as they undertake the complex task of determining how to treat a patient with a possible infection.

Adverse Drug Events

Adverse drug events (ADEs) are defined by the World Health Organization as "any response to a drug which is noxious, unintended, and which occurs at doses normally used in man for the prophylaxis, diagnosis, or therapy of disease." ADEs can range in severity from drowsiness or nausea to anaphylaxis and death. It has been estimated that in the United States that drug-related morbidity and mortality costs more than $136 billion per year.[34]

The process of recognizing ADEs differs from that of drug monitoring at the time of drug dispensing; this latter process has become a standard part of computerized pharmacy systems. The alerting systems embedded in modern-day pharmacy dispensing systems typically evaluate ordered medications against a list of contraindications based on known allergies, expected reactions with other patient medications, or the information from

the clinical laboratory that can be expected to affect the drugs given or the dosage of those medications. In contrast, the goal of an ADE detection system is to determine the existence of a drug reaction from the patient data collected during the routine documentation of patient care.

An ADE recognition subsystem has been implemented in the HELP system.[35–36] This ADE subsystem continuously monitors patients for the occurrence of an ADE. The system does so by inspecting the patient data entered at the bedside for signs of rash, changes in respiratory rate, heart rate, hearing, mental status, seizure, anaphylaxis, diarrhea, and fever. In addition, data from the clinical lab, the pharmacy, and the medication charting applications are analyzed to determine possible ADEs.

The system evaluates all of the patients in the hospital and generates a daily computer report indicating which patients have possible ADEs. A clinical pharmacist then follows up on these patients and completes the evaluation using a verification program. This program provides a consistent method of completing the diagnostic process. A scoring system (the Naranjo method) is used to score the ADEs as definite (score ≥ 9), probable (score 5–8), possible (score 1–4), or unlikely (score 0).[37] The physicians caring for each patient are notified of confirmed ADEs by the pharmacist who does the evaluation.

The existence of an application for diagnosis of ADEs has increased the frequency with which these events are recognized and documented in the hospital setting. Using a voluntary reporting method, nine ADEs were recorded in the one-year period from May 1, 1988 to May 1, 1989. In the period from May 1, 1989 to May 1, 1990, while the program was in use, 401 adverse drug events were identified.

An additional effect of this program appears to be a reduction in the number of severe ADEs seen. During the year beginning in January of 1990, 41 ADEs occurred. In this time frame, physicians were notified of verified ADEs only if they were classified as severe or life threatening. In two subsequent periods (the year of 1991 and the year of 1992) early notification of physicians was practiced for all severities of ADE. Numbers of severe ADEs decreased to 12 and 15 during the follow-up time periods ($p < 0.001$).

In an effort to understand the impact of the drug reactions that were the target of this application, the costs of ADEs were examined. In studies that used the computer tools described above, investigators found that length of hospital stay for patients with ADEs was increased by 1.91 days and that costs resulting from the increased stay were $2,262. The increased risk of death among patients experiencing ADEs was 1.88 times.[38] Thus, the cost savings and impact on quality of care in reducing ADEs was substantial.

These tools leverage the fact that the majority of the data necessary for their function is available in the HELP system's integrated database. They illustrate the potential for computerized diagnostic applications to impact

patient care not just by assisting with the choice of interventions, but also by focusing clinical attention on those cases where the interventions chosen have put the patient at risk.

Nosocomial Infections

In the previous example, a rule-based system was used to suggest the diagnosis of adverse drug events for a group of patients undergoing therapy in the hospital. Another application in use at the LDS Hospital is designed to recognize nosocomial, or hospital acquired infections.[39] The program serves a need recognized by the JCAHO that requires ongoing surveillance for hospital-acquired infections.

The process of detecting nosocomial hospital infections serves a recognized clinical purpose. Control measures based on this information are believed to be important in interrupting the spread of hospital-acquired infections. Evidence suggests that intensive surveillance programs may be linked to reduced rates of infection. However, the process can be expensive. Traditional techniques require infection control personnel to manually screen all appropriate patients on a routine basis.

The computerized surveillance system used in LDS Hospital relies on data from a variety of sources to diagnose nosocomial infections. Information from the microbiology laboratory, nurse charting, the chemistry laboratory, the admitting office, surgery, pharmacy, radiology, and respiratory therapy are used. Once each day, a report is produced detailing the computer's findings. This report can be used to follow up on the patients for whom there is evidence of nosocomial infection.

In studies done to compare the computer-based surveillance of nosocomial infections to the traditional, manual approach, 217 patients were determined to be possible victims of hospital-acquired infection (out of 4,679 patients discharged in a two-month period). This included 182 patients identified by the computer and an overlapping 145 patients recognized by traditional means. Of these patients, 155 were confirmed to have nosocomial infections.

For the group of 155 patients, the computer's sensitivity was 90% with a false positive rate of 23%, while the infection control practitioners demonstrated a sensitivity of 76% and a false positive rate of 19%. When the hours required to use each approach were estimated, the computer-based approach was more than twice as efficient as the entirely manual technique.

The nosocomial infection tool, like the ADE recognition system, uses Boolean logic in a relatively simple diagnostic process. In an effort to extend the process of managing hospital-acquired infections, an extension to the infection control system was developed. The goal of the enhancement was to predict which patients were likely to contract a nosocomial infection in the hospital in the future. The tool is based on different decision algorithms. Data from patients with infections acquired in the hospital were combined

with data from a control set of patients, and a group of statistical programs were used to identify risk factors. Logistic regression using these risk factors was used in the development of tools that could estimate the risk of hospital-acquired infection for inpatients. The resulting system is capable of predicting these infections in 63% of the population who are ultimately affected.[40]

Antibiotic Assistant

The third application in this group is an example of a multipronged approach to the task of supporting medical decision making. As a part of ongoing research into the use of computers in medical care, the Infectious Disease Department at LDS Hospital developed a tool to help clinicians make informed decisions concerning the administration of antibiotics.[41,42] The "antibiotic assistant" application provides three basic services. First, it assembles relevant data for the physicians so they can determine whether a specific patient is infected and what sorts of interventions might be appropriate. Information such as the most recent temperature, renal function, and allergies are presented. Second, the system suggests a course of therapy appropriate to that patient's condition. Finally, the program allows the clinician to review hospital experience with infections for the past six months and the past five years. One of the options of the program allows the clinician to review the logic behind the computer's suggestions while another presents brief monographs on the appropriate use of each antibiotic in the hospital formulary.

The diagnostic processes embedded in this application are derived from data extracted from the HELP system and analyzed on a monthly basis. The goal of the analysis is to define the probability of each potential pathogen as a causative agent for a certain class of patient. Six clinical variables are used in this process. These variables were identified through a statistical analysis of 23 proposed data elements. They include the site of infection, the patient's status (inpatient or outpatient), the mode of transmission (community- or hospital-acquired), the patient's hospital service, the patient's age, and the patient's sex.

The result of this monthly analysis is an assessment of the likelihood of each pathogen for every combination of the patient-related variables. For example, once the analysis is complete, the percentage of hospital-acquired bacteremias due to *Escherichia coli* in male patients age 50 or less who are on the cardiovascular service will be stored in the program's knowledge base. The analytic programs also evaluate susceptibility data to determine which antibiotics are likely to cover the most probable pathogens for each combination of patient variables.

This probabilistic knowledge is then filtered through a set of rules created by infectious disease experts. These rules adjust the output of the first phase to include criteria representing basic tenets of antibacterial therapy. For

example, the susceptibility information garnered from the historical data would be updated to indicate that amikacin should be used only for infections due to gram-negative organisms.

The resulting knowledge base is used by the antibiotic assistant program to make presumptive diagnoses of infectious organisms and to suggest treatments appropriate to these organisms. It remains up-to-date through monthly updates of its knowledge base. By offering the monographs and explanations mentioned above and by allowing the clinicians to browse its knowledge base, it provides large amounts of information in addition to its suggestions.

Research into Complex Diagnostic Applications

The systems described above have had a clear and measurable effect on improving health care provided in the hospital setting. The dream of even more sophisticated and inclusive systems were presented more than 30 years ago. In 1959, Ledley and Lusted described the application of methods from the realm of symbolic logic and statistical pattern recognition to problems in medicine.[43] They proposed that these tools be used to assist in the diagnostic process and in other problems involving medical decision making. Computer systems were the enabling technology that was predicted to bring these tools to the bedside.

A variety of researchers have accepted the challenge of Ledley and Lusted and produced experimental systems designed to diagnose a variety of illnesses. A number of these systems are mentioned elsewhere in this book. Within the HELP system, researchers have created and tested several DDSS. Two of these are described below.

An important portion of the value of computerized diagnostic tools lies in the development of well-designed models of the diagnostic process to assist in the complex clinical decision-making tasks. Physicians clearly exercise their diagnostic knowledge not only when they assign a diagnostic label to a patient, but also during processes as diverse as reading medical reports and critiquing the clinical behavior of their peers. Below, we give examples of experimental systems that: (1) assist with data collection; and (2) help assess the quality of medical reports.

The applications described below benefit from a long-standing interest in Bayesian techniques for probability revision among researchers using the HELP system. For more than 20 years, the HELP system has contained a frame-based decision support subsystem capable of capturing and employing Bayes' equation to assess probabilistically the support for diagnoses provided by various combinations of clinical data.[14] Approaches to decision support, such as those described in Chapter 2 of this book, have been and continue to be key areas of research in the HELP medical informatics community.

Assisting Data Collection

Efforts to direct data collection in the HELP system have concentrated on the patient history. The goal has been to identify tools that could effectively collect a medical history appropriate for use in diagnostic decision support applications. While earlier efforts focused on history appropriate to a wide variety of diseases,[44] more recent efforts have focused on acquiring data bearing on pulmonary diseases.[45,46]

Three techniques for collecting the history were explored. The first was a simple branching questionnaire. This approach takes full advantage of the hierarchical relationship between more and less specific questions. For instance, if the question "Have you had chest pain with this illness?" was answered "Yes," then more specific questions such as "Is your chest pain brought on by exertion?" were asked. Alternately, if the answer to the first question were "No", the more specific questions would not be asked.

The second technique has been called decision-driven data acquisition (DDA). With this technique, a frame-based, Bayesian expert system analyzes all data available at any point in the patient interview. The individual disease frames determine which additional information is needed to evaluate the likelihood of the particular disease. Each frame proposes one or more questions. From this list, a supervisory program selects a group of five questions, which are then presented to the patient. The system passes through this cycle multiple times until criteria are met indicating that no additional data are needed.

A third approach has also been tested. It is similar to the DDA method except that it was adapted for use in a setting where the patient was not present at a computer terminal. The approach begins when a paper questionnaire containing screening questions is presented to a patient. Staff members enter the answers into the computer, and the patient's data are compared to the diagnostic frames. The questions are scored in a filtering process, and then from 0 to 40 additional questions are printed for the patient to answer. After the patient answers these additional questions, the answers are entered into the computer and the process is completed.

The branching questionnaire mode of data collection and the DDA mode were tested on inpatients at the LDS Hospital. Fifty patients took a DDA managed history and 23 received a history managed by the branching questionnaire program. Figure 8.2 illustrates the results.

On average, the DDA mode took a significantly ($p < 0.05$) shorter time to run (8.2 minutes) and asked significantly fewer questions (48.8 questions) than did the branching questionnaire (19.2 minutes and 137 questions, respectively). The two-stage, paper questionnaire was tested separately on patients coming to the X-ray department for chest X-rays. It appeared to perform similarly to the interactive DDA mode. It should be noted that there was no significant difference between the techniques in terms of

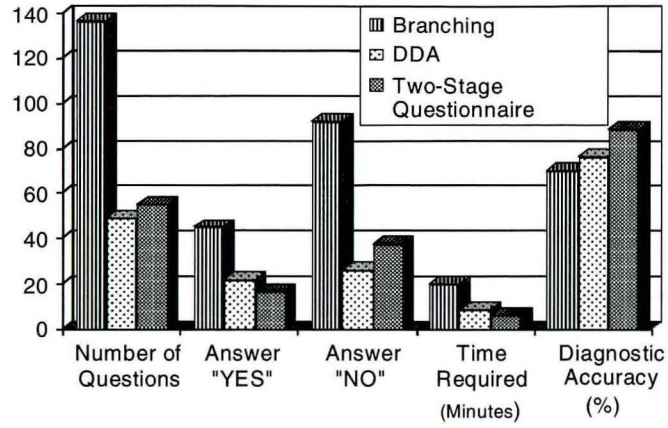

FIGURE 8.2. A comparison of techniques for collecting the patient history.

diagnostic accuracy. Using history alone, all three succeeded in placing the patient's correct disease in a five-member differential diagnostic list from 70–88% of the time.

Assessing the Quality of Medical Reports

A second example of an alternative use of diagnostic knowledge comes from a study of result reporting in the radiology department. The central goal of this project was to develop a technique for measuring the quality of X-ray reporting without requiring the review of radiographs by multiple radiologists. This is in contradistinction to typical approaches for evaluating the accuracy of radiologists. Typically, audit procedures in the radiology department require multiple readings of a select set of X-rays.[47–51] The results of the repeated readings are used to define a "gold standard" for the films. Then the individual radiologists are compared to the gold standard.

The technique developed as a part of this project was based on a simple premise. Each examination was a test of the radiologist's accuracy. Instead of comparing the abnormalities reported to a standard formulated through multiple readings, the description in the report was evaluated in comparison to the patient's overall diagnostic outcome. In the case of chest X-rays, the standard was the list of final diagnoses (ICD-9 codes) integrated into the patient's record at the time of discharge. The report generated by the radiologist was successful to the extent that it supported the process that led to one of the discharge diagnoses.

While a variety of algorithms can be used to link the findings represented in the X-ray report to the final diagnosis, we have demonstrated the success

of a variation on Shannon Information Content in discriminating among physicians reading chest X-rays. Shannon Information Content[52] is a mathematical formalism for assessing the informational value of messages. We have modified it to provide a measure of the information produced by the radiologists as *they* interpret an X-ray. The assumption inherent in this usage is that the information contained in an X-ray report can be expected to alter the likelihood of the various diseases that a patient might have. Information Content is calculated from the change in probability of these diseases.

For this technique to work, a diagnostic system was required that was capable of discriminating among diseases producing abnormalities on the chest radiograph. The information content was calculated from the change in disease probability induced by the findings recorded in the chest X-ray report. A Bayesian system provided the required probabilities.

Our evidence for the success of this technique came from two studies. In the first, we used expert systems technologies to demonstrate discrimination in a controlled experiment.[53] In this experiment, five X-ray readers read an identical set of 100 films. The assessment produced by the diagnostic logic program gave results consistent with the differing expertise of the readers and similar to the results of a more standard audit procedure.

In a second study of this audit technique, we extended the test environment into the realm where we hope to use it clinically.[54] We tested a group of radiologists following their standard procedure for interpreting radiographs. Each chest X-ray was reviewed, the report dictated and transcribed only once, as is typical with most radiologists' daily work. The goal of the study was to test the ability of a knowledge-based approach to measure the quality of X-ray reporting, without requiring repeated reading of the radiographs.

This technique used a modified version of the Shannon Information Content measure, and was designed to assess both the positive information contributed by X-ray findings relevant to a patient's disease, and the negative information contributed by findings which do not apply to any of the patient's illnesses. X-ray readers were compared based on the bits of information produced. We used 651 chest X-ray reports, generated by a group of radiologists, that were compared to the patients' discharge diagnoses using a measure of information content. The radiologists were grouped according to whether they had received additional (post residency) training in chest radiology. The "trained" radiologists produced 11% more information than the "untrained" radiologists (0.664 bits as opposed to 0.589 bits, significant at $p < 0.005$).

The average information content calculated successfully discriminated these groups. However, it is an overall measure. Examination of the interaction between the groups of radiologists and disease subgroups indicates that the score can also discriminate at the level of different diseases ($p < 0.05$). This suggests that the technique might not only discriminate overall

quality of X-ray interpretation, but it might also be of use at pinpointing the specific diseases for which an individual radiologist may be failing to generate effective information.

Infrastructure for an Enterprise Clinical Diagnostic Support Systems

In order to build and test the variety of CDSS applications described above, an environment conducive to the development of decision support applications is necessary. The HELP system served this role for more than two decades. During that time, the development and maintenance of an infrastructure, designed to sustain an effective CDSS, became a central tenet of the system.

Now, a new medical computing environment is replacing the HELP System as the core of IHC's Electronic Health Record. This system is known as HELP2. Based on our experience with the HELP system,[55] a new decision support infrastructure has been developed for this new platform.[56] This infrastructure is comprised of five main modules: *data-drive*, *time-drive*, *rule node*, *dispatch node*, and *configuration manager*. Figure 8.3 illustrates the design.

Data-drive is the module responsible for activating the rules whenever any clinical data are stored in the database (new, updated, or logically deleted). Whenever data are stored in the clinical data repository, a copy is forwarded to the *data-drive* module. The data instances are filtered using a configuration file that identifies data for which decision rules exist. Only those that match continue to be processed. They are transformed into a standard data representation and sent to the *time-drive* module. This allows

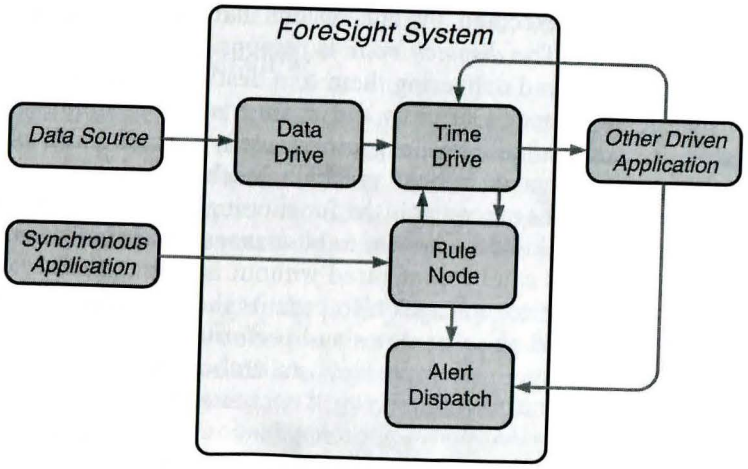

FIGURE 8.3. CDSS infrastructure.

a temporal offset between the receipt of the data and the execution of the rules.

Data that arrive in the *time-drive* module can be held there for a predetermined amount of time before they are delivered to the *rule node*. The objective is to be able to activate the rules at certain times of the day, or after a certain period of time. The holding time can be from seconds to years. In most cases, data that come from the *data-drive* typically have no waiting time, and are immediately delivered to the *rule node*.

The *rule node* was designed to allow wide choice in the methods used for processing the data. It can run different inference engines, allowing different representations of knowledge. We have tested with rule in pure java code as well as logic-executed in third-party inference engines. The *rule node* receives the data and verifies which rules or protocols should be executed. Besides *data-drive* and *time-drive*, the rule node can also be activated synchronously, i.e., directly by an application. If the activating application were an interactive application, it would be able to activate a needed rule set directly and receive in reply the computed decisions. These could then be presented to the waiting user.

If additional data are necessary to execute triggered rules, the data are retrieved from the database and converted into the same common data model. This common data model has a marked benefit as we transition the EHR from HELP to HELP2. Currently, the clinical data are stored in two completely different databases, the HELP system and the HELP2 system. These systems have different data structures and "dictionaries" (coding systems). Translating the data to a common data model allows the development of rules independent of the data location or structure. Rule developers have no need to know were the data are physically located and/or its structure or codes. This facilitates maintenance of the rules when migrating data from a legacy system to a new platform.[57]

After the rules are executed, the conclusions that are generated are sent to the *dispatch node*. The *dispatch node* is responsible for saving the conclusions to the EHR and delivering them to a destination specified by the user or the rule developer. Currently, the *dispatch node* can send the rules' conclusion (e.g., alerts, critiques, suggestion, etc.) to pagers, cell phones, email, and to an electronic "in-box" specific to each user.

A *configuration manager* controls the functioning of the all the modules. It is Web-based and allows the system to be managed and configured from any browser. Modules can be configured without having to deactivate the system. The configuration manager also permits the monitoring of salient system functions including error states and performance.

This collection of modules represents an embodiment of the lessons learned from the original CDSS developed over more than two decades for the HELP system. New decision support applications designed and built for HELP2 provide a daily test of our success in learning from our earlier experiences with CDSS.

Intermountain Healthcare's Clinical Knowledge Management Infrastructure

As IHC intensifies the transition from its legacy inpatient information system (the HELP system) to the new component-based clinical information system (HELP2), a new definition of computable medical knowledge has evolved. The examples of CDSS described above were designed to intervene in select medical decisions by providing focused and specific observations or suggestions. The new definition has grown to embrace systems that access collections of more general advice while still respecting the context provided by a selected patient's data and the applications invoked by the user.

The new definition applies to a variety of informational interventions including: (1) tools that reach across the Internet to query commercial and public collections of medical advice, to bring back references appropriate to the medical context surrounding the query; (2) systems that query local collections of problem-specific clinical guidelines to provide context-specific advice on medical care. This advice seeks to promote decisions that are consistent with IHC's care standards; and (3) collections of orders designed to provide a context-specific starting point for clinicians using IHC's new Computer-based Physician Order Entry (CPOE) system.

These broader goals have led to a revised view of the environment required for authoring and maintaining medical knowledge. This view is embodied in a comprehensive clinical knowledge management (CKM) strategy, which is being implemented within the HELP2 computing environment. Below, we briefly discuss this strategy and its implementation. The focus, instead of being on examples, is on the processes of coordinating development and exploitation of computerized medical knowledge and tools to support these processes.

Infrastructure Overview

A key strategy, adopted by Intermountain Healthcare, for promoting consistency and quality in clinical care, is the development and deployment of problem-specific guidelines detailing salient features of that care. These guidelines may be delivered as textual advice suited to the clinical circumstances, or as lists of suggested orders designed to provide an initial order set in a CPOE package.

The strategy for managing the largely descriptive knowledge represented is based on coordinated initiatives that identify and disseminate clinical best practices to help reduce clinical variability and improve disease management processes and outcomes. These initiatives, known as "*Clinical Programs*,"[58] are developed by interdisciplinary teams supported by specialized workgroups. Development teams and workgroups are recruited from practicing clinicians who provide both domain knowledge and local or regional

representation. A senior physician, recognized as a system-wide domain expert, is commonly the leader of these teams.

In addition to practicing clinicians, each team is also staffed with outcomes analysts, data architects, knowledge engineers, and clinical education professionals. Development teams and workgroups are responsible for the creation of corporate-wide care process models, data collection tools, provider and patient educational materials, clinical documentation templates, and different kinds of computerized decision support elements, such as rules, protocols, care plans, and order sets. These groups are also responsible for the selection and customization of external knowledge sources obtained from public domain sources, or through licensing from commercial vendors.

Content development priorities are established by guidance councils, taking into account the most prevalent and/or variable diagnostic conditions and clinical work processes, complemented by key patient safety processes. The Clinical Programs that have been established so far at IHC cover the following medical specialties and subspecialties: cardiovascular medicine, intensive medicine, neuromusculoskeletal diseases, oncology, pediatrics, preventive care, primary care, surgery, and women and newborns.

Tools to Manage Clinical Knowledge

A complete software infrastructure to support the clinical knowledge management strategy just described has also been developed. The software infrastructure aims at supporting distributed and collaborative processes for authoring, reviewing, and deployment of knowledge content. During the authoring and review phases, all the knowledge content is stored and organized by a *knowledge repository* (KR).

The KR is the cornerstone of the clinical knowledge management software infrastructure. The KR has been implemented using a flexible database model and can be used to store multiple categories of knowledge content, ranging from unstructured narrative text to well structured documents and executable logic modules. Each KR record is considered a *knowledge document* that is preferably represented in XML, but many of the most common *multipurpose internet mail extensions* (MIME) formats are also supported.[59]

Every knowledge document is associated with a *header* XML document that is used to store detailed document *metadata*. The *header* is used to implement the KR's version control mechanism, providing a detailed record of all the changes and enhancements made to any given knowledge document. In terms of searching and retrieving knowledge documents from the KR, a set of specialized services has been created, leveraging existing XML document transformation and presentation standards.[60] The KR currently provides services to find, retrieve, and/or manipulate the knowledge documents according to the needs of various client applications. However, content manipulation is limited to instances stored natively as XML documents.

Authoring and review processes for KR documents are supported by two web-based applications: the *Knowledge Authoring Tool*" (KAT), and the *Knowledge Review Online* (KRO). KAT is an authoring environment that allows clinical experts to create knowledge documents using XML as the underlying representation formalism.[61,62] The authoring environment generates XML instances using data entry templates created from document models expressed in XML Schema.[62] The templates are used to guide and enforce the underlying structure of each knowledge document, implementing a variety of data types that can be used to create simple narrative documents, as well as richly tagged structured documents. The current version of KAT is being used to author 10 different types of documents, ranging from order sets for IHC's CPOE system to corporate nursing care standards.

The main function of KRO is to support an open and distributed review process, where practicing clinicians, i.e., end-users of the knowledge documents, have the opportunity to provide direct feedback to the document authors. The implementation of KRO exposes all the KR knowledge documents to nearly all IHC clinicians through IHC's intranet. Whenever a review is submitted, the author is promptly notified by e-mail. Reviews are also stored in the KR and can be accessed by any other KRO user. Also through KRO, clinicians can subscribe to e-mail alerts that keep them informed about updates and modifications to the documents they have selected. The functions available in KRO are designed to be exposed as simple Web services, enabling users to submit a review or to subscribe to an e-mail alert from within the clinical applications that they routinely use to take care of patients (CPOE, Results Review, etc.).

Application of the Clinical Knowledge Management Infrastructure to Computer-based Physician Order Entry

In the next generation of medical information systems, a fundamental tool for delivering decision support will be a computerized version of the medical order entry system. Both the critiquing and suggestion-based approaches described above are most effective in an environment where the physician personally documents his diagnostic and therapeutic decisions through a direct interaction with the computer. Intermountain Healthcare's approach to implementing CPOE illustrates the use of the knowledge management tools described above.

IHC is in the process of developing a new CPOE system. The CPOE system is a module of the new HELP2 system, and it is being gradually implemented at all IHC's hospitals and outpatient facilities. The CPOE implementation strategy is based on context specific *order sets* as a key factor to encourage physicians' acceptance of the new system.

The development of these order sets utilizes the CKM infrastructure described above, with the underlying assumption that order sets are, in fact,

intervention tools to promote the implementation of clinical care processes that embody best practices and evidence-based guidelines and protocols.[63] Once fully implemented, more than 3,500 physicians will be routinely using the new CPOE system.

The effective development of order sets requires a constant collaboration between clinical experts responsible for authoring the order sets and the clinicians who use these sets. Direct and continuous feedback is probably the most efficient mechanism to request fixes or suggest enhancements to the content of the order sets. The dialogue established between authors and users promotes open collaboration and provides a sense of co-ownership of the resulting order sets. IHC considers this process vital for the overall success of the CPOE implementation, and the clinical programs are fully committed to this approach.

Currently, the editorial process for the creation and maintenance of order sets is initiated and controlled exclusively by the lead author. Development teams or workgroups are responsible for nominating the lead authors. Using KAT, the author can create an order set by simply filling the template that has been designed specifically for order sets.[61] Once the authoring phase is completed, the author can publish the order set, so others can review its content and analyze its appropriateness.

As indicated above, the review phase is supported by KRO. Within KRO, every comment and suggestion regarding an order set is instantaneously made available to the author and to the other reviewers. If suggestions made by reviewers require modifications to the order set, the author can make those modifications using KAT and promptly publish a new version of the order set. The authoring and review cycle can be repeated several times, until the content of the order set is considered adequate for clinical use. The approval for clinical use results from the consensus of the group that nominated the lead author. Once the order set is approved, the author is responsible for activating it. The activation is obtained by just changing the status of the order set to "active." At this point, the order set is automatically made available to the CPOE system.

Once order sets are made available to the CPOE system, clinicians begin to use them during the ordering process. In reality, the activation of a brand new order set for clinical use marks the beginning of a secondary review cycle, where authors start receiving feedback from the actual users of the order sets. During this secondary review cycle, the authors are again responsible for analyzing and adopting, or not, the modifications suggested by the users.

At this stage, the most difficult challenge for the author is to try to understand and accommodate the needs of the different CPOE deployment settings. In essence, the lead author, supported by the corresponding development team or workgroup, is directly responsible for making sure the order sets are not only current with published evidence and accreditation requirements, but also reflect and accommodate the peculiarities of the

different clinical settings. All these activities have to be performed in a timely fashion, and in harmony with previously defined best practices. The solution implemented by IHC is based on a collaborative knowledge management approach, where knowledge experts retain the authority to create and modify most of the knowledge content necessary for the CPOE system.

The process used to test and revise CPOE is being put through a series of small prototypes. Select groups of physicians (e.g., teams from the ICUs, groups of surgeons) volunteer to develop order sets and to use the application that allows them to be viewed and modified, and used as the orders for a specific patient. Their experience with this process is used to revise the order sets and the software that delivers them.

The main complaints relate to the absence of a connected order communications system. The physicians create their orders using a computerized tool, but then are required to provide a printed version to the ward clerks for further processing. This extra step will be eliminated when a new order communication system, currently on the drawing boards, is put into service and integrated with the interactive CPOE application.

Summary

In this chapter, we have reviewed a number of hospital-based applications that provide medical decision support. These applications can be categorized in a variety of different ways. We have found it profitable to think of these systems in terms of their relationship to the data, and of their interfaces with their users. These foci should be helpful to future system developers and implementers, as they reflect on the environment required for the success of decision support applications.

We have also attempted to emphasize the range of sophistication that can be found in a clinically operational CDSS. Applications using simple logic can contribute a great deal to the quality of care provided in a clinical setting. Programs that use more complex techniques and that strive to provide the more sophisticated decisions associated with disease recognition can also contribute. Among the diagnostic applications currently functioning in hospital settings, those that focus on specific, limited diagnostic goals with a recognizable target audience have been more successful. General-purpose diagnostic programs, while capable of producing interesting results, have yet to find an audience for which they can provide a routine, valued support function.

The lessons learned from the information systems used in hospitals are diffusing rapidly into the outpatient setting. Less expensive hardware, more flexible software, and an environment that increasingly values the efficiencies that computers can offer are encouraging the development of systems for a wide range of clinical settings. As this process occurs, the lessons gleaned by developers of CDSS systems in a hospital setting provide a

springboard for the decision support systems of the future. These systems will embody, in their software infrastructure, computing models derived from experiments conducted in environments like the HELP system.

As new CDSS systems incorporate the infrastructure and decision models developed in the past, these next-generation systems will also incorporate approaches to knowledge engineering and maintenance that have evolved as a part of the research described above. These knowledge management practices reflect a philosophy of development and continuous review shared by a community of caregivers. Adherence to this approach will do much to reduce the challenges associated with implementing potentially disruptive CDSS technologies, by involving the medical community in their creation and growth.

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