CHAPTER 4

Hospital-Based Decision Support

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Decision support technologies are becoming increasingly available to medical practitioners. In recent years, a variety of programs designed to assist with drug dosing, health maintenance, diagnosis and other clinically relevant decisions have been developed for the medical market. Increasing ease of access to personal computers is partially responsible for this growth. So is the interest in automated medical decision-making that has grown from an expanding awareness of the successes of medical computing.

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 served hospitals and have supported the patient care given there.[1,2] 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 and on personal computers.

Contributors to the body of knowledge of applying computer systems to clinical practice include the several sites where hospital-based, medical decision support have been implemented and studied. Among the leaders in these efforts have been groups at the Regenstrief Institute in Indianapolis,[3] Columbia Presbyterian Medical Center in New York,[4] and Beth Israel Hospital in Boston.[5] Recent efforts to incorporate decision support into order entry systems at

the Brigham and Women's Hospital in Boston[6] and Vanderbilt University Medical Center in Nashville[7] are helping to define the direction that hospital-based computing will follow in the future.

In this chapter, we will discuss medical decision support applications that help provide clinical care in a hospital setting. The principal source of the examples come from the HELP Hospital Information System (HIS) located at the LDS Hospital in Salt Lake City and developed by the members of the Department of Medical Informatics of the University of Utah.[8] As a part of our description of decision support applications in the HELP system, we will discuss the data used and the mechanism through which suggested decisions are communicated to the user. In addition we will review a set of applications, developed and tested within the HELP system, that include an element of "diagnostic" decision support.

Truly "diagnostic" systems have been a perpetual theme in medical informatics research. However, systems featuring a diagnostic paradigm are rarely found in routine hospital clinic services. More common are systems that depend on simple algorithms to inform and remind users of important clinical data or of medical facts which may change 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 which are described below.

The HELP system includes two types of clinical diagnostic decision support systems (CDDSS). The first type focuses on narrowly circumscribed medical conditions; these systems are in daily clinical use. The systems include those that recognize clinical syndromes such as adverse drug events or those that attempt to determine from microbiology data and other information which pathogens are important causes of infection. The second type of diagnostic systems are those that attempt to discriminate among a group of important diagnostic entities using raw medical data. These diagnostic systems often attempt the challenging task of managing large degrees of uncertainty using pattern matching algorithms. Several of these types of systems have been, or are being, tested in the HELP environment. Below we describe experience with three of these more aggressive diagnostic programs.

THE HELP SYSTEM

The overall setting for much of the work described here is the HELP Hospital Information System (HIS) operating in the LDS Hospital. HELP stands for Health Evaluation through Logical Processes and is a culmination of more than 20 years of development and testing.[8] It currently operates on high availability hardware supplied by the Tandem Computer Corporation. Recently, principal software components of the HELP system have also been installed in seven of the hospitals operated by Intermountain Health Care (IHC). At the LDS Hospital, the information system communicates with users and developers through approximately 1,250 terminals and more than 200 printers. The system is interfaced to a variety of other computer systems including a billing system, a laboratory system, an electrocardiography 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 administrative functions, and the software tools needed to maintain and expand these components. The integrated clinical database contains a variety of patient data kept online during the patient's stay. This database can be accessed by health care professionals at terminals throughout the hospital. Terminals allow the entry of pertinent clinical data into the HELP system by all personnel who are involved in patient care. Table 4.1 is a partial list of the data in the system.

Use of the HELP system for decision support 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.[9] This set of tools has led to the successful development of expert systems in blood gas interpretation,[10] intensive care settings,[11] and medication monitoring,[12] to name a few. The syntax used in the decision system is currently being extended to allow use of Arden Syntax, an American Society for Testing and Materials (ASTM) standard for medical decision logic.[13] The HELP System hardware and software environment has provided the setting for the implementation and testing of the decision support tools described below.

Table 4.1. Partial list of data in HELP system

Clinical Data Routinely Captured by the HELP Hospital Information System	
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

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.[14] 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 that respond to recorded decisions to alter care (typically new orders) 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; and (4) retrospective quality assurance applications where clinical data are abstracted from patient records and 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 on the HELP system which monitors common laboratory results and detects and alerts for potentially life-threatening abnormalities in the data acquired. This 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 they become available. Instead, the principal review time determinant 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.[15-16]

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 care givers.[17-20] This system

was constructed by reducing a set of 60 alerts developed during a previous pilot system development[21] to the 10 most important conditions (Table 4.2).

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 the logic.

Once the logic was deemed acceptable, an experiment was designed to evaluate the effect of the system on several intermediate outcome 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 entered 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 significantly more 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. The length of time in the life-threatening condition dropped in each of the alerting subgroups analyzed. 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.[22] In the inpatient environment, where the severity of illness is steadily increasing, there is a strong potential for better alerting systems to improve quality of patient care.

Table 4.2. Alerts for which computerized alerting logic was created

Alerting Condition	Criteria
Hyponatremia (NAL)	$Na^+ < 120$ mEq/l
Falling Sodium (NAF) mEq/l	Na^+ fallen 15+ mEq/l in 24 hr. and $Na^+ < 130$
Hypernatremia (NAH)	$Na^+ > 155$ mEq/l
Hypokalemia (KL)	$K^+ < 2.7$ mEq/l
Falling Potassium (KLF)	K^+ fallen 1+ mEq/l in 24 hr. 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%

Critiquing Systems

In the alerting example described above, the computer system responded to elements in the data base 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.

In recent years it has become increasingly apparent that, while the transfusion of blood products is an important, often life-saving therapy, 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, in addition, 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) released a document outlining nine steps to be taken in the review of institutional blood usage.[23] Central to this document was a

requirement for health care 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 blood transfusions and to assist in ensuring compliance with criteria for proper use of blood products.[24-26] 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 into the blood-ordering program is a critiquing tool designed to ascertain the reason for every transfusion and to compare the reason to strict criteria specific to the type of transfusion planned. For instance, when an order is made for packed red blood cells, the criteria in Table 4.3 below are used to critique the order.

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, but he or she is required to enter (as free text) the reasons for the decision to override the system.

The criteria used are the result of an effort by the LDS Hospital medical staff. The criteria were developed primarily by using 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.

Table 4.3. Simplified criteria for ordering packed 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)

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 a 6-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 from 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 both the status of the patient and also the 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 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 intervention

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 system 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 it has 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 ARDS patients was driven by research into the effectiveness of a new therapeutic intervention in 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 of the 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 who received the external lung treatment and a control group who did not. 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 ($ECCO_2R$).[27-29] 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 ventilatory 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 its scope, 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 seven survivors in the $ECCO_2R$ group (33%) and eight in the conventional therapy group (42%).[30] The study group concluded that there was no significant difference between $ECCO_2R$ and conventional treatment of severe ARDS. However, the percentage of severely ill patients of this type who survived was usually less than 15% and the 42% survival in the control group was unexpected. The results led the researchers to suspect that the quality and uniformity of care provided through the use of computerized protocols had resulted in a significant improvement in patient outcomes.

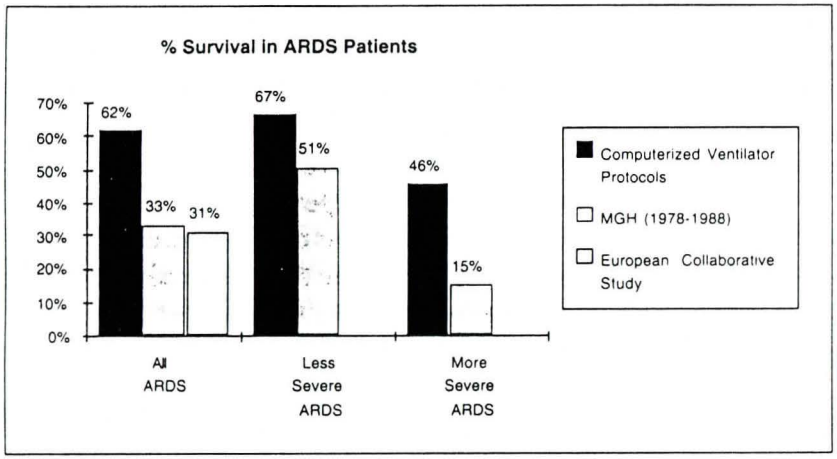

Fig. 4.1. Comparative results for groups managing ARDS patients.

As a consequence, development and study of these protocols has continued. Figure 4.1 summarizes the results of their use in the 111 LDS Hospital patients and compares these results to those of two other groups (Massachusetts General Hospital (MGH) and a group in Europe interested in the problem of treating ARDS).

It should be noted that here we have limited our example of systems for suggesting therapeutic interventions 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 WITH 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 productively in the diagnostic process. Clinical diagnostic decision support systems (CDDSS) differ from the decision support systems described above. Decision support systems can draw attention to specific data elements and/or can synthesize therapeutic suggestions based on 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 making therapeutic interventions. Diagnostic decisions may require a system with different goals, interfaces, and decision algorithms than the applications previously described.

Two types of diagnostic applications are described below. They differ in the degree with which the developers have solved the problem of providing a clinically useful service. The first type represents modest 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 CDDSS comes from the family of applications that attempt to simulate the more extensive and flexible diagnostic behavior of physicians. Those discussed here are either preliminary research whose clinical application remains in the future or work in progress whose utility is a subject of ongoing evaluation. The status of these applications in terms of preliminary data and experience limited to a research and development environment is 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 drug-related morbidity and mortality costs more than $136 billion per year.[31]

The process of recognizing ADEs differs from the drug monitoring at the time of drug dispensing that 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.[32-33] 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 are possible ADE victims. A clinical pharmacist 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).[34] 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 wtih 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.[35] 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 HELP's integrated data base. 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 in the LDS Hospital is designed to recognize nosocomial, or hospital acquired infections.[36] The program serves a need recognized by the JCAHO, which 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 screen manually 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 lab, the admitting office, surgery, pharmacy, radiology and respiratory therapy are used. Once each day a report is produced

detailing the computer's suggestions. This report can be used to followup the patients for whom there is evidence of nosocomial infection.

In studies done to compare the computer-based ascertainment 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 2 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.[37]

Recently, an assessment of a computerization of local clinician-derived practice guidelines used to recommend antibiotics has been conducted.[38] During a seven-year study, the fraction of patients who received antibiotics increased each year. However, the total cost of antibiotics decreased from almost 25% to only 13% of the total drug expenditures. Fewer doses of antibiotics and less expensive antibiotics were used as a result of the system's recommendations.

These computerized systems also monitor for that subset of surgical procedures for which prophylactic antibiotics are recommended

(i.e., total hip replacement). For these procedures, antibiotics are often missed or given at the wrong time. In addition, once begun, these antibiotics are frequently not discontinued at the recommended time. In the absence of infection, a small number of doses is generally all that is required.

Based on computerized reminders, the number of patients who were given prophylactic antibiotics appropriately has increased from 40% of those who needed them to over 99%. In addition, the average number of antibiotic doses given as a part of prophylaxis decreased from 19 in the first year to only 5.3 doses at the end of the seven-year period. The accumulating experience suggests that computer-assisted support of antibiotic use can improve antibiotic use, reduce costs and stabilize the emergence of antibiotic-resistant pathogens.

Antibiotic Assistant

The third application 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 has developed a tool to help clinicians make informed decisions concerning the administration of antibiotics.[39] The "antibiotic assistant" 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 6 months and the past 5 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 first 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 analysis programs also evaluate susceptibility data to determine which antibiotics would probably cover the likely 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.[40] 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 CDDSS. 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. 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.[8] Statistical 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,[41] more recent efforts have focused on acquiring data bearing on pulmonary diseases.[42-43]

Three techniques for selecting questions 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 was "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. The answers are entered into the computer and the patient's data are compared to the diagnostic frames. The questions are scored by 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 4.2 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 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.

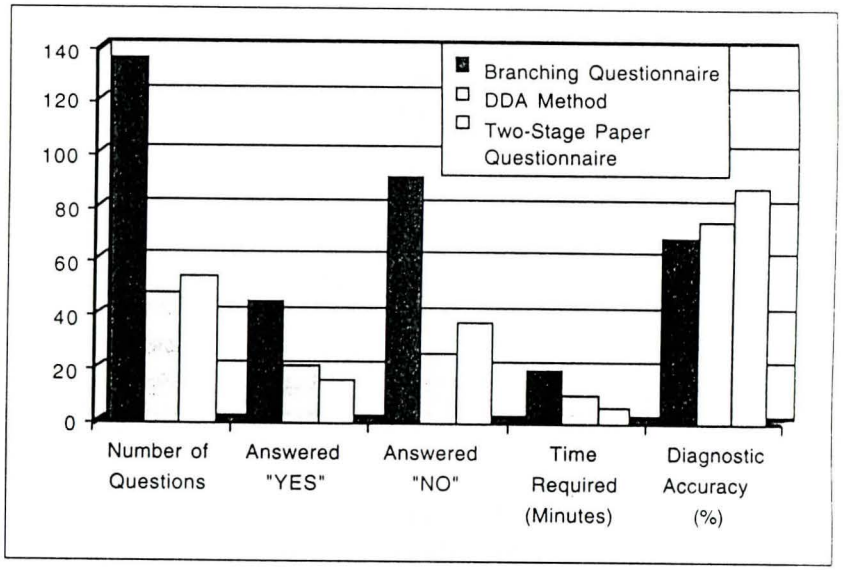

Fig. 4.2. A comparison of techniques for collecting the patient history.

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.[44-48] 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[49] 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.[50] 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.[51] 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.

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 might be helpful to future system developers and implementers to 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 CDDSS. 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 to 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 CDDSS in the hospital setting should provide a springboard for the decision support systems of the future.

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