Clinical Decision Support Systems for Addressing Information Needs of Physicians

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Clinical practice is a complex cognitive process comprising a variety of different types of problem-solving tasks that are involved in diagnosis and therapy planning. In addition, physicians must follow progress in clinical research and incorporate ever-growing new knowledge into clinical practice.

Two reports from the Institutes of Medicine in the USA – "*To err is human: building a safer health system*" in 2000 [1], and "*Crossing the quality chasm: a new health system for the 21st century*" in 2001 [2] – called attention to the sizable gaps between best practice and actual practice. In addition, concerns about patient safety regarding the large number of preventable medical errors were raised. The first report, by Kohn et al. [1], claims: "Indeed, between the health care that we now have, and the health care we could have, lies not just a gap, but a chasm," and also, "Information is often not available to those who need it when they need it. As a result patients often do not get care they need or do get care they don't need." The report highlighted the potential of using information technology, and in particular clinical decision support systems, to aid clinicians in gathering relevant data, making clinical decisions, managing medical actions more effectively, and thereby achieving fewer practice errors, a higher standard of care, and reduced costs [2].

This paper reviews research and applicative efforts in the field of CDSS and its current status and impact. Specifically, various types of CDSS are depicted. First, alert, critique and reminder systems are presented. Next, research projects aiming to computerize clinical practice guidelines and expert systems are described. Finally, performance evaluation and rules for developing and implementing CDSS are discussed.

Problems of information encountered by physicians

Covell et al. [3] measured physicians' information needs. They showed that for every three patients seen by physicians there were two unanswered clinical questions. Forty percent of the questions were described as questions of fact, 44% were questions of medical opinion, and 16% related to non-medical information. Similar studies have shown that physicians have approximately one question for every one to two patients encountered [4,5]. Although physicians have many questions about optimal care while they are seeing patients, they pursue only about 30% of their questions. This level of information needs prevails in primary care as well as among specialty care physicians, and holds also for urban and rural physicians [5].

Several studies evaluated the rate and impact of adverse events in health care organizations caused partly by information gaps. Adverse events are defined as injuries caused by medical management. Studies of randomly selected hospital discharges in New York State (30,000 cases) [6] and Colorado/Utah (15,000 cases) [7] reported that adverse events occur in 2.9–3.7% of hospitalizations. Fifty percent were minor, 7–14% resulted in death, 2.6% resulted in permanent disabling injury, 53–58% were preventable, and 28% were due to negligence (failed to meet reasonable standards of care).

In an ambulatory care setting, Gandhi and co-authors [8] estimated that 3% of visits are due to adverse drug events, and that 770,000 people are injured due to adverse drug events in the United States every year, of whom 7000 die. The Institutes of Medicine 2000 report [1] focused a great deal of attention on the issue of medical errors and patient safety. The report indicated that as many as 44,000 to 98,000 people die in hospitals each year due to medical errors.

Furthermore, the medical information explosion and the vast quantities of new knowledge increase the necessity of being informed and updated. It is estimated that today's experienced physician needs close to 2 million pieces of information to practice medicine. The scope of knowledge in medicine encompasses a multiplicity of diagnostic and therapeutic choices available for patient care, including thousands of medications, variations, combinations, routes, dosages, a few thousand specific laboratory tests, and hundreds of radiology procedures. In addition, clinical decisions should take into account the time constraints on practitioners. Consequently, medical errors occur with a high toll due to the large gaps between evidence

CDSS = clinical decision support systems

and practice as well as the fact that many guidelines are not followed.

The first report mentioned above (*"To err is human: building a safer health system"*) [1] emphasized the importance of CDSS in addressing problems of physicians' information needs in order to improve the quality of health care. Thus, clinical decision support systems are expected to fill the existing information gap by bringing relevant data and knowledge to the point of care.

Clinical decision support systems

CDSSs are computer systems designed to impact clinicians' decision making about individual patients at the point of care when these decisions are made. Thus, a CDSS is any computer program that helps health professionals to make clinical decisions. The disadvantage of such a broad definition is that it includes any computer system that stores, retrieves, or presents medical data or knowledge. To further specify the meaning of CDSS Wyatt and Spiegelhalter [9] proposed a more focused definition. In their view, a CDSS is an active knowledge system that uses two or more items of patient data to generate case-specific advice. By this definition, electronic textbooks and World Wide Web pages like Medline are not CDSS.

CDSSs are typically designed to integrate a medical knowledge base, patient data, and an inference engine to generate case-specific advice. The knowledge base is the part of an expert system that contains the facts and rules needed to solve problems. The inference engine is a processing program in an expert system. It derives a conclusion from the facts and rules contained in the knowledge base using various artificial intelligence techniques [Figure 1].

There is growing attention to preventable medical errors and the sizable gaps between best practices and actual practices. Consequently, there is a growing interest in the use of Clinical Decision Support Systems in aiding clinicians to make clinical decisions, manage medical actions more effectively, and thus achieve reduced practice errors, a higher standard of care, and reduced costs.

CDSS based on EMR and Physician Order Entry systems

Electronic medical record systems are increasingly being incorporated into health care organizations. EMR systems interface with a wide variety of data sources to form the complete record (including laboratory data, imaging results, etc.). Thus, EMR systems contain a vast amount of patients' data that can be accessed by CDSS.

EMR = electronic medical record

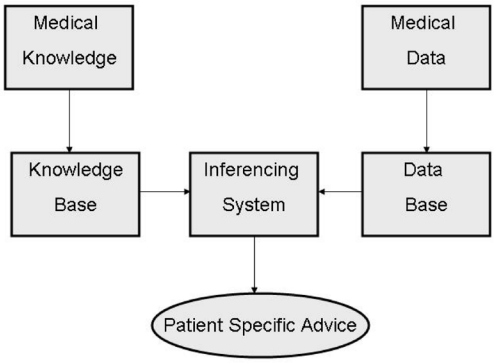

Figure 1. Schematic representation of the components of a typical CDSS

The Computerized Physician Order Entry system is an application that allows physicians to write all orders. Using the CPOE system improves the quality of drug and other orderings by enabling a streamlined process like dose selection from menus and enforcing complete orders. Bates et al. [10] showed that the rate of medication errors significantly decreased when a computerized physician order entry system was used.

Coupling CDSS with the CPOE system provides relevant information to physicians at key times in the decision-making process. This information may be based on checks of the patient's background, like drug allergy, drug-drug interaction and so forth. Moreover, policies and guidelines specific to a patient's condition can be presented to physicians at the time of ordering

Alert, critique, and reminder CDSS

Alerting systems are programs that function continuously, monitoring clinical data as they are stored in the patient's electronic record. They are designed to test specific types of data against predefined criteria. The timing and character of the messages vary with the alerting goals. An example is a system that monitors common laboratory results and detects, and alerts for, potential life-threatening abnormalities in the data acquired.

In a study by Kucher et al. published in the *New England Journal of Medicine* [11], electronic alerts were shown to prevent venous thromboembolism in hospitalized patients. Implementation of this alert program increased physicians' use of prophylaxis treatment and markedly reduced the rates of deep vein thrombosis and pulmonary embolism in hospitalized patients at risk. Kuilboer and team [12] developed a system integrated with the general practitioners' electronic medical records based on guidelines for asthma and chronic obstructive pulmonary disease. They examined several asthma and COPD monitoring-related parameters and treatment behavior in a randomized clinical

CPOE = Computerized Physician Order Entry
COPD = chronic obstructive pulmonary disease

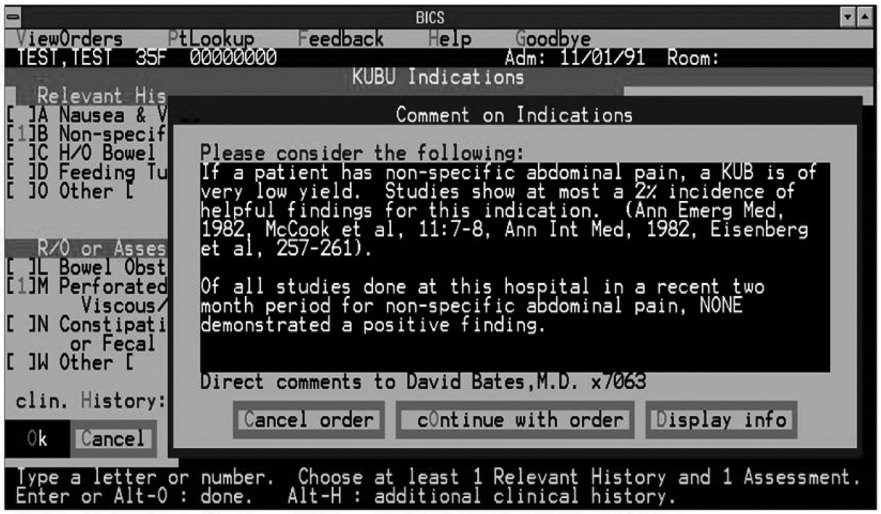

Figure 2. A typical screenshot of a message generated by a critique system for an abdominal X-ray order (kidney, ureter, bladder), taken from the clinical information system at the Brigham and Women's hospital in Boston.

trial conducted in 32 practices. In the intervention group the number of contacts and peak flow measurements increased whereas the number of cromoglycate prescriptions decreased. They concluded that the system changed the manner in which physicians monitored their patients and, to a lesser extent, their treatment behavior.

In contrast to alerting systems, *critiquing* systems are CDSSs that begin functioning when an order for a medical intervention is entered into an information system. For instance, Harpole and co-workers [13] measured how real-time evidence-based critiques on the appropriateness of abdominal radiograph orders affected physician decision making. Evidence-based critiques were presented to ordering clinicians in two kinds of situations: a) an abdominal X-ray was likely to have a low probability of providing useful information, or b) an alternative view(s) was more appropriate given the clinical circumstances. They found that although physicians were reluctant to cancel their order they were willing to change to different views [Figure 2].

A *reminder* system works behind the scenes, reminding the clinician to follow desired practice guidelines and policies. An example would be a reminder to order a specific test because a particular medication had been prescribed for the patient. The rules of this in general are of the form: "if on drug A and no test B for X months, then order test B."

Computerizing reminders and prevention guidelines improves adherence to evidenced-based medicine. Dexter et al. [14] showed that computerized reminders significantly increased the rate of administering preventive measures in hospitalized patients. In ambulatory settings, Shea and colleagues [15] performed a meta-analysis of randomized controlled trials to assess the overall effectiveness of computer-based reminder systems in preventive care, and concluded that such systems are clearly effective in improving prevention services.

Computer-interpretable clinical practice guidelines

Clinical practice guidelines are being advocated as a means to disseminate research findings, standardize care, improve quality of care, and increase the cost-effectiveness of services [16]. However, studies have found that compliance with guidelines in practice has not been satisfactory [17,18].

Much of the research on CDSS has focused on developing formalisms for modeling clinical guidelines. This can be achieved by representing guideline knowledge in a formalism that enables computer-based execution and supports automatic inference. Such formalisms are known as Computer-Interpretable Guideline modeling methodologies, or CIG. With CIG formalisms patient-specific recommendations can be generated during patient encounters in order to increase compliance with guidelines. The knowledge contained in guidelines is difficult to formalize due to the fact that evidence-based recommendations are often incomplete and vague, and do not constitute a full care process. Several methodologies have been developed to support the transition from narrative guidelines to CIG implementations. They include a) methodologies for marking-up narrative guideline elements in order to assess a guideline's quality and completeness and map it to CIG formalisms, and b) CIG formalisms. Several CIG formalisms were developed: Asbru, EON, GLIF, GUIDE/NewGuide, SAGE, PROforma and GLARE [19-25]. These formalisms differ in their goals, computation model, execution across heterogeneous clinical information systems, management of temporal knowledge, the elements used to structure guideline knowledge, and the degree to which they support workflow integration [Figure 3].

Specifying a narrative guideline as a CIG is a difficult task, yet the resulting application cannot be easily shared by different institutions and software systems. Therefore, sharing encoded knowledge is a challenging goal. The specification of standard methods to support such sharing is a major focus in the field.

Expert systems

Artificial Intelligence is the field in computer science that studies how a computer program can be developed to mimic human intelligence such as reasoning, learning, problem solving and decision making. The Expert system is an artificial intelligence program that represents and applies knowledge to provide expert quality advice. It can be applied to diagnosis, prognosis, treatment selection, and prevention. In such systems, there are two main challenges: representation of the knowledge and acquisition of knowledge.

CIG = computer-interpretable guideline

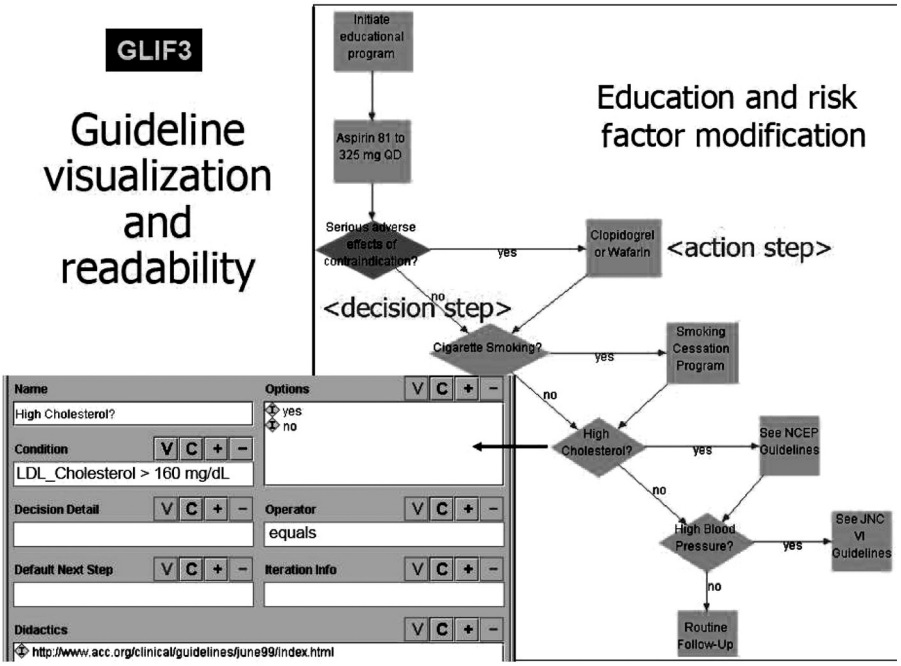

Figure 3. Graphic representation for a guideline in the GLIF (Guideline Interchange Format) model. The education and risk factors modifications in a guideline for stable angina are shown. On the lower left is the specification for the "high cholesterol?" decision step.

Several methods were used to represent the knowledge in these systems. Among them are rule based (based on "if-then" rules), Bayesian network, pattern matching and neural networks. Acquiring the knowledge for an expert system is based either on human experts or on hard scientific data. Eliciting knowledge from experts is a difficult process; it traditionally involves interviews, observation of experts in the field setting, examining experts at work while they "think aloud," and questionnaires. Van Ast et al. [26] described, validated and demonstrated an approach for knowledge base construction based on expert opinions. They showed that human experts can provide reliable information about the frequency of occurrence of manifestations in epileptic seizures.

Hard scientific data can be extracted from various types of medical literature like research reports, reviews, meta-analyses, etc. Scientific data can also be acquired by using machine-learning methods. This is the branch of artificial intelligence that studies systems that learn. Such systems improve their performance with experience by learning from examples. Some CDSSs have the capacity to learn, leading to the discovery of new phenomena and the creation of medical knowledge. These machine learning systems can be used to develop the knowledge bases used by Expert systems. Examples of such machine learning techniques are neural networks and decision induction trees.

Efforts have been made to construct Diagnostic CDSSs as an expert knowledge-based system to support the process of diagnosis by offering differential diagnosis given a set of input data. Diagnostic CDSSs were developed based on various clinical knowledge representation models. Many efforts were made to develop Diagnostic CDSSs for specific clinical problems; pioneering projects were de-Dombal's system for the diagnosis of acute abdominal pain based on a Bayesian decision model (1972) and Mycin, a rule-based system for supporting the diagnosis and treatment selection of infectious diseases (1976). However, only a few models were developed and implemented to support the process of diagnosis in a broader clinical context like general internal medicine. Key projects are QMR (quick medical reference), DXplain and Isabel. QMR [27] is an evolution of the Internist system that was developed at Pittsburgh University in 1980. QMR used a non-Bayesian decision model and its database consists of 750 diseases and 5000 clinical findings [Figure 4]. However, this system is not in routine use. DXplain [28], which was developed in 1987 at Harvard University, is used for educational and clinical purposes.

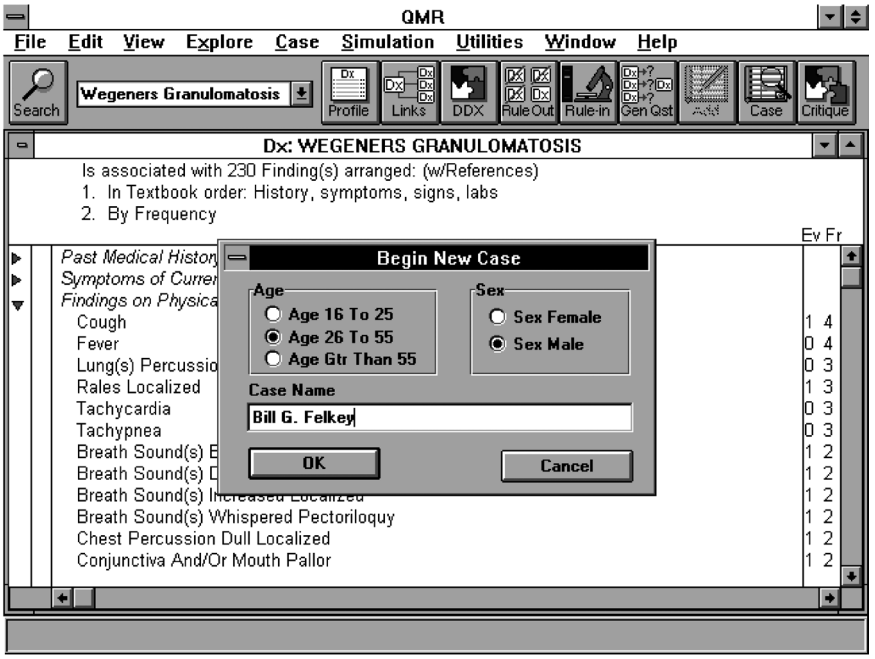

Figure 4. A new case screenshot of the QMR system

Its decision model is a modified form of Bayesian logic and the database consists of 2200 diseases and 5000 findings. Another system, Isabel [29], is a web-based diagnostic decision support system created in 2001 to offer diagnosis decision support at the point of care. Isabel covers all ages (neonates to geriatrics) and uses a database of 2500 diseases. More than 20,000 users are registered to the Isabel system.

Effectiveness of CDSS

Performance evaluation of CDSS is a complex issue. With regard to Diagnostic CDSS, despite years of research and heavy investment these systems are not used in daily practice. Some evaluation studies showed unsatisfactory results [30]. One problem is that these evaluation studies were designed to compare the systems' performance against a panel of expert physicians. However, while in early Diagnostic CDSS these systems were seen as the "Greek Oracle" that can replace professionals [31], this approach was abandoned in favor of one where they provide decision support rather than replace physicians [32,33]. Thus, the newer way of evaluating their performance is by measuring the degree of support in the diagnostic process. Still, many physicians do not trust these systems. Other reasons for the failure of Diagnostic CDSS to be incorporated into practice are: unresolved scientific issues, dependence on an electronic medical record system to supply data, and failure to fit naturally into the routine process of care [34]. At present, interaction of the user with the system is by active data entry, but it is expected that in the future such systems will be incorporated into electronic medical record systems from which they will extract data.

Systematic reviews of CDSS in general show that, when effective, CDSSs change processes of care (e.g., appropriate ordering of tests, correct drug dosing) and improve practitioner performance, but the effects of CDSS on patient outcomes have been insufficiently studied [35,36]. Garg and colleagues [35] identified 100 randomized and non-randomized controlled trials that evaluated the effect of implementing a CDSS compared with care provided without a CDSS. The variables included practitioner performance where 62 out of 97 studies reported improvement with CDSS, and patient outcomes where 7 of 53 studies reported improvement.

In a systematic review of 70 randomized controlled trials, Kawamoto et al. [37] found that CDSS significantly improved clinical practice in 68% of trials. They identified the following features as independent predictors of improved clinical practice: automatic provision of decision support as part of clinician workflow, provision of recommendations rather than merely assessments, and provision of decision support at the time and location of decision making. Of 32 systems possessing all these features, 30 (94%) significantly improved clinical practice.

Wetter [38] listed the following factors as being significant for developing CDSS: a) timely advice, b) workflow integration (workflow integration involves representation of organizational knowledge to facilitate the integration of CDSS with clinical workflow); c) integration into the information technology environment, d) flexibility, e) response to user needs, f) physicians' ability to change the knowledge base, and g) maintenance and extension of the knowledge base.

As encouraging data were published regarding the benefits of CDSS in a few studies, some shortcomings of CDSS were also exposed. Examples include excess alerts leading to reduced effectiveness of alerts ("alert fatigue") and potential errors caused by incorrect implementation of CDSS systems. Han and co-authors [39] observed an unexpected increase in mortality coincidental with CPOE implementation among children who were transported for specialized care. Koppel et al. [40] found that a CPOE system might facilitate the risk of medication error. Examples include fragmented CPOE displays that prevent a coherent view of patients' medications, pharmacy inventory displays mistaken for dosage guidelines, ignored antibiotic renewal notices placed on paper charts rather than in the CPOE system, separation of functions that facilitate double dosing and incompatible orders, and inflexible ordering formats generating wrong orders. They concluded that as CPOE systems are implemented, clinicians and hospitals must be alert to errors that these systems may cause in addition to errors that they prevent.

Standards that form the infrastructure for CDSS are being increasingly developed and adopted to enable sharing. Developing and promoting standards is the work of standard development organizations of which Health Level 7 (HL7) and CEN (European Committee for Standardization) are most relevant for CDSS developers.

Summary

Clinicians routinely practice in a state of incomplete information – about the patient, and about medical knowledge pertaining to patients' care. Consequently, there is now growing interest in the use of CDSS to bring decision support to the point of care. CDSS can impact physician behavior in routine practice. Nonetheless, CDSSs are meant to support humans who are ultimately responsible for the clinical decisions, rather than replace them. Although the adoption of CDSS has proceeded at a slow pace, there is a widespread recognition that CDSSs are expected to play a crucial role in reducing medical errors and improving the quality and efficacy of health care. This will be facilitated by the gradual maturation of electronic health record systems and the emergence of standard terminologies and messaging standards for the exchange of clinical data.

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Every society honors its live conformists and its dead troublemakers

Mignon McLaughlin (1915-1983), American journalist and author