Clinical Decision Support Systems: Perspectives in Dentistry

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Abstract: Clinical decision-support systems (CDSSs) are computer programs that are designed to provide expert support for health professionals making clinical decisions. The goal of these systems is to help health professionals analyze patient data and make decisions regarding diagnosis, prevention, and treatment of health problems. This article discusses the characteristics of such systems, addresses the challenges in developing them, identifies potential barriers for their use in clinical practice, and provides perspectives for the future.

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Clinical decision-support systems (CDSSs) are computer programs that are designed to provide expert support for health professionals making clinical decisions.[1] These systems use embedded clinical knowledge to help health professionals analyze patient data and make decisions regarding diagnosis, prevention, and treatment of health problems. Examples of such systems can be found in several disciplines in health care: dentistry, medicine, and pharmacy, among others.

The following scenario is an example in which an electronic dental record and a CDSS exist. Consider a situation where a patient requires dental care. A patient calls the office assistant to schedule an appointment with the dentist for a follow-up on a treatment for an ongoing problem. The patient complains of tooth pain. The assistant registers the patient for an appointment that same day. When the patient arrives for the appointment, he is asked to provide information on his health status as well as treatment preferences by answering a computer-based questionnaire that enters data directly into the electronic oral health record. Automated alerts generated by the system remind the dentist of health problems that may impact the patient's oral health; for example, the patient smokes and has a previous diagnosis of subacute bacterial endocarditis (SBE), indicating that attention should be given to cancer screening and this patient may need prophylactic antibiotic. While assessing the patient's problem, the provider completes the electronic tooth charting information, including recording the caries lesions and periodontal health. Specific caries risk questions are automatically shown to the provider. The clinical decision-support system then classifies the patient according to the caries risk assessment, which includes sugar intake, inadequate exposure to fluoride, recent restorations for caries, last visit to the dentist, etc. A suggested treatment plan is automatically generated by the CDSS. In addition, information tailored to this specific patient is provided in a separate document, such as educational materials on the increased risk of oral cancer in a person who smokes.

In this scenario, there are several examples of decision support applications. CDSS applications may be standalone systems, or they may interact with other tools such as an electronic dental record, an order entry system, or a radiology system. They may deliver a recommendation for the patient's treatment and future evaluation as well. CDSSs may also generate alerts regarding potentially dangerous conditions for a patient (drug allergies), or they may remind clinicians of routine tasks such as more frequent screening for oral cancer in a smoker or for periodontal diseases in a patient with diabetes, or even to perform tasks such as the use of prophylactic antibiotics in a patient with SBE. Other applications not listed in the example, such as radiology systems or patient education tools, may provide dentists with additional evidence or other types of information. Radiology systems, for instance, may generate messages if a radiograph is taken too often or if a radiographic examination is due. CDSSs may provide information tailored to the patient's needs, a list of journal articles, or simply general knowledge on dentistry.

History

The use of computers to assist health professionals in their activities has been studied since the 1950s. Initial work was focused on the development of diagnostic systems.[2] Ledley (a dentist) and Lusted[3] were the first to address this possibility. They described the use of punch cards for indicating relationships between diseases and their manifestations. An experimental prototype was described in a later publication.[4] Problems including the limitations of the scientific foundation and the resistance by practitioners to accept a system that was not integrated into their usual workflow prevented the widespread establishment of the system.[1]

Since then, researchers have applied different methods to provide clinical applications with knowledge. F.T. de Dombal et al.[5] studied the diagnostic process using Bayesian probability theory. Their system, the Leeds abdominal pain system, used sensitivity, specificity, and disease-prevalence data for various signs, symptoms, and test results to calculate the probability of seven reasons for abdominal pain (appendicitis, diverticulitis, perforated ulcer, cholecystitis, small-bowel obstruction, pancreatitis, and non-specific abdominal pain). In a controlled prospective comparison study, the system's overall accuracy (91.8 percent) was significantly higher than that of the most senior member of the clinical team who saw each case (79.6 percent).[5] This system was used in a variety of settings but never obtained the same degree of accuracy in other environments as it did in the original settings, even after adjustments were made for different prior probabilities of disease. The Pathfinder system[6] for diagnosis of lymph nodes pathology, also a Bayesian system, was built on the foundation set by de Dombal and colleagues.

Shortliffe et al. used a different approach in the development of the MYCIN system.[7] Knowledge of infectious diseases in MYCIN was represented as a set of rules, each containing content derived with expert collaboration. It was one of the first programs to address the problem of reasoning with uncertain or incomplete information, incorporating a calculus of uncertainty called *certainty factors*. The performance of the MYCIN system was evaluated on therapy selection for cases of bacteremia[8] and meningitis.[9] The results of this evaluation indicated that the programs' therapy recommendations were consistent with those of the expert's 90.9 percent and 65 percent of the times for bacteremia and meningitis, respectively. Many of the expert system development techniques currently in use were first developed or based in the MYCIN project.[10]

Stimulated by increased research on CDSSs, several other representational schemas were used in clinical applications. Hybrid systems, for example, combine deductive rules and probabilistic reasoning in the same CDSS. Perhaps the best known of the hybrid systems are the general medical consultation systems QMR[11] (1985), DXplain[12] (1986), and Iliad[13] (1987).

More recent work on CDSSs has focused on integration of these applications with clinical databases. These integrated systems take advantage of data already recorded for other purposes in order to avoid redundant data entry in the provision of alerts and reminders. These CDSSs may monitor data in a large health care organization or may be part of an electronic patient record installed in a single clinical office or clinic.

Research has also been done on eliciting patients' preferences for therapeutic options, which can help health care professionals to gain a better understanding of aspects of these options that are important from the patient's perspectives.[14] Ruland et al. have shown that eliciting patients' symptoms and preferences and providing clinicians with this information prior to consultation can be an effective and feasible strategy to improve patient-centered care.[15]

Characteristics and Types of CDSSs

Most CDSSs have four basic components: inference engine (IE), knowledge base (KB), explanation module, and working memory (Figure 1). The IE is the main part of any such system. The IE uses the knowledge on the system and the knowledge about the patient to draw conclusions regarding certain conditions. The IE controls what kind of actions need to be taken by the system. For example, it de-

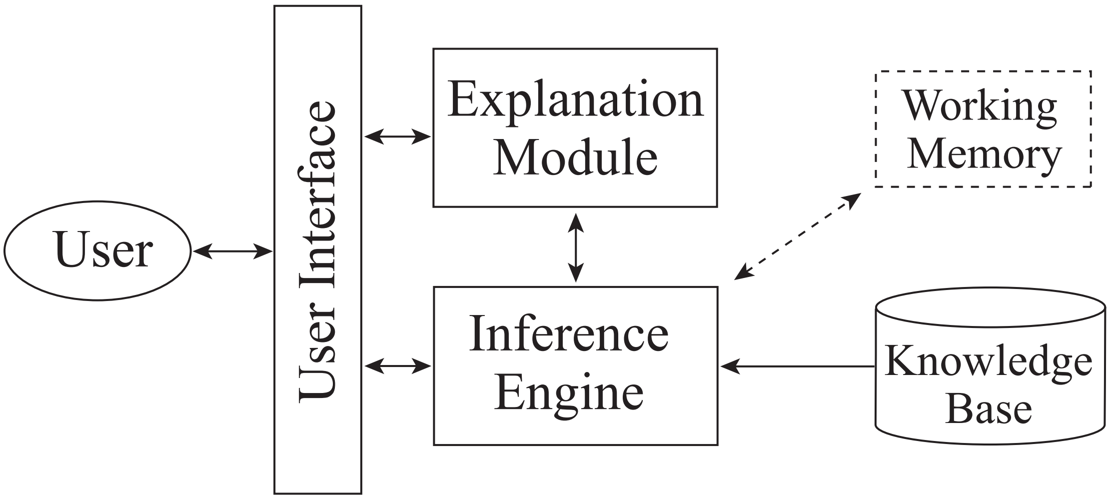

Figure 1. Elements of a typical CDSS

termines the route of alerts and reminders in an alerting system, or the conclusions to be displayed in a diagnostic system. The knowledge used by the IE is represented in the KB. In a system for management of caries, the KB will contain knowledge on risk factors for new lesions and risk scores. Knowledge bases may be built with the help of a domain expert or by an automated process. In the first case, a knowledge engineer (expert on building KBs) with the help of a clinical domain expert creates, edits, and maintains the KB. In an automated process, knowledge is acquired from external resources such as databases, books, and journal articles by a computer application. Creating such knowledge bases can be a complex task. Fortunately, tools have been created to facilitate the acquisition and elicitation of KBs. An example of such a tool is Protégé,[16,17] a knowledge-based development environment.

The collection of patient data may be stored in a database or may exist in the form of a message. This collection is known as "working memory." Patient data may include demographics (i.e., date of birth, gender), allergies, medications in use, previous dental or medical problems, and other information.

The last component, the explanation module, is not present in all CDSSs. This module is responsible for composing justifications for the conclusions drawn by the IE in applying the knowledge in the KB against patient data in the working memory.

CDSSs can work on synchronous mode; that is, the application communicates directly with a user who is waiting for the output of the system. A typical example is a system that checks for drug-drug interactions or possible patient allergy to a medication when a provider is writing a prescription. In asynchronous mode, CDSSs perform their reasoning independently of any users awaiting its output. An example is the generation of a reminder for an annual visit for checkup and hygiene.

CDSSs can be classified as open- or closed-loop systems. In an open-loop system, the CDSS draws the conclusions but takes no action directly of its own. An application that generates an alert or reminder is an example of such systems. The final decision on the action to be taken, if any, is made by the clinician. In the closed-loop system, the action can be implemented directly without the intervention of a human.

Other important types of CDSSs are event monitors, consultation systems, and clinical guidelines. An event monitor is a software application that receives copies of all data available in electronic format in an institution and uses its knowledge base to send alerts and reminders to clinicians when deemed appropriate.[18] In consultation systems, a clinician enters details of a case (e.g., patient demographic information, clinical history, physical examination findings, and test results) into the system, and the system, in turn, provides a list of problems that may explain the case and suggest actions to be taken.

Clinical guidelines have been incorporated into CDSSs. Typically, they are developed by groups of clinical experts and disseminated by the government or by professional organizations. These practice clinical guidelines represent formal statements of recommended best practices with regard to a particular health condition. To improve sharing of such guidelines, researchers have tried to develop standard knowledge representations such as the Arden Syntax[19] or the GuideLine Interchange Format (GLIF).[20] Arden Syntax is an ANSI (American National Standards Institute) standard for representing computable clinical knowledge. In the Arden Syntax, each decision rule is called a medical logic model (MLM). Each MLM contains sufficient logic to make a single clinical decision. Figure 2 shows one such MLM and its representation in the Arden Syntax. Figure 2 is an example of a simplified medical logic module designed to send an alert to healthcare providers whenever a patient's serum digoxin level is low and the patient is taking digoxin. The GuideLine Interchange Format (GLIF) is a computer-interpretable format for the representation of clinical practice guidelines developed by the InterMed collaboration (a joint project of laboratories at Harvard, Stanford, Columbia, and McGill universities). It is designed as a general purpose language for development and implementation of guideline-based clinical decision support systems with applications in different clinical domains. In addition to providing patient-specific recommendations, it can also be used for quality assurance and medical education.

```
evoke:
  /* evoke on storage of a serum digoxin level */
  storage_of_digoxin;;

logic:
  /* exit if the digoxin level is 0 */
  if digoxin <= 0 then
      conclude false;
  endif;

  /* get the last valid potassium */
  potassium := last(raw_potassiums);

  /* exit if no hypokalemia is found */
  if potassium < 3.3 then
      ; /* send an alert */
  conclude true;
  else
      conclude false;
  endif;
  ;;

action:
    write "The patient's serum digoxin level indicates that the patient is taking digoxin. The patient's most recent potassium level is low, and the hypokalemia may potentiate the development of digoxin-related arrhythmias.";
  ;;
```

Figure 2. Example of a simplified MLM

This figure represents an example of a simplified medical logic module (MLM) designed to send an alert to healthcare providers whenever a serum digoxin level is low and the patient is taking digoxin. There are three main parts in this simplified MLM: evoke slot, logic slot, and action slot. The evoke slot defines the situation that causes the rule to be triggered (serum digoxin level); the logic slot encodes the decision logic of the rule; and the action slot defines the procedure to follow if a positive conclusion is reached.

Knowledge Representation

Another way of characterizing CDSSs is by the way knowledge is represented. Knowledge representation is how to convert knowledge to a form that a computer can reason with. Various representation schemas have been proposed and implemented, each of them having its own strengths and weaknesses.[10] According to Minsky,[21] to solve difficult problems, we need to use several different representations, because none of the representations individually is adequate for all the different functions involved in representing a particular domain.

CDSS knowledge representation can be classified into the following generic categories: algorithmic, neural networks, probabilistic, and logical/deductive (rule-based). In addition, hybrid systems use more than one category of KR.

Algorithmic systems use logical classification methods, represented as decision trees and flowcharts that lead the user to a desired end point. This approach does not depend on large sample sizes of data and can be applied across patient populations. One of the major problems involving algorithmic systems is the lack of flexibility with which the decision points are incorporated into the statements of the program. This method does not incorporate uncertainty. In addition, changes in knowledge may require substantial rewriting of the system. In a complex system, decisions may be impossible to understand and revise. Examples of applications with this approach include recommendation of chemotherapy drugs for breast cancer[22] and a diagnostic aid for oral pathology.[23,24]

Neural networks are algorithms that require training to create a set of solutions to a problem. After training, these algorithms can make decisions on new problems with incomplete facts; they are commonly used in pattern recognition problems. Neural networks (NN) were first implemented in the 1940s[25] as a biological model of the brain. Applications based on NN "learn" from information received from external resources, rather then applying a set of specific decisions. The NN methodologies have been particularly successful at narrow and well-defined clinical problems such as classifying textual output of images,[26] diagnosis support,[27-29] and prognosis evaluation.[30,31] NNs have also been commercialized for image recognition and are used in uterus cervix cytology labs.[32] In addition, NN have been applied in dentistry to identify people at risk of oral cancer and pre-cancer[33] and for lower third molar treatment planning decisions.[34]

Probabilistic systems incorporate rates of diseases or problems in a population and the likelihood of various clinical findings in order to calculate the most likely explanation for a particular clinical case. These systems typically employ Bayes Theorem, which is a mathematical model that accounts for the prevalence of disease in a population and the characteristics of a particular patient to calculate the probability that a particular patient has a particular disease. While the advantage of probabilistic systems is that their output reflects the relative likelihood of diagnosis or success of treatment, they may be limited by the fact that the necessary probabilities either are not known or are derived from a population at least somewhat different from the patient in a particular case. One of the earliest examples of a successfully used probabilistic system was the previously discussed CDSS created by de Dombal et al. described above. Examples of Bayesian systems in dentistry include the Oral Radiographic Differential Diagnosis (ORAD), a program to assist in oral radiographic diagnosis,[35] and a system that assists pulpal diagnosis.[36]

Logical/deductive systems use branching logic—a collection of if-then rules—to make decisions. While the if-then rules of a logical/deductive system allow representation of the branching questions used by experts to make clinical decisions, they may overemphasize certain diseases if they are not adjusted for the rarity or prevalence of particular diseases. Noteworthy early logical/deductive systems include Bleich's software that diagnosed acid-base disorders and Shortliffe et al.'s MYCIN system. An example of application in dentistry is RHINOS, a consultation system for diagnosis of headache and orofacial pain.[37]

A variant of rule-based systems is the critiquing model, a program that reacts to proposed diagnosis or treatment with agreement or alternatives. Examples of such a system are HT-ATTENDING, HyperCritic, and RaPiD. Both HT-ATTENDING[38] and HyperCritic[39] are systems designed to critique the management of hypertensive patients. RaPiD uses both an automated and critiquing model for removable partial denture design.[40]

Hybrid systems attempt to overcome these drawbacks by combining both deductive rules and probabilistic reasoning in the same CDSS. They use features of several or all the previously described systems along with heuristics to assist clinicians in making decisions. Work on hybrid systems dates back to HEME, a system used to diagnose blood diseases in 1950s.

Several other representational schemas were also used in clinical applications. The HELP system and the event monitor at Columbia University are examples of systems that used procedure representation schemas.[19,41-43] Starren and Xie studied different representations for cholesterol management: first-order logic, frames, and production rules.[44-46]

Lessons learned from these systems revealed the feasibility of encoding clinical knowledge, and helped researchers to clarify both the strengths and limitations of knowledge representation approaches. There is a gradual change in attitudes and increasing acceptance of computer decision tools by healthcare professionals. However, this enthusiasm can diminish if researchers don't ensure that the products of their research respond to real world needs and are sensitive to the logistical requirements of the practice settings in which clinicians work.[1]

Clinical Applications in Dentistry

There has been research and development of CDSSs in dentistry for over two decades.[47,48] These systems have utilized different types of knowledge representation and have addressed several major areas of dental practice. Different modalities and requirements for dental decision support systems are described in articles by White,[49] Benn et al.,[50] and Brickley et al.[51]

In a comprehensive 1996 review of the literature on decision support applications in dentistry, White[49] identified over thirty decision support systems. He grouped these systems into seven subareas of dentistry: dental emergencies and trauma, orofacial pain (differential diagnosis), oral medicine (management of oral diseases in the neck and head), oral radiology (interpretation of radiographic lesions and automated interpretation of dental radiographs), orthodontics (analysis of facial growth, landmark identification of cephalometric radiographs, and treatment planning), pulpal diagnosis, and restorative dentistry (removable partial denture design). White also classified the systems according to the knowledge representation used, including algorithmic, statistical, rule-based, and image processing systems. White described the need to integrate the decision support systems into the practice environment, by providing real-time quality assurance, better support in treatment planning, and improvement of data analysis.

Publications since 1996 have described the development of neural networks in oral surgery,[34] caries management,[52,53] pretherapy decisions in patients with head and neck cancer,[54] and intelligent agents for treatment planning.[55,56]

Present and Future

In the last decade, the practice of evidence-based practice has gained strength, encouraging health care providers to use the best current evidence in clinical practice and health services. CDSSs are designed to provide relevant and current evidence to providers to substantially improve health care quality[57-59] and potentially reduce errors in practice.[60] In parallel, there has been a large and rapidly growing number of health care professionals and students with access to new technologies. For instance, more than 85 percent of all dentists use computers in their offices, and the number of clinical uses for the computer is increasing. Although most of this growth is due to the use of patient accounting, billing, and scheduling systems, the clinical use of information technology in the dental profession has increased substantially in the past ten to twenty years.[61] These changes have affected society's and health professionals' expectations of health care practice and delivery.

In a recent review, Schleyer et al.[62] listed the most common administrative and clinical technologies and classified them into "must-have," "nice-to-have," and "optional" technologies. "Must-have" applications are defined as essential to the functioning of a dental practice. Recall and reminders systems, which are CDSSs, were cited among the "must-have" applications. Despite the recognized need for CDSSs, the implementation of these systems has been limited. There are several reasons for this slow implementation: lack of formal evaluation of these systems, challenges in developing standard representations, lack of studies about the decision making process, the cost and difficulties involving the generation of knowledge bases, and practitioner skepticism about the value and feasibility of decision support systems, among others.

The validity of CDSSs is regularly established in narrow domains under varying conditions and technologies. However, many systems have not been formally evaluated, and their value for clinical practice may not have been established. Some CDSSs follow the costly development path of medical devices and FDA approval, while the majority of systems are not bound by these rigorous criteria. Generally, CDSSs are proliferating as fragmented and isolated systems with a few clinic- or hospital-wide exceptions in academic centers. In parallel, the public awareness of safety and quality has accelerated the adoption of generic knowledge-based CDSSs.

Another barrier, the structured data entry process, remains a challenge for all clinical information systems including CDSSs. Information technology applications for dental practice continue to develop rapidly[62] and will hopefully contribute to the removal of part of the data entry barrier. For example, a significant portion of relevant clinical facts is progressively more computable. The development of voice recognition software coupled with language understanding and new research in digital imaging may remove the barrier of laborious data entry. In addition, the adoption of diagnostic codes for use in dentistry will positively affect the development of such systems. Dental diagnostic codes allow for a better representation of conditions dentists encounter in their practices, such as patient outcomes, physical findings, dental diagnosis, risk factors, and functional status. In that regard, the American Dental Association has been working on the release of the Systematized Nomenclature of Dentistry (SNODENT).[63] The addition of these codes with the commonly used procedure codes could allow for a richer analysis of the evidence available present on the oral health records with consequent improvement in patient care.[64]

In his analysis of decision making in dentistry, Schleyer[65] identifies the need for studies on how dental practitioners make clinical decisions and what information they need to do so. Theoretical models of decision making that describe when and how decisions are made during the care process are the foundations of a successful system.

Finally, of all the above-mentioned barriers, the substantial cost of knowledge acquisition and knowledge maintenance remains the most challenging problem for the sustainability of CDSSs. The lack of rigorous studies (i.e., clinical trials) to identify evidence that supports best practices in patient care is also a significant barrier. In order to benefit from CDSSs, knowledge bases should consist of the best evidence available. Fortunately, new knowledge engineering methods and tools are being formally evaluated, including knowledge acquisition, knowledge representation, and knowledge reuse. The current research focus is on rigorous studies to find new evidence. These approaches can facilitate the knowledge acquisition and knowledge reuse. However, still to be explored are the legal and economical implications of sharing such knowledge bases.

From an educational perspective, educators have expressed concerns that health care professionals are not well prepared to meet society's expectations with regard to evidence-based practice and the use of information technology in the delivery of health care. Several societies and schools have proposed changes in their objectives and competencies to enhance the skills of graduates in evidence-based practice and use of information technology.[66-69] The Commission on Dental Accreditation of the American Dental Association,[68] for instance, recommends that graduates must be competent in the use of critical thinking and problem solving related to comprehensive care of patients and in the use of information technology resources in dental practice. Basic knowledge may include computer literacy, skills in accessing and critically reviewing scientific literature, and knowledge bases. As the curriculum moves in this direction, students hopefully will become increasingly competent in different aspects of research and technology. This enhanced capacity among new dental practitioners will, in turn, hopefully afford opportunities to improve evidence-based practices, increase conformity with patient care guidelines, and increase practitioners' willingness and ability to use decision support tools.

In summary, there are still many challenges to be overcome. The future of CDSSs depends on the adoption of evidence-based practice, progress in developing useful programs, the adoption of standards to allow interoperability, the reduction of logistical barriers to implementation, understanding of the complex and changing nature of clinical knowledge, and proper validation of the programs. Additional challenges are related to the legal implications inherent to the development and use of such innovations.

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