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An Introduction to Clinical Decision Support Systems

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Library support of clinical decision-making ranges from passive (traditional library collections of books and journals) to highly active (professional services, such as clinical medical librarians, LATCH, and informationists). Support of mobile computing resources and subscriptions to point-of-care services, such as UpToDate and DynaMed, moves libraries toward interactive resources to aid healthcare providers in their decisions about specific patient questions but stops short of the tools described here that specifically support clinical decision making. Librarians seeking to add robust clinical decision support systems should partner with clinicians and medical educators to weigh usability, ability to integrate with electronic health records and other systems, accuracy, reliability, depth of knowledge base, and improvements to process and patient outcomes, along with costs, which can be substantial.

KEYWORDS *Clinical decision support systems, CDSSs, diagnostic decision support systems, DDSSs*

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**BACKGROUND:
EVOLVING LIBRARY AND LIBRARIAN IN SUPPORT OF INFORMED CLINICAL
DECISION-MAKING**

Roles and services. Health sciences librarians have long recognized that informed clinical decision-making drives their mission. In the 1970s and 1980s librarians began to take active roles in the provision of health care, serving as clinical medical librarians and attending patient rounds with the health care team so questions that arose could be answered quickly.¹⁻⁴ LATCH was a program that attached paper copies of relevant literature to a patient's health record for the convenience of health care providers.¹ In the 1980s, a joint vision between the Association of American Medical Colleges and librarians prompted a series of grants and projects to integrate multiple information systems, including electronic health records, bibliographic information, prescribing systems, financial management systems, and health images. In this vision, any health database that could be connected, would be, to create new integrated advanced information management systems, or IAIMS.⁵

As personal digital assistants became popular and programs were developed that could be loaded onto a PDA to be carried in a pocket, librarians assumed roles promoting the resources and teaching clients how to use them.⁶⁻⁹ Although more information systems than true clinical decision support systems, these resources, such as Epocrates, a drug and disease information reference tool for handheld devices, moved into mainstream use and allowed health practitioners to make informed decisions about individual patients.

In more recent times, librarians have found important roles in supporting clinical care by teaching evidence-based searching to health providers. In some cases, librarians and informationists are embedded once again into the health care team, as they were in the 1970s, to

provide rigorous searching and quick results to facilitate informed decisions by health care providers.¹⁰

Collections. Collection development librarians have had many options for providing support for clinical decision-making. The traditional method of support has been relevant books and journals, such as the *Merck Manual* and other tools referred to as “white coat pocket” references or guides. As nonprint media collections became popular in the libraries of the 1970s and 1980s, standalone clinical decision support systems (CDSSs), such as CADUCEUS, Iliad (distinct from the interlibrary loan program), and DXplain entered library collections.¹¹⁻¹³ These programs, sometimes supplied on collections of floppy disks, allowed health providers to enter a series of symptoms and then provided a list of possible diagnoses. Closely related were simulation programs that presented cases for medical training, and required the learner to ask appropriate questions or order relevant “test” results to arrive at the appropriate simulated diagnosis and treatment.

Most libraries have moved toward online textbooks and resources to provide quick access to key information. Some products have taken information from primary sources, such as journals or consensus of experts in a field, and combined that information with accepted clinical guidelines and protocols to create value-added tools specifically designed to support clinical care. Two examples are DynaMed and UpToDate. As mentioned previously, mobile devices and tools like InfoRetriever, ePocrates, and Micromedex help provide drug information, clinical guidelines, calculators, and emergency medicine resources at the point of care.

There is a growing body of evidence that library and medical information resources lead to improved health outcomes,¹⁴⁻¹⁶ however not all libraries routinely add resources to their

collections that are specific to supporting individual patient questions. Adding CDSSs is a logical evolutionary step for librarians who wish to actively support informed health decisions.

PROBLEMS LEADING TO DEVELOPMENT OF CLINICAL DECISION SUPPORT SYSTEMS

The Volume of Information

Although the purpose of a medical education many years ago might have been to provide a physician with all the information needed for a lifetime of informed medical decision making, that time is long gone.

Medical educators of the middle and latter 19th century were the first physicians in history to feel the real shock of the information explosion in medical science. By the 1870s, an enormous increase in medical information was radically transforming medical thought and practice, and the amount of medical literature began to become overwhelming. Even more important was an insight of revolutionary proportions: the recognition that medical knowledge is not something fixed but something that grows and evolves.¹⁷

Today the sheer volume of medical information, termed a journalistic blastoma even in 1935,¹⁸ can be inundating. On June 15, 1997, PubMed listed access to 9 million citations via MEDLINE.¹⁹ Today PubMed provides access to more than 20 million citations.²⁰ In addition to printed materials, physicians now have electronic journals, websites, RSS feeds, streaming videos, and blogs to review.

Lack of sufficient information when making medical decisions can negatively affect patient outcomes. Having so much information that it becomes confusing and overwhelming can have the same effect. “Information overload” is a term used to describe the difficulties one can

have when facing so much information that it is impossible to review it all before making a decision. In 2002, Case cited "... omissions, error, delays, filtering, lowering standards, delaying and escaping"²¹ as some of the coping mechanisms for information overload.

Unanswered Questions

Study after study have documented that physicians have many questions during patient encounters, with most of these questions going unanswered. Covell reported that physicians had two unanswered questions for every three patients seen.²² Ely observed that family medicine physicians had 3.2 questions per ten patients seen, and physicians sought the answer to the question in only 36% of the cases.²³ Gorman found that physicians had one question for every one to two patients seen. He reported more than half (56%) of the physicians pursued answers if they thought an answer existed and half of the questions regarded urgent answers.^{24,25} Most physicians asked the most convenient source of information, other physicians, rather than turning to the medical library.

Today online and mobile resources may have changed how physicians approach questions and studies. Several years ago it was reported that 70% of residents said they used a PDA daily,²⁶ and today it seems likely that most residents would be using smart phones. It seems only a matter of time before Covell's classic study is replicated, this time measuring if (how) mobile computing devices have changed the findings and if more of the questions in patient encounters are answered. Nonetheless, unanswered physician questions have been and remain a powerful motivator for developing computer-based clinical decision support systems.

Lack of Time

Coupled with information overload, physicians often report they do not have enough time to pursue answers or use new innovations. Ely found that 64% of questions were not pursued, and

when the questions were pursued, less than two minutes was allotted per search. Most physicians with questions asked other physicians.^{23,27,28} Few physicians conducted literature searches.²⁹

Graber's study of medical students (2009),³⁰ discusses the tendency for clinicians to "solve problems by 'satisficing,' accepting the first diagnosis that seems to adequately explain all the facts at hand, without a conscious consideration of other possibilities." The theme of lack of time in physicians' practice is recurrent throughout the literature, often used to explain physicians' reluctance to accept new innovations.

Medical Errors and Adverse Events

A decade ago the Institute of Medicine publication, *To Err is Human*, documented that medical errors killed more people than motor vehicle accidents or breast cancer.³¹ In 2001 medication errors were pervasive and accounted for the largest number of errors, often being cited as the cause of injury and death in hospitals.³¹⁻³³ Studies in other nations indicated that their situations might be even worse.³⁴⁻³⁷ A RAND study found that patients consistently received recommended care only slightly more than half of the time³⁸ and a follow-up study on pediatric care using similar measures found that children received recommended care slightly less than half the time.³⁹ Kaushal and Bates documented millions of adverse events each year, many of which might be avoidable.⁴⁰⁻⁴² Despite an ambitious goal to reduce medical errors and save lives, the reduction in errors and adverse events has fallen short.⁴³

In response to information overload, unanswered questions, and medical errors and adverse events, computer-based clinical decision support systems have been developed.

WHAT IS A CLINICAL DECISION SUPPORT SYSTEM?

Haynes et al defined CDSSs as "...information technology-based systems designed to improve clinical decisions-making. Characteristics of individual patients are matched to a computerized

knowledge base, and software algorithms generate patient-specific information in the form of assessments of recommendations.”⁴⁴ The goal of using CDSSs is improved health care at the point of need, avoidance of adverse events, and reduced costs.

The most basic and longstanding type of CDSSs issues alerts. Alerts can include:

- Reminders that immunizations or mammograms are due
- Warnings in clinical monitoring or when clinical test results are beyond normal ranges
- Prescribing systems that identify drug-drug interactions, dosage errors or allergies
- Image recognition and interpretation
- Failure to follow practice guidelines, and more.

Another type of CDSS is used for prognosis. One common example that health consumers might be familiar with would be a calculation of the likelihood of a heart attack within x number of years, given a particular weight, reported exercise, family history, and certain laboratory values.

Another clinical example is APACHE, the Acute Physiology and Chronic Health Evaluation system, which is uses physiology variables to predict in-hospital mortality in intensive care units.

Some CDSSs are used to help health practitioners select among many diagnostic variables and options, and are called diagnostic decision support systems or DDSSs. DDSSs rarely make decisions for individuals, but rather are used to assist the human using them. In DDSSs, the tool might recommend potential diagnoses based on the choices, but the user must interact with the tool to refine and clarify inputs. Yet another type of health care decision support tools is consumer health decision support systems, which are appearing more and more on the Web. In these cases, online tools attempt to help patients faced with difficult health care choices.⁴⁵

Types of CDSSs

To understand CDSSs, consider the elements in clinical decision making. The clinician must decide what questions to ask, what data to gather, which tests to perform, and, after the diagnosis is made, what treatments or processes to use. To be effective, clinicians must have accurate data, pertinent knowledge, and appropriate problem solving skills.⁴⁶

CDSSs can be simple or very complex. For example, they might operate with a basic knowledge bank and inference engine, or with neural networks or artificial intelligence. Many CDSSs include a large knowledge bank of medical information and an inference engine that takes action using that information. Knowledge-based CDSSs operate on IF-THEN rules, using compiled data and rules for making sense of that data. System operators input the knowledge base and the rules. One example for a drug interaction rule might be: IF NSAIDS are taken AND Prozac® is prescribed, THEN alert the operator. Another approach, the Bayesian method, uses calculated probabilities to determine the likelihood that a potential solution is correct. Yet another type of CDSSs uses machine learning, a subset of artificial intelligence, where the computer extracts learning from a large database. A very basic type of computer “learning” might be applied to answer online customer questions. The customer enters a question. The computer searches for a potential answer based on past successful responses. After the potential answer is delivered, the computer asks the user if the answer was useful. If the user says “yes,” the computer “learns” that this is a good response. If the user says “no,” the computer attempts another answer. This example deviates from model machine learning, however, as ideally the computer learns automatically, without human intervention. Clearly this approach is not generally advocated in clinical care where experimentation in care delivery is to be avoided. For more information on how CDSSs work, see Musen, Shahar and Shortliffe⁴⁶, Deneke⁴⁷, and Abassi⁴⁸.

Some Examples

Knowledge-based systems designed to assist physicians at the point of care were first documented in the 1950s.⁴⁹ Some examples include MYCIN, developed in the 1970s by Stanford University to aid treatment of bacterial diseases;⁵⁰ DXplain from Massachusetts General Hospital, released in 1986, still functional today, and covering 2400 diagnoses;^{11,51} and Isabel from Isabel Healthcare, a comprehensive tool currently available.⁵²

Octo Barnett and DXplain. Documentation of systems used as signaling devices for medical records and in medical research first started appearing in the 1950s.⁴⁹ In the 1960s, the introduction of integrated circuits and operating systems allowed more hospitals to create patient information monitoring systems. One of the most notable began in 1962 when Dr. G. Octo Barnett, the head of the Laboratory of Computer Science at the Massachusetts General Hospital (MGH), and Bolt, Beranak and Newman (BBN), a Cambridge consulting firm, together secured funding from the National Institutes of Health (NIH).⁵³

BBN developed PDP-1, one of the first time-sharing computer systems^{54,55} and realized that the system could be very useful in a hospital setting. NIH agreed to fund the project with the stipulation that BBN would work with MGH to implement the systems. One of the first projects that came from this partnership was a drug ordering module in which physicians would enter prescriptions into a system that would check dosage and directions for accuracy. During testing the physicians had to continue to use their normal non-computerized method of prescription delivery for comparison, and upon evaluation, the physicians preferred the old system.⁵⁶

One of the most well known systems developed at MGH during that time was the MGH Utility Multi-Programming System (MUMPS). The programming language MUMPS was developed by a research assistant of Dr. Barnett, Neil Pappalardo.⁵⁵ MUMPS uses standard

arithmetic and Boolean statements and the ability to manipulate text strings and data files.⁵⁷

Other advantages include portability, scalability, and multitasking. It was first used in hospitals for patient records and quickly branched out into admissions and laboratory reporting. MUMPS is currently used in hospitals throughout the nation, as well as in many other industries. Some librarians will recognize MUMPS as the programming language for one of the first online library catalogs, LIS (Library Information System), originating at Georgetown University and adopted by many other health sciences libraries.⁵⁸

DXplain. Under Octo Barnett, an early diagnostic decision support system was developed at the Laboratory of Computer Science at MGH almost 25 years ago.⁵⁹ Upon release, the knowledge base contained approximately 500 diseases and now includes more than 2400 diseases and 5000 clinical findings.⁵¹ DXplain is a differential diagnosis system that has two roles. The first is that of a reference or case analysis tool. Upon receiving patient data, it presents a ranked list of possible diagnoses, along with the reasoning behind why each diagnosis was selected as a possibility. The manner in which it selects possible diagnosis is very similar to the 1 to 5 rating used in Internist/QMR. The second role is of a medical textbook with descriptions and up to ten current references for each disease.

DXplain is self-contained but is now accessed completely through the Web.⁴⁶ It predominantly is used in hospitals and medical schools as an educational aid and consultation tool.⁶⁰ During a two month study at St. Mary's Hospital in Rochester, MN Internal Medicine, thirty residents were asked to use the system and then evaluate it at the end of the study period.⁶¹ The majority of residents answered that the system was helpful, made them consider probable diagnoses, and was easy to use.⁶¹

CADUCEUS, Internist, QMR. During its lifecycle, from the 1970s to 2001, CADUCEUS/Internist/QMR, designed at the University of Pittsburgh, was considered one of the most extensive knowledge bases, ultimately with information on more than 750 disorders and almost 4,500 interrelated findings or disease manifestations.¹³ It is an early example of a CDSS that used artificial intelligence. The aim was that Internist would use the “hypothetico-deductive” approach to diagnose all areas of internal medicine and neurology.⁶² The knowledge base was created by clinicians, senior physicians, and medical students over the decade. They worked on the project to determine the list of pertinent findings associated with each disease.⁴⁶ In an effort to establish medical informatics in the curriculum, medical students were offered internships and allowed to create and add disease profiles to the knowledge base.¹³

The system was one of the first to use probability rankings. Since many of the disorders contained in the system were very rare and not well documented, the developers created an *ad hoc* scoring scheme to encode the relationships between specific findings and diseases.⁴⁶ This scheme assigned two numbers to the relationship between each disease and associated finding. Frequency weight (FW) was given a scale of 1 to 5, and evoking strength (ES) a scale of 0 to 5. For frequency weight, 1 would indicate that the finding is hardly ever seen with the disease and 5 would mean that the finding is always present in the disease. Likewise for evoking strength, a 0 would mean that on the basis of this finding alone, a particular disease would never be diagnosed and for an ES of 5, all patients with the disease would have the finding. A third number, the import number, also had a value from 1 to 5 and helped to control symptoms that should or should not be disregarded during diagnosis or how important that finding is to a disease.¹³

Over the years, and with the development of desktop “micro-computing” and continued growth and development, Internist evolved into QMR (Quick Medical Reference). Where

Internist simply gave a best explanation for symptoms, QMR would suggest a number of possible diagnoses that could help narrow the range of possibilities.⁴⁶ QMR improved on Internist's interactions by reducing input and retrieval time, and by allowing the clinician to have a more participatory role.

A number of problems arose for QMR. Although it had an extensive knowledge base, if the disease was not in the system, there was no way it could be returned as a diagnosis. Diseases, findings, and relationships already entered in the system needed to be continually updated as medical knowledge of each evolved.⁶³ This became a massive task as more knowledge was entered and more relationships created. Although its knowledge base eventually grew to represent more than 750 diseases and 5,000 clinical findings and more than 50,000 possible relationships between the two,⁶³ QMR was last updated in 2001 and is no longer being maintained.⁶⁴ It has however, been used as base model for other knowledge-based system derived ontologies.

MYCIN. MYCIN was an interactive software system developed at Stanford University in the mid-1970s. It began as an experiment to identify infectious diseases based on symptoms and test results and then recommend antibiotics. The experiment compared MYCIN's recommendations on meningitis cases to those of a physician. These results were sent to specialists who had no knowledge which results were reported from MYCIN and that were reported from the physicians. In this blind experiment, MYCIN out-performed its human counterparts.⁶⁵

MYCIN is considered an expert system because its results should be similar to those of an expert in the field. Using "artificial intelligence," MYCIN could ask further questions about the patient, suggest appropriate testing, offer possible diagnoses and recommend course of

treatment. It used goal-directed reasoning or backward chaining in an IF – THEN method to search its knowledge base.

There were a number of issues that kept MYCIN from ever being put into practice. The amount of time of each session with MYCIN often took more than 30 minutes. Another concern was that physicians may trust the computer instead of what they may think is the correct course of action simply because the suggestions came from a computer. There was also the question of accountability: Who would be liable if the machine makes a mistake in diagnosis? Those problems notwithstanding, the biggest obstacle MYCIN faced was that it was designed before desktop computing and the Internet.⁶⁵

Iliad. Another “expert” CDSS system, Iliad was developed at the University of Utah School of Medicine.^{66,67} Understanding the limitations of a knowledge frame system like DXplain and QMR for linking each disease to all possible symptoms, developers used a frame-based version of the Bayes model to design Iliad. Clusters were also used to avoid the necessity of independent manifestations of diseases that are required in Bayesian models.¹²

Version 4.5 was released in March of 1997 with a data dictionary of more than 1,500 diagnoses and almost 12,000 related findings.⁶⁷ Iliad’s initial purpose was to provide simulated training to internal medicine students.¹² Iliad can operate in two modes, either as a consultation tool or as a simulation tool.

As a training aid, Iliad creates hypothetical cases by generating a set of patient symptoms and observations. Based upon the case, students enter what they believe to be the correct diagnosis.⁶⁸ Iliad scores the entered data and compares it with other possible diagnoses, giving participants feedback on the probability of each answer being correct. Users can then ask questions about the “patient findings.” Prompted by questioning, the system will provide

information on lab results, history, etc., to help students become exposed to diseases that may be uncommon and allow them to hone diagnostic skills.

As a consultation tool, information on actual patients is entered into the system. Based upon what is entered, Iliad prompts the user for more information if needed or suggests possible diagnoses with explanations of how it came to that conclusion.⁶⁹ Iliad can also offer advice on steps that should be taken next.

VisualDx. VisualDx is another CDSS that is gaining in popularity. VisualDx was originally developed by Logical Images in the late 1990s as a “visual” aid to help health care providers, whose specialties were not dermatology, diagnose skin conditions.⁷⁰ Since its introduction, VisualDx has widened its scope to include pulmonary, oral, ophthalmic, drug eruption and radiology images.

Rather than searching by diagnosis, VisualDx is organized by symptoms and other visual clues. Modules include age, immune status or body location. Once a particular module is chosen, a search begins by allowing the user to enter patient findings. As each finding is entered, VisualDx helps build and refine ranked visual differential diagnosis.⁷¹ Within each diagnosis, multiple images at different stages of disease progression are displayed. Each diagnosis also includes a synopsis of the diagnosis, ICD-9 codes, therapy, associated findings and more.⁷¹

With more than 19,000 images and 900 diseases VisualDx can be used for clinical diagnosis, emergency preparedness, and medical education.⁷¹ VisualDx can be used at the point-of-care and is downloadable on many mobile devices including iPhones, iPads and Androids. In March of 2010, VisualDx partnered with UpToDate to offer a more fluid process for users of both products and integrating clinical and visual diagnostic information.

Isabel. One of the most comprehensive diagnostic decision support tools available today is Isabel. Isabel was created by Jason Maude after his daughter, Isabel, nearly died from a misdiagnosis of symptoms arising from chicken pox. Maude, with the help of Dr. Joseph Britto, created Isabel to improve patient safety and quality of care.^{52,72} To date, three Isabel systems have been released. The first focused on pediatrics and was released in June of 2002; the adult system launched in January 2005; and the bioterrorism diagnosis reminder system followed in June 2005.⁵²

A web-based product, Isabel, can be used at the point-of-care by clinicians or as a teaching tool for faculty and students. It is comprised of two parts, the Isabel Diagnosis Checklist System, and the Isabel Knowledge Mobilizing System.⁷³ Physicians enter age, gender and clinical features into the Diagnosis Checklist. Isabel then searches a database that contains more than 11,000 possible diagnoses and over 4,000 drugs and heuristics.⁵² It returns a set of the results that a physician should consider when making a diagnosis. The system also gives alerts for those diagnoses where special attention should be focused.

Once a set of possible diagnoses is delivered by the Diagnosis Checklist, the physician can click on the diagnosis name to obtain additional information on the diagnosis that includes a description of the disease, its signs and symptoms, causes, and options for treatment. The Knowledge Mobilizing system also offers access to additional online resources that include textbooks, disease specifics, and recent advances in treatment, as well as links to other online resources that may be freely available such as PubMed and MedlinePlus, or available via subscription, such as MD Consult and UpToDate.⁷³

Isabel PRO can be integrated with the electronic health record. Isabel has been tested in more than 23 published studies and clinical trials and was adopted by the American Medical

Association (AMA) in 2009 to be used in its online health information solutions platform.⁷⁴ A thorough description of Isabel for librarians was published by Vardell and Moore in 2011.⁷³

THE EVALUATION OF CDSSs

Berner wrote that an ideal CDSS would include high quality assistance with the differential, appropriate management suggestions, user satisfaction, aspects of usability, and more.⁷⁵ The ultimate success of CDSSs might be evaluated or measured by such things as decreased costs, improved processes and time saved, or, most importantly, patient outcomes, including decreased adverse events. A number of comprehensive approaches to the evaluation of clinical decision support systems have been conducted, but rarely, if ever, are all these elements reported in the evaluations.

A comparative evaluation of four clinical decision support systems was conducted and published in 1994.⁷⁵ This study found that although the systems never included all possible diagnoses, they did provide a mean of two additional possible diagnoses in addition to those diagnoses most obvious to the clinicians studied.

In 1998, a systematic review on the effects of clinical support systems on physician decisions and patient outcomes was published.⁷⁵ This highly cited article concluded that, at the time, systems utilized to support diagnosis had not amalgamated enough compelling evidence to prove that they improved diagnostic performance.

Over the years, three systematic reviews have come from McMaster University.⁷⁶⁻⁷⁸ These studies have examined the impact of CDSSs on physician performance and patient outcomes. Rather than looking at outcomes product-by-product, these studies looked at reports of outcomes and included all types of CDSSs. The 2004 review by Garg, et al examined 100 mostly randomized controlled trials, and drew the conclusion there was evidence that use of CDSSs did

result in improvement in clinical care processes. Patient outcomes were harder to measure. Less than half of the studies included measures of patient outcomes, and only 13% of the studies showed a statistically significant patient outcome improvement.

In contrast, a 2011, study by Romano and Stafford tested the hypothesis that higher quality of care should be associated with the use of electronic health records, including those with clinical decision support and electronic guideline-based reminders and alerts.⁷⁹ Using the National Ambulatory Medical Care Survey, they reviewed 20 previous quality indicators, and used multiple regressions to assess the relationship of electronic health records (EHRs) and clinical decision support (CDS) to those indicators. They found no consistent association between EHRs and CDS and better quality. Critics of the study responded that EHRs without CDS should not be expected to affect specific quality indicators, and asked the question of whether EHR with CDS had been designed to address the specific 20 quality indicators.⁸⁰ The debate on whether and how CDSSs improve outcomes continues.

PURCHASING CONSIDERATIONS

Purchasing CDSSs for library collections is a complex decision. If librarians believe in the potential of computer decision support to improve the quality of care, and believe that CDSS purchase falls within the scope of their collection development policies, then partnership with health care providers and educators to form a selection team is imperative. In selecting such a resource, the decision team should test the systems, ideally in side-by-side comparisons. The list of requirements for such a system might include usability and user satisfaction, ability to integrate with electronic health records and other health systems, accuracy, reliability, depth of knowledge base, and improvements to process and patient outcomes, as well as costs, which can be substantial.

BARRIERS TO ADOPTION

The many barriers to adoption of new health technologies, and especially health information technologies, are not a new topic. In reflecting on his projects and examining other projects that have since been undertaken, Dr. Barnett commented on recurring themes:

“first, the magnitude of the problem is usually grossly underestimated...second, the computer industry has often displayed a considerable lack of understanding and of sophistication... third, the hospitals have rarely made the depth of commitment of both administrative and professional staff that is required to develop and implement a viable system.”⁵⁵

This slow adoption pattern of clinical decision support systems is similar to that of telemedicine and of electronic health records. Technologies that common sense would tell us should help improve the quality of care and reduce costs, are often slowed because of difficulty in proving that individual innovations do improve quality and reduce costs. It is even more difficult to obtain enough evidence to generalize proof to the degree needed for wide scale implementation. The conflicting evaluation studies described above are good examples of the difficulty in moving from the evaluation of one project to widespread generalization.

Another recurring theme in the implementation of medical information technologies is that most barriers are not due to the technologies themselves, but rather to human factors slowing the diffusion of the innovation. In a takeoff on Everett Rogers' five stages of diffusion⁸¹ of innovation, Frederick Knoll colorfully identified five stages of medical technology acceptance in a Healthcare Information and Management Systems Society (HIMSS) presentation on return on investment and the EHR as:

1. Abject horror

2. Swift denunciation
3. Profound skepticism
4. Clinical evaluation
5. Acceptance as the standard of care.⁸²

Even when effectiveness can be demonstrated, medical information innovations often do not catch on rapidly. Physicians are very busy, and there is neither time nor reward for being innovative in medical day-to-day practice. For many medical innovations, acceptance as the standard of care and full adoption does not take place until the use of the innovation is mandated. Usually for an innovation to be mandated, it must be found to be financially beneficial and safe. Along with financial incentives to adopt new technologies, there must be disincentives for not adopting the new technology. The innovation must adhere to privacy and security standards. Not only must the advantages be demonstrated by respected opinion leaders and early adopters, the innovation must be seamlessly integrated into existing work practices.

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