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Review

Quality of health care: informatics foundations

Abstract: In this article we will discuss in what ways computer systems can contribute to the quality of healthcare and on which principles of informatics successful systems are founded. Section 2 presents an overview of studies that investigate the usefulness of decision support, and Section 3 discusses factors that determine the success of decision support systems. The foundations of guideline systems are presented in Section 4. Section 5 offers a brief review of physician order entry, and Section 6 presents a discussion of medical risk management and the results of Japanese studies in this area.

1. Background

In the past, clinical information systems were used in healthcare mainly for administrative purposes and for recording medical patient data. The medical data concerned medication, clinical laboratory results, EKG analyses and radiology reports, for example. Narratives, including medical history, results of physical examination and progress notes were often only recorded on paper.

Other groups were developing decision support systems (DSS) in order to raise the quality of healthcare. These were usually stand-alone systems designed to help physicians solve a diagnostic or therapeutic problem. Solving therapeutic problems mainly concerned dosage determinations. Diagnostic problems usually were differential diagnosis problems. The physician or nurse had already limited the search space to a few hypotheses that were further analysed by the decision support system. The decision support systems used statistical methods (Bayes' rule, regression, pattern recognition methods like linear discriminant analysis, etc.), fuzzy logic or decision trees.

Later, artificial intelligence (AI) approaches (symbolic reasoning) were introduced. Instead of statistical programs, where physicians made decisions on the basis of calculated probabilities that were difficult to interpret, now the programs were able to explain their decisions by showing the reasoning steps that led to the solution. Related to AI research is research concerning neural networks and genetic algorithms. These approaches are also used in some diagnostic systems.

A number of diagnostic systems covered a broad range of diseases: Internist [1], QMR [2], Iliad [3] and Dxplain [4]. Diseases that explain the entered findings are displayed and hints are given to ask for other findings in order to reduce the number of possible diagnoses. The main disadvantage of these systems was that they were usually slow and because the systems were stand-alone, the physician or nurse had to evoke the program and had to enter a large amount of data.

Blois [5] argued that computer support makes most sense at the end of the clinical judgment process. He compared this process with a funnel, with its large diameter at the onset of the process and its small end at the conclusion. The decreasing diameter of the funnel represents the shrinking cognitive span required by the physician. For situations at the beginning of the process, the totality of possibilities must be confronted; whereas for situations at the end of the process, the task domain is already structured through previous human effort, an abstraction is available, and only a little common sense knowledge may be required. Physicians can readily deal with the first type of broad and unstructured situation. They also perform well in more structured settings, although there are a growing number of specific and computable processes that may enable a computer to outperform physicians here.

Decision support programs such as protocol systems and reminder systems not only help in decision-making but also support therapy decisions and management of the patient.

The question is whether computerized decision support makes the health-care process more efficient and/or leads to better patient outcomes. And if so, does this imply that physicians or nurses will automatically use these systems, or are there also other factors that influence the success of a decision support system?

Medical risk management is another area where the use of Information and Communication Technology (ICT) can be very useful. Compared to other industries, quality management of health care services has not been successful. A 1999 Institute of Medicine (IOM) report estimates that between 44,000 to 98,000 hospital patients die each year due to medical errors [6].

Risk management is a process of identifying, assessing and evaluating risks that have adverse effects on the quality, safety and effectiveness of service delivery, and taking positive action to eliminate or reduce these effects. Medical record review, clinical incident reporting and other methods can detect adverse events. Incidents are events that produce, or have the potential to produce, unexpected or unwanted outcomes that affect the safety of patients, users or other persons. However, if the documents are paper-based, it will take time and consume health care resources to communicate, archive them and later feed the results back [7].

Risk management is also important to ICT applications. Information systems can contain wrong code, standards for communication can be incorrectly applied, knowledge in decision support systems can be wrong, etc. Therefore, and especially for decision support systems, it should be clear that the systems are not hazardous instead of providing useful advice [8].

The primary objective of the quantitative approach of medical risk management is to electronically collect data on incidents and to evaluate the possible causes of these incidents is [9]. Incident reports (IR) are analyzed to determine latent and active errors and to rank the incidents in order of risk severity. Action is then planned and implemented to prevent the event from recurring. Effective actions include simplifying systems, standardizing procedures, introducing constraints, using reminders and checklists, providing timely information, and facilitating small-group interactive education.

Incident-reporting systems may produce potentially valuable information, but seriously underestimate the true level of incidents [10]. Deming [11] suggested 14 principles for the transformation of quality management in medical service. Among them, he listed, "Require statistical evidence of quality of incoming materials, such as pharmaceuticals, serums and equipment. Inspection is not the answer. Inspection is too late and unreliable. Inspection does not produce quality. The quality is already built in and paid for." The importance of applying industrial quality management science to health care was already pointed out a decade ago [12]. However, only advanced ICT is able to acquire and integrate the care process data.

A suitably designed electronic patient record system (EPR) will be a potent tool for directly identifying sources of health care incidents, errors and accidents and will provide quantitative information. The EPR can be used on the site of health care for quick and easy safety checks. For example, by scanning the identification bracelet on a patient's wrist that patient's EPR will appear on the computer screen. Then the bar code on the drug to be given at that time, ordered by the patient's doctor, is scanned. If all is fine, the computer gives no alert and instantly changes the medical record to show that the treatment was given.

The EPR database provides a quantitative basis for risk and quality management, since the medical record includes information about the process and outcome of a patient's health care. If the methodology is established, quality management in health care will reach the same level as that of the production of goods. Quality management would be enhanced if a quality manager were allowed to link EPR data within an institution. Institutional or patient permission should be obtained for accessing these data for quality management purposes provided a security policy guideline is followed.

2. Do decision support systems help?

The debate over health system reform and the intensive search for cost-effective methods repeatedly highlight the need for adequate technology assessment of clinical information systems. Initially DSS were largely conceived as oracles, with clinicians seen as passive recipients of the system's advice. Early evaluation studies therefore focused on the accuracy of information generated by the computer system (e.g. [2-4]). Not all studies describe the performance using similar metrics and consequently it is difficult to compare the results. Berner et al. examined the performance of four DSS on a common set of cases and proposed a set of scores to describe different aspects of their performance [13].

The question of primary interest nowadays is the extent to which the system improves the diagnostic hypotheses of clinicians, not the extent to which its advice is correct. Since most broad-based, general DSS produce a list of diagnoses for each case, their effect on the process of care is not directly evident, even if we have determined the performance of the system. In addition as Elstein et al. [14] indicate, the issue is not how well the DSS reasons to a conclusion given a complete database. Rather, given the necessarily incomplete database that a puzzled clinician might have assembled in the workup of a diagnostically challenging case, to what extent does the DSS improve the quality of the differential diagnosis and/or suggest the relevant clinical findings needed to reach a more definitive conclusion. Friedman et al. [15] showed that "hands-on" use of diagnostic DSS can influence the diagnostic reasoning of clinicians. The overall increase in diagnostic quality scores due to a DSS was shown to be between the effect size typically considered small and medium in magnitude.

Balas et al. [16] systematically reviewed randomised controlled clinical trials of computer interventions and demonstrated significant improvements in the process and outcome of care due to these interventions. The most frequently studied and most successful interventions included patient and physician reminders, computer-assisted patient education and computerized treatment planners. Since the authors employed the vote-counting method for evaluating success rates, the magnitude of the effect could not be determined.

Shea et al. [17] carried out a meta-analysis of studies that investigated (via randomised controlled trials) the potential of reminder systems to improve preventive services in ambulatory settings. Sixteen separate randomised controlled studies were identified. The preventive services were grouped into six categories (vaccinations, breast cancer screening, colorectal cancer screening, cardiovascular risk reduction, cervical cancer screening and other preventive services). The studies showed that in four out of six categories, computer reminders increased preventive practices compared with a control group. The overall increase in the odds ratio attributable to computer generated reminders compared with the control condition across different preventive services was found to be 77%. The interpretation of this effect in terms of an absolute increase in delivery of preventive services to patients depends on the baseline prevalence of compliance with the recommended preventive service. For example, if the baseline is 50%, this increase in odds ratio implies an increase to 64%.

The findings imply that the physicians and other providers accepted the recommendations implicit in the alerts. The authors indicate that preventive services are an area where despite many areas of ongoing controversy a consensus exists regarding a substantial number of practices. They conclude that it is more important that users reach a consensus on appropriate guidelines than that they accept the computer as a way of delivering reminders (since manual reminders were also effective, although less than computer reminders). Austin et al. [18] analysed trials that assessed the effects of computer-based reminder systems on cervical cancer screening and tetanus immunization. This meta-analysis demonstrated a beneficial effect in both cases.

Johnston et al. [19] reviewed evidence from controlled trials of the effects of computer-based clinical decision support systems on clinical performance and patient outcome. Four different types of support were identified: drug dose determination, diagnosis, enhancing quality of preventive and active medical care. Of the 28 studies, ten studied patient outcome and only three of them showed statistically significant benefits. This small number may be due to small sample sizes. DSS for dose determination and diagnosis hardly were effective. Again reminders and feedback generally had positive effects on the process but effects on patient outcomes could hardly be shown.

In a follow-up review (Hunt et al. [20]) it was concluded that given the new evidence it is now reasonable to use decision support systems for potentially toxic, intravenously administered medications. These medications can be more effectively titrated than without using a decision support system. No new clinical trials of diagnostic decision aids were found. The authors concluded that decision support systems can enhance clinical performance for drug dosing, preventive care, and other aspects of medical care, but not convincingly for diagnosis.

Balas et al. [21] studied whether prompting physicians improved preventive care. They concluded that prompting leads to a significant improvement in health maintenance: the cumulative health maintenance rate difference (defined as the ratio of the number of preventive care actions to the number of eligible physician-patient encounters) was 13.1%. The method of presenting the prompt (attachment to the record, computer monitor display, tagged progress notes) did not have an effect on the clinical response. Also the method by which the prompts were generated (computerized or not) did not lead to significant differences.

Oxman et al. [22] determined the effectiveness of different types of interventions in improving health professional performance and health outcomes. They emphasize that several interventions (educational material, conferences, outreach visits, local opinion leaders, patient mediated interventions, audit and feedback, reminders, etc.) have been found to improve provider performance and to a lesser degree health outcomes. They drew an analogy between trials of interventions to improve the performance of healthcare professionals and drug trials. There are no wonder drugs; often several medications are needed, along with lifestyle and environmental changes, to effect clinically important changes in health status. It is the same with the alteration of health professional performance: many interventions have modest or negligible practical effects when used alone. However, when coupled with other strategies the effects may be cumulative and significant.

Clinical practice guidelines are systematically developed statements to assist practitioner and patient decisions about appropriate healthcare for specific clinical circumstances [23]. Studies have shown the benefits of using clinical guidelines in the practice of medicine [24]. Although the importance of guidelines is widely recognized, health care organizations typically pay more attention to guideline development than to guideline implementation for routine use in daily care. Implementing guidelines in computer-based DSS promises to improve the acceptance and application of guidelines. According to the IOM, DSS are in fact crucial elements in long-term strategies that promote the use of guidelines [25].

3. What factors determine the success of decision support systems?

Clinicians complain that they have less time available than in the past because of increasing patient volumes, greater demands for documentation and the complexity of modern practice. To be successful, decision support systems therefore have to be faster than the current way of working. According to Payne [26], advice based on guidelines is most useful if the recommendations are based on each patient's data. These data should be available in machine-processible form instead of having to be entered by the user, which costs more time.

Decision support systems can be passive, containing heavily indexed information that must be searched by the users. Passive display of guideline documents in the literature, on the Web, or on other electronic media for example is not always an effective or reliable method for obtaining decision support since it takes time to retrieve the guideline and find the relevant information and because it is not always directly clear what the quality of the guideline is.

The success of active decision support systems depends to a large extent on the direct availability of patient data. Current electronic patient records provide a repository of patient data that can be used by the DSS. These data can only be used when they are stored in the same format as needed by the DSS and when the semantics of the data is the same. Standardisation of terminology is therefore very important.

Additionally, the systems should be incorporated into the workflow of the clinic. Healthcare delivery is a complex effort with labour divided among many professions. Decision support systems should be designed to fit into this workflow as smoothly as possible, because changing the workflow of many professionals is difficult.

Decision support systems sometimes come under criticism as examples of cookbook medicine because they appear to provide knowledge of a clinical nature, to show initiative, and to correct physician behaviour. Questions may arise about whether they might increase malpractice liability if a clinician chooses to ignore a suggestion from the system [27]. However, it should be made clear to the user that the system functions as an active partner, providing important information at the right time so that the clinician can make the right decision about a patient's care.

4. Informatics foundations of decision support systems

Reggia and Tuhrim [28] documented many of the early approaches to computer-assisted medical decision-making. Artificial intelligence approaches are described in Miller [29]. The approaches can be characterized by the way the knowledge is represented and by the type of reasoning (inference method) that is carried out. Reggia and Tuhrim discern a number of methodologies:

- **conventional programming methods** -(formulas and branching logic as knowledge representation and calculation with formulas or traversal of branching logic as inference method),
- **statistical pattern classification** (prior and conditional probabilities or discriminant functions as knowledge representation and calculation of posterior probabilities, calculation of discriminant scores as inference method),
- **production rules** (rules as knowledge representation and deduction as inference method) and cognitive models (frames, semantic networks as knowledge representation and hypothesize and test (abduction) as inference method).

The reminder systems that were described in the studies Shea et al. [17] investigated shared the above-mentioned design philosophy: an expert system monitors the clinical database and makes use of a knowledge base in which the logic that triggers the reminders is represented. The reminders are data-generated rather than sought by the user.

The knowledge usually is elicited from experts. Knowledge discovery techniques (data mining, machine learning) are also used to extract knowledge from existing databases. The knowledge, however obtained, has to be represented in a way that the DSS can reason with it. Knowledge editors are usually available to enter knowledge in the right format.

We will focus here on issues concerning the representation of guidelines. Implementation of guidelines in DSS is not easy. Guidelines are usually in narrative form and have to be formalized before they can be used in DSS. Also the terminology used in the guidelines can impede implementation, especially when they have to be integrated with electronic patient records, because the terminology that is used in both is likely to be different. To facilitate the (re-)use of a guideline among different institutions, the representation should support the use of standard medical terminology.

In order to alleviate the problem of disseminating guidelines to other institutions a formal guideline model is needed. A formal and expressive guideline model will provide 1) an in-depth understanding of the clinical procedures addressed by the guideline; 2) a precise and unambiguous description of the guideline; and 3) a means for automatic parsers to execute guidelines. The representation formalism must be able to represent relatively simple guidelines that model independent modular rules, but also complex ones that use notions such as temporal abstraction and scheduling.

Guidelines contain decisions and actions as individual steps. Decisions are expressed by means of logical expressions and therefore the guideline representation formalism must support some form of (temporal) logic and uncertainty handling. Entry points (depending on the patient state) have to be used as an entrance into a complex guideline for a specific patient. In a similar way exit points have to be defined. Although the format of these expressions is similar to the logical expressions used in decisions, in complex guidelines they should be distinguished from these normal decision points.

Actions refer to clinical interventions and information gathering. Again these actions must be expressed in terms of domain-specific concepts. Since guidelines describe a process, the representation formalism must allow the representation of the order in which actions and decisions have to be carried out. In this section we will describe a number of published guideline models.

The Arden syntax [30] was developed as a response to the inability to share medical knowledge among different institutions. The representation encodes modular guidelines as Medical Logic Modules (MLM). Each MLM contains a production rule that relates a set of input conditions to a particular set of actions to take. Most MLMs are triggered by clinical events. Since the guidelines are modelled as independent modular rules, the syntax is usually used for representing simple guidelines, like the ones providing alerts in feedback systems. The Arden syntax does not support standard terminologies. Therefore sharing of MLMs among institutions is not that easy. Since MLMs are modular rules there are no concepts that correspond to entry points. Instead MLMs contain an evoke slot in which events are specified that will fire an MLM.

The Guideline Interchange Format (GLIF) was developed to model guidelines in terms of a flowchart that consists of structured scheduling steps, representing clinical actions and decisions. The intended purpose of GLIF is to facilitate sharing of guidelines between various institutions by modelling guidelines in such a manner that the guidelines are understandable by human experts as well as by automatic parsers used in different clinical decision support systems. GLIF is an object-oriented representation, consisting of a set of classes that describe characteristic guideline entities (e.g. actions and decisions), attributes for those classes and data types for the attribute values.

The first published version of GLIF [31] distinguishes a number of guideline steps (action, conditional, branch and synchronization). Conditional steps model decision points and direct flow from one guideline step to another. Branch steps direct flow to multiple guideline steps. Attributes of the branch step specify whether all, some or only one of these steps should actually be carried out and in which sequence. Synchronization steps are used in conjunction with branching steps. The multiple guideline steps that follow a branch step always converge in a corresponding synchronization step.

In GLIF2 most of the attributes were text strings that were not easily interpretable by parsers. To address this and other issues a new version, GLIF3 [32], is now under development. It includes among others a more formal expression syntax and a number of new guideline steps.

PROforma [8, 33] is a knowledge composition language supported by acquisition and execution tools with the goal of supporting guideline dissemination in the form of expert systems that assist patient care through active decision support and workflow management.

PROforma addresses two aspects of the guideline development and implementation process. First it defines an abstract model that represents the general clinical decision-making process, called the domino model. The model assumes that a trigger may lead to the recognition of some kind of clinical problem, which requires a solution. The next step is to apply some kind of problem solving process to identify possible solutions to the problem. These possible solutions are then evaluated to determine the strengths and weaknesses of each solution. Based on the outcome of the evaluation, a care provider can decide to adopt a certain solution by selecting the corresponding care plan. Alternatively, a care provider can decide that additional data (for example based on new patient data) are required to select the most favourable solution. Once a care plan has been adopted, the sequence of clinical actions needed to execute the plan is scheduled and carried out. Finally, executing a care plan may involve new clinical actions that require additional clinical patient data such as relevant symptoms and additional lab data.

To represent the domino model PROforma defines a task ontology that contains all concepts required to model various types of guidelines. Each guideline is modelled as a plan consisting of a sequence of tasks (plans, decisions, actions and enquiries). Guidelines are stored using the Red Representation Language, a time-oriented knowledge representation language [8].

Asbru is a guideline representation formalism, developed at Stanford University and the Vienna University of Technology and is part of the Asgaard project, which focuses on the application of time-oriented clinical guidelines [34]. The Asbru language is a plan representation language that represents clinical guidelines as time-oriented skeletal plans.

EON, also developed at Stanford University, is a component-based architecture used to build decision-support systems that reason about guideline-directed care [35]. Similar to GLIF, the guideline model of EON, called Dharma, is object-oriented and consists of classes that describe guideline entities as a sequence of structured temporal steps. Besides the Dharma guideline model, the EON architecture also contains a number of run-time components, used to construct execution-time systems.

When a guideline model is available, tools can be designed that support the specification of guidelines. Some examples of knowledge editors are described in the literature [33], [36] and [37].

5. Physician Order Entry

Computer programs to improve quality in healthcare work best when integrated into the background of clinical workflow. As McDonald and many others have shown [38], physicians can get an A on factual tests, but sometimes get B's or C's in real life settings when their performance is compared against quality measures. The major problem seems to be a failure to attend to a situation rather than a lack of knowledge. The attention of physicians is diverted by increasing workloads, increasing complexity of care management, increasing demands for documentation and the resulting decrease in time for each clinical encounter. Clinical computing systems that have alerts and reminders, clinical checklists, and clinical practice guidelines as active components seem to be effective and generally well accepted.

Curiously, the wide practice variation that results from non-adherence to these types of rules rarely can be shown to affect patient outcomes such as long-term survival. One area of computer-based crosschecking that has shown the most promise in the past several years has been Physician Order Entry (POE).

POE is not new. The very first hospital-wide systems like the Technicon system at El Camino Hospital in California in the early 1970's had POE. These systems in recent years have been shown to dramatically cut down on medication errors and have the potential to reduce costs as well. In the United States, influential business groups like Leapfrog have backed such systems as well. In the coming years, POE is likely to be the informatics application with the greatest impact on healthcare quality.

The physicians' direct order entry system implemented in the Osaka University Hospital [39] saved human power and increased the efficiency of the hospital functions. All orders and reports except the pathological examination orders and the corresponding reports were electronically exchanged. There has been a great deal of discussion about ways to implement an EPR, including a computerized physician order entry system [40]. Because of the improved man-machine interface, most Japanese physicians and nurses are now in favor of direct order entry [41]. However, data input and output covering the same content as a paper-based medical record still are a major problem for physicians. An integrated design with dynamic templates for structured data entry, the possibility of multiple display modes and a dynamic problem oriented system may provide a solution.

6. Medical risk management

Osaka University Hospital, a Japanese national university hospital, reengineered its paper-based incident reporting system into a computerized integrated reporting, notification, and tracking system [42].An on-line Incident Reporting System (OIRS) was developed to collect anonymous IR via a reporting form available on the Intranet Web. By using a template, the process to write an IR was simplified and the IR is much easier to complete. Instead of writing a narrative report, now it is mainly a matter of checking off boxes. An example of the data input screen is shown in Figure 1. The structured data entry of incidents also facilitates root cause analysis. However, some data elements, including a detailed description of the case, causes, and possible ways to prevent similar incidents still have to be reported in free-text.

In July 2001 the medical quality management department of the Osaka University Hospital started to operate the OIRS to decrease the time needed to complete an incident report, to collect more precise data about the incident and to provide members of the hospital committee for risk management with instant access to all IR generated by the hospital staff. IR are stored in a database and available for future root cause analyses. The organizational structure is illustrated in Figure 2.

Anonymity and freedom from punitive action are essential for increasing the number of reports. Reports of potential errors provide valuable insight into the system's vulnerabilities, whereas timely input and review of reports by means of information technology enables a rapid systematic PDCA (Plan-Do-Check-Act) cycle for preventing medical errors and providing a valuable link between the risk, quality, and safety functions of the organization. The new system was designed to streamline the error-reporting process and reduce the occurrence of future medical errors, with a goal of increasing patient safety and encouraging better reporting.

A non-random sample of hospital employees including physicians, nurses and other medical staff submitted incident reports anonymously. From July 2000 through December 2001, 1550 incidents were reported. Nurses reported 73%, physicians including

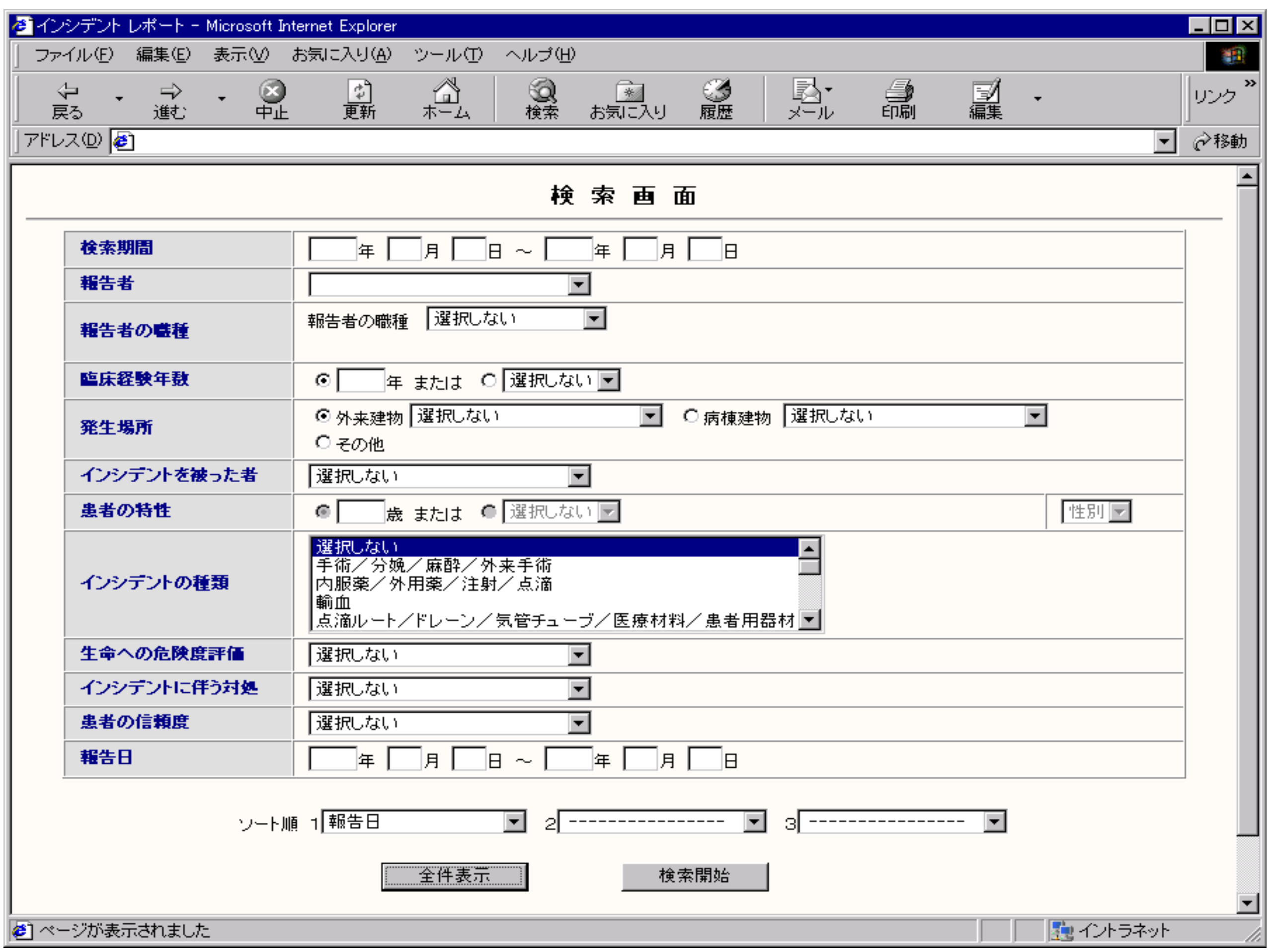

Fig. 1 A sample of structured data entry in the On-line Incident Report System (OIRS) in the Osaka University Hospital

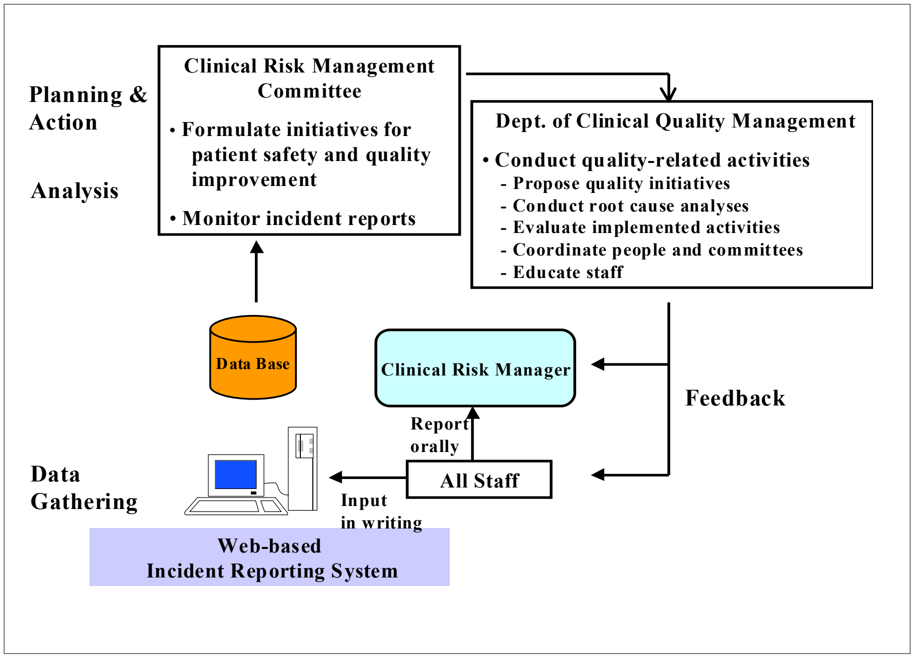

Fig. 2. The organization and the process from data gathering to feedback in the

trainees 16%, and pharmacists 7% of the reports. Drug prescription and medication related errors comprised 43% of the total number of incidents. The relatively high reporting rate of physicians may indicate that the OIRS has been well accepted by the hospital staff as an efficient tool for the prevention of medical errors. From the reported IR the true rate of incidents cannot be inferred, however.

Because of the successful operation of the above-mentioned ordering and reporting system, an electronic patient record system (EPROU) was installed in January 2001 in the Osaka University Hospital [43]. The EPROU features 1) physicians' direct structured data entry, 2) multi-modal output of registered clinical data and 3) a dynamic problem-oriented system. To increase the operability and the utility of the EPR, the system made use of structured data entry using dynamic templates [44]. The EPROU viewer provides an integrated view of information of each patient [45].

The EPROU database stores medical event data. A 'medical event' is an abstract concept which includes information from the records of healthcare providers, ordering and processing data, examination reports, image header data, and so on. All these data are transferred to the EPROU database [46].

The EPROU database only contains one database file. One record corresponds to one medical event. Medical event ID, patient ID, medical event type, department, transaction time, validate time, user ID, and several other items are stored. No deletion or editing is allowed. Data protection is essential. EPROU has a mechanism for making a message digest for each record. Thus illegal changes of the record can be detected. When the data is transferred from the server to the client, the data is encoded to avoid theft or change during transmission. The files stored in PCs are also encoded to protect the data.

One study using EPROU data concerned the determination of the distributions of the length of stay (LOS) of in-patients in the hospital as a function of diagnosis procedure combinations (DPC), the Japanese version of diagnosis related group (DRG). Information about 10,687 patients discharged during the period from April 2000 to March 2001 was analyzed. The average LOS value in the fiscal year 2000 was 31.7 days (including patients from the department of psychiatry, with an average LOS of 78.8 days). In total 51.2% of the patients could be classified into 80 DPC categories (Japanese DPC version 1.0). The low percentage is due to the immaturity of the DPC system. DPC-specific LOS distributions were determined and the mean, median and standard deviation for each DPC were calculated.

The results showed that most DPC-specific distributions were not normal but rather similar to log-normal distributions and that some distributions were multi-modal. For all DPCs the mean values and standard deviations were larger than corresponding data obtained from other national hospitals. The study showed that DRG or DPC specific distributions of length of hospital stay, extracted from an EPR, provide statistical evidence of medical quality. As the principle of quality control clearly indicates, the larger standard deviation should be made smaller and the long mean LOS should be reduced by quality management interventions such as application of evidence-based guidelines and critical pathways. The concept is shown in Figure 3.

Conclusion

It is apparent from the literature that DSS that are mainly developed for the purpose of diagnosis do not have a large impact on the process and outcome of health care. Despite the many publications concerning diagnostic systems, their use in clinical practice seems to be rather limited. This may be partly due to the fact that many of these systems start with a differential diagnosis

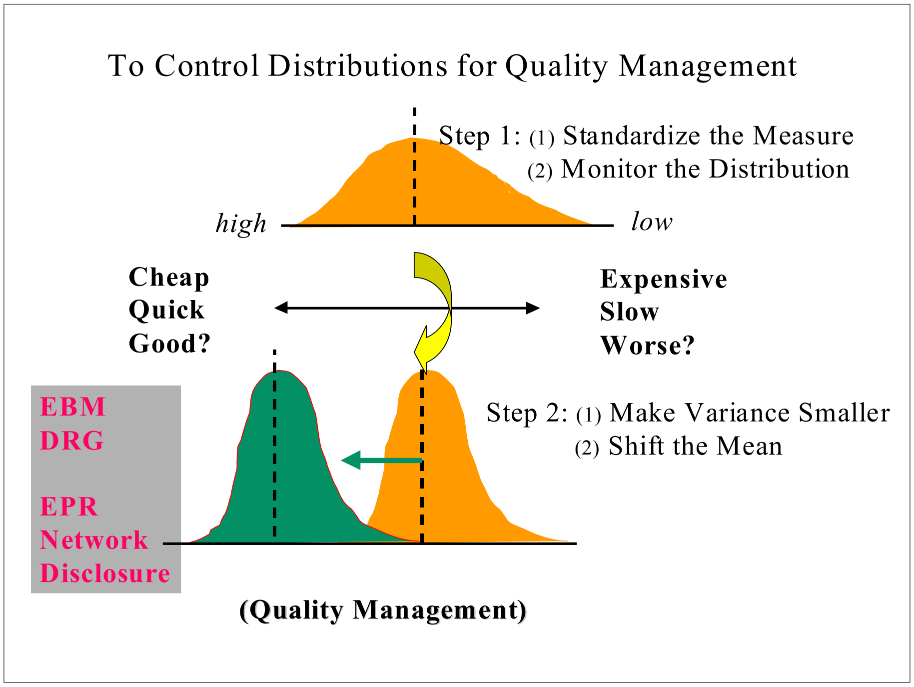

Fig. 3. Conceptual illustration of the controlling distributions for the quantitative management of health care.

and then try to determine the patient's disease or condition, which does not save the physician significant amounts of time. Reminder systems, on the other hand, do appear to have an impact on health outcomes.

Guideline systems can be useful in supporting the physician or nurse in managing patients, but a standard guideline model must be developed so that guidelines can be effectively shared across systems. A great deal of promising research is currently being carried out with respect to guideline models and tools for entering guidelines into DSS.

Finally, medical risk management can be aided by electronic patient records and physician order entry systems, which can not only provide guidance but also produce valuable data about errors and their causes.

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