# Clinical Decision Support Systems:
# An Effective Pathway to Reduce Medical Errors and Improve Patient Safety

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## 1. Introduction

### 1.1 Background

Medical errors are both costly and harmful (Hall, 2009). Medical errors cause tens of thousands of deaths in U.S. hospitals each year, more than from highway accidents, breast cancer, and AIDS combined (SoRelle, 2000). A phone survey by the National Patient Safety Foundation found that 42 percent of over 100 million Americans believed that they had personally experienced a medical mistake (Louis & Harris Associates, 2007). The 1999 Institute of Medicine report stated that medical errors were the eighth leading cause of death in the U.S., killing between 44,000 and 98,000 people each year (Kohn et al., 2000). Another study indicated 225,000 deaths annually from medical errors, including 105,000 deaths due to "non-error adverse events of medications" (Starfield, 2000). Medical errors threaten the quality of health care, increased healthcare costs, and add to the medical malpractice crisis (Studdert et al., 2005). According to the Patient Safety in American Hospitals Study Survey by HealthGrades (HealthGrades, 2004; HealthGrades, 2007; HealthGrades, 2008; HealthGrades, 2009), the number of deaths in U.S. hospitals each year that are reportedly due to medical errors has been disturbingly high since 2000:

1.  Based on a study of 37 million patient records, an average of 195,000 people in the U.S. died due to potentially preventable, in-hospital medical errors in each of the years from 2000 through 2002.
2.  Approximately 1.16 million patient safety incidents occurred in over 40 million hospitalizations for the Medicare population yielding a three-percent incident rate. These incidents were associated with $8.6 billion of excessive costs during 2003 through 2005. Although the average mortality rate in Medicare patients from 2003 through 2005 was approximate 21.35 percent and overall rates have been declining, medical errors may still have contributed to 247,662 deaths.
3.  Patient safety incidents cost the federal Medicare program $8.8 billion and resulted in 238,337 potentially preventable deaths from 2004 through 2006.
4.  Approximately 211,697 patient safety events and 22,771 Medicare deaths could have been avoided with a savings of $2.0 billion from 2005 through 2007.

These numbers indicate the magnitude of savings in both lives and dollars from improved patient safety.

## 1.2 Health information technology adoption in the U.S.

Health information technology (HIT) offers an opportunity to transform healthcare and make it safer (Bates & Gawande, 2003; Parente & McCullough, 2009). With the advent of electronic medical records (EMRs) and computerized physician order entry (CPOE), the maintenance of patient information has become easier. The EMR provides the clinician with a longitudinal source of patient information including diagnostic history, previous encounter history, drug allergies, and other relevant information. A computer-assisted decision support system can be designed to help clinicians collect critical information from raw clinical data and medical documents in order to solve problems and to make clinical decisions. A clinical decision support system (CDSS) links health observations with medical knowledge in order to assist clinicians in decision making. The embedding of a CDSS into patient care workflow offers opportunities to reduce medical errors as well as to improve patient safety, to enhance drug selection and dosing, and to improve preventive care. It is less certain whether a CDSS can enhance diagnostic accuracy (Bakken et al., 2008; Bates et al., 1998; Bates et al., 2001; Bates et al., 2003; Hunt et al., 1998; Kaushal et al., 2001a; Kaushal et al., 2001b). A CDSS can assist clinicians in reducing some errors and costs (ActiveHealth Management, 2005; Bates et al., 2001; Bates & Gawande, 2003; Bates et al., 2003; Berner, 2007; Chaudhry, 2008).

## 2. Significance

### 2.1 Clinician approach to health information technology

The U.S. national healthcare expenditures are projected to reach $2.6 trillion in 2010 and $4.7 trillion in 2019 (Foster & Heffler, 2009). President Barack Obama has called for wider use of HIT to help control rising healthcare costs. In February of 2009, Congress passed the HITECH Act (Health Information Technology for Economic and Clinical Health) which provided financial incentives to physicians and hospitals to adopt HIT. However, clinician acceptance of HIT remains critical to the success of efforts to use electronic medical records (EMRs) to reduce healthcare costs. Clinicians often view EMRs as costly, awkward, and disruptive of their workflow. Many clinicians remain reluctant to adopt EMRs. A recent survey of 423 physicians by the Massachusetts Medical Society (Chin, 2004) found that while 85% believe that doctors should adopt electronic prescribing, 49% say they do not intend to do so. Further, although 89% believe that doctors should record patient summaries electronically, 48.5% do not intend to do so. Another survey of 500 health care providers found that 52% thought the stimulus package would have little or no success in encouraging HIT adoption in the U.S. (IVANS, 2009).

### 2.2 Characteristics of clinical decision support systems

A CDSS is a computerized system that uses case-based reasoning to assist clinicians in assessing disease status, in making a diagnosis, in selecting appropriate therapy or in making other clinical decisions. There are three key elements of a successful CDSS (Musen et al., 2001):

1.   *Access to accurate clinical data*,
2.   *Access to pertinent medical knowledge*
3.   *Ability to use appropriate problem solving skills*.

An effective CDSS involves six levels of decision making: alerting, interpreting, critiquing, assisting, diagnosing and managing (Pryor, 1990). Alerts are a vital component of a CDSS.

Automated clinical alerts remain an important part of current error reduction strategies that seek to affect the cost, quality, and safety of health care delivery (Kuperman et al., 2007; Raschke et al., 1998; Smith et al., 2006). The embedded knowledge component in a CDSS combines patient data and generates meaningful interpretations that aid clinical decision making (Liu et al., 2006). An effective CDSS also summarizes the outcomes, appraises and criticizes the caring plans, assists clinicians in ordering necessary medications or diagnostic tests, and initiates a disease management plan after a specific disease is identified (Colombet et al., 2005; Friedlin et al., 2007; Garg et al., 2005; Wadhwa, 2008; Wright et al., 2009).

### 2.3 The architecture of a clinical decision support system

Several practical factors contribute to the success of a CDSS. These factors include (1) considering the potential impact on clinical workflow, (2) creating an intuitive and configurable user interface, (3) delivering decision support in real time at the point of care, and (4) providing actionable alerts/reminders/recommendations that are succinct and relevant to patient care (Friedlin et al., 2007; Kawamoto et al., 2005). The minimum required technical architecture for a CDSS is identified as (1) a skilled communication engine to access disparate data, (2) a mandatory clinical vocabulary engine to perform semantic interoperability, (3) an optimized patient database to facilitate disease management, (4) a modular knowledge base to mine adequate diagnostic and therapeutic information, and (5) an effective inference engine to expedite decision making by relating embedded knowledge to ongoing problems (Pestotnik, 2005). How to best use a CDSS to influence clinician behavior is still a challenge in the clinical domain to provide high-quality care at lower cost (Bates & Gawande, 2003; Jao et al., 2008b).

The development of an effective CDSS has a significant impact on clinician's practice plans. The introduction of such a system will provide clinicians a useful guideline through which they can replicate their decisions on similar clinical cases. Furthermore, an effective CDSS can reduce the variation of clinician's practice plans that plagues the process of healthcare delivery. The dynamic environment surrounding patient diagnosis complicates its diagnostic process due to numerous variables in play; for example, individual patient circumstances, the location, time and physician's prior experiences. An effective CDSS reduces variation by reducing the impacts of these variables on the quality of patient care.

## 3. Major issues

### 3.1 Medical errors

Reducing medical errors requires an environment of continuous disclosure and analysis; an environment which is in conflict with the current medical liability climate (Clinton & Obama, 2006). Five common types of medical errors include (1) prescribing erroneous medications, (2) inappropriately ordering laboratory tests for the wrong patient at the wrong time, (3) filing system errors, (4) dispensing the wrong medications, and (5) failing to promptly respond to abnormal laboratory test results (Dovey et al., 2003). Accessing the EMR is the first step to controlling medical errors (Hillestad et al., 2005; Wang et al., 2003). Studies show improved patient safety from the use of EMR in hospitals and ambulatory care that primarily relies on alerts, reminders, and other components of CPOE in reducing adverse drug events (Bates et al., 1998; Bates et al., 2001). The concept of the Problem-Oriented Medical Record advocated by Weed builds a sound structure for medical decision-

making that can lead to error reduction (Bayegan & Tu, 2002; Weed, 1968a; Weed, 1968b; Weed, 1968c).

## 3.2 The significance of accurate medication and problem lists

The need for a problem list (or diagnosis list) is clear. The problem list and medication list (list of prescribed drugs) provide an essential overview of diagnoses and treatment. The problem list is a critical part of the medical record because it contains the patient's active and resolved medical problems while the medication list contains the prescribed drugs for each diagnostic problem.

Optimal medication and problem lists accurately reflect ordered medications and ongoing problems. The problem list helps physicians check against potential prescribing errors, reminds them of issues often forgotten, and improves communication among health care providers (Simborg et al., 1976; Starfield et al., 1979). An accurate problem list facilitates automated decision support, clinical research, data mining and patient disease management (Hartung et al., 2005; Jao et al., 2004; Johnston et al., 1994; Rothschild et al., 2000). An accurate computerized medication list is a direct outgrowth of computerized physician order entry (CPOE) and e-prescribing, while an inaccurate medication list creates risks and adversely affects quality of health care (Kaboli et al., 2004; Rooney, 2003). Proper management of the medication and problem lists reduces the potential for medication and diagnostic errors.

## 3.3 Current state of problem list compliance

Since 2006, the maintenance of the diagnosed problem list has been mandated as a patient safety feature by the Joint Commission of Accreditation Health Organization. A computerized problem list in the EMR is more readily accessible than the paper chart, and codified terms in the medication and problem lists create an opportunity to implement clinical decision support features, including knowledge retrieval, error detection, and links to clinical guidelines (Wasserman & Wang, 2003). Nonetheless, accurate maintenance of the problem list and medication list is difficult in practice.

Despite previous research confirming that the problem list is vital to the evidence-based practice of medicine, physician compliance in creating an accurate medication and problem list remains unsatisfactory (Brown et al., 1999; Rowe et al., 2001). A recent case report ascribed the death of a female patient to the failure to maintain her ongoing problem list by her primary care physician (Nelson, 2002). According to another medical report, one in every 10 patients admitted to six Massachusetts community hospitals suffered serious and avoidable medication errors (Wen, 2008). In a review of 110 discharge medication lists in the Augusta Mental Health Institute of Maine, 22% contained errors (Grasso et al., 2002).

## 3.4 Clinician attitudes toward and knowledge of CDSS

A survey of physician attitudes showed that the perceived threat to professional autonomy was greater for CDSS than for an EMR (Walter & Lopez, 2008). Other results indicate that the degree of clinician acceptance of a CDSS seems to be correlated with their attitudes about their professional role and their attitudes towards the computer's role in disease management and decision-making (Toth-Pal et al., 2008). Other significant barriers to CDSS adoption have been ascribed to insufficient level of computer skills among clinicians and time constraints on clinicians. Studies have shown that lacking a useful CDSS at the point of

care hinders informed clinical decision making and coordination of patient care (Kaushal et al., 2003; Sittig et al., 2006).

Clinicians are typically challenged by the complex interplay of multiple disease parameters with surrounding factors (e.g., the disease agent, the environment, the patient's description of self symptoms, the results from laboratory testing, the physician's capability of observation, etc.) that determine how a disease will present itself and how it will be perceived by a clinician. Lack of awareness of relevant scientific evidence and time constraints were the most often cited physician barriers to implementing effective decision-making in clinical practice (Cabana et al., 1999; Edwards & Elwyn, 2004; Graham et al., 2003).

### 3.5 Assessment of physician compliance on clinical documentation

Surveys and audits of medical records reveal that the diagnosed problem list and prescribed medication list are often inaccurate, out of date, or incomplete. Previous audits of patient charts at the University of Illinois Hospital (UIH) showed that problem list maintenance is haphazard (Galanter et al., 2008; Hier, 2002; Jao et al., 2008a). In many patient charts multiple versions of the problem list coexist; some lists lack critical problems (clinical diagnoses); other lists have many resolved or inactive problems. Similarly, many medical records contain numerous and inconsistent medication lists, which do not reflect the actual medications taken by a specific patient. Medication lists are often obsolete (containing medications no longer prescribed) or incomplete (lacking medications that are prescribed), while multiple reconciled versions of the medication list coexist in the same medical record. Most medical records make no attempt to establish medication-to-problem relationships or ordering by indication.
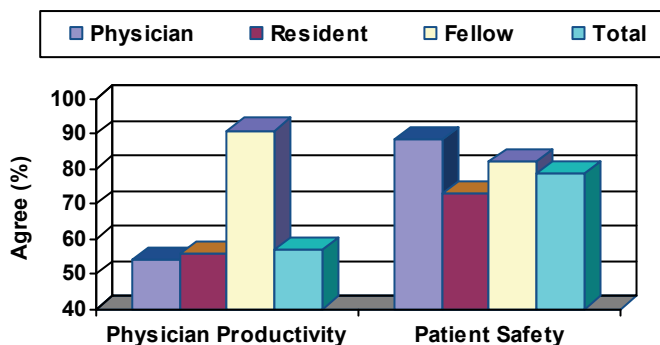


Fig. 1. Survey assessment of physician's knowledge regarding benefit contribution from the improvement of clinical documentation by the CDSS

To assess physician knowledge, attitudes, and practice patterns related to issues in problem list documentation, an online survey was distributed to more than 800 health care practitioners at the UIH. Among the 97 respondents, 30% were attending physicians, 68% were residents, and 12% were fellows (Jao et al., 2008b). The majority of respondents were reluctant to diligently maintain medication and problem lists, indicating a continuing gap in quality of documentation. According to the results of this survey, approximately 50 percent

of surveyed providers said that (1) the problem lists were not well maintained in their own clinical units, (2) approximately 55 percent said that they audit and maintain the medication and problem list on their own behalf, and (3) approximately 42 percent said that they failed to update the centralized medication and problem lists after including a problem list in each of their own progress notes. Respondents felt that the CDSS could improve problem list documentation and would benefit patient safety more than physician productivity (as shown in Fig. 1).

## 4. Current trends

### 4.1 Barriers of CDSS implementation

Human knowledge and inspection is used to detect and correct errors in medical records. However, Bates et al. ascribed weak error-reduction strategies to the use of human knowledge and inspection in medical error discovery (Bates et al., 2001). The World Health Organization mandates reducing medical errors, providing high-quality disease-centred evidence/information, and lowering cost in health care by full adoption of e-Health strategies through full development of HIT, especially adopting a patient-centred EMR (WHO, 2005). A recent study suggested that the aggressive integration of clinical evidence from health care research into diagnostic decisions could influence patient outcomes by improving clinical diagnosis, reducing unnecessary testing, and minimizing diagnostic errors. However, significant barriers must be overcome to achieve this goal (Garg et al., 2005; Richardson, 2007). There are several potential impacts to clinical practice due to these common barriers (see Table 1).

### 4.2 Embedding CDSS implementation within CPOE and EMR

Recent studies indicate that an evidence-based CDSS works best when it is embedded within a CPOE system (Gross & Bates, 2007; Trivedi et al., 2009; Wolfstadt et al., 2008). It is critical to design a useful CDSS so that it improves a clinician's workflow, it provides satisfactory system performance, and results in acceptable system reliability. Moreover, organizational factors, such as the leadership support, strong clinician champions and financial support, play a role in the success of CDSS implementation.

A useable CDSS typically requires multifaceted domain knowledge that is expressed as inference rules in a computable, explicit and unambiguous form (Kuperman et al., 2006). Characteristics of individual patients are matched to a computerized knowledge base, and software algorithms in the CDSS generate patient-specific recommendations that are delivered to clinician-users of the EMR. (Garg et al., 2005). A recent study has identified three key elements for fully realizing the potential of a CDSS (Osheroff et al., 2007):

1. The best available clinical knowledge is well organized, accessible to clinicians, and encapsulated in a format that facilitates effective support for the decision making process
2. A useful CDSS is extensively adopted, and generates significant clinical value that contributes financial and operational benefits to its stakeholders.
3. Both clinical interventions and knowledge undergo constant improvement through user feedback, experience, and data analysis that are easy to aggregate, assess, and apply.

| Categorized Barriers | Potential Impacts to clinical practice |
|---|---|
| **Evidence-Related** | |
| • Lack of supportive research evidence | • Decision may not be able to draw an acceptable conclusion or judgment |
| • Incomplete or contradictory evidence | • Decision may be infeasible to the clinical case |
| • Inaccessible evidence at the point of care | • Evidence could be not be reached to assist practitioners in decision making |
| **Clinician-Related** | |
| • Lack of in-depth knowledge in the specific nature of evidence | • Could not make full use of evidence to the specific type of a diagnostic problem |
| • Failure to use the CDSS or non-acceptance of computerized recommendations | • Could not efficiently manipulate evidence or adapt recommendations to accommodate the variance of diagnoses |
| • Obedience to others' diagnostic decision | • Will not employ independent analytic thought and reasoning on evidence |
| **System-Related** | |
| • Multiple requirements (e.g., billing and EMR) converge to stress clinicians for coding patient's disease with accurate diagnoses | • Throughput-oriented concerns may discourage the deliberate processes of analytic diagnostic thinking |
| • External incentives (e.g., reimbursement, patient satisfaction, quality demerits, malpractice) through the use of research evidence | • Desire for rewards or fear of punishments may influence diagnostic strategies more strongly than analytic thought using research evidence |
| • Poor usability or integration into practitioner's workflow | • Good system performance depends on the motivational effect of the developer's enthusiasm, creation of more usable and integrated software, better access to technical support and training, and improved on-site promotion and tailoring |

Table 1. Common barriers to integrate research evidence into clinical practice

## 4.3 CDSS and patient safety

The quality and safety of health care leaves much to be desired (Leape & Berwick, 2005; McGlynn et al., 2003). Enhanced patient safety encompasses three complementary activities: preventing errors, making errors visible, and mitigating the effects of errors. Improvement and automation in a CDSS can assist clinicians making errors visible and augmenting error prevention. A CDSS provides several modes of decision support, including alerts, reminders, advice, critiques, and suggestions for improved care. In this way, CDSSs are able to decrease error rates by influencing physician behaviour, improving clinical therapy, and improving patient outcome (survival rate, length of patient stay, and cost). Computerized alerts can also allow rapid data collection from a large number of practices over a wide population (Johnson et al., 1991).

## 4.4 A CDSS example
### 4.4.1 The goal

To assist physicians in maintaining the accuracy and completeness of the problem and medications lists within the EMR, the Problem List Expert (PLE©) was developed at the University of Illinois Hospital (UIH) (Jao et al., 2008). This system was designed to test the hypothesis that a CDSS can assist in effectively identifying and maintaining problem-medication matches in the EMR. When medication and problem list mismatches were detected by the CDSS, expert clinicians examined the EMR to identify the nature of mismatches and causes for the mismatches including missing problems, inactive or resolved problems, missing medications, or duplicate prescribing.

### 4.4.2 The core of CDSS

The core of the PLE© is three linked database tables: the medication data dictionary, the problem data dictionary, and medication-problem relationship table. There were approximately 1,250 medication items in the UIH drug formulary added to the medication data dictionary. There were over 15,000 problem items (derived primarily from ICD-9-CM) added to the problem data dictionary. The database model is constructed as a network in which medications and the problems are associated by many-to-many relationships. Fig. 2 illustrates the structural model of the knowledge base. To simplify data query, each item in the medication data dictionary and each item in the problem data dictionary are connected by a common key attribute, an indication. In medicine, an indication is defined by the National Cancer Institute as "a sign, symptom, or medical condition that leads to the recommendation of a clinical treatment, a laboratory test, or a treating procedure" (http://cancernet.nci.nih.gov/Templates/db_alpha.aspx?CdrID=348991). Each medication can be linked with its associated indications that can be represented as a group of relevant clinical problems. Fig. 3 represents the hierarchical network model of the working database structure. Each normalized problem item in the problem data dictionary can be mapped to a unique ICD-9-CM (the International Classification of Diseases, Ninth Revision, Clinical
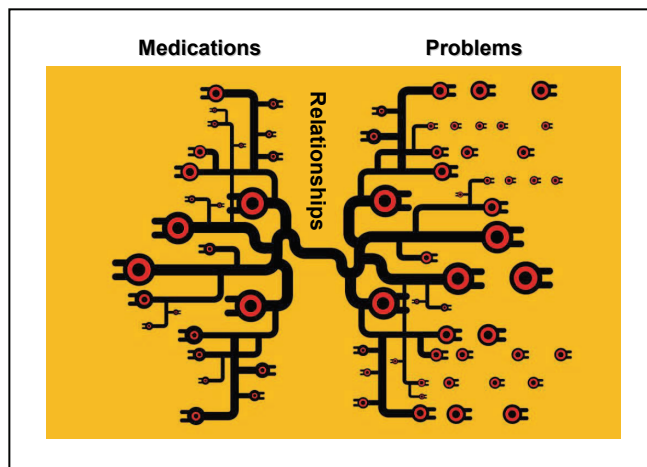


Fig. 2. The complex relationships are to connect prescribed medications to ongoing problems in the EMR.
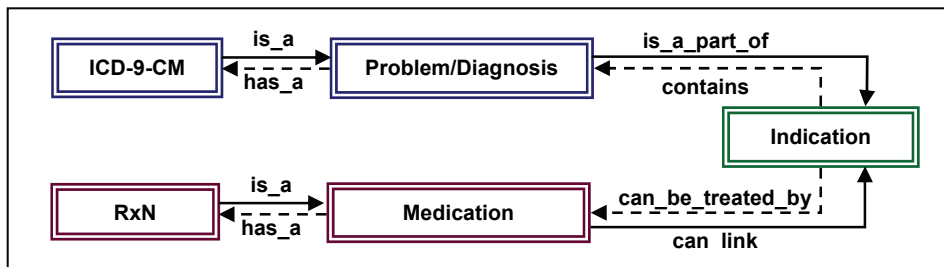
Fig. 3. Link medication orders to problems and diagnoses through the associated indications in a network model. All relationships in a hierarchical database are either one-to-one (1:1) or one-to-many (1:N). For example, each diagnostic problem item **has a** unique ICD-9-CM code when each ICD-9-CM code **is a** diagnostic problem. It is a one-to-one relationship between each problem and its associated ICD-9-CM code, and between each medication and its associated RxN (drug number). It is a one-to-many relationship between each indication and its related problems and medications.

Modification) code as defined by the Center for Disease Control and Prevention (CDC) (http://www.cdc.gov/nchs/about/otheract/icd9/abticd9.htm). Each normalized medication item in the medication data dictionary can be mapped to a unique self-defined drug number. Therefore, each ordered medication can be easily mapped by computer algorithm to one or more clinical problem(s) using established medication prescribing standards. This mapping methodology facilitates knowledge management and expedites clinical decision support.

### 4.4.3 Methodology of decision support

The PLE© was designed to simulate both a CPOE for ordering medication and an EMR for recording medication and problem lists. The PLE© assisted clinician experts in reviewing 140 patient records in three clinical units (general internal medicine, neurology, and rehabilitation) and discovering medication-problem mismatches (instances in which a medication was prescribed but had no indication on the problem list). Natural language processing assists in screening and matching the medications to problems. The matching algorithm in PLE© examines each medication on the Medication List by linking its indications to the indications for those problems on the Audited Problem List through the defined association in the Medication-Problem Relationship Table of the PLE©. A machine-learning algorithm is employed to correctly distinguish and classify the medications and problems entered in the CPOE. A data-mining algorithm is employed to discover the pattern and the relationship between the prescribed medications and the ongoing problems in the EMR. The data-mining algorithm facilitates the medication-problem matching and database management within a large set of data. Several common types of medication list errors (for example, unnecessary medications, inadvertently added medications, and missing medications) and problem list errors (for example, failure to remove inactive or resolved problems and failure to add active problems) may risk patient safety and can be fixed by physicians during chart audits.

Other key components of the PLE© are a patient data repository and a user interface. Through the enhanced user interface, physicians are able to create new patient records,

create problem lists, and order medications. When a new medication is ordered through the CPOE, the PLE$^©$ assists in checking if an appropriate problem is on the active problem list that is an indication for the medication ordered. Fig. 4 shows the infrastructure and workflow of the PLE$^©$ implementation, where the problem list obtained from UIH's EMR is termed the Reported Problem List; the medication list obtained from UIH's EMR is termed the Medication List, the list for medication-problem relationships based upon clinician expert review is termed the Audited Problem List. The order of data entry was the patient's Reported Problem List, Audited Problem List, and Medication List, which were saved in the Patient Data Repository without patient identities. The PLE$^©$ first examined the existence of entered items in the Medication Data Dictionary and the Problem Data Dictionary. The PLE$^©$ adopted computer algorithms for knowledge updating and discovery. New data will be automatically added in the corresponding data dictionaries accordingly.
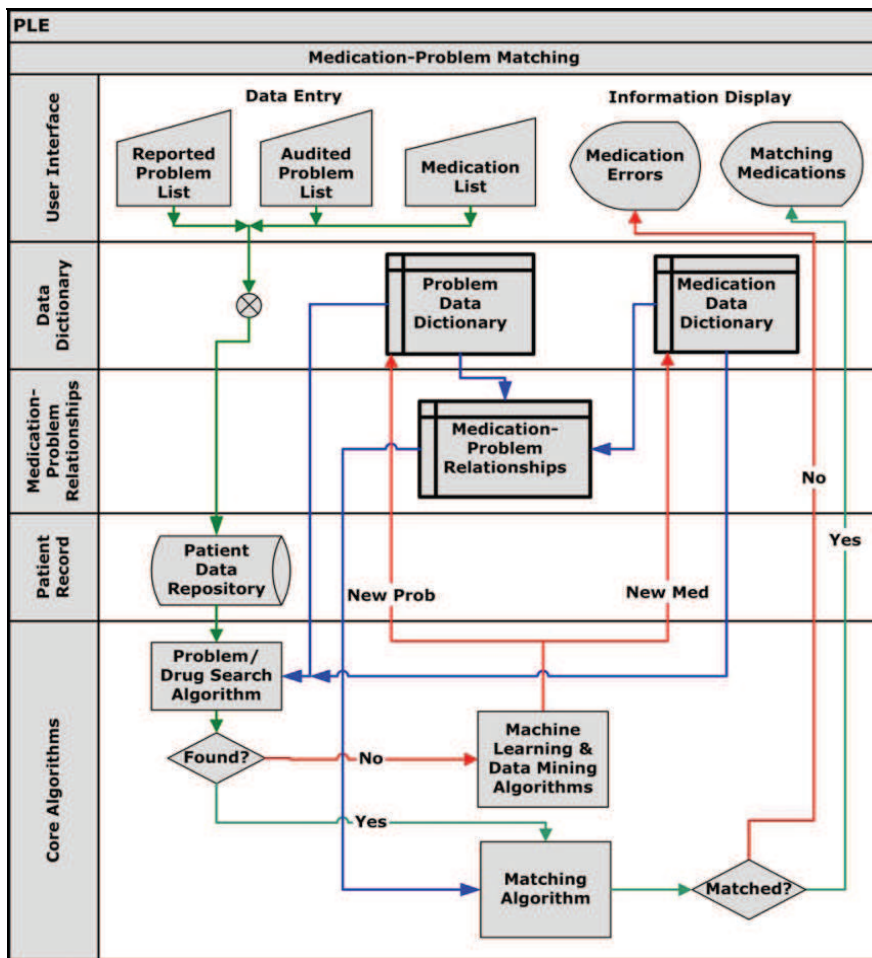


Fig. 4. The infrastructure and workflow of the PLE$^©$ implementation.

### 4.4.4 Results

The PLE$^{©}$ automates the maintenance of the medication and problem lists and detects likely medication-problem mismatches as visible medication and diagnostic errors on the screen of the EMR. With regard to the problem list, The PLE$^{©}$ found that approximately 11% of patient records had no problems listed on the Reported Problem List. Approximately 11% of patient records were perfectly matched (i.e., the count on the Reported Problem List equalled the count on the Audited Problem List). The remaining 78% of patient records showed various levels of problem deficiency on the Reported Problem Lists (i.e. the audit showed that problems were missing from the Reported Problem List).

The PLE$^{©}$ was programmed so that is was able to suggest the addition of non-specific problems that corresponded to common medications orders for treating problems which are generally unlisted on the problem list: for example, the medication "bisacodyl" for treating the problem "constipation," the medication "famotidine" for treating the problem "gastric acid," and the medications "acetaminophen" and "ibuprofen" for treating the problem "pain," etc. Most of these common medications are related to nursing diagnoses that are commonly not added to the problem list by physicians (e.g. fever, pain, constipation, etc.) This feature in the PLE$^{©}$ (matching common medications to minor non-recurrent problems) reduces the likelihood of finding medication-problem mismatches. The improvement rate of medication-problem matches on the problem lists was equal to the variance of the percentages of matched medications on the Medication List in the individual inpatient unit before and after expert chart review.

One approach to improve poor physician compliance with maintenance of the problem list is to link the ordering of medications to the problem lists by using a CDSS to automate the process of maintaining the EMR. In other words, when a medication is either ordered by CPOE or ePrescribing, the CDSS automates the process of adding the appropriate problem (the indication for the medication) to the problem list. The PLE$^{©}$, an innovative CDSS, automates the maintenance of both medication and problem lists in the EMR. It exploits advanced decision support strategies to yield higher patient safety by improving the accuracy of the medication and problem lists. It effectively identifies potential medical errors to some degree and improves problem list documentation in the EMR.

## 5. Future challenges

The potential to develop more sophisticated computerized alerts and other types of CDSS will grow as more clinical data becomes accessible electronically. Automated computerized-based applications utilize the accurate and structured clinical information available in the EMR to improve patient care and lower costs. Preliminary studies have shown that the CDSS is an essential cornerstone of efforts to reduce medical errors and improve patient safety. Future challenges to implementing a CDSS that automates the maintenance of the medication and problem lists include: (1) it may not work at an acceptance level of accuracy to make it clinical useful; (2) it may be too cumbersome to use so that clinicians are resistant to using it; and (3) the decision support algorithms may fail to work in some specific cases because of the complexity of medical decision-making.

CDSSs can assist in preventing adverse drug reactions, reducing inappropriate drug dosing, and reinforcing the use of effective prophylactic measures, (Trowbridge & Weingarten,

2001). Sittig et al. listed ten grand challenges in clinical decision support, including improving the user interface to facilitate data entry and clinical workflow; disseminating best practice evidences in the CDSS design, development, and implementation; summarizing precise patient-level information in the real time performance; prioritizing and filtering useful recommendations to the clinician for decision making; creating a reusable system architecture for sharing executable CDSS modules and services among different health care providers; combining feasible recommendations for patients with comorbidities; prioritizing CDSS content development and implementation; creating an internet-accessible CDSS and data repositories for widespread adoption; using free text information to drive decision support in the clinical domain; and mining large set of accurate clinical data to create an innovative CDSS (Sittig et al., 2008).

An electronic ordering (e-Ordering) of diagnostic imaging services has been proposed by the newly formed Imaging e-Ordering Coalition (The Coalition, Washington). This e-Ordering system will be supported by a CDSS that will guide clinicians to order the most appropriate diagnostic tests. The e-Ordering system will electronically document the appropriateness of each order and provide value-assurance to the patient and measurable, comparable data to the payer (insurer).

## 6. Conclusion

The preponderance of evidence indicates that CDSSs are effective to some degree in the preventing medical errors and in improving patient safety, especially when embedded within an EMR and directly intercalated into the care process. CDSSs are generally able to alter physician behaviour and influence the process of care. Although the results of support CDSSs have been far less positive when applied to the problem of improving clinical diagnosis, or improving ongoing care of patients with chronic diseases, advances can be expected in the future.

An effective CDSS can assist users of an EMR to significantly reduce medical errors and thus making healthcare more efficient and promoting the quality of health care. Despite the federal government's recent unveiling of grants and incentives for the adoption of HIT, health care providers still face numerous challenges in transitioning to the full adoption of EMR systems (Hart, 2009). Nonetheless, CDSS remains a critical factor in reaping benefits from the adoption of EMRs.

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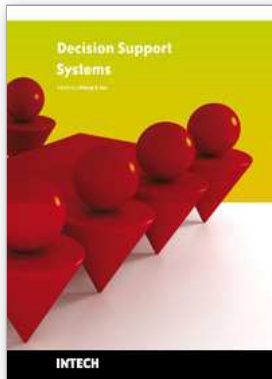
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Decision support systems (DSS) have evolved over the past four decades from theoretical concepts into real world computerized applications. DSS architecture contains three key components: knowledge base, computerized model, and user interface. DSS simulate cognitive decision-making functions of humans based on artificial intelligence methodologies (including expert systems, data mining, machine learning, connectionism, logistical reasoning, etc.) in order to perform decision support functions. The applications of DSS cover many domains, ranging from aviation monitoring, transportation safety, clinical diagnosis, weather forecast, business management to internet search strategy. By combining knowledge bases with inference rules, DSS are able to provide suggestions to end users to improve decisions and outcomes. This book is written as a textbook so that it can be used in formal courses examining decision support systems. It may be used by both undergraduate and graduate students from diverse computer-related fields. It will also be of value to established professionals as a text for self-study or for reference.

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