Improving Health Management through Clinical Decision Support Systems

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Chapter 1
Overview of Clinical Decision Support Systems in Healthcare

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ABSTRACT

Clinical Decision Support Systems (CDSS) are software designed to help clinicians to make decisions about patient diagnosis using technical devices such as desktops, laptops and iPads, and mobile devices, to obtain medical information and set up alert systems to monitor medication. A Clinical Decision Support System has been suggested by many as a key to a solution for improving patient safety together with Physician Based Computer Order Entry. This technology could prove to be very important in conditions such as chronic diseases where health outlay is high and where self-efficacy can affect health outcomes. However, the success of CDSS relies on technology, training and ongoing support. This chapter includes a historical overview and practical application of CDSS in medicine, and discusses challenges involved with implementation of such systems. It discusses new frontiers of CDSS and implications of self-management using social computing technologies, in particular in the management of chronic disease.

INTRODUCTION

Clinical Decision Support Systems are software applying "active knowledge systems which use two or more items of patient data to generate case-specific advice" (Wyatt & Spiegelhalter, 1991, p. 3). CDSS are information systems designed to improve clinical decision making 'at the point in time that decisions are made' (Berner, 2007, p. 3). The systems use technical devices such as desktops, laptops, iPads and mobile devices to derive medical information from data repositories to support the decision making process in a health organization. Patient characteristics are matched to knowledge database sets, and software algorithms generate patient-specific recommendations (Garg et al., 2010), as well-designed clinical decision support systems have been shown to improve the quality of health care with the use of clinical guidelines (Lamy et al., 2008).

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The notion of using CDSS has been around for more than 50 years (Kulikowski & Weiss, 1982).

The early CDSS were developed in the 1970s, derived from expert systems where developers tried to emulate machines to think like expert clinicians when treating patients (Stowa et al., 2006). From these early studies, there was growing recognition that they could assist clinicians with routine tasks by providing various functionalities (Callen, Johanna, Westbrook, & Braithwaite, 2006; Georgiou, Lam, & Westbrook, 2008) that would assist clinicians with accurate diagnosis and minimize human error (Kawamoto, Houlihan, Balas, & Lobach, 2005).

However, the adoption of CDSS to their full capacity has not been as substantial as expected. There are barriers to their implementation (Aarts & Koppel, 2009) and challenges to accessing and linking the myriad of information that exists in silos. These challenges remain to be resolved (Sittig et al., 2008).

The potential to improve health via CDSS has been shown to be positive, and work is being done in the domains of geriatrics (Vairaktarakis et al., 2015), in pediatrics, education, laboratories, radiology and health administration.

This chapter covers the development and application of CDSS and discusses functionalities, limitations and challenges with the adoption of new technology. The chapter provides guidelines for better uptake of CDSS and provides a critique of various problems with, and reactions to, their application.

Development of CDSS in Medicine

The development of CDSS in medicine stems from artificial intelligence. Artificial intelligence (AI) systems are intended to support healthcare workers with tasks that rely on the manipulation of data and knowledge. Types of AI that are intended to support clinical decisions are referred to as Expert Systems (Goodman, Grad, Pluye, Nowacki, & Hickner, 2012).

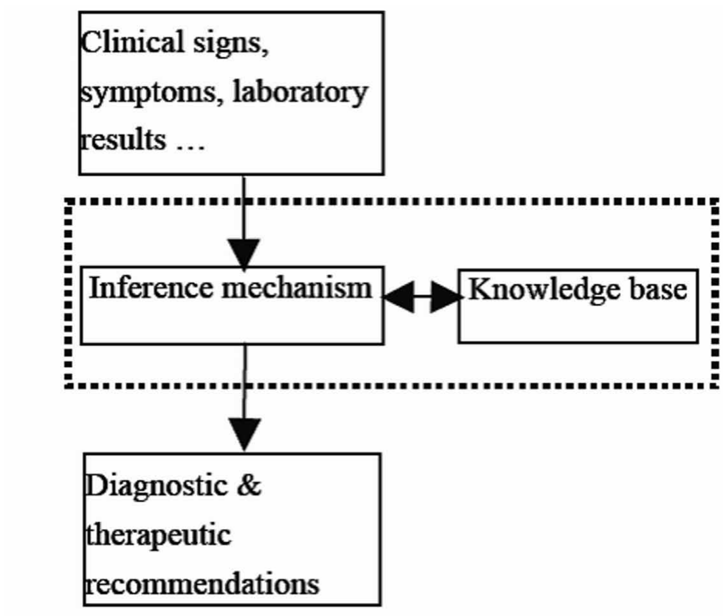
Expert systems are the commonest type of CDSS in routine clinical use. Research into the use of artificial intelligence in medicine started in the early 1970s and produced a number of experimental systems. In the first decade of research, most systems were developed to help clinicians in the process of diagnosis during an encounter with a patient. Most of these early systems did not develop further than the research laboratory, partly because they did not gain sufficient support from clinicians to permit their routine use.

CDSS can be broadly divided into two groups: knowledge-based or non-knowledge based. Knowledge-based systems are the commonest type of CDSS technology in routine clinical use, also known as *expert systems*. The knowledge-based system uses compiled clinical knowledge to provide clinical consultation. By far the majority of CDSS in medicine are knowledge-based (Berner, 2007). Non-knowledge-based systems do not use a knowledge base but use a form of artificial intelligence, machine learning, more like ‘trial and error’, that finds patterns in clinical datasets, learning the type that is similar to one way that humans learn (Kabachinski, 2013). There are two such types: neural network and genetic algorithms. The development and the application of expert systems in the clinical setting are explained in Figures 1 and 2.

There are many different types of CDSS and they deploy a range of technical functionalities, but a typical CDSS has medical knowledge, a database that contains patient details and an inference engine to generate case-specific advice, as can be seen in Figure 1. These systems contain clinical knowledge, signs, symptoms and laboratory results.

The general model of expert system has an inference mechanism which contains rule-based systems with specifically defined tasks. There are many variations in the system but the typical system is

Figure 1. General model of expert system



represented in the form of a set of rules (Aleksovska-Stojkovska, 2009; Buchanan & Shortliffe, 1984). The system allows reasoning with data from individual patients to come up with reasoned conclusions.

According to Perreaults and Metzger, CDSS have to fulfil four basic functions (Andrews, 2013; Caplan et al., 2012):

1. Administrative information: - Supporting clinical coding and documentation, authorization of procedures and referrals.
2. Clinical information: - Keeping patients on research and chemotherapy protocols; tracking orders, referrals follow-up, and preventive care.
3. Financial information: - controlling the cost by avoiding duplicate or unnecessary tests.
4. Decision support - Supporting clinical diagnosis and treatment plan processes; promoting use of best practices, condition-specific guidelines, and population-based management

The following table shows a practical application of CDSS use in medicine in chronological order.

Current Application of CDSS in Medicine

The application of CDSS has been broad. It has been widely used in an educational setting by nurses through the “Five Step” module (Levett-Jones et al., 2010) and by trainee doctors in internal medicine (Barnett, Cimino, Hupp, & Hoffer, 1987). The system has been adopted by non-specialists such as community doctors (Farion, Michalowski, Wilk, O’Sullivan, & Matwin, 2010), as well as by specialists using sophisticated digital methods (O’Sullivan, Fraccaro, Carson, & Weller, 2014).

Figure 2. Doctor's writing (Matt Golding, with permission)

A historical overview of CDSS has been presented in chronological order in Table1. The following section discusses a wide array of CDSS that are applied and in use now, not only in clinical management but in pathology, radiology, and education, as well in administration and management.

Acute Care Systems

HELP System

A knowledge-based hospital information system (HIS) has a standard web browser, written in PERL invoked by an apache web server linked with a PostgreSQL database. The system provides decision support in hepatic surgery. It has alerts, reminders, data interpretation and patient diagnostic and management suggestions, and clinical protocols. The system supports hospital information systems including admission, discharge, order entry and decision support.

It has alert systems, such as Ardent syntax and medical logic module (MLM) to send alert messages to HIS. The system can also be set up to send reminders, data interpretation and patient diagnosis facilities, patient management suggestions and clinical protocols. The only drawback is that the cases available are limited in number (Haug et al., 1994; Jorm, Shepherd, Rogers, & Blyth, 2012).

- POEMS: Post-Operative Expert Medical System, which interprets clinical data in real time, (Knies, Burton, & Sala, 2012). The system is embedded within hospital information systems.
- Post-operative care decision support VIE-PNN: Vienna Expert system for Prenatal Nutrition of Neonates. This is a rules based system, providing post-operative care decision support (Smailyte, Jasilionis, Ambrozaitiene, & Stankuniene, 2012).
- NéoGanesh: A closed loop based knowledge system for ICU ventilator management (Sun, Austin, & Kalra, 2012).

- In internal medicine: management of Cardiovascular Disease (CVD) (Peiris et al., 2009; Peiris, Usherwood, Weeramanthri, & Patel, 2011), in controlling diabetes (Ogunyemi et al., 2010; Wan, Makeham, Zwar, & Petche, 2012), Venous Thromboembolism (Durieux, Nizard, & Ravaud, 2000) and interpretation of Liver Function Test (Chevirier, Jaques, & Lovis, 2011).
- In recent times evidence of increasing use of CDSS is seen in the pediatric critical care unit (King, Baloglu, & Scanlon, 2015), in the interpretation of bilirubin levels in children (Devgun et al., 2015).

Laboratory Information Systems (LIS)

One of the areas of medicine that has been transformed rapidly with expert systems in the last two decades has been that of laboratory information systems (Baron & Dighe, 2014). Use of expert systems in the process of automation in pathology has had a huge impact on the efficiency of the work by reducing turnaround times, thereby increasing efficiency markedly and reducing human errors (Streitberg, Bwititi, Angel, & Sikaris, 2009).

Laboratory expert systems usually do not intrude into clinical practice and clinicians do not interact with them. LIS is normally a part of HIS. Within LIS, there can be many small programs, called middleware, such as Remisol (Blick, 2013; Cervinski & Polito, 2011; Hewett & LabPlus, 2010) or IT 3000 (Morling, Moulds, Ivey, Adamski-Loats, & Barnes, 2012) that sit on the top layer to facilitate work flow (Zhao, Qiao, & Raicu, 2015). Laboratory staff might have some involvement with setting up the rule criteria, but clinicians do not interact with them. For the pathologist, the system cuts down the workload of generating reports, without removing the need to check and correct reports.

With computerized order entry, an expert system, some laboratories have a ‘virtual lab’ where minimum staff are employed. Some examples of LIS are:

- GERMWATCHER: Hospital integration with laboratory analysis of nosocomial infections (Patel et al., 2011) (Kahn, Steib, Fraser, & Dunagan, 1993)
- HEPAXPERT I, II (Adlassnig & Horak, 1991) and III (Chizzali-Bonfadin, Adlassnig, Kreihsl, Hatvan, & Horak, 1997) which interpret serology tests of hepatitis A, B, C and D.
- HEPAXPERT III is a knowledge-based system which contains 16 rules for Hepatitis A and 131 rules for Hepatitis B, is available on World Wide Web and results can be sent via email. This is an advance on HEPAXPERT I which in turn is a stand-alone with no connection to external databases. HEPAXPERT II has a database that can interpret and provide database management and can connect to LIS and HIS.
- Pathology Expert Interpretative Reporting System (PEIRS): A rule-based system which went into routine use with approximately 200 rules and grew rapidly over a four year period (1990-1994) to over 2000 rules. It monitors adult drug poisoning. PEIRS interprets about 80-100 reports a day with a diagnostic accuracy of about 95% (Edwards, Compton, Malor, & Lazarus, 1993) .
- Pulmonary Consult System (PUFF): A pulmonary hierarchical rule-based system which can interpret pulmonary function tests. This was one of the earliest medical expert systems used, and many thousands of cases later, it is still in routine use (Aikins, Kunz, Shortliffe, & Fallat, 1983; Snow, Fallat, Tyler, & Hsu, 1988).

Table 1. Taxonomy of CDSS in medicine

Name of CDSS	Technology	Description
CASNET/Glaucoma (1960) developed at the Rutgers University and implemented in FORTRAN. (Fleming, Kirby, & Penny, 2012)	Expert clinical knowledge was represented in a causal-associational network (CASNET) model for describing disease processes.	Diagnosis and treatment for Glaucoma
AAPHelp: de Dombal's system for acute abdominal pain (Debono, Greenfield, Black, & Braithwaite, 2013)	Bayesian approach adopted. 304 patients suffering from abdominal pain of acute onset were tested. The computer system provided 91.8% accuracy whereas senior members of the clinical team reached 79.6% accuracy.	Diagnosis of acute abdominal pain to support need for abdominal surgery.
INTERNIST-I (1974) (Miller, McNeil, Challinor, Masarie Jr, & Myers, 1986)	Rule based expert system – tree structured database that links diseases with symptoms. Did not use Bayesian or statistical methods, as it tried to emulate how physicians would diagnose patients. First system that dealt with multiple conditions.	Developed to diagnose complex problems in general internal medicine. It used patient observations to deduce a list of compatible disease states. Disadvantage: uses only a small portion of information needs.
MYCIN (1976), Developed by Ted Shortliffe and colleagues at Stanford University (Avillach et al., 2013)	Rule based expert system using If-Then rules; domain-specific rather than general rules.	Diagnosis of bacteremia by providing consultative advice from data available from microbiology and clinical chemistry from the directed observations entered by clinicians. Provides explanation of infectious disease therapy and justifies specific recommendations.
PIP (Present Illness Program) (1970), built by MIT and Tufts-New England Medical Center (Fouad et al., 2013)	Rule-based approach used.	Diagnosis of renal disease from a large set of data. Had ability to generate hypotheses about disease processes.
Dendral	1st Artificial Intelligence program to emphasize the power of specialized knowledge over generalized problem-solving methods	Was programmed to help organize chemists elucidate molecular structures.
EMYCIN (1980) - Essential MYCIN, developed at Stanford (Buchanan & Shortliffe, 1984)	Rule-based, domain-independent framework was used; outgrowth of Dendral	An example of EMYCIN is PUFF (Bottacchi et al., 2012), a system designed to interpret pulmonary function tests for patients with lung disease.
ABEL (1980), Developed at the Laboratory for Computer Science, MIT, in the early 1980s. (Harris et al., 2010)	Expert system, causal reasoning used.	Acid-Base and Electrolyte program. An expert system, for the management of electrolyte and acid-base derangements.
ONCOCIN developed at Stanford University. (da Silva et al., 2012)	A rule-based medical expert system. The first DSS which attempted to model decisions and sequencing actions over time, using a customized flowchart language.	ONCOCIN was designed to assist physicians with the treatment of cancer patients receiving chemotherapy.
DXplain, developed by Massachusetts General Hospital, Harvard Medical School. (Barnett et al., 1987).	DSS uses database containing 2,200 diseases, and ranks conditions based on probabilities of 5,000 conditions.	Educational system: Combines clinical findings including signs, symptoms, and laboratory results to produce a ranked list of diagnoses; also provides differential diagnosis as well as further testing options.
QMR (Quick Medical Reference) (Huntington et al., 2012)	Was written in Turbo Pascal, works on any PC. DSS with knowledge base containing more than 700 diseases and 5,000 symptoms, signs and laboratory results.	Extensive database which provides a quick medical reference to assist clinicians

Ref: adapted from Coiera, 2002 (Coiera, 2002).

Educational Systems

- DXPLAIN. This is an internal medicine expert system. A user interacts with this system using various prompts. DXPLAIN takes a list of conditions and provides a possible diagnosis, (Barnett et al., 1987).
- ILLIAD (Warner et al., 1988): This is an internal medicine expert system using simulated case studies.
- Allergy Expert System (AED): This is an expert system used for diagnosis and treatment of allergy related conditions and using a PC shell programming environment (Walecki, Nowaczek, Porębski, & Obtułowicz, 2006a)
- Education for students: This is an educational model developed to enhance nursing students' ability to identify and manage clinically 'at risk' patients. It has the 'five rights' of clinical reasoning to assess patients (Levett-Jones et al., 2010).

ISSUES WITH CLINICAL DECISION SUPPORT SYSTEMS

There are many benefits of CDSS, but adoption has been slow. What are some of benefits and drawbacks of CDSS?

According to Sintchenko and Gardsden, the potential benefits fall into the following categories:

- ***Patient safety***: Improved patient safety by minimizing errors with medications, illegible entries from bad handwriting, misinterpretations and inadequate information.
- ***Continuity of patient care***: Improved quality of care with patient follow-up, providing evidence-based medicine, providing up-to-date clinical documentation that is better coordinated and shared among all treating clinicians and patients.
- ***Healthcare economics***: Improved turnaround time with computer ordering, reducing duplication and tests through faster processing and minimizing errors using delta checks, thus reducing health costs (Sintchenko & Garsden, 2002; Waegemann, 2002}

Patient Safety – Reduction in Medication Errors and Adverse Drug Reactions (ADR)

CDSS are considered to be the solution to solve problems with adverse drug reactions, The interest in using technology to prevent medication errors is growing rapidly (Forni, Chu, & Fanikos, 2010; Seger, Jha, & Bates, 2007). Numerous studies have shown that the use of Information Technology (IT) will improve patient safety and care, mostly through a reduction of errors (Buntin, Burke, Hoaglin, & Blumenthal, 2011; Garg et al., 2010; Kuperman, Reichley, & Bailey, 2006).

There is evidence that despite improvements in medicine, there are many who die from preventable medical errors among industrialized nations. An alarming report from the US Institute of Medicine indicates that as many as 98,000 people have died of preventable medical errors. Similarly, studies from two London-based hospitals found that 11% of admitted patients experienced adverse events, of which 48% were preventable, and 8% led to death (Kawamoto et al., 2005).

Nurses play an important role in patient care and quality. As many as one third of errors that are harmful to patients occur while nurses are administering medication to patients (Cloete, 2015), with many errors reported as being due to breakdown in communication. A reduction in errors has been reported with the implementation of a sign-out checklist (Lam, 2011).

In France, statistics on hospital admissions due to Adverse Drug Related events (ADR) are significant. In the period 2006-2007, there were 143, 915 hospital admissions due to ADR. In one public hospital in the same period, there were 2,692 admissions, of which 97 were related to ADR. The study shows that 32% of these were preventable (Bénard-Laribière, Miremont-Salamé, Pérault-Pochat, Noize, & Haramburu, 2015). The implementation of rule-based computer engines can suggest clinical interventions and mitigate preventable ADR in community hospitals without an advanced information technology application (Seger et al., 2007).

At first glance, IT solutions seem to provide the answer for all errors, but a retrospective study over the period 2005-2011 in England shows the co-existence of both technical and human errors. However, of the 850 events analyzed, human errors were four times higher than technical errors (Magrabi et al., 2015). Hence there is a need for IT to reduce human errors.

The use of technology has been shown to reduce errors in a specialized area of radiography. Uptake of IT in imaging/text analysis has been around since the 1970s but the uptake has been slow. Computer Aided Detection has become essential in the diagnosis of breast nodules through mammograms (Liu, 2015; Lo, Chang, Huang, & Moon, 2015; Sultan et al., 2015). These technologies use a neural network that can be adopted with use and learned from the system (Liu, 2015). However the question arises: to what extent can diagnosis be made using CDSS? Chen et al. conducted a study of the correlation between sonography of a solid breast mass and CDSS using text analysis and neural networks, one form of expert systems. The study showed that of 140 breast nodules examined, 95% were accurately identified by the CDSS. Since a neural network is trainable, an improvement in this area is likely (Chen, Chang, & Huang, 1999) provided that correct evaluation is done.

Patient Care: Evaluation of CDSS

The benefit of CDSS is hard to measure and there have been very few high quality studies to show any improvement in patient outcomes (Mollon et al., 2009). Most evaluation has focused on performance in the laboratory setting and this is mainly due to a lack of reliable tools with which to study user behavior (Sintchenko & Garsden, 2002).

When it comes to patient care, nurses play the major role, as they spend most time with patients, and normally manage the administration of medications. Patient charts recorded by nurses are considered as quality assurance. In a study done in a neonatal intensive care unit, a questionnaire was used to evaluate the use of technology on accuracy and quality, time, and health care information exchange. There was a lot of positive feedback on the use of technology; however it was evident that there were problems with the design of the system.

Workplace guidelines for patients with hypoglycemia, where interactive CDSS have been built into electronic health records, have shown some success (Harrison, Stalker, Henderson, & Lyerla, 2013), although the effectiveness of the guidelines needs to be proven (Shojania et al., 2010).

A limited number of studies have examined whether the alert system was working adequately in a CDSS in a routine clinical setting and whether relevant patient detail was generated for the end-user (Zheng, Padman, Johnson, & Diamond, 2005). A randomized trial on the use of alert systems in patients with acute kidney injury showed that the alert system did not improve clinical outcomes for patients (Wilson et al., 2015).

Many published works on evaluation of CDSS have focused on user satisfaction, and many challenges need to be addressed in structuring such studies. Studies on the effects of CDSS on practitioner performance and patient outcomes have shown that there was a positive change in practitioner performance by 52% but only a 30% change in patient impact. Overall, few studies have found positive patient outcomes (Jaspers, Smeulers, Vermeulen, & Peute, 2011), and there are mixed reports on the effectiveness of alert systems. All of the above studies, however, have led to improvement in the adoption of technology and better design of programs to suit clinical conditions.

Health Care and Economics

The ultimate motive for using CDSS is to minimize medical error, improve quality of care, reduce duplication of tests and thereby reduce overall health costs. Studies relating to the impact of CDSS have focused on cost-saving as a result of reduction in medical error and changes in management. These studies have limitations in their design and mostly lack an evaluation process. Nonetheless they show promise in many areas of medicine, as below.

In the hospital setting, intensive care units (ICU) are one of those areas where health utilization is very high. Within ICU, one of the highest costs comes from the use of ventilators. Weaning is the process of discontinuing mechanical ventilation. Use of CDSS in the weaning process has been shown to be successful in a study of 380 patients in ICU. The sensitivity was 87.7%, which is higher than the 61.4% determined by physicians, and the number of days of using a ventilator was significantly reduced by 5.2 days, leading to an overall saving of US$1,500 per patient (Jiin-Chyr et al., 2013).

Chronic disease management is another area continuously challenging the health budget in most nations and poses a heavy financial burden on the health system. Diabetes affects 22.3 million people in the USA; it is a major cause of heart disease and stroke. It is the 7th major cause of death. In the USA alone, costs associated with diabetes rose from $174 billion in 2007 to $245 billion in 2013 a rise of 41% (Herman, 2013). Patients with diabetes have two to four times the risk of having a myocardial infarct than those without. Diabetes can be a primary reason for renal failure, non-primary limb amputations and blindness. The use of CDSS in controlling diabetes has shown some improvement in care and some reduction in cost (14%) has been documented (Oxendine, Meyer, Reid, Adams, & Sabol, 2014).

Significant errors in antibiotic prescriptions are reported to have arisen from lack of up-to-date information (Sintchenko, Coiera, & Gilbert, 2008). Another study regarding the dose of antibiotics in 1,187 renal patients showed that using CDSS saved up to $116,000 because of more accurate dispensing and more accurate dosing (Helmons et al., 2007).

SOLUTIONS AND RECOMMENDATIONS

CDSS are software that relies on technology. The systems require ongoing education, training and adequate technology. The use of CDSS embedded within either LIS or HIS can replace existing trained staff, hence posing a threat to employment. CDSS can be harmful if the systems do not function properly or are not incorporated well into the current systems.

Multiple pop-up messages and alert systems can be a nuisance to users and can delay test results.

The system is a written set of rules. Consequently, if there are exceptions or glitches in the system, there is a chance that wrong diagnoses could be made. The system only works if stringent delta checks (algorithm to check results) are done. However, it is impossible to have a perfect solution for all cases presented and impossible to have rules written for all conditions. This can have a significant impact on the delivery and safety of patient care (Castillo & Kelemen, 2013).

For CDSS to be successful, the following three areas need to be considered carefully:

- System capabilities
- Software capabilities
- Human factors: ongoing training and education

System Capabilities

The system should have the ability to link to the datasets that currently exist in silos (Sittig et al., 2008) and be able to be coordinated and shared amongst authorized health practitioners. However, this is often hindered by a lack of legible hand writing, organizational structure and non-standardized terminologies (Sintchenko & Garsden, 2002).

The system could be improved by taking the following steps:

- Combine the Electronic Health Record (EHR) with a clinical data warehouse (CDW) with online analytic processing (OLAP) (Ledbetter & Morgan, 2001)
- Make it easier to use for clinicians who have limited computer background
- Have an up-to-date medical knowledge-based engine
- Provide correct, culturally sensitive and accurate interpretations
- Justify interpretations; provide validation rules
- Have easy access from clinicians' work and home
- Learn from users; i.e. evolve and improve as a result of user criticism and analysis of user sessions.
- Be confidential and secure. Install adequate system backups to protect patient data from being lost, and provide protection from hackers

Software Capabilities

Software capabilities that are currently available and can be implemented within LIS and HIS are:

- *Diagnostic support.* This must have knowledge inference. Use of AI, including expert systems like fuzzy logic, neural networks, or simply rule-based decision, can help in making decisions. Some are already embedded within LIS, and others are embedded within HIS. There are other software capabilities such as *Riskman*, which is used to do 'root cause analysis', written independently to enhance quality assurance
- *Alerts and reminders*. In a real time situation a reminder can be set up to assist clinicians and patients for many different areas such as advice on antibiotics, monitoring of warfarin levels, and in the control of hypoglycemia in diabetes.
- *Middle ware*. The use of middle ware embedded into LIS has revolutionized laboratory medicine. An accurate rule-based system can improve workflow and minimize human errors. Through the

delta check the system alerts technicians to check the patient sample if the results are different from previous results.

- *Prescribing decision support systems (PDSS).* One of the commonest clinical tasks is the prescription of medications. PDSS can assist by checking for drug-drug interactions, dosage errors, and if connected to an EMR, for other prescribing contraindications such as allergy. PDSS are usually well received because they support a pre-existing routine task, and as well as improving the quality of the clinical decision, they usually offer other benefits such as automated script generation and sometimes electronic transmission of the script to a pharmacy.
- *Computer Order Entry (CPOE).* Computer Order Entry together with CDSS can minimize duplication of tests, reduce human error from bad handwriting and wrong doses, save costs caused by duplications, and avoid unnecessary repetition of tests.
- *Image recognition.* Many clinical images can now be automatically interpreted, from plain X-rays through to more complex images such as angiograms, CT and MRI scans. Neural networks are applied in the diagnosis of solid breast nodules (Chen et al., 1999; Chen, Chien, & Kuo, 2015), and detection of malaria by CellaVision (Racsa et al., 2015). Artificial intelligence and pattern recognition are applied in cervical cancer detection (Bountris et al., 2015)
- *Quality Control software*. This is used to identify and analyze root causes and try to minimize medical error (Lederman, Dreyfus, Matchan, Knott, & Milton, 2013). Software such as Riskman can be implemented in the system to track sources of error in order to reduce human errors and minimize mistakes.
- *System back up and security levels*. A regular backup to protect personal information and to foolproof hardware/software security is essential, as information security in the healthcare sector is a growing concern, particularly in light of the national push for EMR to be shared among clinicians (Appari & Johnson, 2010). A strategy to protect genetic privacy is recommended (Erlich & Narayanan, 2014).

Human Factors, Threats to Employment

Early predictions forecast that there would be ‘as many as two workers’ in pathology laboratories (Kricka, Polsky, Park, & Fortina, 2015). This has not been possible to date, but the emphasis on cost effective operations in laboratories, as well as consolidating various sections of pathology (hematology, biochemistry, microbiology, immunology and anatomical pathology) into core laboratories, is becoming a trend in many hospitals (Kricka et al., 2015).

Certainly, health services of the 21st century show a paradigm shift in many areas. Re-engineering of the pathology laboratory through automation has caused massive staff cuts in many areas of pathology (Kricka et al., 2015). Another area where the use of IT has posed a threat to employment is that of pharmacy. The use of CPOE with CDSS has enabled pharmacies to reduce adverse drug reactions, particularly from illegible hand writing that could affect the dosage of medication. The study of the effects of drug related problems (DRP) found by clinical pharmacists identified 8% CDSS/CPOE alerts. This is a starting point, as the more sophisticated programs with pharmaceutical indications and drug reactions are written to the system, the better the performance will be (Zaal et al., 2013). The study also showed that many unnecessary alerts were audited by the pharmacists. At this stage of programming, the system is not yet sophisticated enough to overrule intervention by them. However, with the development of better programming, fewer staff will be required.

The next medical field where there is a threat to employment is in the area of digital imaging.

Hematology is a branch of pathology where red cell analysis is a key feature of study. Light microscopy is a gold standard for diagnosis but it is labor-intensive and time-consuming. CellaVision is an automated image analysis system that uses neural networking to analyze digital images of samples at high magnification and compares these images on a database of cells pre-classified according to red blood cell morphology. A study of the sensitivity of CellaVision was done with 212 abnormal blood smears in the Calgary Laboratory Services. The study showed that CellaVision had acceptable specificity but lacked consistency (Horn et al., 2015), and thus required human input.

In another study, the impact of using CDSS software in primary care nurse-led telephone triage was studied in England. To get the maximum benefit of CDSS, nurses required technical and clinical competencies to be able to capture patients' problems into CDSS (Murdoch et al., 2015).

FUTURE RESEARCH DIRECTIONS

That there has been a rapid adoption of IT in health and consequently increased use of CDSS in medicine is evident. Combined CDSS/CPOE has shown successes in many studies of adverse drug reactions, and with sophisticated programs it has the potential to reduce drug related problems even further (Murdoch et al., 2015).

There are, however, some continuing barriers. Many expert systems are now in routine use in acute care settings, clinical laboratories, and educational institutions, and are incorporated into electronic medical record systems. They are proving to have some success, but the uptake has been slow and the effectiveness of CDSS seems to vary.

The prediction of pathology laboratories being run by only two scientists has not eventuated, but the virtual laboratory might not be impossible, given the speed of development. Though well-programmed machines can reduce human errors, they lack the heuristic skills of experienced scientists/ clinicians. There needs to be a balance between the automation of pathology laboratories and human input. There are skeptics, however, e.g. in regard to employment, distrust of software, lack of training and mismatch between user need and supplier.

Information sharing among treating physicians is challenging, as each medical institution has its own record keeping system, which can cause information loss, misdiagnosis, duplication of tests and repetitive drug prescription (Wu & Wang, 2014). There is a push for a web-based cloud platform that can overcome this problem, though it is in its infancy (Kaur & Chana, 2014; Kulkarni, Shelke, Patil, Kulkarni, & Mohite, 2014).

With sophisticated CDSS systems combined with electronic health records, there is a capacity to learn, leading to the discovery of new phenomena and the creation of medical knowledge (Castaneda et al., 2015). These machine learning systems can be used to develop:

- Knowledge bases used by expert systems to authorize and scan images to diagnose, and to provide texts to generate reports and interpret results (Castaneda et al., 2015).
- Virtual laboratories with complete re-engineering of laboratories to automation (Kricka et al., 2015)
- Smart Healthcare Platform Construction Based on Cloud Computing that can support remote healthcare, chronic illness management and rural healthcare centres (Zhang, Zhang, & Liu, 2014).

There is a global push for big data, bringing disparate datasets for electronic health records to be available and shared among treating clinicians. There is a push for personally controlled electronic health records to be controlled by patients and carers to provide them with autonomy:

"Maybe we're not that far away from the home sick bay idea.

Future parent: "Doctor, what's wrong with my child?"

Dr. Hologram: "Nothing at all ma'am, all bio indicators and CDSS reports indicate a clean bill of health with no current maladies. Send him to school!" (Kabachinski, 2012, p.432).

CONCLUSION

The advancement of IT in medicine has shown a quantum leap in the last three decades. The historical overview and the application of CDSS in medicine have been discussed above. With computers being ubiquitous, ways to utilize CDSS to increase efficiency, thereby reducing medical error and reducing costs, is showing promise. However, despite technological advancement, the full potential of CDSS has not been explored and much more work needs to be done in the area of evaluation and exploration.

Available evidence on the impact of CDSS to deliver improvements in the quality, safety and efficiency of health has been described. Reductions in medication and adverse drug reaction events alone appear impressive. To date, the majority of studies have been undertaken in the United States and importantly, most have involved CDSS systems that have been internally developed and customized for individual health care organizations. The question as to whether the impressive results from already available systems will be more widely applied is yet to be answered.

Barriers such as de-skilling, fear of losing employment, undermining of experience, machine phobia and legal issues remain to be answered. Ongoing education to support staff to narrow the gap is required.

In addition, the success of the implementation of CDSS and CPOE will depend on successful IT integration (Aarts & Koppel, 2009) and continued support by senior management. Building a system with increasingly complex decision rules is an arduous task that requires passion, the time of developers, financial support from vendors, and support from collaborating physicians. Use of CPOE with CDSS has shown improvement in reducing blood bank errors.

With the health budget escalating and with global issues of an aging population with associated chronic conditions, more emphasis should be put on the use of CDSS for self-efficacy to ensure one's health. This could prove in the long run to result in substantial savings in costs.

REFERENCES

Aarts, J., & Koppel, R. (2009). Implementation Of Computerized Physician Order Entry In Seven Countries. *Health Affairs*, *28*(2), 404–414. doi:10.1377/hlthaff.28.2.404 PMID:19275996

Adlassnig, K. P., & Horak, W. (1991). Innovations in software: Hepaexpert-I: automatic interpretation of tests for hepatitis A and B. *Computing*, *8*(2), 118–119.

Aikins, J. S., Kunz, J. C., Shortliffe, E. H., & Fallat, R. J. (1983). PUFF: An expert system for interpretation of pulmonary function data. *Computers and Biomedical Research, an International Journal*, *16*(3), 199–208. doi:10.1016/0010-4809(83)90021-6 PMID:6347509

Aleksovska-Stojkovska, L. (2009). Clinical decision support system for managing asthma in school-age children. *IEEE, 17th Telecommunications forum TELFOR 2009, Nov*, 24-26.

Andrews, P. N. (2013). A Discussion of Clinical Decision Support Services. *Clinical Obstetrics and Gynecology*, *56*(3), 446–452. doi:10.1097/GRF.0b013e31829cb0bf PMID:23787710

Avillach, P., Coloma, P. M., Gini, R., Schuemie, M., Mougin, F., Dufour, J. C., & Trifirò, G. et al. (2013). Harmonization process for the identification of medical events in eight European healthcare databases: The experience from the EU-ADR project. *Journal of the American Medical Informatics Association*, *20*(1), 184–192. doi:10.1136/amiajnl-2012-000933 PMID:22955495

Barnett, G. (1987). DXplain: An evolving diagnostic decision-support system. *Journal of the American Medical Association*, *258*(1), 67–74. doi:10.1001/jama.1987.03400010071030 PMID:3295316

Baron, J. M., & Dighe, A. S. (2014). The role of informatics and decision support in utilization management. *Clinica Chimica Acta*, *427*, 196–201. doi:10.1016/j.cca.2013.09.027 PMID:24084507

Bénard-Laribière, A., Miremont-Salamé, G., Pérault-Pochat, M.-C., Noize, P., & Haramburu, F. (2015). Incidence of hospital admissions due to adverse drug reactions in France: The EMIR study. *Fundamental & Clinical Pharmacology*, *29*(1), 106–111. doi:10.1111/fcp.12088 PMID:24990220

Berner, E. S. (2007). Clinical Decision Support Systems: Theory and Practice. In K. Hannah & J. B. Marion (Eds.), *Health Informatics*. New York: Springer. doi:10.1007/978-0-387-38319-4

Blick, K. E. (2013). Providing Critical Laboratory Results on Time, Every Time to Help Reduce Emergency Department Length of Stay How Our Laboratory Achieved a Six Sigma Level of Performance. *American Journal of Clinical Pathology*, *140*(2), 193–202. doi:10.1309/AJCPNUTIPQTRRG0D PMID:23897254

Bottacchi, E., Corso, G., Tosi, P., Morosini, M. V., De Filippis, G., Santoni, L., & Negrini, C. et al. (2012). The cost of first-ever stroke in Valle d'Aosta, Italy: Linking clinical registries and administrative data. *BMC Health Services Research*, *12*(1), 372–372. doi:10.1186/1472-6963-12-372 PMID:23110322

Bountris, P., Kotronoulas, G., Tagaris, T., Haritou, M., Spathis, A., Karakitsos, P., & Koutsouris, D. (2015). *CxCaDSS: A Web-Based Clinical Decision Support System for Cervical Cancer.* Paper presented at the 6th European Conference of the International Federation for Medical and Biological Engineering. doi:10.1007/978-3-319-11128-5_188

Buchanan, B. G., & Shortliffe, E. H. (1984). *Rule-based expert systems* (Vol. 3). Addison-Wesley Reading.

Buntin, M. B., Burke, M. F., Hoaglin, M. C., & Blumenthal, D. (2011). The benefits of health information technology: A review of the recent literature shows predominantly positive results. *Health Affairs*, *30*(3), 464–471. doi:10.1377/hlthaff.2011.0178 PMID:21383365

Callen, L.J., Johanna, I., Westbrook, M.H.A., & Braithwaite, J. (2006). The Effect of Physicians' Long-term Use of CPOE on Their Test Management Work Practices. *Journal of American Medical Informatics Association, 13*, 643-652.

Caplan, A. G., Sulaiman, S. N., Mangin, A. D., Ricauda, A. N., Wilson, D. A., & Barclay, L. (2012). A meta-analysis of "hospital in the home". *The Medical Journal of Australia*, *197*(9), 512–519. doi:10.5694/mja12.10480 PMID:23121588

Castaneda, C., Nalley, K., Mannion, C., Bhattacharyya, P., Blake, P., Pecora, A., & Suh, K. S. et al. (2015). Clinical decision support systems for improving diagnostic accuracy and achieving precision medicine. *Journal of Clinical Bioinformatics*, *5*(1), 4. doi:10.1186/s13336-015-0019-3 PMID:25834725

Castillo, R. S., & Kelemen, A. (2013). *Considerations for a Successful Clinical Decision Support System*. Academic Press.

Cervinski, M. A., & Polito, F. A. (2011). Implementing a Real-Time Moving Averages Program in the Clinical Lab. *Advance Healthcare network, 20* (7), 56.

Chen, D.-R., Chang, R.-F., & Huang, Y.-L. (1999). Computer-aided diagnosis applied to US of solid breast nodules by using neural networks 1. *Radiology*, *213*(2), 407–412. doi:10.1148/radiology.213.2.r99nv13407 PMID:10551220

Chen, D.-R., Chien, C.-L., & Kuo, Y.-F. (2015). Computer-Aided Assessment of Tumor Grade for Breast Cancer in Ultrasound Images. *Computational and Mathematical Methods in Medicine*, 2015. PMID:25810750

Chevirier, R., Jaques, D., & Lovis, C. (2011). Architecture of a Decision Support System to Improve Clinicians' Interpretation of Abnormal Liver Function Tests. In A. Moen, S. K. Anderson, J. Aarts, & P. Hurlen (Eds.), User Centred Networked Health Care (pp. 195-199). IOS Press.

Chizzali-Bonfadin, C., Adlassnig, K.-P., Kreihsl, M., Hatvan, A., & Horak, W. (1997). A WWW-accessible knowledge base for the interpretation of hepatitis serologic tests. *International Journal of Medical Informatics*, *47*(1), 57–60. doi:10.1016/S1386-5056(97)00092-0 PMID:9506393

Cloete, L. (2015). Reducing medication errors in nursing practice. *Nursing Standard*, *29*(20), 50–59. doi:10.7748/ns.29.20.50.e9507 PMID:25585768

Coiera, E. (2002). Updates in Medicine, Health Informatics. *The Medical Journal of Australia*, *176*, 1–20.

da Silva, M. E., Coeli, C. M., Ventura, M., Palacios, M., Magnanini, M. M., Camargo, T. M., & Camargo, K. R. Jr. (2012). Informed consent for record linkage: A systematic review. *Journal of Medical Ethics*, *38*(10), 639–642. doi:10.1136/medethics-2011-100208 PMID:22403083

Debono, D. S., Greenfield, D. R., Black, D. A., & Braithwaite, J. (2013). *Engaging with electronic medication systems in everyday practice: how is it done and what are the implications for medical imaging?* Paper presented at the The Australasian Conference on Error in Medical Imaging, Melbourne, Australia.

Devgun, M. S., Chan, M. K., El-Nujumi, A. M., Abara, R., Armbruster, D., & Adeli, K. (2015). Clinical decision limits for interpretation of direct bilirubin—A CALIPER study of healthy multiethnic children and case report reviews. *Clinical Biochemistry*, *48*(1), 93–96. doi:10.1016/j.clinbiochem.2014.10.011 PMID:25445233

Durieux, P., Nizard, R., Ravaud, P., Mounier, N., & Lepage, E. (2000). A Clinical Decision Support System for Prevention of Venous Thromboembolism: Effect on Physican Behavior. *Journal of the American Medical Association*, *283*(21), 2816–2821. doi:10.1001/jama.283.21.2816 PMID:10838650

Edwards, G., Compton, P., Malor, R., Srinivasan, A., & Lazarus, L. (1993). PEIRS: A Pathologist Maintained Expert System for the Interpretation of Chemical Pathology Reports. *Pathology*, *25*(1), 27–34. doi:10.3109/00313029309068898 PMID:8316495

Erlich, Y., & Narayanan, A. (2014). Routes for breaching and protecting genetic privacy. *Nature Reviews. Genetics*, *15*(6), 409–421. doi:10.1038/nrg3723 PMID:24805122

Farion, K., Michalowski, W., Wilk, S., O'Sullivan, D., & Matwin, S. (2010). A tree-based decision model to support prediction of the severity of asthma exacerbations in children. *Journal of Medical Systems*, *34*(4), 551–562. doi:10.1007/s10916-009-9268-7 PMID:20703909

Fleming, M., Kirby, B., & Penny, I.K. (2012). Record Linkage in Scotland and its applications to health research. *Journal of Clinical Nursing, 21*, 2711–2721.

Forni, A., Chu, H. T., & Fanikos, J. (2010). Technology utilization to prevent medication errors. *Current Drug Safety*, *5*(1), 13–18. doi:10.2174/157488610789869193 PMID:20210714

Fouad, M. N., Lee, J. Y., Catalano, P. J., Vogt, T. M., Zafar, Y., & Syed, W. (2013). Enrollment of Patients With Lung and Colorectal Cancers Onto Clinical Trials. *Journal of Oncology Practice*, *9*(2), e40–e47. doi:10.1200/JOP.2012.000598 PMID:23814523

Garg, X. A., Adhikari, J. K. N., McDonald, H., Rosas-Arellano, M. P., Devereaux, J. P., Beyene, J., & Haynes, R. B. et al. (2010). Effects of Computerized Clinical Decision Support Systems on Practitioner Performance and Patient Outcomes. A Systematic Review. *Journal of the American Medical Association*, *293*(10), 1223–1238. doi:10.1001/jama.293.10.1223 PMID:15755945

Georgiou, A., Lam, M., & Westbrook, J. (2008). *Monitoring the Impact of CPOE on Healthcare Delivery - A Benefits Realisatioin Approach*. Paper presented at the HIC Australia's Health Informatics Conference.

Goodman, K., Grad, R., Pluye, P., Nowacki, A., & Hickner, J. (2012). Impact of knowledge resources linked to an electronic health record on frequency of unnecessary tests and treatments. *The Journal of Continuing Education in the Health Professions*, *32*(2), 108–115. doi:10.1002/chp.21133 PMID:22733638

Harris, B. S., Glazier, H. R., Tompkins, W. J., Wilton, S. A., Chevendra, V., Stewart, A. M., & Thind, A. (2010). Investigating concordance in diabetes diagnosis between primary care charts (electronic medical records) and health administrative data: A retrospective cohort study. *BMC Health Services Research*, *10*(1), 347–347. doi:10.1186/1472-6963-10-347 PMID:21182790

Harrison, R. L., Stalker, S. L., Henderson, R., & Lyerla, F. (2013). Use of a Clinical Decision Support System to Improve Hypoglycemia Management. *Medsurg Nursing*, *22*(4), 250–263. PMID:24147323

Haug, P. J., Gardner, R. M., Tate, K. E., Evans, R. S., East, T. D., Kuperman, G., & Warner, H. R. et al. (1994). Decision support in medicine: Examples from the HELP system. *Computers and Biomedical Research, an International Journal*, *27*(5), 396–418. doi:10.1006/cbmr.1994.1030 PMID:7813202

Herman, W. H. (2013). The economic costs of diabetes: Is it time for a new treatment paradigm? *Diabetes Care*, *36*(4), 775–776. doi:10.2337/dc13-0270 PMID:23520368

Hewett, R., & LabPlus, Auckland. (2010). Annual Scientific Meeting of the NZIMLS, Bay of Islands, Northland 2010. *NZ J Med Lab Science*, 94.

Horn, C. L., Mansoor, A., Wood, B., Nelson, H., Higa, D., Lee, L. H., & Naugler, C. (2015). Performance of the CellaVision® DM96 system for detecting red blood cell morphologic abnormalities. *Journal of Pathology Informatics, 6*.

Huntington, E. S., Bansi, K. L., Thorne, C., Anderson, J., Newell, L. M., Taylor, P. G., & Sabin, A. C. et al. (2012). Using two on-going HIV studies to obtain clinical data from before, during and after pregnancy for HIV-positive women. *BMC Medical Research Methodology*, *12*(1), 110–110. doi:10.1186/1471-2288-12-110 PMID:22839414

Jaspers, M. W. M., Smeulers, M., Vermeulen, H., & Peute, L. W. (2011). Effects of clinical decision-support systems on practitioner performance and patient outcomes: a synthesis of high-quality systematic review findings. *Journal of the American Medical Informatics Association, 18*(3), 327-334.

Jiin-Chyr, H., Yung-Fu, C., Wei-Sheng, C., Tan-Hsu, T., Tainsong, C., & Chian, J. Y. (2013). Clinical Verification of A Clinical Decision Support System for Ventilator Weaning. *Biomedical Engineering Online*, *12*, 1–14. doi:10.1186/1475-925x-12-s1-s4 PMID:23289769

Jorm, R. L., Shepherd, C. L., Rogers, D. K., & Blyth, M. F. (2012). Smoking and use of primary care services: Findings from a population-based cohort study linked with administrative claims data. *BMC Health Services Research*, *12*(1), 263–263. doi:10.1186/1472-6963-12-263 PMID:22900643

Kabachinski, J. (2013). A look at clinical decision support systems. *Biomedical Instrumentation & Technology*, *47*(5), 432–434. doi:10.2345/0899-8205-47.5.432 PMID:24099257

Kahn, M. G., Steib, S. A., Fraser, V. J., & Dunagan, W. C. (1993). *An expert system for culture-based infection control surveillance.* Paper presented at the Annual Symposium on Computer Application in Medical Care.

Kaur, P. D., & Chana, I. (2014). Cloud based intelligent system for delivering health care as a service. *Computer Methods and Programs in Biomedicine*, *113*(1), 346–359. doi:10.1016/j.cmpb.2013.09.013 PMID:24139021

Kawamoto, K., Houlihan, A.C., Balas, E.A., & Lobach, F.D. (2005). Improving clinical practice using clinical decision support systems: a systematic review of trials to identify features critical to success. *BMJ*. doi:10.1136/bmj.38398.500764.8F

King, A. L., Baloglu, O., & Scanlon, M. C. (2015). *The Role of Technology and Medical Devices in Enhancing Pediatric Cardiac Critical Care Outcomes. In Pediatric and Congenital Cardiac Care* (pp. 355–365). London: Springer.

Knies, G., Burton, J., & Sala, E. (2012). Consenting to health record linkage: Evidence from a multi-purpose longitudinal survey of a general population. *BMC Health Services Research*, *12*(1), 52–52. doi:10.1186/1472-6963-12-52 PMID:22390416

Kricka, L. J., Polsky, T. G., Park, J. Y., & Fortina, P. (2015). The future of laboratory medicine -- A 2014 perspective. *Clinica Chimica Acta*, *284*. doi:10.1016/j.cca.2014.09.005 PMID:25219903

Kulikowski, C. A., & Weiss, S. M. (1982). Representation of expert knowledge for consultation: The CASNET and EXPERT projects. *Artificial Intelligence in Medicine*, 51.

Kulkarni, G., Shelke, R., Patil, P. B. N., Kulkarni, V., & Mohite, S. (2014). *Optimization in Mobile Cloud Computing for Cloud Based Health Application.* Paper presented at the Communication Systems and Network Technologies (CSNT), 2014 Fourth International Conference on. doi:10.1109/CSNT.2014.120

Kuperman, G. J., Reichley, R. M., & Bailey, T. C. (2006). Using Commercial Knowledge Bases for Clinical Decision Support Opportunities, Hurdles, and Recommendations. *Journal of the American Medical Informatics Association*, *13*(4), 369–371. doi:10.1197/jamia.M2055 PMID:16622160

Lam, M. K. (2011). How good is New South Wales admitted patient data collection in recording births? *Health Information Management Journal*, *40*(3), 12–19. PMID:22006432

Lamy, J.-B., Ellini, A., Ebrahiminia, V., Zucker, J.-D., Falcoff, H., & Venot, A. (2008). Use of the C4.5 machine learning algorithm to test a clinical guideline-based decision support system. *Studies in Health Technology and Informatics*, *136*, 223–228. PMID:18487735

Ledbetter, C. S., & Morgan, M. W. (2001). Toward best practice: Leveraging the electronic patient record as a clinical data warehouse. *Journal of Healthcare Information Management*, *15*(2), 119–132. PMID:11452574

Lederman, R., Dreyfus, S., Matchan, J., Knott, J. C., & Milton, S. K. (2013). Electronic error-reporting systems: A case study into the impact on nurse reporting of medical errors. *Nursing Outlook*, *61*(6), 417–426.e415. doi:10.1016/j.outlook.2013.04.008 PMID:23838568

Levett-Jones, T., Hoffman, K., Dempsey, J., Jeong, S. Y.-S., Noble, D., Norton, C. A., & Hickey, N. et al. (2010). The ‘five rights’ of clinical reasoning: An educational model to enhance nursing students’ ability to identify and manage clinically ‘at risk’ patients. *Nurse Education Today*, *30*(6), 515–520. doi:10.1016/j.nedt.2009.10.020 PMID:19948370

Liu, B. (2015). Application of Artificial Neural Networks in Computer-Aided Diagnosis *Artificial Neural Networks*, 195–204. PMID:25502383

Lo, C. M., Chang, R. F., Huang, C. S., & Moon, W. K. (2015). Computer-Aided Diagnosis of Breast Tumors Using Textures from Intensity Transformed Sonographic Images. Paper presented at the 1st Global Conference on Biomedical Engineering & 9th Asian-Pacific Conference on Medical and Biological Engineering. doi:10.1007/978-3-319-12262-5_35

Magrabi, F., Baker, M., Sinha, I., Ong, M.-S., Harrison, S., Kidd, M. R., . . . Coiera, E. (2015). Clinical safety of England’s national program for IT: a retrospective analysis of all reported safety events 2005 to 2011. International Journal of Medical Informatics.

Miller, R. A., McNeil, M. A., Challinor, S. M., Masarie, F. E. Jr, & Myers, J. D. (1986). The INTERNIST-1/quick medical REFERENCE project—Status report. [PubMed]. *The Western Journal of Medicine*, *145*(6), 816.

Mollon, B., Chong, J. Jr, Holbrook, A. M., Sung, M., Thabane, L., & Foster, G. (2009). Features predicting the success of computerized decision support for prescribing: A systematic review of randomized controlled trials. [PubMed]. *BMC Medical Informatics and Decision Making*, *9*(1), 11–11. doi:10.1186/1472-6947-9-11

Morling, A., Moulds, R., Ivey, J., Adamski-Loats, J., & Barnes, K. (2012). Efficient haematology testing through hardware and software automation. *Australian Journal of Medical Science*, *33*(3), 96.

Murdoch, J., Barnes, R., Pooler, J., Lattimer, V., Fletcher, E., & Campbell, J. L. (2015). The impact of using computer decision-support software in primary care nurse-led telephone triage: Interactional dilemmas and conversational consequences. [PubMed]. *Social Science & Medicine*, *126*, 36–47. doi:10.1016/j.socscimed.2014.12.013

O'Sullivan, D., Fraccaro, P., Carson, E., & Weller, P. (2014). Professional Issues. Decision time for clinical decision support systems. *Clinical Medicine*, *14*(4), 338–341. doi:10.7861/clinmedicine.14-4-338 PMID:25099829

Ogunyemi, O., Mukherjee, S., Anim, C., Hindman, D., George, S., Ilapakurthi, R., . . . Dayritc, M. (2010). CEDRIC: A Computerized Chronic Disease Management System for Urban, Safety Net Clinics. In Safran (Ed.), MEDINFO 2010. IOS Press.

Oxendine, V., Meyer, A., Reid, P. V., Adams, A., & Sabol, V. (2014). Evaluating Diabetes Outcomes and Costs Within an Ambulatory Setting: A Strategic Approach Utilizing a Clinical Decision Support System. *Clinical Diabetes*, *32*(3), 113–120. doi:10.2337/diaclin.32.3.113 PMID:26246682

Patel, V. N., Dhopeshwarkar, R. V., Edwards, A., Barron, Y., Likourezos, A., Burd, L., & Kaushal, R. et al. (2011). Low-income, ethnically diverse consumers' perspective on health information exchange and personal health records. *Informatics for Health & Social Care*, *36*(4), 233–252. doi:10.3109/17538157.2011.554930 PMID:21851182

Peiris, D. P., Joshi, R., Webster, R. J., Groenestein, P., Usherwood, T. P., Heeley, E., & Patel, A. A. et al. (2009). An Electronic Clinical Decision Support Tool to Assist Primary Care Providers in Cardiovascular Disease Risk Management: Development and Mixed Methods Evaluation. *Journal of Medical Internet Research*, *11*(4), 1438–1455. doi:10.2196/jmir.1258 PMID:20018588

Peiris, D. P., Usherwood, T. P., Weeramanthri, A. C., & Patel, A. (2011). New tools for an old trade: A socio-technical appraisal of how electronic decision support is used by primary care practitioners. *Sociology of Health & Illness*, *33*(7), 1002–1018. doi:10.1111/j.1467-9566.2011.01361.x PMID:21671947

Racsa, L. D., Gander, R. M., Southern, P. M., McElvania TeKippe, E., Doern, C., & Luu, H. S. (2015). Detection of Intracellular Parasites by Use of the CellaVision DM96 Analyzer during Routine Screening of Peripheral Blood Smears. *Journal of Clinical Microbiology*, *53*(1), 167–171. doi:10.1128/JCM.01783-14 PMID:25378575

Seger, A. C., Jha, A. K., & Bates, D. W. (2007). Adverse drug event detection in a community hospital utilising computerised medication and laboratory data. *Drug Safety*, *30*(9), 817–824. doi:10.2165/00002018-200730090-00007 PMID:17722972

Shojania, G. K., Jennings, A., Mayhew, A., Ramsay, C., Eccles, M., & Grimshaw, J. (2010). Effect of point-of-care computer reminders on physician behaviour: A systematic review. *Canadian Medical Association Journal*, *182*(5), 216–225. doi:10.1503/cmaj.090578 PMID:20212028

Sintchenko, C., Coiera, E., & Gilbert, G. L. (2008). Decision support systems for antibiotic prescribing. *Current Opinion in Infectious Diseases*, *21*(6), 573–579. doi:10.1097/QCO.0b013e3283118932 PMID:18988320

Sintchenko, V., & Garsden, H. (2002). *Clinical Decision Support: New Approaches to Usability Study.* Paper presented at the HIC, Melbourne, Australia.

Sittig, D. F., Wright, A., Osheroff, J. A., Middleton, B., Teich, J. M., Ash, J. S., & Bates, D. W. et al. (2008). Grand challenges in clinical decision support. *Journal of Biomedical Informatics*, *41*(2), 387–392. doi:10.1016/j.jbi.2007.09.003 PMID:18029232

Smailyte, G., Jasilionis, D., Ambrozaitiene, D., & Stankuniene, V. (2012). Educational inequalities in cancer incidence and mortality in Lithuania: A record linkage study. *Cancer Epidemiology*, *36*(5), e279–e283. doi:10.1016/j.canep.2012.05.009 PMID:22705124

Snow, M., Fallat, R., Tyler, W., & Hsu, P. (1988). Pulmonary consult: Concept to application of an expert system. *Journal of Clinical Engineering*, *13*(3), 201–206. doi:10.1097/00004669-198805000-00010

Stowa, J. P., Hart, K. G., Higlett, T., Georgea, C., Herkesd, R., McWilliamd, D., & Rinaldo, B. (2006). Development and implementation of a high-quality clinical database: The Australian and New Zealand Intensive Care Society Adult Patient Database. *Journal of Critical Care*, *21*(2), 133–141. doi:10.1016/j.jcrc.2005.11.010 PMID:16769456

Streitberg, G. S., Bwititi, P. T., Angel, L., & Sikaris, K. A. (2009). Automation and expert systems in a core clinical chemistry laboratory. *Journal of the Association for Laboratory Automation*, *14*(2), 94–105. doi:10.1016/j.jala.2008.12.001

Sultan, L. R., Bouzghar, G., Levenback, B. J., Faizi, N. A., Venkatesh, S. S., Conant, E. F., & Sehgal, C. M. (2015). Observer Variability in BI-RADS Ultrasound Features and Its Influence on Computer-Aided Diagnosis of Breast Masses. *Advances in Breast Cancer Research*, *4*(01), 1–8. doi:10.4236/abcr.2015.41001

Sun, S., Austin, T., & Kalra, D. (2012). A data types profile suitable for use with ISO EN 13606. *Journal of Medical Systems*, *36*(6), 3621–3635. doi:10.1007/s10916-012-9837-z PMID:22399066

Taylor, L. K., Bentley, J., Hunt, J., Madden, R., McKeown, S., Brandt, P., & Baker, D. (2012). Enhanced reporting of deaths among Aboriginal and Torres Strait Islander peoples using linked administrative health datasets. *BMC Medical Research Methodology*, *12*(1), 91–91. doi:10.1186/1471-2288-12-91 PMID:22747900

Tourassi, G. D. (1999). Journey toward Computer-aided Diagnosis: Role of Image Texture Analysis 1. *Radiology*, *213*(2), 317–320. doi:10.1148/radiology.213.2.r99nv49317 PMID:10551208

Vairaktarakis, C., Tsiamis, V., Soursou, G., Lekkas, F., Nikolopoulou, M., Vasileiadou, E., & Alexiou, A. (2015). *A computer-aided diagnosis system for geriatrics assessment and frailty evaluation. In GeNeDis 2014* (pp. 69–77). Springer.

Walecki, P., Nowaczek, M., Porębski, G., & Obtułowicz, K. (2006a). Allergy Expert System (AES)-A Computer-Assisted Diagnosis. *Bio-Algorithms and Med-Systems*, *2*(4), 13–20.

Walecki, P, Nowaczek, M, Porębski, G, & Obtułowicz, K. (2006b). Allergy Expert System (AES)-A Computer-Assisted Diagnosis. *Bio-Algorithms and Med-Systems, 2*.

Wan, Q., Makeham, M., Zwar, A. N., & Petche, S. (2012). Qualitative evaluation of a diabetes electronic decision support tool: Views of users. *BMC Medical Informatics and Decision Making*, *12*(61). PMID:22759239

Warner, H., Haug, P., Bouhaddou, O., Lincoln, M., Sorenson, D., Williamson, J., & Fan, C. (1988). Iliad as an expert consultant to teach differential diagnosis. In *Proceedings of the 12th Symposium on Computer Applications in Medical Care (SCAMC)*. IEEE Computer Society Press.

Wilson, F. P., Shashaty, M., Testani, J., Aqeel, I., Borovskiy, Y., Ellenberg, S. S, . . . Lin, J. (2015). Automated, electronic alerts for acute kidney injury: A single-blind, parallel-group, randomised controlled trial. *Lancet*, (Feb), 25. PMID:25726515

Wu, F., & Wang, H. (2014). *A Cloud Platform for Clinical Information Exchange Based on Web Services.* Paper presented at the Applied Mechanics and Materials. doi:10.4028/www.scientific.net/AMM.556-562.6007

Zaal, R. J., Jansen, M., Duisenberg-van Essenberg, M., Tijssen, C. C., Roukema, J. A., & van den Bemt. (2013). Identification of drug-related problems by a clinical pharmacist in addition to computerized alerts. *International Journal of Clinical Pharmacology, Therapy and Toxicology*, *35*(5), 753–762. PMID:23715760

Zhang, M., Zhang, R., & Liu, C. S. (2014). *Research on Smart Healthcare Platform Construction Based on Cloud Computing*. Paper presented at the Advanced Materials Research, Solo, Indonesia. doi:10.4028/www.scientific.net/AMR.998-999.1219

Zhao, D., Qiao, K., & Raicu, I. (2015). Towards Cost-Effective and High-Performance Caching Middleware for Distributed Systems. *International Journal of Big Data Intelligence.*

Zheng, K., Padman, R., Johnson, M. P., & Diamond, H. S. (2005). Understanding technology adoption in clinical care: Clinician adoption behavior of a point-of-care reminder system. *International Journal of Medical Informatics*, *74*(7-8), 535–543. doi:10.1016/j.ijmedinf.2005.03.007 PMID:16043083

ADDITIONAL READING

Adeyemi, S., Demir, E., & Chaussalet, T. (2013). Towards an evidence-based decision making healthcare system management: Modelling patient pathways to improve clinical outcomes. *Decision Support Systems*, *55*(1), 117–125. doi:10.1016/j.dss.2012.12.039

Adlassnig, K.-P., & Horak, W. (1995). Development and retrospective evaluation of Hepaxpert-I: A routinely-used expert system for interpretive analysis of hepatitis A and B serologic findings. *Artificial Intelligence in Medicine*, *7*(1), 1–24. doi:10.1016/0933-3657(94)00023-L PMID:7795713

Aikins, J. S., Kunz, J. C., Shortliffe, E. H., & Fallat, R. J. (1983). PUFF: An expert system for interpretation of pulmonary function data. *Computers and Biomedical Research, an International Journal*, *16*(3), 199–208. doi:10.1016/0010-4809(83)90021-6 PMID:6347509

Bani Amer, M. (2010). An adaptive neurofuzzy technique for determination of blood acidity. *Computer Methods in Biomechanics and Biomedical Engineering*, *13*(6), 685–691. doi:10.1080/10255840903448033 PMID:20146128

Barnett, G. O., Cimino, J. J., Hupp, J. A., & Hoffer, E. P. (1987). DXplain: An evolving diagnostic decision-support system. *Journal of the American Medical Association*, *258*(1), 67–74. doi:10.1001/jama.1987.03400010071030 PMID:3295316

Chen, D.-R., Chang, R.-F., & Huang, Y.-L. (1999). Computer-aided diagnosis applied to US of solid breast nodules by using neural networks 1. *Radiology*, *213*(2), 407–412. doi:10.1148/radiology.213.2.r99nv13407 PMID:10551220

Coiera, E. (2002). Updates in Medicine, Health Informatics. *The Medical Journal of Australia*, *176*, 1–20.

Cramm, J. M., & Nieboer, A. P. (2014). Short and long term improvements in quality of chronic care delivery predict program sustainability. *Social Science & Medicine*, *101*, 148–154. doi:10.1016/j.socscimed.2013.11.035 PMID:24560235

Farshi, M. R., Jebreili, M., & Abdinia, B. (2015). Comparison of Manual and Electronic Methods of Nursing Record: A Nurse's Perspective. *International Journal of Pediatrics (2345-5047), 3*(1), 367.

Fatima, I., Fahim, M., Guan, D., Lee, Y.-K., & Lee, S. (2011). *Socially interactive CDSS for u-life care.* Paper presented at the Proceedings of the 5th International Conference on Ubiquitous Information Management and Communication, Seoul Korea.

French, D. D., Campbell, R. R., Sabharwal, S., Nelson, A. L., Palacios, P. A., & Gavin-Dreschnack, D. (2007). Health care costs for patients with chronic spinal cord injury in the veterans health administration. *The Journal of Spinal Cord Medicine*, *30*(5), 477. PMID:18092564

Gibert, K., García-Rudolph, A., Curcoll, L., Soler, D., Pla, L., & Tormos, J. M. (2009). Knowledge discovery about quality of life changes of spinal cord injury patients: Clustering based on rules by states. *Studies in Health Technology and Informatics*, *150*, 579–583. PMID:19745377

Gill, J. M., Mainous, A. G. III, Koopman, R. J., Player, M. S., Everett, C. J., Chen, Y. X., & Lieberman, M. I. et al. (2011). Impact of EHR-Based Clinical Decision Support on Adherence to Guidelines for Patients on NSAIDs: A Randomized Controlled Trial. *Annals of Family Medicine*, *9*(1), 22–30. doi:10.1370/afm.1172 PMID:21242557

Grace, A., Mahony, C., O'Donoghue, J., Heffernan, T., Molony, D., & Carroll, T. (2013). Evaluating the effectiveness of clinical decision support systems: The case of multimorbidity care. *Journal of Decision Systems*, *22*(2), 97–108. doi:10.1080/12460125.2013.780320

Guessoum, S., Laskri, M. T., Djellali, H., & Khadir, M. T. (2012). Combining Case and Rule Based Reasoning for the Diagnosis and Therapy of Chronic Obstructive Pulmonary Disease. [Article]. *International Journal of Hybrid Information Technology*, *5*(3), 145–159.

Heselmans, A., Van de Velde, S., Ramaekers, D., Vander Stichele, R., & Aertgeerts, B. (2013). Feasibility and impact of an evidence-based electronic decision support system for diabetes care in family medicine: Protocol for a cluster randomized controlled trial. *Implementation Science; IS*, (8): 83. PMID:23915250

Jeffery, R., Iserman, E., & Haynes, R. (2013). Can computerized clinical decision support systems improve diabetes management? A systematic review and meta-analysis. *Diabetic Medicine*, *30*(6), 739–745. doi:10.1111/dme.12087 PMID:23199102

Kalra, J., Kalra, N., & Baniak, N. (2013). Medical error, disclosure and patient safety: A global view of quality care. *Clinical Biochemistry*, *46*(13–14), 1161–1169. doi:10.1016/j.clinbiochem.2013.03.025 PMID:23578740

Lee, Y.-H., Hu, P. J.-H., Cheng, T.-H., Huang, T.-C., & Chuang, W.-Y. (2013). A preclustering-based ensemble learning technique for acute appendicitis diagnoses. *Artificial Intelligence in Medicine*, *58*(2), 115–124. doi:10.1016/j.artmed.2013.03.007 PMID:23623208

Lorch, J. A., & Pollak, V. E. (2014). Continuous Quality Improvement in Daily Clinical Practice: A Proof of Concept Study. *PLoS ONE*, *9*(5), 1–11. doi:10.1371/journal.pone.0097066 PMID:24844323

Main, C., Moxham, T., Wyatt, J. C., Kay, J., Anderson, R., & Stein, K. (2010). Computerised decision support systems in order communication for diagnostic, screening or monitoring test ordering: Systematic reviews of the effects and cost-effectiveness of systems. *Health Technology Assessment*, *14*(48), 1–227. doi:10.3310/hta14480 PMID:21034668

Musen, M. A., Middleton, B., & Greenes, R. A. (2014). *Clinical decision-support systems Biomedical Informatics* (pp. 643–674). Springer.

Pasricha, A., Deinstadt, R., Moher, D., Killoran, A., Rourke, S., & Kendall, C. (2013). Chronic Care Model Decision Support and Clinical Information Systems Interventions for People Living with HIV: A Systematic Review. *JGIM: Journal of General Internal Medicine*, *28*(1), 127–135. doi:10.1007/s11606-012-2145-y PMID:22790615

Raipure, G. S., & Gupta, S. (2013). Decision Support System In Medical Science Using OLAP & Data Mining. *International Journal Of Computer Science And Applications, 6*(2).

Sahota, N., Lloyd, R., Ramakrishna, A., Mackay, J. A., Prorok, J. C., Weise-Kelly, L., & Haynes, R. B. et al. (2011). Computerized clinical decision support systems for acute care management: A decision-maker-researcher partnership systematic review of effects on process of care and patient outcomes. *Implementation Science; IS*, *6*(6), 91. doi:10.1186/1748-5908-6-91 PMID:21824385

Singh Tomar, P. P., Singh, R., & Saxena, P. K. (2012). A Medical Multimedia based Clinical Decision Support System for Operational Chronic Lung Diseases Diagnosis and Training. *International Journal of Computers and Applications*, *50*, 1.

Tran, K., Morra, D., Lo, V., Quan, S. D., Abrams, H., & Wu, R. C. (2014). Medical Students and Personal Smartphones in the Clinical Environment: The Impact on Confidentiality of Personal Health Information and Professionalism. *Journal of Medical Internet Research*, *16*(5), e132. doi:10.2196/jmir.3138 PMID:24855046

Wachter, R. M. (2010). Why diagnostic errors don't get any respect—and what can be done about them. *Health Affairs*, *29*(9), 1605–1610. doi:10.1377/hlthaff.2009.0513 PMID:20820015

Yang, Z., Fong, S., Fiaidhi, J., & Mohammed, S. (2012). Real-Time Clinical Decision Support System with Data Stream Mining. *Journal of Biomedicine & Biotechnology*, *2012*, 1–8. PMID:21836813

KEY TERMS AND DEFINITIONS

Artificial Intelligence: The theory and development of computer systems able to perform tasks normally requiring human intelligence, such as visual perception, speech recognition, decision-making, and translation between languages.

Bayesian Approach to Statistics: Modelling of some uncertainties using parametric measures into a probabilistic model for prediction of some aspects that are unknown or unsure.

Computerised Physician Order Entry (CPOE): A process of electronic entry of medical practitioner instructions for the treatment of patients (particularly hospitalized patients) under his or her care.

Computer Tomography (CT): An imaging method that uses x-rays to create pictures of cross-sections of the body.

Clinical Decision Support System (CDSS): A health information technology solution to support physicians and other health professionals with clinical decision making process.

Data Mining: An analytic process designed to explore data in the search for consistent patterns and systematic relationship between variables, and then to validate the findings by applying detected patterns to new subsets of data. The goal of data mining is prediction.

Electronic Health Record (EHR): A systematic collection of personal information in electronic form.

Expert Systems: Part of a general category of computer applications known as artificial intelligence, whereby a computer system can emulate decision making abilities of humans. They are knowledge-based systems that require a knowledge engineer, an individual who studies how human experts make decisions and translates the rules into terms that a computer can understand.

Hospital Information Systems (HIS): An element of health informatics that deals with administrational needs of hospitals. HIS uses a network of computers to collect, process; retrieve patient care and administrative information from various departments for all hospital activities to satisfy the functional requirements of users. HIS has components such as laboratory, pharmacy, radiology, user management's configurations, medical archiving facilities, and digital health records, as well as security aspects.

Laboratory Information Systems (LIS): An element of health informatics that deals with the operational needs of laboratories. It has a software computer program that processes, stores and manages data from all stages of medical processes and tests. Some functions include digital pathology, document imaging, specimen tracking and security and clinical pathology.

Magnetic Resonance Imaging (MRI): A medical imaging technique that uses magnetic fields and radiofrequency waves to acquire very detailed images of the body.

Middleware: Is the software that connects software components or enterprise applications. It is a software layer that lies between Hospital Information System (HIS) and Laboratory Information System (LIS). It acts as consolidator and integrator and is custom-programmed to suit the needs of organization.

Neural Network: A system of programs or data structures with interconnected group of nodes, akin to the network of neurons in a brain. A neural network usually involves a large number of processors that stimulate behaviour of biological neural networks as in pattern recognition, language processing and problem solving.

Prescribing Decision Support Systems (PDSS): PDSS can assist by checking for drug-drug interactions, dosage errors, and if connected to an EMR, for other prescribing contraindications such as allergy.

APPENDIX

Table 2. Application of CDSS

System	Technology	Description
ACUTE CARE SYSTEMS		
HELP system (Kuperman et al., 1990; Kuperman et al., 1991). Acute Care Systems	Standard web browser, written in PERL invoked by apache web server linked with PostgreSQL database Decision support in hepatic surgery alerts, reminders, data interpretation and patient diagnostic, patient management suggestions, as well as clinical protocols.	Supports HIS including admission, discharge, and order entry, as well as decision support Limitation: Limited cases available.
POEMS: Post-operative expert medical system (Knies et al., 2012)	System embedded with hospital information systems	Post-operative care decision support
VIE-PNN: Vienna Expert system for Prenatal Nutrition of Neonates (Smailyte et al., 2012)	Rule based system	Parental nutrition planning for neonatal ICU combining nutrition planning with knowledge of experienced physicians.
NéoGanesh (Sun et al., 2012)	Closed loop based knowledge system	ICU ventilator management Interprets clinical data real time
SETH (Taylor et al., 2012)	Runs on microcomputer	Clinical toxicology advisor.
	Internal Medicine	
LABORATORY INFORMATION SYSTEMS		
GERMWATCHER(Patel et al., 2011) (Kahn et al., 1993)	Hospital integration with laboratory	Analysis of nosocomial infections
HEPAXPERT I, II (Adlassnig & Horak, 1991) and III (Chizzali-Bonfadin et al., 1997)	Hepaxpert I is Stand-alone no connection to external database. Hepaxpert II is a database and can interpret and provide database management. Can connect to LIS and HIS. Hepaxpert III is a knowledge based system contains 16 rules for HepA, 131 rules for Hep B, available on WWW and results can send via email.	Interprets serology tests of hepatitis A, B, C and D
Acid-base expert system (Harris et al., 2010)	Expert System. Causal reasoning	Interpretation of acid-base disorders
MICROBIOLOGY/PHARMACY (Morrell et al., 1993)		Monitors renal active antibiotic dosing
PEIRS: Pathology Expert Interpretative Reporting System (Edwards et al., 1993)	Rule based, went into routine use with approximately 200 rules and grew rapidly over four year period (1990-1994) to over 2000 rules.	Monitors adult drug poisoning. PEIRS interpreted about 80-100 reports a day with a diagnostic accuracy of about 95%.
PUFF: Pulmonary Consult System (Snow et al., 1988)	Pulmonary hierarchical rule based system. One of the earliest medical expert systems used. Many thousands of cases later, it is still in routine use.	Interprets pulmonary function tests
EDUCATIONAL SYSTEMS		
DXPLAIN (Barnett et al., 1987)	User interacts with system with various prompts. Dxplain takes list of conditions and provides possible diagnosis	Internal medicine expert system

Continued on following page

Table 2. Continued

System	Technology	Description
ILLIAD (Warner et al., 1988)	Expert system using simulated case studies.	Internal medicine expert system
AED: Allergy Expert System (Walecki, Nowaczek, Porębski, & Obtułowicz, 2006b)	PC shell programming environment	Expert system to diagnosis and treatment of allergy related conditions
'Five rights' clinical reasoning (Levett-Jones et al., 2010)	Computer software, interactive	Uses steps to assess critically ill patients
QUALITY ASSURANCE AND ADMINISTRATION		
Colorado medicaid utilization review system		Quality review of drug prescribing practices
Managed second surgical opinion system		Aetna Life and Casualty assessor system
MEDICAL IMAGING		
Computer imaging (Tourassi, 1999)	CAD, using neutral network to diagnose conditions	Diagnosis based on image texture i.e. text diagnosis of breast neoplasm
Computer Aided Detection (Liu, 2015; Lo et al., 2015; Sultan et al., 2015).	Neural network to diagnose mammograms	Diagnosis of breast nodules through mammograms. 95% accuracy is shown.
Performance of Cellavision DM96 (Horn et al., 2015)	Neural network to diagnose red cells	Diagnosis of Red blood cells.
Smits and Leyte (2014) Performance of Cellavision: white cells	Neural network to diagnose white cells	Diagnosis of white blood cells.