Clinical Decision Support System: Characteristics, Effectiveness and Challenges

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Abstract

From the first related documentation in 1950s, there are progressive increase of studies and researches about these systems to support clinicians and health professionals in decision-making. This paper shows a brief summary about Clinical decision support system (CDSS), focusing on definitions, characteristics, effectiveness and challenges. Besides the classification based on computer-science methodology, this study also provides certain positive outcomes of CDSS as well as current constraints following with solutions for the future's improvement.

1 Introduction

With the extremely large increase of medical information and knowledge (Faria et al., 2015), there could not be avoided from the limitation of clinicians in memory and decision (Norman, 1987). Therefore, since the early stage of computers, researchers have found the way to develop a machine which can assist physician's decision making (Shortliffe and Buchanan, 1975).

There are certain definitions for a clinical decision support system (CDSS) from the Haynes (2010)'s simple definition to the sufficient explanation of Hunt (1998) which is described how CDSS works. In this paper, the CDSS was defined as "information systems designed to improve clinical decision making" (Garg, 2005).

Tracing back to the first idea of CDSS, Nash (1954) pointed that some traditional methods such as books and cards could not contain the giant data of medicine. Therefore, he offered a solution for doctors who looked up the valid information, namely a "mechanical table". From that, there has been an increase of studies about this system, especially in health informatics (Faria et al., 2015).

However, the more IT use in health care does not mean the more its effectiveness (Faria et al., 2015).

In this paper, it is answered the following questions: (1) What are characteristics of CDSS? (2) Can CDSS improve the clinical outcome or successfully support clinicians in practice? (3) What are challenges when implementing CDSS and solutions for each issue?

This study is following with six sections; the first section introduces CDSS's definition, history, recent trend and impact. Second section refers methodology adopted to achieve the references. The third section is presents about characteristics and classifications of CDSS. Forth section clarifies effectiveness while fifth section explains the challenges and suggested solutions. Finally, conclusions are pointed in the last section.

2 Methodology

The paper provides a literature-based summary which is applied the manual search of specific libraries, such as Google Scholar, ScienceDirect, PubMed, Springer, Wiley, IEEE Xplore, Research Gate.

The search terms are CDSS, Clinical decision support system, type CDSS, AI in CDSS, health system, health information technology, knowledge-based CDSS, non-knowledge-based CDSS. Supplementary methods of finding studies by hand searching in the references lists of retrieved articles.

Our inclusion criteria were totally peer-reviewed journals evaluating CDSS's impact on healthcare, including positive and negative outcomes. These papers can be randomised and non-randomised controlled trials, literature reviews, and systematic reviews. Our exclusion criteria were non-English studies, and not peer-reviewed article journals.

3 Characteristics

The purpose of these systems is not to replace the human role, just support decision-makers by providing the relevant knowledge or recommendations (Miller, 1990). Three main reasons for that are (1) systems are not perfect and have errors, which leads to fail (Miller, 1990); (2) systems cannot balance between costs and benefits for each suggestion and for particular patients and situations (Shortliffe, 1987); (3) clinicians always have a more complete picture of specific patients than systems (Barnett et al., 1987).

There are numerous CDSS's classifications because each researcher defined them by their own purposes and criteria (Chung et al., 2015). For example, Fraccaro et al. (2015) classified into three main types depending on its operation: passive, semi-active and active systems. In contrast, according to CDSS's functions, Shortliffe (1987) distinguished by three types whereas Wright and Sittig (2008) categorized them into six types.

From the perspective of computer-science methodology, CDSS may be divided into two main groups with the following definitions.

(i) Knowledge-based system is a system having a knowledge database (Mylopoulos, 1996).

(ii) Non-knowledge-based system does not have a knowledge store but uses machine learning and other techniques to find the pattern in clinical data (Chung et al., 2015).

3.1 Knowledge-based system

In knowledge-based system, the patients' characteristics are matched to the medical knowledge base to deliver recommendations by software algorithms (Garg, 2005).

Clearly, in the study by Shortliffe and Buchanan (1975), they highlighted that many of knowledge-based systems generate the outputs by using the conditional probability rules ("if-then" formula), which helps to contain the huge medical information from textbooks and professionals. Furthermore, they pointed out six advantages of knowledge-based systems, including the use of general and judgmental knowledge, ease of modification, search, decision explanation, augmented instruction.

An example of this type of CDSS is DXplain which was used more than 500 hours at over 40 sites in United States, Canada, and Japan (Barnett et al., 1987). Also, Isabel from Isabel Healthcare was implemented worldwide from 2015 and supports thousands of diagnoses (Vardell and Moore, 2011). In addition, the ODCRARS system assisted clinicians in cardiac risk assessment (Farooq and Hussain, 2016).

3.2 Non-knowledge-based system

With the development of Artificial Intelligence (AI), professionals have been applied AI into CDSS to increase its performance (Fernandes et al., 2020). Many technique are used in these systems, such as machine learning (Farooq and Hussain, 2016), logistic regression (LR), classification and regression decision trees algorithms (CART), random forests classifier, deep artificial neural network (ANN) and support vector machines (SVM) (Fernandes et al., 2020).

These systems are relied on algorithm to identify medical patterns directly learned from clinical data instead of knowledge base, which can avoid from the dependence of knowledge (Farooq and Hussain, 2016).

One of these systems is proposed by Kim and Chung (2015) for tracking chronic disease patients by using life pattern and psychological state to report the critical situations. Besides, Georga et al. (2009) presented the system applied data mining to predict the glucose level in diabetic patients. Another example is the MLDPS which uses machine learning and feature selection techniques to triage cardiac chest patients.

4 Effectiveness

There are several studies providing the positive impacts of CDSSs in practitioner performance, risk decrease and patient outcome, which lead to cost saving.

4.1 Practitioner performance

The positive outcomes of CDSS in practitioner performance are confirmed by many symmetric reviews. For instance, in the review by Garg (2005), he found that 64% of 97 controlled trials improved the practitioner performance in diagnosis, preventive care, disease management, drug dosing, or drug prescribing. The same result is revealed in another symmetric review by Hunt (1998) when 66% controlled clinical trials showed that CDSS had benefits to physician performance

(43 out of 65 studies), especially preventive care systems with 74% reported positive findings. Similarly, Kawamoto et al. (2005) highlighted 68% CDSS had the impact on clinical practice, especially if the CDSS was designed with adequate features, the positive outcome could be reached to 94% of 32 cases.

According to specific areas, Pombo et al. (2014) reviewed 25 studies of CDSS related acute and chronic pain and concluded that 84% of them improved practitioner performance. With the greater sample of studies (45 studies), Njie et al. (2015) emphasized that CDSS had benefits in clinician practices for preventive care, clinical tests and treatments. A similar conclusion in the literature-review by Hunt (1998) showed that 14 studies out of 19 studies (74%) had benefits in preventive care reminder systems which remind physicians about blood pressure assessment, vaccinations, Papanicolaou tests, and cancer screening.

In particular, the evaluation result with real data of the system proposed by Dehghani Soufi et al. (2018) for distinguishing the triage level of patients is significant with 99.44% accuracy compared to 86.6% of the traditional method and 98.5% documentation completeness compared to 76.72% of the old method.

4.2 Risk decrease

Many studies agreed that CDSS can reduce risk by preventing the adverse events and detecting errors (Bates and Gawande, 2003, Kaushal et al., 2003) because 91% adverse drug events can be preventable based on the survey of six hospital (Balthasar et al., 2009).

There are 3 out of 7 trials in the study by (Kaushal et al., 2003) presented the remarkable improvements in antibiotic medical errors. An example of antibiotic risk decrease is highlighted in the study by Evans et al. (1998) with several measures, which totally gained benefits after applying CDSS, including allergy drug order, excess drug dosages, the mean of excessive drug dosage days and adverse events, especially the hospital expenditure, hospital stay time. Another symmetric review by Wolfstadt et al. (2008) demonstrated that half of the retrieved studies reporting the high decrease of adverse drug events.

Certain specific systems had been evaluated, following to the optimistic results. For examples, use of CDSS decreased antibiotic prescribing and macrolide prescriptions in children with 31.7% versus 39.9% without CDSS, 6.2% versus 9.5% without CDSS, respectively (Bourgeois et al., 2010). Relating to deep-vein thrombosis, Kucher et al. (2005) concluded that alert systems helped to reduce the risk by 41%, whereas 83% decrease in risk events (including mortality) in the study by Haut et al. (2012). Another system evaluation showed that CDSS detected 44% the harmful cases of 596 true-positive alerts without clinicians' recognition (Raschke et al., 1998).

4.3 Patient outcome

Evidences in patient outcome are listed in the review of Hunt (1998) with 6 of 14 studies finding benefits and Bright et al. (2012) with conclusion of that CDSS improved morbidity outcomes.

Particularly, the appropriate fraction of prescriptions improved by 13% in dose and by 24% in frequency as well as the stay days lightly decreased in the study by Chertow et al. (2001). A similar findings in the trial by Rosenfeld et al. (2000) are 68% of ICU mortality decrease (compared to 46% without CDSS), 33% hospital decrease (vs 30), 44% ICU incidence decrease (vs 50%), 34% ICU staying length (vs 30%) and 33% ICU costs (vs 36%). Another CDSS implementation's result is examined by Khan et al. (2010), in which, CDSS reduced the hospitalisation's rate, emergency room visits (25% reduction), which leads to cost savings (11% for hospitalisation and 27% for emergency visits).

5 Challenges and solutions

Despite effectiveness described above, they are still limited in use within clinical practice (Sutton et al., 2020)

5.1 Insufficient patient outcome

Although certain reviews evaluated the impact of CDSS on patient outcome, the effects are still insufficient and inconsistent (Garg, 2005, Hunt, 1998).

In the study by Garg (2005), the majority of 52 trials measured patient outcomes had not enough statistical power to identify the differences. Only 7 trials proved the improvement, but no study showed the positive findings in critical factors such as mortality.

Hunt (1998) highlighted in his symmetric review that not many studies measured the patient outcome, and just few of them reported benefits. There are inconsistent results between 7 trials related warfarin dosing systems. Also, just 20% CDSS in chest and abdominal pain diagnosis were effective.

The same conclusion happened in a cardiovascular disease systematic review by Njie et al. (2015) when insufficient amount of studies related patient outcome and findings for risk factor outcomes were inconsistent. Ali et al. (2016) observed that just week to modest positive results in diabetes care indicators.

The explanations for the inconsistent results are the complexity of the measure process and the lack of evaluation standard (Randolph, 1999). To solve this obstacle, it should be established a process or a principle for evaluating CDSS performance (Randolph, 1999, Miller, 2009). Meanwhile, researchers are encouraged to conduct more CDSS evaluation in clinical practice (Sim, 2001), especially focusing on major outcomes such as morbidity and mortality in the long term (Murphy, 2014).

5.2 Excessive intervention

While speed of response is very important for clinicians (Bates, 2003), one of the major problems of CDSS is difficult in accessing, interacting, and perform speed (Barnett et al., 1987, Shortliffe, 1987). Another factors that affects the speed are unexpected interruptions while incomplete process (Miller, 2009), excessive alerts and “false positive” warnings (Shortliffe, 1987).

To agree with the point, Kawamoto et al. (2005) identified that computer-process systems had greater benefits than manual-process systems and the system delivered advice at the point of care better performed than the delayed system. They also analysed that the rate of success for automatic interventions (75%) was significantly higher than human interventions (0%).

The root cause of the problems is the implementation of CDSS poorly integrated into workflow, which is proved by the low adoption level in RCTs (Ali et al., 2016). Therefore, CDSS should be fitted into clinicians’ daily practices by balancing between several resources and issues such as human and technologies (Ali et al., 2016, Sim, 2001) and delivering services in real time with minimum waiting time (Miller, 2009, Kilsdonk et al., 2017). Furthermore, CDSS should be simple to use with less intervention requirements (Miller, 2009, Kilsdonk et al., 2017, Bates, 2003) due to the limitation of clinician’s knowledge of such systems (Fraccaro et al., 2015). Giving training and education for physicians before CDSS implementation and having IT support in their workplace could increase in their acceptance (Kilsdonk et al., 2017).

The excessive “false-positive” alerts, which can make physicians skip the actual meaningful warnings (Shortliffe, 1987), can be overcame by reviewing the rules, logs and periodic maintenance to limit the events but highly important and relevant alerts (Horsky et al., 2012).

5.3 Imperfect knowledge base

The decision making process is relied to knowledge or data from medical text-books and expert knowledge to increase the quality of these recommendations (Barnett et al., 1987). However, while the advanced clinicians’ expectations on CDSS quality is high (Miller, 2009), there is no totally perfect, accurate and comprehensive knowledge base, either printed or computer-based, especially some diseases still have few data (Shortliffe and Buchanan, 1975), or just depend on the visual appearance (Barnett et al., 1987).

Ideally, CDSSs should automatic update their knowledge and data base by connecting to the latest articles (Sim, 2001). In the long-term, there is a need for authorized departments to coordinate together to buid a comprehensive medical knowledge (Miller, 2009).

5.4 Limitation of interpretation

The CDSS’s limitations on explanation, interpretations justification and poor quality interpretation are obstacles for clinicians’ system usage (Barnett et al., 1987).

Kawamoto et al. (2005) determined the factors’ success in CDSS by literature-review and stated that the systems recommending actions besides assessments had more benefits than the systems that just deliver only disease suggestions. Also, the system providing the explanation for their recommendations were more likely succeed than the system without their reasons.

This means CDSS should provide enough interpretations such as assessments, recommendations, explanations for their advice to ultilise their knowledge (Shortliffe, 1987). Moreover, vocabulary and knowledge presentation's standards could be useful for CDSS's interpretation (Sim, 2001).

5.5 Poor design

Horsky et al. (2012) presented that developing a well-used system was not simple, especially with CDSS, it was very complexity with trade-off variables, such as analysis, intervention requirements, accuracy, ease to use, waiting time, etc., which may have errors. These system's performance can be reduced by the lack of good design, implementation, maintenance, and even, the lack of technical guideline for developers.

In the study by Kawamoto et al. (2005), the systems that developing all four features (automatic fit into clinical workflow, recommendations came with assessments, deliver at point of care, and computer-based decision support) had more significant increase in clinical performance than the systems without any of four features (94% compared to 46% in 32 systems).

To meet users' satisfaction, there is a need for including physicians, health professionals and other stalk holders in the beginning stage to build the comprehensive design of these system (Sim, 2001, Kilsdonk et al., 2017), in either implementation stage and maintenance by collecting users' feedbacks, interviews, suggestion as well as to establish the technical guideline or standards for CDSS development (Horsky et al., 2012).

5.6 The constraint of interoperability

The systems that integrated with other systems are more probably succeed than stand-alone system (Kawamoto et al., 2005). The reasons for this problem are (1) the lack of standards about interoperability and data, which prevents CDSS from binding with other systems due to different terminology (Ahmadian et al., 2011); (2) the weak collaboration in institutions and hospitals departments, which limits the data routine and update in a workplace (Shortliffe, 1987).

To maximize the CDSS's impact, appropriate standardization of data (Ahmadian et al., 2011) and interoperability (Kim and Chung, 2015)as well as the acceptance for sharing data within institutions and hospitals are necessary (Shortliffe, 1987).

6 Conclusion

This literature-based paper gives a general summary of CDSS which has been increasingly discussed in recent decades. The classification of CDSS based on methodology divides the system into two types: knowledge-based system and non-knowledge-based system. The effectiveness of CDSS in clinical practices is pointed, including practitioner performance, risk decrease, and patient outcome. Also, there are several limitations that need to be addressed in the future, especially insufficient patient outcome, excessive intervention, imperfect knowledge base, limitation of interpretation, poor design, and constraint of interoperability.

Despite of the certain challenges we need to cope with, CDSS still has the bright future by improving the clinical performance. Most of studies related to CDSS just pointed the one side such as evaluation test, symmetric reviews, challenge review, solution proposal, etc. Therefore, this paper covers the broader summary to give the adequate information and contrast them by its outline of effectiveness and challenges. Also, solutions listed for each challenge is for the future's improvement of these system.

The limitation of this paper is that because of page number's limitation, it is hardly to put more charts or tables to summarise the content. The number of high-quality studies related to CDSS's effectiveness is insufficient, and these effective areas are restricted. Due to length of this paper and the lack of supportive studies, some challenges are not presented such as the limited areas of application.

References

L. Ahmadian, M. Van Engen-Verheul, F. Bakhshi-Raiez, N. Peek, R. Cornet & N. F. De Keizer 2011. The role of standardized data and terminological systems in computerized clinical decision support systems: literature review and survey. *Int J Med Inform,* 80**,** 81-93.

S. M. Ali, R. Giordano, S. Lakhani & D. M. Walker 2016. A review of randomized controlled trials of medical record powered clinical decision support system to improve quality of diabetes care. *Int J Med Inform,* 87**,** 91-100.

L. Hug Balthasar, J. Witkowski Daniel, M. Sox Colin, A. Keohane Carol, L. Seger Diane, Yoon Catherine, E. Matheny Michael & W. Bates David 2009. Occurrence of adverse, often preventable, events in community hospitals involving nephrotoxic drugs or those excreted by the kidney. *Kidney International,* 76**,** 1192.

G. Octo Barnett, James J. Cimino, Jon A. Hupp & Edward P. Hoffer 1987. DXplain: An Evolving Diagnostic Decision-Support System. *JAMA,* 258**,** 67-74.

David W ; Kuperman Bates, Gilad J ; Wang, Samuel ; Gandhi, Tejal ; Kittler, Anne ; Volk, Lynn ; Spurr, Cynthia ; Khorasani, Ramin ; Tanasijevic, Milenko ; Middleton, Blackford 2003. Ten Commandments for Effective Clinical Decision Support: Making the Practice of Evidence-based Medicine a Reality. *Journal of the American Medical Informatics Association,* 10(6)**,** 523–530.

David W. Bates & Atul A. Gawande 2003. Improving Safety with Information Technology. *The New England Journal of Medicine,* 348**,** 2526-2534.

Fabienne C. Bourgeois, Jeffrey Linder, Sarah A. Johnson, John Patrick T. Co, Julie Fiskio & Timothy G. Ferris 2010. Impact of a Computerized Template on Antibiotic Prescribing for Acute Respiratory Infections in Children and Adolescents. *Clinical Pediatrics,* 49**,** 976-983.

Tj Bright, A. Wong, R. Dhurjati, E. Bristow, L. Bastian, Rr Coeytaux, G. Samsa, V. Hasselblad, J. W. Williams, M. D. Musty, L. Wing, As Kendrick, Gd Sanders & D. Lobach 2012. Effect of Clinical Decision-Support Systems A Systematic Review. *Ann. Intern. Med.,* 157**,** 29-U77.

Glenn M. Chertow, Joshua Lee, Gilad J. Kuperman, Elisabeth Burdick, Jan Horsky, Diane L. Seger, Rita Lee, Aparna Mekala, Jean Song, Anthony L. Komaroff & David W. Bates 2001. Guided Medication Dosing for Inpatients With Renal Insufficiency. *JAMA,* 286**,** 2839-2844.

Kyungyong Chung, Raouf Boutaba & Salim Hariri 2015. Knowledge based decision support system. *Information Technology and Management,* 17**,** 1-3.

M. Dehghani Soufi, T. Samad-Soltani, S. Shams Vahdati & P. Rezaei-Hachesu 2018. Decision support system for triage management: A hybrid approach using rule-based reasoning and fuzzy logic. *Int J Med Inform,* 114**,** 35-44.

R. Scott Evans, Stanley L. Pestotnik, David C. Classen, Terry P. Clemmer, Lindell K. Weaver, James F. Orme, James F. Lloyd & John P. Burke 1998. A Computer-Assisted Management Program for Antibiotics and Other Antiinfective Agents. *The New England Journal of Medicine,* 338**,** 232-238.

B. M. Faria, J. Goncalves, L. P. Reis & A. Rocha 2015. A Clinical Support System Based on Quality of Life Estimation. *J Med Syst,* 39**,** 308.

Kamran Farooq & Amir Hussain 2016. A novel ontology and machine learning driven hybrid cardiovascular clinical prognosis as a complex adaptive clinical system. *Complex Adaptive Systems Modeling,* 4.

M. Fernandes, S. M. Vieira, F. Leite, C. Palos, S. Finkelstein & J. M. C. Sousa 2020. Clinical Decision Support Systems for Triage in the Emergency Department using Intelligent Systems: a Review. *Artif Intell Med,* 102**,** 101762.

Paolo Fraccaro, Dympna O′Sullivan, Panagiotis Plastiras, Hugh O′Sullivan, Chiara Dentone, Antonio Di Biagio & Peter Weller 2015. Behind the screens: Clinical decision support methodologies – A review. *Health Policy and Technology,* 4**,** 29-38.

Amit X ; Adhikari Garg, Neill K. J ; Mcdonald, Heather ; Rosas-Arellano, M. Patricia ; Devereaux, P. J ; Beyene, Joseph ; Sam, Justina ; Haynes, R. Brian 2005. Effects of Computerized Clinical Decision Support Systems on Practitioner Performance and Patient Outcomes: A Systematic Review. *JAMA,* 293(10)**,** 1223–1238.

E. Georga, V. Protopappas, A. Guillen, G. Fico, D. Ardigo, M. T. Arredondo, T. P. Exarchos, D. Polyzos & D. I. Fotiadis 2009. Data mining for blood glucose prediction and knowledge discovery in diabetic patients: the METABO diabetes modeling and management system. *Conference proceedings : ... Annual International Conference of the IEEE Engineering in Medicine and Biology Society. IEEE Engineering in Medicine and Biology Society. Conference***,** 5633-5636.

Elliott R. Haut, Brandyn D. Lau, Franca S. Kraenzlin, Deborah B. Hobson, Peggy S. Kraus, Howard T. Carolan, Adil H. Haider, Christine G. Holzmueller, David T. Efron, Peter J. Pronovost & Michael B. Streiff 2012. Improved Prophylaxis and Decreased Rates of Preventable Harm With the Use of a Mandatory Computerized Clinical Decision Support Tool for Prophylaxis for Venous Thromboembolism in Trauma. *Archives of Surgery,* 147**,** 901-907.

R.B. & Wilczynski Haynes, N.L. 2010. Effects of computerized clinical decision support systems on practitioner performance and patient outcomes: Methods of a decision-maker-researcher partnership systematic review. *Implementation Science,* 5**,** 12.

J. Horsky, G. D. Schiff, D. Johnston, L. Mercincavage, D. Bell & B. Middleton 2012. Interface design principles for usable decision support: a targeted review of best practices for clinical prescribing interventions. *J Biomed Inform,* 45**,** 1202-16.

Dereck L ; Haynes Hunt, R. Brian ; Hanna, Steven E ; Smith, Kristina 1998. Effects of Computer-Based Clinical Decision Support Systems on Physician

Performance and Patient Outcomes: A Systematic Review. *JAMA,* 280(15)**,** 1339–1346.

Rainu Kaushal, Kaveh G. Shojania & David W. Bates 2003. Effects of Computerized Physician Order Entry and Clinical Decision Support Systems on Medication Safety: A Systematic Review. *Archives of Internal Medicine,* 163**,** 1409-1416.

Kensaku Kawamoto, Caitlin A. Houlihan, E. Andrew Balas & David F. Lobach 2005. Improving clinical practice using clinical decision support systems: A systematic review of trials to identify features critical to success. *British Medical Journal,* 330**,** 765.

Shamima Khan, Charles D. Maclean & Benjamin Littenberg 2010. The Effect of the Vermont Diabetes Information System on Inpatient and Emergency Department Use: Results from a Randomized Trial. *Health Outcomes Research in Medicine,* 1**,** e61-e66.

E. Kilsdonk, L. W. Peute & M. W. Jaspers 2017. Factors influencing implementation success of guideline-based clinical decision support systems: A systematic review and gaps analysis. *Int J Med Inform,* 98**,** 56-64.

Sung-Ho Kim & Kyungyong Chung 2015. Emergency situation monitoring service using context motion tracking of chronic disease patients. *The Journal of Networks, Software Tools and Applications,* 18**,** 747-759.

Nils Kucher, Sophia Koo, Rene Quiroz, Joshua M. Cooper, Marilyn D. Paterno, Boris Soukonnikov & Samuel Z. Goldhaber 2005. Electronic Alerts to Prevent Venous Thromboembolism among Hospitalized Patients. *The New England Journal of Medicine,* 352**,** 969-977.

R. A. Miller 2009. Computer-assisted diagnostic decision support: history, challenges, and possible paths forward. *Adv Health Sci Educ Theory Pract,* 14 Suppl 1**,** 89-106.

Randolph A. Miller 1990. Why the Standard View is Standard: People, Not Machines, Understand Patients' Problems. *The Journal of Medicine and Philosophy: A Forum for Bioethics and Philosophy of Medicine,* 15**,** 581-591.

E.V. Murphy 2014. Clinical decision support: effectiveness in improving quality processes and clinical outcomes and factors that may influence success. *The Yale journal of biology and medicine,* 87(2)**,** 187–97.

John ; Chaudhri Mylopoulos, Vinay ; Plexousakis, Dimitris ; Shrufi, Adel ; Topologlou, Thodoros 1996. Building knowledge base management systems. *The VLDB Journal,* 5(4)**,** 238–263.

F. A. Nash 1954. Differential diagnosis, an apparatus to assist the logical faculties. *Lancet (London, England),* 266**,** 874-875.

G. J. Njie, K. K. Proia, A. B. Thota, R. K. C. Finnie, D. P. Hopkins, S. M. Banks, D. B. Callahan, N. P. Pronk, K. J. Rask, D. T. Lackland, T. E. Kottke & Force Community Preventive Services Task 2015. Clinical Decision Support Systems and Prevention: A Community Guide Cardiovascular Disease Systematic Review. *Am J Prev Med,* 49**,** 784-795.

L.A. Norman 1987. Computer Programs to Support Clinical Decision Making. *JAMA,* 258(17)**,** 2374–2375.

Nuno Pombo, Pedro Araújo & Joaquim Viana 2014. Knowledge discovery in clinical decision support systems for pain management: A systematic review. *Artificial Intelligence In Medicine,* 60**,** 1-11.

Adrienne G. ; Haynes Randolph, R. Brian ; Wyatt, Jeremy C. ; Cook, Deborah J. ; Guyatt, Gordon H. 1999. How to use an article evaluating the clinical impact of a computer-based clinical decision support system. *JAMA, The Journal of the American Medical Association,* 282(1)**,** 67.

Robert A. Raschke, Bea Gollihare, Thomas A. Wunderlich, James R. Guidry, Alan I. Leibowitz, John C. Peirce, Lee Lemelson, Mark A. Heisler & Cynthia Susong 1998. A Computer Alert System to Prevent Injury From Adverse Drug Events: Development and Evaluation in a Community Teaching Hospital. *JAMA,* 280**,** 1317-1320.

A. Brian Rosenfeld, J. Todd Dorman, J. Michael Breslow, J. Peter Pronovost, J. Mollie Jenckes, J. Nancy Zhang, J. Gerard Anderson & J. Haya Rubin 2000. Intensive care unit telemedicine: Alternate paradigm for providing continuous intensivist care. *Critical Care Medicine,* 28**,** 3925-3931.

E.H. Shortliffe 1987. Computer Programs to Support Clinical Decision Making. *JAMA,* 258(1)**,** 61–66.

Edward H. Shortliffe & Bruce G. Buchanan 1975. A model of inexact reasoning in medicine. *Mathematical Biosciences,* 23**,** 351-379.

Ida ; Gorman Sim, Paul ; Greenes, Robert a ; Haynes, R. Brian ; Kaplan, Bonnie ; Lehmann, Harold ; Tang, Paul C 2001. Clinical Decision Support Systems for the Practice of Evidence-based Medicine. *Journal of the American Medical Informatics Association,* 8(6)**,** 527–534.

R. T. Sutton, D. Pincock, D. C. Baumgart, D. C. Sadowski, R. N. Fedorak & K. I. Kroeker 2020. An overview of clinical decision support systems: benefits, risks, and strategies for success. *NPJ Digit Med,* 3**,** 17.

E. Vardell & M. Moore 2011. Isabel, a clinical decision support system. *Med Ref Serv Q,* 30**,** 158-66.

Jesse Wolfstadt, Jerry Gurwitz, Terry Field, Monica Lee, Sunila Kalkar, Wei Wu & Paula Rochon 2008. The Effect of Computerized Physician Order Entry with Clinical Decision Support on the Rates of Adverse Drug Events: A Systematic Review. *Journal of General Internal Medicine,* 23, 451-458.

A. Wright & D. F. Sittig 2008. A four-phase model of the evolution of clinical decision support architectures. *Int J Med Inform,* 77, 641-9.