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ABSTRACT

Clinical decision-making is complex and uncertain and is dependent on accurate and timely information that is typically managed through Information Technology (IT) solutions. One particular class of IT that is becoming increasingly prevalent in the medical community is Clinical Decision Support Systems (CDSS). This paper will discuss results of the use of a CDSS that was developed for assisting triage decision making of pediatric abdominal pain in the Emergency department. We show how different user groups (staff physicians and residents) use the CDSS input variables in their triage decision making models.

Keywords

CDSS, medical decision making

INTRODUCTION

The research described in this paper uses empirical results from a clinical trial of a specific clinical decision support system (CDSS) to show that there are differences in how clinician groups of the same specialty, but different level of expertise, use expert generated CDSS input variables in their decision making activities. Based on these results and other established literature on expert / novice decision making, some implications for CDSS design are presented.

Clinical decision-making is a complex process frequently complicated by a variety of uncertainties. It is dependent on accurate and timely information, yet clinicians rarely have all the information they need readily at their disposal. Further, evidence based medicine and decision making (EBM) proponents argue for clinical decision making to include the integration of clinical expertise with the best available clinical evidence generated by high quality research (Sackett, Rosenberg, Gray, Haynes and Richardson, 1996). EBM is gaining support and momentum, and has been called the new paradigm for medicine (Haynes, 2002).

The expectation of EBM is increasingly burdening the already time-stretched clinician. What has resulted is an environment where clinicians are dependent (or should be dependent) on massive amounts of information and knowledge to make decisions that are in the best interest of the patient. These information and knowledge sources come in the forms of electronic medical records, clinical practices guidelines, academic and practitioner journals among others. Increasingly, information technology (IT) solutions are being used as a knowledge transfer mechanism to ensure that clinicians have access to appropriate knowledge sources to support and facilitate medical decision making. One particular class of IT that the medical community is showing increased interest in is CDSS.

According to a well accepted definition, a CDSS is “any program designed to help health-care professionals make clinical decisions” (Musen, Shahar and Shortcliffe, 2001). Decision models used in CDSS, especially those providing patient management and diagnostic advice are normally based on expert knowledge, either discovered from past data or elicited from medical books or practice guidelines. The quality of any patient specific CDSS is at least partially reliant on the quality of the underlying decision model(s). These models have to reflect clinical expertise – and such an expertise is associated with expert decision makers. Reliance on the expert knowledge implies that clinicians using such systems have to provide input variables to the CDSS that can be correctly collected and interpreted only with an appropriate level of expertise. That is, only experienced clinicians will be able to provide CDSS input variables in a reliable and comprehensive manner, while inexperienced clinicians will be forced to gather information and make assessments for activities that they may lack the clinical acumen to do accurately. Such a situation may not only diminish the usefulness of the CDSS and validity of the advice generated by the system, but also might lead to the rejection of the system by novice clinicians as forcing them to evaluate a patient in a way that they are not accustomed to. This study seeks to explore how different classes of CDSS users take into consideration expert-generated CDSS inputs into their clinical decision making.

CDSS users, especially in a teaching hospital, can be categorized using the classical taxonomy of novice or expert decision makers. Differences between these two classes of decision makers have been widely documented in the decision making and medical literature. It has been stated that in complex domains such as medicine, it typically takes 10 years of training before one can be considered an expert (Prietula and Simon, 1989). Over time, experts develop a capability to systematize information and to form complex networks of knowledge that is stored in long term memory (Arocha, Wang and Patel, 2005; Prietula and Simon, 1989). Novices lack these knowledge networks and thus when are faced with new informational cues, they need to produce more hypotheses than experts (Kushniruk, 2001), and are unable to filter out irrelevant cues (Patel, Arocha and Kaufman, 1994; Patel and Groen, 1991), and resultantly take a longer time in making their decisions.

Customizing CDSS technology for users of different expertise has been proposed by several researchers (Kushniruk, 2001; Patel, Arocha, Diermeier, How and Mottur-Pilson, 2001), but to our knowledge the research presented in this paper is one of the first that provides empirical evidence gathered through a prospective evaluation of a CDSS. In classical CDSS designs, residents and staff physicians would be treated as a single user group and thus would be interacting and accessing the same interface and underlying decision models.

The purpose of this paper is to explore the use of a CDSS by two classes of users each of whom represents a different level of expertise. In this study, staff physicians are considered expert decision makers and residents are considered novice decision makers. Our study is based on the results of a clinical trial of a CDSS that was developed for helping with triage decisions of pediatric abdominal pain in the Emergency Department (ED) (Farion, Michalowski, Slowinski, Wilk and Rubin, 2004). On the basis of collected data, we evaluate differences between these two groups and draw more general conclusions for supporting clinical decision-making with technology. This study contributes to medical expertise decision making literature and addresses a call for a better understanding of real decision makers making ill structured decision in a naturalistic setting as mediated by technology (Kushniruk, 2001).

The research question we seek to answer is:

> what importance do residents and staff physicians place on expert generated CDSS decision model input variables in making their clinical decisions?

This paper is organized as follows. First, a brief description of the Mobile Emergency Triage (MET) CDSS is presented along with an explanation of the input variables that are used by the system. Next, descriptions of the sample and data collection procedures are provided, along with the analysis techniques used. This is followed by a discussion of the results and implications for CDSS design.

CDSS: MET-AP

The MET system was designed and developed to support ED physicians in making triage decisions about children with abdominal pain. The MET system consists of a server that interfaces with a hospital's electronic patient record system using the HL7 protocol (Quinn, 1999); and a client that resides on a PDA. The client facilitates the collection of clinical data during examination by physicians and also supplies the triage support function. The client is used directly at the point of care (anytime anywhere).

The MET client provides a series of interfaces to collect the 11 out of 13 input variables shown in table 1 that are used by the abdominal pain triaging algorithm (the remaining two variables, gender and age, are extracted automatically from the electronic patient record system). The collected data gets transferred to the server for persistent storage and usage in other Hospital Information Systems. The input variables and triage decision making model were developed using retrospective chart analysis and knowledge discovery techniques based on rough set theory (Pawlak, 1991; Slowinski, 1995). The decision model is represented as decision rules that are easy to comprehend and interpret by physicians, and therefore are well accepted in clinical practice (for example, the Ottawa Ankle Rule (Rae, 2001)).

Based on the values of the input variables the client uses the rule-based decision model to offer a suggested triage decision which can be one of the following three options:

Discharge: patient can be discharged home as their pain is caused by a non-serious problem

Consult: surgeon is called because acute appendicitis is suspected

Observation/Investigation: further in-hospital evaluation is required to determine the cause of the pain, as a serious cause is likely

Input Variable Name and Description	Possible Values
Age	0-6, >= 7 years
Localized guarding: localized muscle sustained contraction noted when palpating the abdomen	Absent, Present
Duration of pain	<=24 hrs, 1-7 and >7 days
Shifting of pain	Absent, Present
Site of maximal pain	Right lower quadrant (RLQ), lower abdomen, other
Type of maximal pain	continuous, other
Previous visits in the Emergency Room (ER) for abdominal pain during the last 48 hours (irrespective of site)	yes, no
Rebound tenderness: pain felt at site of maximal tenderness, produced by altering intra-abdominal pressure	absent, present
Gender	male, female
Temperature	<37, 37-39, >= 39 Cel
Site of maximal tenderness	RLQ, lower abdomen, other
Vomiting	yes, no
WBC (white blood cells)	<=4000, 4000-12000, >=12000

Table 1. Abdominal Pain Triaging Input Variables

Discretizations for numerical input variables were developed based on medical practice. All input variables that indicated an abdomen location (site of maximal pain, site of maximal tendernes) were collected by clinicians clicking on an abdomen pictogram on the mobile device. A screen capture showing the interface for 'site of pain' is provided in figure 1. The resulting input variable values (RLQ, lower abdomen, other) and corresponding areas on the abdomen were defined by surgeons and ED physicians. Figures 2 and 3 show MET screen captures for 'type of pain' and 'temperature' respectively.

Figure 1: MET-AP Screen Capture for Site of Pain

Figure 2. MET-AP Screen Capture for Type of Pain

Figure 3: MET-AP Screen Capture for Temperature

METHODS

This study of staff physician and resident decision making was part of a larger clinical trial that was designed to evaluate MET-AP clinical accuracy with physicians' triage predictions. Results of that study can be found in Farion, Michalowski, Rubin, Wilk, Correll and Gaboury (2006).

Sample and Data Collection

A convenience sample of 574 eligible children with acute AP, aged 1 to 16 years, were enrolled with consent between July 2, 2003 and February 29, 2004 at the Children's Hospital of Eastern Ontario (CHEO) ED. The treating ED resident or staff physician recorded their findings using MET-AP's electronic structured data screens. Residents and staff physicians were instructed to only record data for those input variables they felt were relevant to the patient's presentation; in particular, there was no requirement to obtain a white blood cell (WBC) count if the clinician felt this information would not influence his/her management decision. Finally, the clinician, blinded to the CDSS recommendation, entered his/her prediction of which triage category the patient was most likely to fit (i.e., discharge, consult surgery, or investigate/observe). This prediction was made at the time of initial assessment, prior to obtaining an abdominal ultrasound or surgical consult, if required. A clinician of the opposite level (i.e., resident, staff physician) completed an independent interrater assessment within one hour of the original assessment, where possible.

Forty staff physicians and one hundred and ten residents enrolled patients. This type of prospective evaluation of CDSS is rare, as all physicians in the live ED environment used the CDSS, not just those few associated with the development team. The ED clinicians had varying degrees of experience with handheld computers before entering the trial. All clinicians received in-depth orientation and training sessions and resultingly all could use the system easily before the trial began. Two hundred and twenty two of the patients were seen by both a resident and a staff physician.

Analysis

The analysis focused on determining which of the CDSS input variables were being used in the clinicians' triage decision. Since our independent variable (triage decision) is categorical, logistic regression was used to determine significant decision making input variables. The goal of logistic regression is similar to linear regression (or other model building techniques); that is "to find the best fitting, yet biologically reasonable model to describe the relationship between an outcome (dependent or response) variable and a set of independent (predictor or explanatory) variables (Hosmer and Lemeshow, 2000). While triage decision initially had three categories, we have collapsed the observation and discharge result into a single category. We have done this because we are primarily interested in the input variables that are used to arrive at a consult decision, as this represents the most important clinical decision of the three possibilities.

Full main effects models were run independently for patients who were seen by residents, and patients who were seen by staff physicians. We are interested in investigating models reflecting the actual behavior of the clinician (not necessarily the decision provided by the CDSS). Typical model building strategies suggest doing extensive univariable analyses for each potential independent variable to determine which variables should be added to the model (Hosmer and Lemeshow, 2000). However, epidemiologic researchers suggest including all clinically and intuitively relevant variables into the initial model regardless of their significance. Because the input variables collected through the CDSS were all derived from a retrospective chart analyses and were based on those that are most commonly used in the medical textbooks and further validated with staff physicians in a hospital, and all of them are widely recognized as being potentially important in triage decisions, they were all included. However, this does not include white blood cell count which has been removed from the study because of extensive missing data. We did study contingency tables for all independent input variables against the triage decision outcome variable to ensure that no 0 cells existed. This basic requirement was met successfully for both resident and staff physician data.

RESULTS

The logistic regression results for residents and staff physicians are shown in tables 2 and 3 respectively. The Nagelkerke's R^2 is .568 and .699 for the resident and staff physician model. This indicates that the staff physician model is a better fit than the resident model.

Of primary interest are the p-values for localized guarding and rebound tenderness for the residents' decision making model. These input variables are highly significant in making the consult decision and are relatively the most dependent on an accurate physical examination. This is not surprising given the educational focus of these input variables as being primary determinants of acute appendicitis. Research has shown that residents often have deficiencies in their physical examination skills, yet they place great clinical importance on the physical exam and desire to have greater educational attention put on those skills (Mangione, Burdick and Peitzman, 1995). We know from past empirical studies that clinicians with different levels of expertise exhibit differences in their ability to collect and interpret information from physical examinations (Pines, Uscher Pines, Hall, Hunter, Srinivasan and Ghaemmaghami, 2005; Yen, Karpas, Pinkerton and Gorelick, 2005). In comparing abdominal examinations of ER pediatric patients undertaken by residents and attending physicians, it was found that all parts of the examination had less than moderate agreement (Yen et al., 2005). Similar results were found in studying abdominal examinations of non-minors by residents and attending physicians (Pines et al., 2005). Additional studies of resident physicians have confirmed that they are deficient in performing physical examinations (Mangione et al., 1995). It has also been claimed that novice physicians have generally weaker information gathering and decision making skills (Johnson and Carpenter, 1986; Mangione et al., 1995).

Variable	β	std. Error	Wald Statistic	p-value	Exp(β)
Age	0.498	0.994	0.251	0.617	1.645
Gender	-0.939	0.528	3.159	0.076	0.391
Pain Duration			0.325	0.850	
Pain Duration (1)	-0.288	0.509	0.319	0.572	0.750
Pain Duration (2)	-5.306	63.417	0.007	0.933	0.005
Pain Site			0.153	0.926	
Pain Site(1)	0.177	0.906	0.038	0.845	1.194
Pain Site(2)	0.440	1.124	0.153	0.696	1.552
Pain Type	0.692	0.511	1.833	0.176	1.997
Vomiting	0.035	0.487	0.005	0.944	1.035
Previous Visit	-6.895	29.973	0.053	0.818	0.001
Temperature			1.327	0.515	
Temperature(1)	0.040	0.489	0.007	0.935	1.041
Temperature(2)	-1.911	1.695	1.271	0.260	0.148
Tenderness Site			9.971	0.007**	
Tenderness Site(1)	2.741	0.944	8.427	0.004**	15.506
Tenderness Site(2)	0.361	1.305	0.076	0.782	1.434
Localized Guarding	1.863	0.508	13.469	0.000***	6.445
Rebound Tenderness	1.503	0.526	8.164	0.004**	4.494
Pain Shifting	0.766	0.514	2.222	0.136	2.151
Constant	-5.142	1.130	20.686	0.000	0.006
Nagelkerke R^2	0.568				

*p < 0.05, **p < 0.01, ***p < 0.001

Table 2: Logistic Regression Analysis for Residents (n = 294 patients)

Variable	β	std. Error	Wald Statistic	p-value	Exp(β)
Age	1.315	1.306	1.013	0.314	3.724
Gender	-0.593	0.528	1.260	0.262	0.553
Pain Duration			0.614	0.736	
Pain Duration (1)	0.377	0.514	0.537	0.464	1.457
Pain Duration (2)	-5.517	20.305	0.074	0.786	0.004
Pain Site			6.862	0.032*	
Pain Site(1)	2.467	0.973	6.429	0.011*	11.790
Pain Site(2)	2.376	1.381	2.960	0.085	10.761
Pain Type	1.611	0.614	6.879	0.009**	5.009
Vomiting	1.299	0.601	4.674	0.031*	3.666
Previous Visit	2.691	1.417	3.604	0.058	14.745
Temperature			2.312	0.315	
Temperature(1)	0.619	0.534	1.343	0.246	1.856
Temperature(2)	2.421	2.097	1.333	0.248	11.254
Tenderness Site			3.194	0.203	
Tenderness Site(1)	1.082	0.953	1.288	0.256	2.950
Tenderness Site(2)	-1.256	1.384	0.823	0.364	0.285
Localized Guarding	1.539	0.556	7.662	0.006**	4.662
Rebound Tenderness	2.306	0.576	16.005	0.000***	10.030
Pain Shifting	0.968	0.560	2.985	0.084	2.633
Constant	-8.380	1.692	24.533	0.000	0.000
Nagelkerke R^2	0.699				

*p < 0.05, **p < 0.01, ***p < 0.001

Table 3. Logistic Regression Analysis for Staff Physicians (n = 385 patients)

Overall, staff physicians have a higher number of significant CDSS input variables in their triage decision model than do residents. Specifically, pain site, pain type, vomiting, localized guarding and rebound tenderness are all significant for staff physicians. Alternatively residents only had tenderness site, localized guarding and rebound tenderness as significant variables. In terms of the 'number of significant variables', these results are consistent with literature on strategic experts which states that experts have complex structures that assist in the recognition and interpretation of environmental signals and events (Lyles and Schwenk, 1992) and that these structures are more complex, contain more links among elements and hence contain more elements then the cognitive structures of less experienced strategists (Day and Lord, 1992; Lurigio and Carrol, 1985).

While each staff physician and resident have their own decision making model, all decision making participants' models will be anchored somewhat by the expert-generated CDSS triage decision making model. This anchoring exists because all participants were prompted for the same inputs, which may be different in content and quantity than if participants were offered no structured data collection tool. These results thus have to be interpreted with caution as the logistic regression may not reflect the complete decision making models of the residents and staff physicians (which is reflected in the reported R^2).

SUMMARY AND CONCLUSIONS

In evaluating the use of a CDSS for abdominal pain ED triage, we found that staff physicians used more more of the CDSS input variables in their triage decision than did residents. The importance of the input variables that required physical examination was underlined by their presence in both staff physicians' and residents' decision making models even though past research suggests that residents have trouble accurately eliciting variables dependent on physical examination.

In order to take into account differences in clinical experience and to ensure appropriate support is available to these different user groups, we propose that the CDSS designers should (a) differentiate between information values provided by the data coming from expert and novice assessments, and (b) implement logical variable thresholds that warn users when a single variable or a combination of variables is out of the expected range.

To design and implement aids that consider information value of the inputs, the input variables used in CDSS models must be categorized. Required variables could be logically categorized based on how difficult they are to elicit; to what extent they are reliant on tacit, explicit, and declarative knowledge; and subsequently be possibly labeled as "low confidence" and "high confidence" variables. While this is a broad categorization, it reflects the ability of different physician user groups to accurately elicit different values of the attributes. According to the proposed categorization, a typical novice physician would have elicitation difficulty with "low confidence" attributes. Therefore, the user interface for the "low confidence" attributes should provide extensive explanations and guidelines to assist the process of collection. Further, provision for recording imprecise or uncertain information (e.g., selecting several values instead of a single one, entering some "confidence" factor associated with a value, or having a discrete option for 'uncertain') should be provided

In clinical decision making often values of selected attributes form a certain pattern that is indicative of an underlying health condition. For example, as stated earlier, for pediatric abdominal pain, certain pain location in concert with presence of guarding are indicative of possible acute appendicitis. It is possible to use information about such patterns to develop context sensitive thresholds for values of individual attributes and their combinations. If values entered by a physician would significantly deviate from these logical thresholds, a CDSS would issue specific warning alerting the physician to this situation. While this will provide additional support for novice physicians, it will also help minimize the potential error between user and technology which has recently been identified as an important source of clinical error (Kohn, Corrigan and Donaldson, 2000).

Many decision models implemented into CDSS encapsulate knowledge that relies on evaluating input variables that require experience and significant clinical acumen. This creates uncertainty about the quality of the recommendations produced by the CDSS. It is clear that customized decision support, taking into account on level of clinical expertise of a physician of given specialty, is required to ensure that inputs into CDSS are accurate. Such expanded support is as important for the acceptance of a CDSS by physicians as the quality of the underlying decision model and user interface.

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REFERENCES

1. Arocha, J.F., Wang, D. and Patel, V. (2005) Identifying reasoning strategies in medical decision making: A methodological guide, Journal of Biomedical Informatics, 38, 2, 154-171.
2. Day, D.V. and Lord, A.G. (1992) Expertise and Problem Categorization: The Role of Expert Processing in Organizational Sense-Making, Journal of Management Studies, 29, 1, 35-47.
3. Farion, K.J., Michalowski, W., Rubin, S., Wilk, S., Correll, R. and Gaboury, I. (2006) Prospective evaluation of MET-AP clinical decision support system for pediatric ED triage of acute abdominal pain, MET Working Paper.
4. Farion, K.J., Michalowski, W., Slowinski, R., Wilk, S. and Rubin, S. (2004) Rough set methodology in clinical practice: Controlled hospital trial of the MET system, In S. Tsumoto, R. Slowinski, J. Komorowski & J. Grzymala-Busse (Eds.), Rough sets and current trends in computing. Heidelberg: Springer Verlag, 805-814.
5. Haynes R.B. (2002) What kind of evidence is it that Evidence-Based Medicine advocates want health care providers and consumers to pay attention to? BMC Health Services Research, 6, 2, 1-7.
6. Hosmer, D.W. and Lemeshow, S. (2000) Applied Logistic Regression (2nd ed.) New York, NY: Wiley Interscience.
7. Johnson, J.E. and Carpenter, J.L. (1986) Medical house staff performance in physical examination, Archives of Internal Medicine, 146, 5, 937-941.
8. Kohn, L.T., Corrigan, J.M. and Donaldson, M.S. (2000) To err is human: building a safer health system, Institute of Medicine. National Academy Press: Washington, DC.
9. Kushniruk, A.W. (2001) Analysis of complex decision-making processes in health care: Cognitive approaches to health informatics, Journal of Biomedical Informatics, 34, 5, 365-376.
10. Lurigio, A.J. and Carrol, J.S. (1985) Probation Officers' Schemata of Offenders: Content, Development and Impact of Treatment Decisions, Journal of Personality and Social Psychology, 48, 5, 1112-1126.
11. Lyles, M.A. and Schwenk, C.R. (1992) Top Management, Strategy and Organizational Knowledge Structures, Journal of Management Studies, 29, 2, 155-174.
12. Mangione, M., Burdick, W.P. and Peitzman, S.J. (1995) Physical diagnosis skills of physicians in training: a focused assessment, Academic Emergency Medicine, 2, 622-629.
13. Musen, M.A., Shahar, Y. and Shortliffe, E.H. (2001) Clinical decision support systems, In E. H. Shortliffe, L. E. Perreault, G. Wiederhold, and L. M. Fagan (Eds.), Medical informatics. Computer applications in health care and biomedicine (2 ed.) New York, NY: Springer, 573-609.
14. Patel, V., Arocha, J.F., Diermeier, M., How, V. and Mottur-Pilson, C. (2001) Cognitive psychological studies of representation and use of clinical practice guidelines, International Journal of Medical Informatics, 63, 3, 147-167.
15. Patel, V.L., Arocha, J.F. and Kaufman, D.R. (1994) Diagnostic reasoning and medical expertise, Psychology of Learning Motivaion, 31, 187-252.
16. Patel, V.L. and Groen, G.J. (1991) The general and specific nature of medical expertise, In: Ericsson, A. and Smith, J. editors. Toward a general theory of expertise: prospects and limits. Cambridge Univ. Press, 93-125.
17. Pawlak, Z. (1991) Rough sets: Theoretical aspects of reasoning about data. Norwell, MA: Kluwer Academic Publishers.
18. Pines, J., Uscher Pines, L. Hall, A., Hunter, J., Srinivasan, R. and Ghaemmaghami, C. (2005) The interrater variation of ED abdominal examination findings in patients with acute abdominal pain, American Journal of Emergency Medicine. 23, 483-487.
19. Prietula, M.J. and Simon, H. (1989) The Experts in Your Midst, Harvard Business Review, 67, 1, 120-124.
20. Quinn, J. (1999) An HL7 (health level seven) overview, Journal of American Health Information Management Association, 70, 7, 32-34.
21. Rae, F. (2001) The Ottawa ankle rule, Journal of Emergency Medicine, 18, 147.
22. Sackett, D.L., Rosenberg, W.M., Gray, J.A., Haynes, R.B. and Richardson, W.S. (1996) Evidence based medicine: what it is and what it isn't, British Medical Journal, 312, 71-72.
23. Slowinski, R. (1995) Rough sets approach to decision analysis, AI Expert Magazine, 10, 8-25.
24. Yen, K., Karpas, A., Pinkerton, J.J. and Gorelick, M.H. (2005) Interexaminer reliability in physical examination of pediatric patients with abdominal pain, *Archives of Pediatrics & Adolescent Medicine*, *159*, 373-376.