Suggested Criteria for Successful Deployment of a Clinical Decision Support System (CDSS)

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***Abstract*—Three criteria are suggested to help design a Clinical Decision Support System (CDSS) that would have a better chance of being successfully deployed in a clinical environment. These criteria have been successfully applied to a CDSS designed to estimate outcomes for neonatal intensive care unit (NICU) patients. The CDSS was deployed in a pilot study at the Children's Hospital of Eastern Ontario (CHEO)'s NICU. The results of the study showed that the accuracy was deemed acceptable by the physicians and the CDSS would meet their expectations when ready for deployment in a clinical environment.**

Keywords-clinical decision support system, successful deployment, neonatal intensive care, estimating outcomes.

I. INTRODUCTION

Clinical decision support systems (CDSSs) have been used for several decades and have the potential to significantly improve patient care and patient safety [1]. Despite this potential, their successful deployment has been limited and in some cases has resulted in conflict between physicians and hospital administrators [2]. When developing a new CDSS, several factors need to be considered to increase the likelihood that it will be integrated into health care delivery. These factors need to be applied at all stages of the development life cycle of the CDSS.

II. METHOD

A literature survey was conducted to determine the most important factors affecting the successful deployment of a CDSS. We discuss how these factors were applied to the development of a CDSS in the neonatal intensive care unit (NICU) at the Children's Hospital of Eastern Ontario (CHEO). This particular CDSS is intended to estimate a number of important clinical outcomes such as mortality, and predict resource utilisation such as expected duration of concentrated nursing care and duration of artificial ventilation. This development is described as a case study in the latter part of the article.

The criteria for a successful deployment of a CDSS can be divided into three main areas: (i) The data entry and the decision algorithms; (ii) the human-computer interaction, including the data acquisition, and the manner in which information is requested from the system; (iii) the output of the CDSS, including the format and type of information supplied.

A. Suggested criteria for successful deployment of a CDSS

(i) Input to the CDSS

The data and information entry into the CDSS is one of the leading causes of failed CDSSs [2, 3]. It is important that a system require the least amount of physician time and be able to update itself [4].

Some systems require users to enter patient data manually, which is very time consuming and disruptive to the delivery of patient care. Manual data entry can be minimized by integrating the CDSS with the hospital information system and electronic health records. A successful CDSS will be able to extract data with limited user interaction. Minimizing the time physicians spend entering data manually will lead to greater satisfaction with the system they are using and will help to ensure time is not being taken from the provision of patient care. Alternatively, if manual data entry is required, system implementation will be more successful if physicians are not expected to input this data. [5].

Another major issue is keeping the CDSS decision algorithm up to date. Since patient management changes from time to time, the CDSS can easily become obsolete. An issue that has been encountered in the past is that CDSSs are often created with soft funding. When the funding runs out, keeping the system up to date is a major challenge, so it is critical that systems be designed to have automated updating features. One way to do this is to have the CDSS retrain itself periodically and automatically [5, 6].

(ii) Human-Computer Interaction

The human-computer interaction is a critical component of a successful CDSS; access to the system should be easy while being secure. Clinicians are busy and have many diverse tasks to perform. According to Bates et. al, speed is of utmost

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importance for physicians, therefore, the decision support system should be designed to use the least amount of physician time possible; this includes time to logon to the system and time to acquire the information desired [5]. It is known that the time a CDSS adds to a patient consultation affects a physician's intention to use it. In a study of an Internet health application which aimed to help physicians determine if a patient requires a referral to a secondary care center, 70 % of doctors intended to use the system if it lengthened patient consultations by 2 minutes compared to only 23 % if the time added was 5 minutes [7].

Moreover, it is more convenient for physicians if the information can be obtained from a mobile CDSS, or one with many terminals, rather than from a single terminal that may be located far away [5]. Another important aspect of the human-computer interaction is the user-interface. The CDSS must be user-friendly, intuitive and provide easy access to information. It has been shown that a CDSS interface works best using a single screen format [4].

(iii) Output

A CDSS should be of clinical value to physicians, improve the quality of care and decrease costs of health care delivery. The CDSS must fit into the physicians' workflow and provide them with useful information. The system output format and type are dependent on what physicians need. Each clinician has different work habits and thus may have different requirements for this function. This makes the development of an effective CDSS more complicated, but this is important for a successful deployment. The manner in which the information is provided should be simple and effective [4], [5].

To achieve the goal of deployment with physicians using the system as part of their workflow, designers of CDSSs must work closely with the users at every step. Without this close partnership, it is more likely that a new system will not be used by physicians. Usability testing is also essential at every critical stage of development. Desirable attributes of CDSSs include smart information and smart alerts. When it comes to clinical decision alerts, there needs to be a balance between too many and too few. Without a sufficient number of alerts, it may be difficult to achieve the clinical and economic benefit of having the CDSS. However, too many alerts cause interruptions to physicians, which is undesirable especially if the alerts have a low specificity (high rate of false alarms). Some doctors prefer more alerts while others only desire to be notified for the most critical ones. This again emphasizes the need for close work with users during development [7].

Many of the failures of early CDSSs were due to the fact that the user had to filter the information and discard erroneous or useless information. This required a lot of user time and the user had to actively interact with the system rather than just be a passive recipient of the output [5], [7]. It is important that the CDSS be able to anticipate the need for information and deliver it in real time without clinicians needing to explicitly ask for it [7].

III. A CASE STUDY: A CDSS FOR NEONATAL INTENSIVE CARE

Premature births are defined as those occurring at less than 37 weeks of gestation. These newborn infants frequently have serious health problems and make up 75% of the population in neonatal intensive care units [8]. The incidence of premature births has increased in the past 20 years, reaching 7.7% in 2003 [9]. This is largely attributed to the rise of in-vitro fertilization which often results in multiple births, obstetrical interventions, higher registration of extremely early-gestation births, ultra-sound based estimates of gestational age, and the sophistication of technology in general. However, the incidence of morbidity in these survivors has not been decreasing, and a trend towards increasingly aggressive intensive care is cited as the reason for the increased number of survivors.

Our research group has developed a CDSS that estimates mortality, common complications such as bronchopulmonary Dysplasia (BPD) which is a chronic lung disorder; severe Intraventricular Hemorrhage (IVH, grade III or IV, that is bleeding in the brain associated with long-term disability; Necrotizing Enterocolitis (NEC), which is a serious intestinal illness; and resource utilisation outcomes such as length of stay and duration of artificial ventilation. The project was conducted with CHEO neonatologists, followed by a pilot test in the NICU [10], [11].

We are developing a Clinical Data Repository (CDR) that automatically collects data from NICU patients in real time and stores the data in a manner that can be easily retrieved for analysis; the data consists of vital signs from bedside monitors, ventilators, pulse oximeters, and laboratory results [12], [13]. The next step will be to train our CDSS to estimate outcomes using real time data. This will allow warnings and alerts to be generated for situations that need attention from physicians and caregivers.

Our CDSS is a feedforward backpropagation artificial neural network with the weight-elimination algorithm, and hyperbolic tangent transfer function; it has one hidden layer with an optimal number of nodes. ANNs have the potential to model complex interactions between variables and the advantage over conventional statistics is that they can be trained to predict outcomes on any database, with multiple input parameters and possible outcomes [14]. They can estimate outcomes for a single patient, whereas statistical tools typically estimate outcomes for a group of patients. First designed in 1993 using Matlab's Neural Ware tool, we have programmed many features into our ANN; for example, when one of the outcomes has a low prevalence (less than 15 % of the total population being studied), we resample from this population randomly, using one third of the database, until we reach an artificial prevalence of 20% to train the ANN [15]. We test the ANN with the true a priori distribution from another third of patient cases unseen previously. This optimizes the sensitivity (true positive cases such as predicting death) and decreases the specificity slightly (estimation of patients who survive). The third dataset is created by sampling ten times from the unseen cases. We also calculate the weights at the

input nodes of the ANN at optimal performance in order to identify variables which have the most impact on estimating the particular outcome of interest. The entire process of finding the optimum performance and best ANN structure (number of hidden nodes) has been automated; our computers automatically adjust nine parameters that maximise the correct classification for the various outcomes of interest [16].

The database used in this work was collected by the Canadian Neonatal Network (CNN), a group of multi-disciplinary Canadian researchers focusing on neonatal and perinatal care. Data collected by the CNN between January 1996 and October 1997 contains information from 17 NICUs, which represents 75% of all tertiary-level beds in Canada [17]. The database contains 20,488 admissions during the 22 month period, for which data was collected on day 1 (admission), day 3, 14 and 28 (or discharge). Although not recently collected, the data has been revalidated in recent publications [18].

IV. RESULTS

The neonatal CDSS system under development by our research group meets the requirements outlined by the three criteria for a successful CDSS. The first condition states that data input should require the least amount of physician time possible and that the system should be self updating to ensure the decision algorithm does not become out of date. The next version of our neonatal CDSS will use data automatically collected from patient monitors and ventilators, and automatically access laboratory and imaging tests; this will significantly decrease the time to input data into the CDSS. The majority of the data will be collected automatically in real time without manual input; however some manual input will still be required such as patient name, bed location, patient weight, gestational age, and Apgar 5 results. This data can be entered by the nurses or ward clerks. Additionally, we will ensure that the CDSS does not become obsolete by using an ANN that is able to self-train with new data being acquired.

The second condition regarding human-computer interaction requires that the user-interface be simple and provide quick access to data. Our CDSS interface was designed to be simple, and easy to use, with minimal training. The CDSS is easy to navigate and users are able to get important information in a timely manner.

For the third condition, regarding output format, we are working closely with the physicians to determine the best way to present the information they require. One improvement we made was the presentation of a risk level (low, medium, or high) of the outcome of interest, rather than presenting physicians with a percentage number, as was the case with our first model.

The first prototype of the neonatal CDSS was tested on 60 patient cases at the CHEO NICU that had a mortality rate of 18.33%. The CDSS presented results as high, moderate, and low risk categories as requested by the neonatologists. Table 1 shows the results of the CDSS's ability to predict. Note that this system used admission data collected within 12 hours after the birth of the infant (CNN database) and was not yet connected to real time data collection which is currently under development. We expect these initial results to be improved with the acquisition of data in real time.

TABLE 1. NEONATAL CDSS MORTALITY PREDICTION RESULTS

Case outcome	Number/ % of cases	Estimated CDSS Risk Category No. cases/ % of outcome		
		High	Moderate	Low
Mortality	11/ 18.3%	2/ 18%	5/ 46%	4/ 36%
Survival	49/ 81.7%	1/ 2%	5/ 10%	43/ 88%

From Table 1, it can be seen that the majority of mortalities were classified by our CDSS as moderate risk (46%), and 63 % of the true mortality cases were labeled either as high or moderate risk. The vast majority of survivors were classified as low risk (88%).

The pilot study also included a short usability test with the neonatologists who used the system. The results showed that the system was easy to use, provided information in a timely manner, was thought to be useful. There was a high interest in the further development and deployment of the system among the participating neonatologists [10], [11].

V. CONCLUSION

In this work, we suggested criteria to enhance the probability that a CDSS will be deployed and used by health care personnel. In applying these criteria to the design of a CDSS for NICU patients, we conclude that they proved to be useful as our physician partners are very interested in the development and potential deployment of the system at the CHEO NICU in Ottawa and plan to use it when it is ready for a clinical environment. Quoting our physician partner at CHEO: "This work is so important and is the way that all of medicine (adult and pediatric) is heading." – Dr. Erika Bariciak, Neonatologist.

In our future work we will continue to add features to our CDSS that will help with the integration of this tool into the real clinical environment according to the three criteria for successful deployment. Work will be done to ensure that the CDSS will train itself periodically, especially when several new patient cases are added to the database. We will also be focusing on automating as much of the data collection, retrieval and analysis as possible.

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