One Size Doesn't Fit All: The Efficiency of Graphical, Numerical and Textual Clinical Decision Support for Nurses

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Abstract— Clinical Decision Support (CDS) systems have the potential of significantly improving the quality and efficiency of patient care, but they need to present information in a way that is easily understandable by health care personnell. In the clinical setting, nurses are often tasked with the care of a large number of patients, and in specific scenarios are in charge of independently making care decisions to improve patient comfort and for symptom relief care. We developed a CDS prototype embedded in a nursing handoff management tool, which provides suggestions to adjust a plan of care based on a patient's profile. We show how presenting patient data and evidence in different forms (textual, tabular, graphical) has an impact on the efficiency of nurse decision making, and how a nurse's graphical literacy influences this process.

Index Terms—Electronic Health Records, Clinical Decision Support, User Studies, User-centered Design

INTRODUCTION

In the context of patient care, Clinical Decision Support (CDS) systems have the objective of improving the quality and efficiency of healthcare professionals' decision-making. As Electronic Health Records (EHR) are expected to be adopted for all U.S. patients by 2015[1], a potential treasure trove of diagnostic, treatment and outcome information is becoming available to build CDS tools for evidence-based care. Moreover, CDS can be offered directly as part of an EHR: a clinician accessing a patient's data would obtain contextualized decision support to assist in delivery of reliable, safe and effective care.

Decision support systems offer information based on the patient to whom the care is provided, but the way this information is presented typically does not depend on any characteristic of the clinician using the system. Information is presented without variations to users who may have different learning or decision-making styles. Customization is absent, limited or too time consuming for a tool that is typically used for short periods at the point of care [2][3]. CDS could be tailored both to the patient and the clinician to truly fit expectations, but it is unknown if such tailoring would improve aspects of decision-making [4][5]. For instance, some clinicians may prefer a narrative description of a patient's status, history and progression, while others may be more comfortable with graphical or numerical display of the same information. We suggest that this preference is not simply a matter of taste, and it can have a real impact on a clinician decision-making efficiency.

In this paper, we present our experience in designing and testing a CDS tool to support nurse decision making. Specifically, we show how different designs and amounts of CDS-provided information have an impact on nurses' decision-making efficiency, and how the efficiency of a design is influenced by a nurse's learning profile.

1 BACKGROUND

Our work has been motivated by the need to assist nurses to improve end-of-life patient care. Dying patients often have moderate to severe pain levels that could be eliminated or reduced to a mild pain level if effective treatments are used consistently[6]–[8].

For these patients, pain and symptom relief care is most often administered by nurses on behalf of the entire healthcare team. An effective CDS tool should point at problems in the current treatment decisions, and guide the nurse toward appropriate changes to the plan of care. This knowledge needs to be delivered in a way that nurses can quickly and accurately interpret and act upon it, in the routine workflow of their already temporally and cognitively demanding work.

Our CDS tool prototype has been embedded within an existing electronic plan of care (POC) system called HANDS (Hands-On Automated Nursing Documentation System). HANDS is an electronic tool that nurses use to track patient care and clinical progress throughout a hospitalization. A hospitalization episode includes all plans of care that nurses document at every formal handoff (admission, shift-change update, or discharge). HANDS uses standardized nomenclatures to describe diagnoses, outcomes and interventions[9]–[11], and has been tested extensively with nurses as part of real-world healthcare delivery for over two years in four hospitals on nine units[12].

Our prototype software for laboratory testing of HANDS allows us to create interactive plans of care for multiple virtual patients. Users can modify the POC (with or without CDS guidance) as they would do in a real hospital setting. Virtual patient scenarios are scripted to react to changes in the POC by improving or worsening of some of the patient outcomes. For instance, a patient with untreated acute pain would have a worse pain level outcome on the next shift, whereas the pain level would improve if some key treatments were put in place.

The key treatments depend on the virtual patient scenario and are designed to match real world intervention outcomes obtained through the analyses of thousands of patients' records in electronic heath records, previous data gathered from the HANDS database, and known best practices from the literature[7][13].

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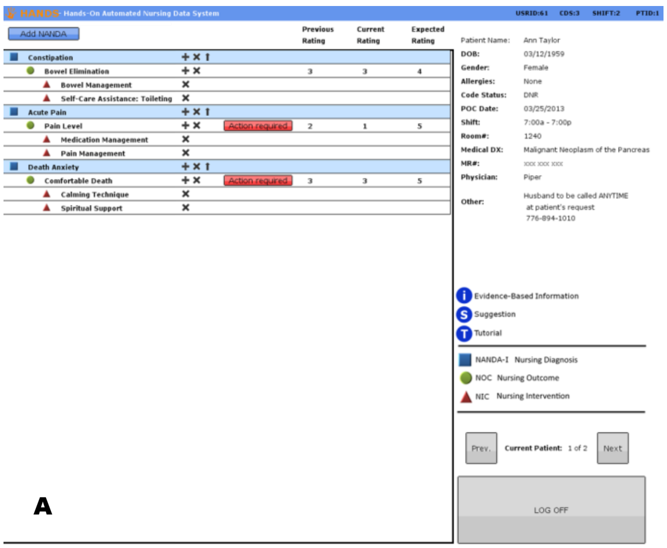

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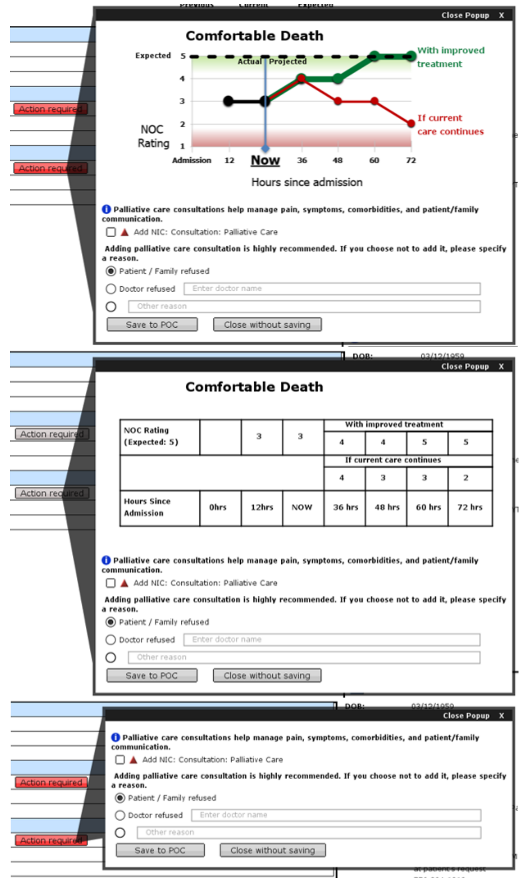

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D

Prototype variant	CDS text & actions	Outcome Trend
HANDS	-	-
Text	Yes	-
Table	Yes	Yes - numerical
Graph	Yes	Yes - graphical

E

Fig 1. **A)** An overview of our plan of care prototype: the left side lists the set of diagnoses , outcomes and interventions for the current patient. The buttons in each row can be used to ✚ add ✖ remove or 🡑 prioritize items in the plan of care. Red buttons on an outcome row notify the user that actions are needed to improve the related outcome. Outcome buttons are only present for CDS versions of the prototype (Text, Table, Graph). When the red button is clicked, an action popup appears with one of the following designs. **B)** In the Graph version, CDS shows a patient's outcome trend through a graph. A green line shows projected outcome if aggressive treatment is put in place. A red line shows projected outcome if the current care continues. A dashed horizontal line indicates the expected value for this outcome, as set by the nurse that added it to the plan of care. **C)** The Table version shows the same outcome information in a table. **D)** The Text version only shows a list of suggested action and text-based evidence, omitting the trend information. **E)** This table is a summary of the CDS variants for the four prototypes.

2 CDS Design

As part of our prior research, we iteratively developed and tested several CDS features for HANDS. We carried out the iterative design, expert evaluation, and user testing of different feature variants, involving a total of 40 registered nurse professionals in our laboratory setting[14]. Through this work, we identified CDS designs that were considered usable, easy to interpret, and reported as valuable to practice by the majority of our subjects [15].

This design consists of one or more alert buttons inserted directly into the patient POC, next to patient outcomes that require attention. By clicking on a button, the nurse accesses a CDS pop-up window, which offers information about the alert, indicates possible solutions and offers a list of changes to the current plan of care (e.g., adding or removing interventions, changing or prioritizing outcomes and diagnoses). Nurses can select the desired changes directly in the CDS window to apply them to the POC.

A piece of potential information shown in the CDS alert popup is a trend for the target patient outcome. The trend tells the nurse how the outcome changed since the patient was admitted (is pain increasing, decreasing or staying the same?) and shows how the outcome may change in the future depending on care choices (e.g., if I keep the current treatment plan, how is pain level going to evolve? If I treat it aggressively, is it going to improve? How quick?). In our previous work, however, we did not simulate the decision-making process to determine which format of the alert would foster decision-making, i.e., the adoption of CDS suggestions.

3 Objective

In this work we had three objectives. First, we wanted to measure the effect of CDS on simulated nursing care of end-of-life patients. Second, we wanted to determine whether a patient outcome trend would improve decision-making. Finally we wanted to assess how different representations of this outcome trend would be perceived and potentially affect the decision-making efficiency.

Our hypotheses were that decision-making efficiency would improve when a CDS was available, and that its efficiency would be increased if the CDS representation matched a nurse's affinity to that representation. In particular, we hypothesized that a graphical representation of trend data would improve decision-making efficiency for nurses with high graph literacy, whereas for nurses with low graph literacy, a numerical or textual representation of trends would perform better. To test these hypotheses we developed four variants of our plan of care prototype, described in Fig 1**.**

To estimate decision-making efficiency, we considered two factors, based on the observation that nurses have limited time to adjust care plans and therefore need to perform target actions quickly. First, we consider the number of target actions added to a patient care plan, based on the patient scenario and the information offered by the CDS. Second, we measured the total time spent by a nurse on

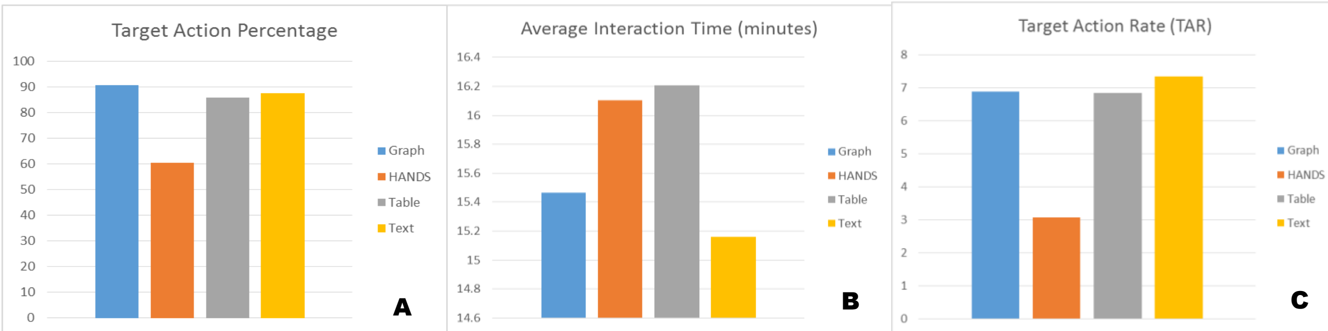

Fig 2. A summary of experiment results. **A)** The average percentage of target actions executed in each prototype group. **B)** The average time (in minutes) users spent adjusting the plan of care for both patients. **C)** The target action rate score in each group (higher values are better).

	HANDS	Text	Table	Graph
Graph Literacy	-0.19 (p=.34)	-0.21 (p=.31)	0.16 (p=.45)	0.60 (p=.003)
Numeracy	-0.06 (p=.75)	-0.01 (p=.96)	0.23 (p=.25)	0.15 (p=0.45)

Table 2. The Kendall tau rank correlations and p values for measured graph literacy and numeracy vs. Target Action Rate (TAR) in each prototype group.

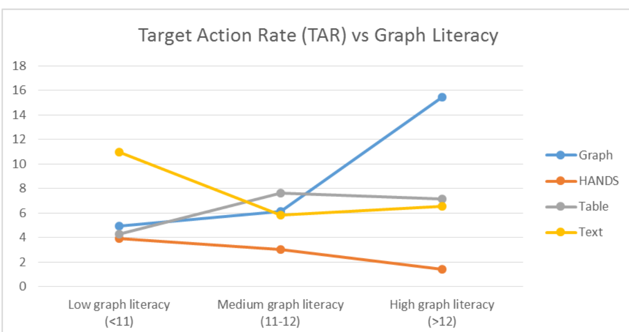

Fig 3. The target action rate trends for each group. Graph literacy scores where in the 8-13 range. Subjects in the low, medium and high graph literacy ranges were 16, 36 and 8 respectively.

interacting with a specific patient's POC. We join these values into a single efficiency estimate we call target action rate (TAR) score, calculated as the percentage of appropriate actions executed over time.

This score can range from 0 to 100, with typical values in our experiments in the 2-10 range (with time measured in minutes). We want to underscore that this indicator is an estimate of a nurse decision-making efficiency, but it gives us a first order, quantifiable measure that can be used for initial analysis of experimental data.

4 Materials and Methods

We recruited a sample of 60 nurses stratified by experience (< 1 year, ≥ 1 year), gender, race, and education (<BSN, ≥ BSN), and we randomly assigned them to one of the four CDS interface groups making sure all demographics were equally represented in each group. The nurse participants were 48 women and 12 men who were 21 to 71 years of age (mean=33.7±10.8); 25 were White, 13 African American, 16 Asian, and 6 other races. The participants were all registered nurses (RNs, newly registered to 44 years of experience; mean=8.1±9.7 years), and 4 had an ADN and 56 had BSN or higher level of education.

At the beginning of the experiment, a facilitator oriented the participant about how to use of the system, and acted as a previous shift nurse, presenting two end-of-life patient care scenarios, with a shift hand-off report and patient assessment. Each participant then interacted with the prototype to modify the plan of care for a simulated shift. After completion of the care scenario, users were asked to complete a post-experiment questionnaire, aimed at defining among other things their learning style, numeracy and graph literacy.

To assess graph literacy, we used the Galesic & Retamero health-related graph literacy test [16].To measure numeracy we used the Fagerlin et al. subjective numeracy scale questionnaire [17]. Participants received $100 for time and travel expenses.

During the simulation, the prototype captured a log of user actions and the time at which they occurred, in addition to the final care plans for each patient at shift end. Audio/video of the user interaction with the prototypes was also captured for cross-checking and to support in-depth analysis. The time stamps and the percentage of accepted CDS-suggested actions were used to compute the target action rate (TAR) score for each user.

5 Results

Fig 2 shows average CDS-suggested actions, interaction times and TAR scores for the four prototype groups (HANDS, Text, Table, Graph). ANOVA showed a significant difference between the HANDS group and the three CDS groups (p=.005). Post-hoc tests showed significant difference between Hands and each of the three CDS groups: Text (p=.008), Table (p=.029), Graph (p=.023); but no significant difference between pairs of the three CDS groups (p values all close to 1). CDS had a statistically significant impact on nurses-decision making: nurses, randomly assigned to any form of CDS performed more of the suggested actions than the nurses randomly assigned to HANDS, the control interface. For the graph and text conditions, they also required less time to adjust the plan of care for both patients. For the table condition, they required approximately the same time as in the no-CDS HANDS prototype. Differences in average times for the four groups are small (~30 seconds).

Based on these results, we may infer that all forms of clinical decision support work equally well in supporting nurse decision-making. To test our further hypotheses, we considered self-reported graph literacy and numeracy to see whether it had an effect on decision making for the four prototype conditions.

Table 2 shows Kendall tau rank correlation of action frequency with graph literacy and numeracy by group: The correlation between graph literacy and action frequency in the Graph group was significant and compelling. In particular, figure 3 shows how the TAR score changed for low, medium and high graph literacy users in the four prototype conditions. For low graph literacy users, the efficiency of graph and table-based CDS was close to the non-CDS prototype: even if use in those conditions applied a high number of appropriate interventions to their patients, they required more time to interpret the CDS information motivating those decisions. Low graph literacy nurses presented with textual information had a higher performance, even if information about a patient's trend (in tabular or graphical form) was unavailable to them. On the other hand, nurses with high graph literacy performed significantly better when the CDS system provided them with a patient outcome trend in graphical form. For nurses with average graph literacy, all three CDS forms perform roughly the same, and are all better than an interface without CDS.

All CDS forms are good in terms of suggesting the correct course of action, but nurses' efficiency (TAR) increases if they use a CDS form that fits their profile of prior learning. Maybe this can be changed using training? Application of this finding indicates that it may be important to develop a set of guidelines to choose efficient CDS for nurses, or design applications that allow nurse to customize or choose the form in which information is presented. The cost benefit for each of these options should be studied before tailored CDS tools are implemented for clinical EHR systems.

6 Conclusion

CDS is an invaluable instrument for nursing practice, and proved useful in general. Any form of CDS is good, assuming it is well designed and user tested to guarantee correct interpretation and usability. But if we want to really optimize the efficiency of nursing decision making one form of CDS does not appear to be enough. The nurse population varies in a number of important ways such as a wide range of experiences, degrees and practice settings, to which we need to provide tools that adapt to this diversity. A limitation of the current study is that it is based on a relatively small sample of 13-16 nurses for each of our prototype groups. The evidence presented in this work supports the continuation of this research with a larger sample of nurses and with an extended set of patient scenarios beyond end-of-life care.

Conflict of Interest

The HANDS software, which includes the NANDA-I, NIC, and NOC standardized nursing terminologies, is owned and distributed by HealthTeam IQ, LLC. Dr. Gail Keenan is currently the President and CEO of this company and has a current conflict of interest statement of explanation and management plan in place with the University of Illinois at Chicago.

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