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Toward Meaningful Care Plan Clinical Decision Support: Feasibility and Effects of a Simulated Pilot Study

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The first author is a principal in the company whose software was modified by the research team specifically for this study and has a conflict management plan in place at the University of Florida. The other authors have no conflicts of interest to report.

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Abstract

Background—Clinical decision support (CDS) tools—with easily understood and actionable information, at the point of care—are needed to help registered nurses (RNs) make evidence-based decisions. Not clear are the optimal formats of CDS tools. Thorough, preclinical testing is desirable to avoid costly errors associated with premature implementation in electronic health records.

Objective—To determine feasibility of the protocol for designed to compare multiple CDS formats, and evaluate effects of numeracy and graph literacy on RN adoption of best practices and care-planning time in a simulated environment.

Methods—In this pilot study, 60 RNs were randomly assigned to one of four CDS conditions (control; text; text+graph; text+table) and asked to adjust the plan of care for two patient scenarios over three shifts. A total of 14 best practices were identified for the two patients and sent as suggestions with evidence to the three CDS groups. Best practice adoption rates, care-planning time, and their relationship to the RN's numeracy and graph literacy scores were assessed.

Results—CDS groups had a higher adoption rate of best practices ($p < .001$) across all shifts and decreased care-planning time in shifts two ($p = .01$) and three ($p = .02$) compared to the control group. Higher numeracy and graph literacy were associated with shorter care-planning times under text+table ($p = .05$) and text+graph conditions ($p = .01$). No significant differences were found between the three CDS groups on adoption rate and care-planning time.

Discussion—This pilot study demonstrates the feasibility of our protocol. Findings show preliminary evidence that CDS improves the efficiency and effectiveness of care-planning decisions, and that the optimal format may depend on individual RN characteristics. We recommend a study with sufficient power to compare different CDS formats, and assess the impact of potential covariates on adoption rates and care-planning time.

Keywords

care plans; decision support; standardized nursing terminologies; usability

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Clinical decision support (CDS) shows promise for improving healthcare, but many concerns have yet to be adequately addressed. Here, CDS is defined as providing clinicians with computer-generated, clinical knowledge and patient-related information that is intelligently filtered and presented at appropriate times to enhance patient care (Teich, Osheroff, Pifer, Sittig, & Jenders, 2005). One major concern is determining the optimal formats of CDS to enable clinicians to make high-quality decisions in daily practice. Increasing electronic health record (EHR) adoption in recent years has resulted in large volumes of data that contain evidence about the impact of healthcare. To date, there has been a substantial focus on what data to collect and the type of evidence needed by clinicians at the point of care. Lagging behind is the research on effects of display formats (e.g., graphical, symbolic, textual) of CDS on quality and efficiency of decision making and whether RN literacy moderates these effects. This pilot study aimed to determine the feasibility of a larger trial using a simulated environment to compare multiple CDS formats, and examine the effects of numeracy and graph literacy on nurses' care-planning decisions.

A main goal of CDS is to enable efficient processing of the large quantity of data in the EHR to support high-quality decisions in clinical practice. The CDS systems offer electronic support at the point of care in a variety of forms, including evidence-based alerts, reminders, guidelines, and best practices (Middleton et al., 2013; Osheroff et al., 2007). There is an extensive literature on medical CDS systems (Bright et al., 2012; Eichner & Das, 2010; Jaspers, Smeulers, Vermeulen, & Peute, 2011), but there are far fewer CDS studies focused on registered nurses (RNs) (Dunn Lopez et al., 2017). The CDS nursing studies have focused on: adherence to specific guidelines (Campion, Waitman, Lorenzi, May, & Gadd, 2011; Dumont & Bourguignon, 2012; Sward, Orme, Sorenson, Baumann, & Morris, 2008; Welch et al., 2015); single condition nursing diagnostic decision making (Fick, Steis, Mion, & Walls, 2011; Lee et al., 2009; Sawyer et al., 2011; Welch et al., 2015); medication dosing (Campion et al., 2011; Dumont & Bourguignon, 2012; Sward, Orme, Sorenson, Baumann, & Morris, 2008); supporting situational awareness (Dowding et al., 2009; Dumont & Bourguignon, 2012; Sward et al., 2008; Welch et al., 2015); and triage decision making (Dowding et al., 2009; Ernesäter, Holmström, & Engström, 2009; Lee et al., 2009). Findings provide preliminary evidence that nursing CDS can improve accuracy (Lee et al., 2009; Yeh et al., 2011) and efficiency of nursing care (Effken, Loeb, Kang, & Lin, 2008; Sawyer et al., 2011) and patient outcomes (Ruland et al., 2010; Welch et al., 2015).

Few studies compared the visual formats of CDS delivered to nurses. The format is nonetheless critical to ensuring that the user can quickly understand and apply the information presented. Creating CDS that are meaningful, generalizable, supportive of nurses' holistic view of the patient, and actionable at the point of care requires iterative building, testing, and refinement. Careful systematic development of CDS is necessary to ensure that it works as intended once implemented in practice. Researchers have found a number of problems in EHR usability testing (Ratwani, Benda, Hettinger, & Fairbanks, 2015) and a paucity of high-quality studies of EHR usability with two thirds performed at prepost implementation without preclinical usability testing reported (Ellsworth et al., 2017). In addition, half of the largest U.S. EHR vendors are not meeting standards for usability testing, with two thirds conducting tests with fewer than the minimum 15 participants, as suggested by the National Institute of Standards and Technology, and one fifth conducting at least half of their tests using subjects with no clinical background (Ratwani et al., 2015). Substandard usability testing may contribute to serious, unintended consequences in the implementation of health information technologies (Graber, Siegal, Riah, Johnston, & Kenyon, 2015; Han et al., 2005; Nebeker, Hoffman, Weir, Bennett, & Hurdle, 2005).

This pilot study is one of a systematic set of studies (Almasalha et al., 2013; Febretti, Lopez et al., 2013; Keenan et al., 2012; Yao et al., 2013) designed to achieve our team's long-term goal, "to deliver useful and meaningful care-planning CDS to nurses at the point of care." It builds upon three preceding iterative cycles that generated the content for the CDS prototypes, and preliminary evidence that graph literacy may predict the most efficient CDS format for an individual (Lopez, Febretti, et al., 2016; Lopez, Wilkie, et al., 2016; Febretti, Lopez, et al., 2013). A high fidelity, simulated environment was utilized in this pilot as a safe and cost-effective step toward the eventual deployment of validated CDS in practice (Kushniruk & Borycki, 2014; Wachter et al., 2003).

Purpose

The study aims are to compare three experimental CDS format groups (text, text+graph, and text+table) to control (No CDS) on RNs' adoption of best practices and care-planning time, and to examine the effects of numeracy and graph literacy on the adoption rates and time. Though the outcomes evaluated at this stage are not patient outcomes, adoption rate of best practices and care-planning time are expected to directly impact the cost and quality of care in clinical practice.

Methods

Design and Sample

In this pilot study, a diverse sample of 60 RNs was recruited in a Midwestern state and randomly assigned to interact with one of four care-planning software conditions in a session consisting of three shifts. It was part of a larger study (R01NR012949) focused on iterative development of CDS and identification of best nursing practices from a large plan of care (POC) database. The four conditions included one with No CDS (control) and three CDS prototypes that included best practice suggestions accompanied by evidence in one of three different formats: text; text+table; and text+graph (Figure 1).

To recruit a purposeful sample, subjects were recruited via flyers posted at student centers of community colleges and universities. Additionally, recruitment e-mails were distributed via a university announcement system, and to individuals affiliated with nursing programs at community colleges and universities and community-based, academic, and veteran's hospitals. Snowball methods were also used. Respondents comprised our sampling frame and were stratified by gender, ethnicity, experience, and education to increase the sample diversity as reported elsewhere (Lopez, Wilkie, et al., 2016).

The study was approved by the university Institutional Review Board and data collected in 2014.

Setting

At the electronic visualization laboratory located at a Midwestern state university college of engineering, we tested the CDS formats in the immersive setting (Febretti, Nishimoto, et al., 2013). The simulated environment included a life-size, simulated nursing station with typical hospital unit sounds and visuals. The study computer with orientation materials, the simulated cases, and the documentation software were located in a quiet space within the simulated nurses station.

Procedures

After informed consent, each RN was randomized to one of the four study groups. We utilized block randomization with a block size of eight to maintain group balance. Group assignment was concealed in a sealed, opaque envelope that was opened by the programmer who then activated the CDS version assigned. All other research staff and the subject were blind to the assignment. A standard protocol was executed by a research assistant (RA) to orient the RN to the basic care-planning software features, and validate understanding and present initial assessments (Shift 1) or updates (Shifts 2 and 3) and other contextual information for two exemplar end-of-life (EOL) patients to the RN. Each RN submitted end of shift POCs for the patients for three hypothetical shifts: one each day for three days. A shift was defined as a consecutive 8-hour period during which the RN was responsible for the care of the two patients. A simulated shift lasted up to 20 minutes and was focused on the RN completing and submitting the POCs for that shift. The subjects were left alone in the simulated nurses station while interacting with the software. When the shift POCs were submitted, the RA re-entered the nurses station and the process was repeated for next shift. At the end of Shift 3, the RNs completed the posttest surveys and received compensation of $100 for time and travel expenses (Figure 2).

Experimental Stimulus

A simulated care-planning experience for two EOL patients across three shifts was the experimental stimulus. The Hands-on Automated Nursing Data System (HANDS) was modified to simulate HANDS (S-HANDS) and served as the basic care-planning software for all four experimental conditions. Control group used the basic (No CDS) S-HANDS version, whereas each CDS group used an S-HANDS version containing one of three CDS prototypes. Diagnoses, interventions, and outcomes were coded respectively with the NANDA-International (NANDA-I) (Herdman & Kamitsuru, 2014), Nursing Interventions Classification (NIC) (Bulechek, Butcher, Dochterman, & Wagner, 2013), and Nursing Outcomes Classification (NOC) (Moorhead, Johnson, Maas, & Swanson, 2014). Two EOL patient scenarios based on real cases were used in this study (see Table, Supplemental Digital Content 1).

The HANDS (2016) is a software program designed for documenting the nursing POCs that are created on admission and updated at every formal handoff (shift change). The S-HANDS has similar functionality to HANDS but includes only NANDA-I, NIC, and NOC terms pertaining to EOL care.

Each of the three CDS prototypes delivered the same 14 best practice suggestions with the evidence presented in one of three different formats (Figure 1). Of the 14, three pertained to Patient 1 and appeared on two pop-up screens while 11 pertained to Patient 2 and appeared on three screens. The evidence supporting the CDS suggestions was derived from the literature and our previous data mining studies (Almasalha et al., 2013; Mercadante, 2014; Yao et al., 2013). The text and graph features were iteratively refined through three cycles of usability testing (Febretti, Lopez, et al., 2013). The short text statements accompanying the suggestions and describing the evidence were presented on popup CDS screens, with additional text information about the evidence accessible by clicking the "i" button. The graph feature, available in the text+graph CDS prototype, illustrated the projected effect of suggested action. The CDS table feature, available in the text+table CDS prototype, presented the same information in tabular form.

Pop-up screens presenting suggestions and evidence were accessed by clicking red, blinking, alert buttons placed next to outcomes requiring attention. When the RN clicked to accept suggestions on a CDS screen, the POC was automatically updated to reflect the new items. If all suggestions on a CDS screen were adopted, the corresponding red button disappeared; if some but not all were adopted, the button remained but stopped blinking. Finally, the red button continued to blink if the RN adopted no suggestions.

RNs in the control group did not have access to CDS suggestions and evidence but could, and did, make changes aligned with the best practice suggestions using the S-HANDS basic functionality. The CDS groups also had the option to bypass the CDS in full or part and make changes to the POC using the basic S-HANDS functionality.

For the second and third shifts, patients' POCs and patient conditions were updated to reflect the changes made by RNs earlier and the effects of those changes. If an RN assigned to a CDS group had not accepted a CDS suggestion on the earlier shift(s), the CDS suggestion reappeared.

Instruments

Independent variable—The independent predictor is a categorical variable representing the four experimental conditions described above.

Covaxriates—In addition to documenting protocol adherence (for study feasibility) via the software and collecting demographic and experience information about the RNs, we assess their numeracy and graph literacy. The Subjective Numeracy Scale (SNS), including eight items with a variety of Likert-type response options ranging from 1–4 or 1–6, was used to measure RNs' numeracy skills. Cronbach's alpha ranged from .82 to .84 (Zikmund-Fisher, Smith, Ubel, & Fargelin, 2007). The 13-item Long Graph Literacy Scale (LGLS) was used to assess RNs' ability to understand health information presented in graphical forms (bar, pie, icon, and line). Reliability and convergent validity with graph comprehension items from existing literacy scales were previously assessed and reported (Cronbach's α =.85, r = .44) (Galesic & Garcia-Retamero, 2011). For the current sample, the Cronbach's alpha was .76 for the SNS and .40 for the LGLS.

Dependant variables—The uptake of the best practice items by RNs was measured by the adoption rate, computed as the percentage of the 14 items adopted. Care-planning time was determined using computer timestamps of user actions and included the time an RN spent reviewing the previous POCs, evaluating the suggestions and related evidence, making decisions, and updating and submitting the POC. Previous studies have shown that nurses spend on average 21.5% (Philipsen et al., 2014) of their time in documentation. Reducing documentation time could thus increase direct patient care time. Feasibility of the study was measured by the proportion of subjects completing the study and amount of missing data.

Analysis

Analysis was conducted using R statistical software. Descriptive statistics including mean, standard deviation, frequency, and percentage were generated. ANOVA and independent samples *t*-tests were used for group comparisons. Linear mixed-effect models with random intercept terms to accommodate between-subject differences were used to examine the effects of CDS, as well as numeracy and graph literacy on adoption rate. Restricted maximum likelihood (REML) method was used to produce estimates of model parameters. Posterior predictive checking, a Bayesian-based diagnostic method, was used to validate model fit (Gelman & Hill, 2006). Statistical significance was set at a two-sided alpha of .05.

Results

Participant Characteristics

Of subjects beginning the pilot study, 100% completed the protocol. The missing data were minimal (0.1%). Table 1 shows participant characteristics. Overall, 60 RNs participated in the study, 80% of whom were female. The participants were between 21 to 71 years old ($M = 33.7$, $SD = 10.8$ years), with 42% Caucasian, 22% Black, 27% Asian, and 10% identified as other races; a small minority (8%) were Hispanic. Nearly all (77%) had at least one year of nursing experience ($M = 8.1$, $SD = 9.7$ years). Most were college graduates, with 23% having an MSN or higher, 70% having a BSN, and 7% having an ADN.

Adoption Rate

The means and standard deviations of the adoption rates over the course of three shifts also appear in Table 1. The adoption rates of the best practice items for CDS group were substantially higher than the control across all shifts: $M = 80\%$, $SD = 20\%$ versus $M = 38\%$, $SD = 15\%$ for Shift 1; $M = 74\%$, $SD = 22\%$ versus $M = 45\%$, $SD = 11\%$ for Shift 2; and $M = 73\%$, $SD = 19\%$ versus $M = 49\%$, $SD = 13\%$ for Shift 3, respectively ($p < .001$ for all three shifts). We also observed that as time progressed, control group RNs added more of recommended CDS items (though not available to them in a CDS format), leading to higher adoption rates in later shifts; while the adoption rates for the CDS groups decreased slightly over time.

Regression analysis confirmed this observation (Table 2). We set the control (No CDS) as the reference and compared each CDS group against it. All CDS groups had significantly higher adoption rates ($p < .001$ for all three CDS groups); the adoption rate of every CDS group decreased over time, significantly for the text ($p = .03$) and text+table groups ($p = .$

001); on the other hand, the adoption rate of the No CDS group increased significantly over time ($p = .001$).

To determine whether there were significant differences among the three CDS groups, we compared this model with a reduced model treating the three CDS groups as a single group. If the difference among the three CDS formats (text, text+table, and text+graph) was not significant, then merging them into a single group will not reduce model fit. A likelihood ratio test showed no significant difference between the two models indicating that adoption rate difference between the three CDS groups was not statistically significant ($p = .20$).

We also compared the adoption rates of individual items at Shift 1 for the No CDS and for the CDS groups (see Figure, Supplemental Digital Content 2.) The adoption rates of the CDS groups were higher for every item, and the difference was significant for all but four items. Two items, add NOC: Immobility Consequences: Physiological and add NIC: Pressure Ulcer Prevention, were adopted by 94% of the control group and therefore there was little room for improvement. For two other items, prioritize Pain and add NIC: Respiratory Monitoring, the CDS group had 16%-20% higher adoption rates, but the difference was not statistically significant in this small sample. For the CDS group, the adoption rates for the six items in the respiratory problem mini-care plan as well as the prioritize Death Anxiety item for Patient 2 were relatively low (59%-70%); whereas the remaining items all had very high adoption rates (89%-100%). In the control group, on the other hand, only four items were in the majority (> 50%) of the POCs, while the prioritize Death Anxiety item and five items related to removing treatments were rarely adopted (0%-13%).

The changes in adoption rates from Shift 1 to Shift 3 were also examined. In the CDS groups, the adoption rates decreased across the three shifts with RNs dropping previously adopted items (four items were dropped by 15% or more of the RNs). In contrast, in the control group, the adoption increased across shifts, with five items being added by 19% or more of the RNs in Shifts 2–3. Closer examination revealed that the drop of items; prioritize Pain, add Positioning, and add Respiratory Monitoring could be attributed to removal of the NANDA-I: Acute Pain from a POC once a patients' pain improved. Similarly, in our simulated scenario, prioritization of the NANDA-I: Death Anxiety resulted in improvement of the related outcome in the subsequent shifts leading some RNs to change the top priority NANDA-I.

Care-Planning Time

The mean and standard deviation of RN care-planning time (in minutes) can also be found in Table 1. There is little difference between CDS groups and the control in the first shift ($M = 8.1$, $SD = 3.4$ minutes for control vs. $M = 7.8$, $SD = 3.7$ minutes for CDS, $p = .80$). At Shifts 2 and 3, however, the CDS group, on average, spent only 70% of the time needed by the control. In Shift 2, the control group spent $M = 3.8$, $SD = 1.3$ minutes versus $M = 2.7$, $SD = 1.5$ minutes for CDS groups ($p = .01$). In Shift 3, the time spent was $M = 3.3$, $SD = 1.3$ minutes versus $M = 2.3$, $SD = 1.5$ minutes in favor of CDS groups ($p = .02$). Comparison among the three CDS groups showed no significant time difference for any of the three shifts.

There was significant, positive correlation between care-planning time and the adoption rate for the control group on the first two shifts ($r = .62$, $p = .01$ for Shift 1 and $r = .57$, $p = .02$ for Shift 2). For the last shift, this correlation was minimal ($r = .11$, $p = .73$). For the CDS groups, the correlations between the care-planning time and the adoption rate were weak and not statistically significant for all shifts.

Numeracy and Graph Literacy with CDS Adoption and POC Entry Time

We did not find any significant association between RN characteristics and adoption rates. Then again, our examination of the relationships between numeracy and graph literacy and time spent care planning revealed two significant findings (Table 3). A higher numeracy score (1 point) was associated with a significant reduction (1.1 minute) in time spent for an RN in the text+table group ($p = .05$). A higher graph literacy score (1 point) was associated with a reduced (0.8 minute) time in the text+graph group ($p = .01$). Regression output details for Tables 2 and 3 are presented (see Table, Supplemental Digital Content 3).

Variation in Care

We compared the number of NANDA-I diagnoses, NOC outcomes, and NIC interventions entered by RNs assigned to different groups (Table 1). The number of NANDA-Is on the POCs stayed constant through the shifts, with the control group entering 1.3 more NANDA-Is into the POCs for the two patients and the difference was significant for all three shifts (Shift 1: $p = .01$; Shift 2: $p = .02$; Shift 3: $p = .01$). We also observed a significantly higher number of NOC labels on the POCs of the control relative to CDS groups through all three shifts (Shift 1: $p = .04$; Shift 2: $p = .02$; Shift 3: $p = .03$), with the number increasing over time for both the control and CDS groups. Regression showed significant group difference at Shift 1 ($p = .04$) and increase over time for CDS groups ($p = .03$). The control had a larger increase over time, but the increase rate difference with CDS groups was not statistically significant ($p = .12$). Similarly, the No CDS group entered more NIC labels than the CDS group and the difference was statistically significant for the latter two shifts (Shift 2: $p = .02$; Shift 3: $p = .001$). Regression analysis showed a significant increase across time in CDS groups ($p < .001$), as well as a significantly higher increase rate over time in the control group ($p < .001$).

Discussion

This pilot study demonstrated feasibility of our innovative protocol and uncovered important trends (some statistically significant)—that justify a larger study powered for differences between CDS groups—instead of just between CDS and No CDS. More specifically, it was feasible to recruit, randomize, orient, and retain a diverse group of 60 RNs through the entire protocol, fully test the automated intervention using a high-fidelity, simulated environment, and collect data with minimal missing data. Surprisingly, we observed statistically significant findings in this small pilot study, but they require confirmation in a larger study. Our analyses of the data revealed findings relevant to planning future studies of CDS in four areas: item adoption rates; time spent care planning; the RNs' graph literacy and numeracy; and overall size of the POC across time.

With regards to the adoption rates of best practices items, we observed that these can be grouped into three distinct categories based on RNs actions in the No CDS group and CDS groups. The first category included those items for which an overwhelming majority (> 90%) of RNs added on the first shift even for the No CDS group (e.g., monitor NOC: Immobility Consequences; add NIC: Skin Surveillance). The second category included items that very few RNs would adopt without CDS support, with a substantial minority (> 30%) not adopting even with CDS (e.g., remove POC elements addressing the NANDA-I Impaired Gas Exchange). The third contained items adopted on the first shift by a large majority of RNs with CDS support and a substantially smaller portion of RNs without CDS support. The items in this category, nevertheless, were eventually adopted by a substantial portion of the No CDS group over time (e.g., prioritize Pain; add NIC: Positioning to treat Pain; add NIC: Palliative Care Consultation).

These findings provide preliminary evidence that CDS can serve as a reminder for RNs to add items that might otherwise be forgotten or added in a less timely manner without CDS. For items most RNs would enter without prompt, though, CDS suggestions might not be necessary. Excessive CDS messages might create alert fatigue, resulting in RNs ignoring appropriate suggestions. On the other hand, it is less clear why some of the CDS items were never adopted. In a follow-up survey of a subsample of our study, 100% of the RNs ($n = 21$) receiving the CDS indicated that the main reason for adopting items was their belief that the suggestion(s) were good for the patient (Sousa et al., 2015). Less than half of the RNs, however, indicated that failure to adopt an item was partly due to a lack of confidence in the evidence, indicating the need to probe more thoroughly for these causes (Sousa et al., 2015). Nonetheless, RNs' unwillingness to adopt CDS suggestions across time indicated that RNs did exercise critical thinking when presented with CDS suggestions.

Our care-planning time analysis also supported the advantages of CDS. Although RNs in CDS groups had to spend time interacting with the CDS user interface and absorbing evidence related to CDS items, they did not spend more time on the POC than RNs in the control group. In fact, they spent significantly less time on updating patients' POCs on subsequent shifts. Furthermore, there was moderately positive and significant correlation between care-planning time and adoption rate in the control group, while the correlation was weak and insignificant in CDS groups. The potential of a well-designed CDS system to reduce care-planning time has major implications for improving RN efficiency and reducing RN workload.

Our pilot study also provided evidence of the potential effects of RNs' numeracy and graph literacy, indicating that these may be important factors in designing CDS. Higher numeracy and graph literacy scores were associated with lower care-planning time in text+table and text+graph groups, respectively. Substantiation of these findings with a larger study has the potential to underscore the efficiencies in decision making that can be gained by tailoring the CDS format to fit users' skills (Lopez, Wilkie, et al., 2016).

Our examination of the POCs' content indicated another potential benefit of CDS. Specifically, we found that RNs in the control group added significantly more NANDA-I problems, NOC outcomes and NIC interventions to the POC in Shifts 2 and 3 compared to the CDS groups. Since the patient scenarios were consistent across all four groups, the findings suggest RNs may be less sure and, as a result, added unnecessary elements when CDS was not available versus when it was available. In contrast, these findings also raise the question of whether RNs will come to be overly dependent on CDS, adopting suggestions without critical evaluation, and failing to identify problems and treatments not presented in the CDS. Both of these hypothesis warrant further study.

Although we did not find significant differences between the three CDS groups in this pilot study with a very small sample size, we did find trends that warrant a further study comparing them. For example, RNs in the text+table group spent about 0.5 minute more than either text group or text+graph group per shift. Furthermore, significant interactions between numeracy and graph literacy with CDS group assignment indicated a potential need for tailoring the CDS format to individual RNs. With a properly powered study, we will be able to identify the optimal CDS format for RN adoption rate and efficiency tailored to RN characteristics.

Despite our attention to study rigor, as with all research, there are some limitations. Our sample size was too small to be considered fully powered. That being said, the data from this study will inform study design and power analysis for future research by this research team and others. Second, one could posit that since no “inappropriate suggestions” were included, we were unable to assess the impact on critical thinking. This may in part be true, however, several of our prompts were designed to promote critical thinking specifically about EOL care. For example, a patient with impaired gas exchange and labored breathing may benefit from Acid Base Monitoring (often through painful invasive blood gas measurement). However, the patient in our scenario is a “do not resuscitate” with end stage chronic obstructive pulmonary disease and a major goal is to move her towards a more comfortable death. Nurses who critically assess this EOL patient are likely to realize that painful and invasive Acid Base Monitoring procedures are no longer indicated. Furthermore, our finding that nurses did not accept all of the decision support is highly suggestive of the critical thinking of the nurse subjects. Finally, a simulated environment—even the one used in this experiment with visual and auditory similarities to a hospital unit—cannot truly reflect the temporal demands and interruptions of a typical acute-care setting. However, we believe that conducting health information technology research under simulated conditions can play a pivotal role in promoting the appropriate design of technologies that are both safe and effective in clinical practice. Technologies introduced into practice without adequate testing have potential for increased workload, frustration, and patient harm.

Conclusion

This pilot study provided rationale for a larger, randomized, controlled trial of our CDS formats and also generated evidence supporting further evaluation of other factors examined. We demonstrated that different formats of CDS can be successfully studied using high-fidelity, simulated environment (setting and software) as a research approach that allowed us to mimic longitudinal conditions in a condensed time period. Further, our simulated conditions offer a safety benefit by enabling the discovery and fixing of unintended consequences of CDS prior to real-world testing. Since big data science in healthcare is expected to yield an increasing amount of evidence in the near term, it is crucial to ensure high quality CDS is available to deliver actionable evidence in a meaningful and useful format at the point of care. To date, research examining the impact of the CDS format on decision making is lagging seriously behind. This innovative pilot study laid the foundation for a larger more generalizable study that will advance CDS science supportive of clinicians' decisions that dramatically improve patient outcomes.

Supplementary Material

Refer to Web version on PubMed Central for supplementary material.

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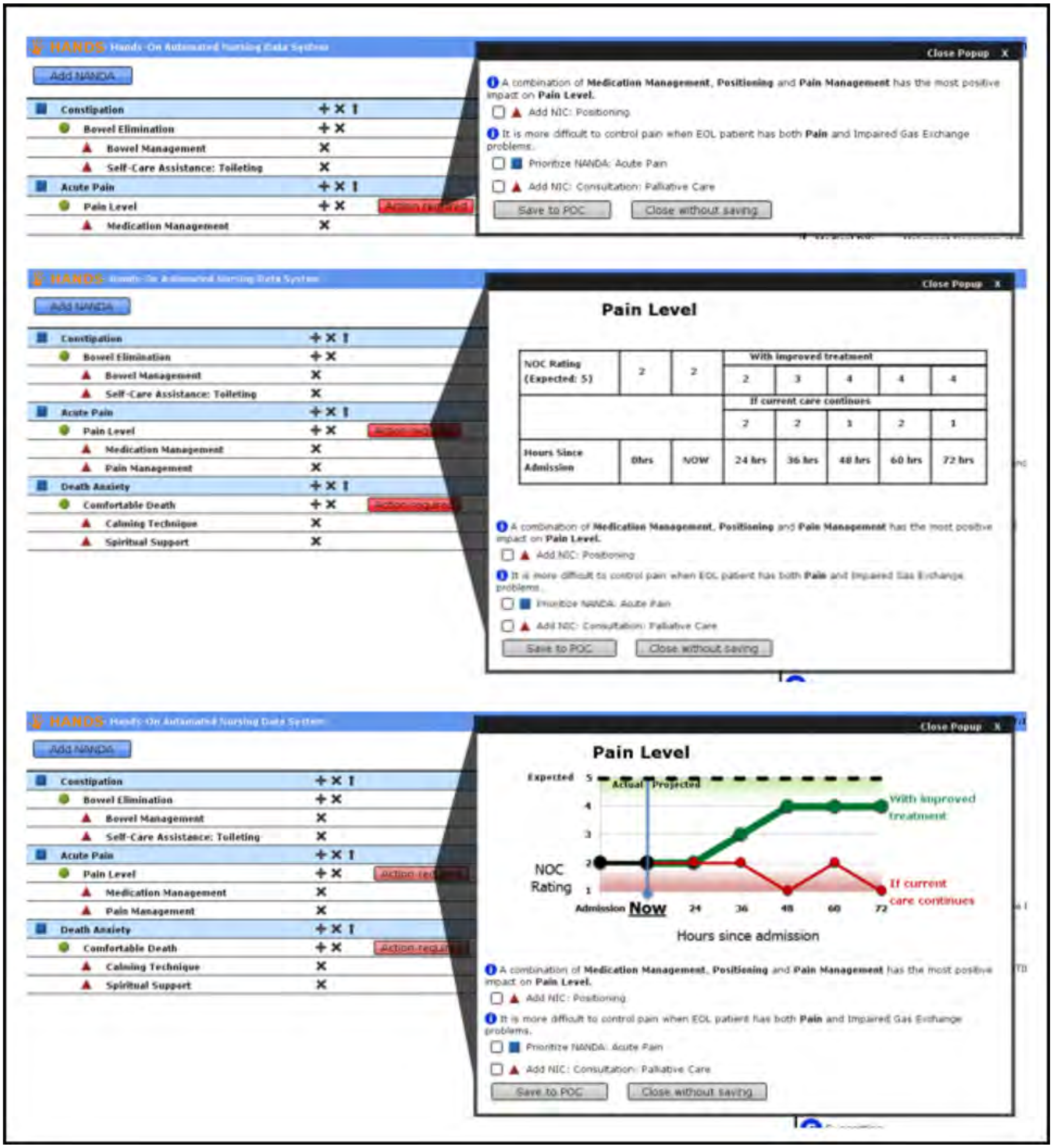

FIGURE 1.

Nursing care plan examples within the three different S-HANDS CDS prototypes. CDS = clinical decision support; NANDA-I = North American Nursing Diagnosis-International; NIC = Nursing Interventions Classification; NOC = Nursing Outcomes Classification; S-HANDS = Modified Version of the Hands-on Automated Nursing Data System; Copyright 2014 HANDS Research Team. Used with permission.

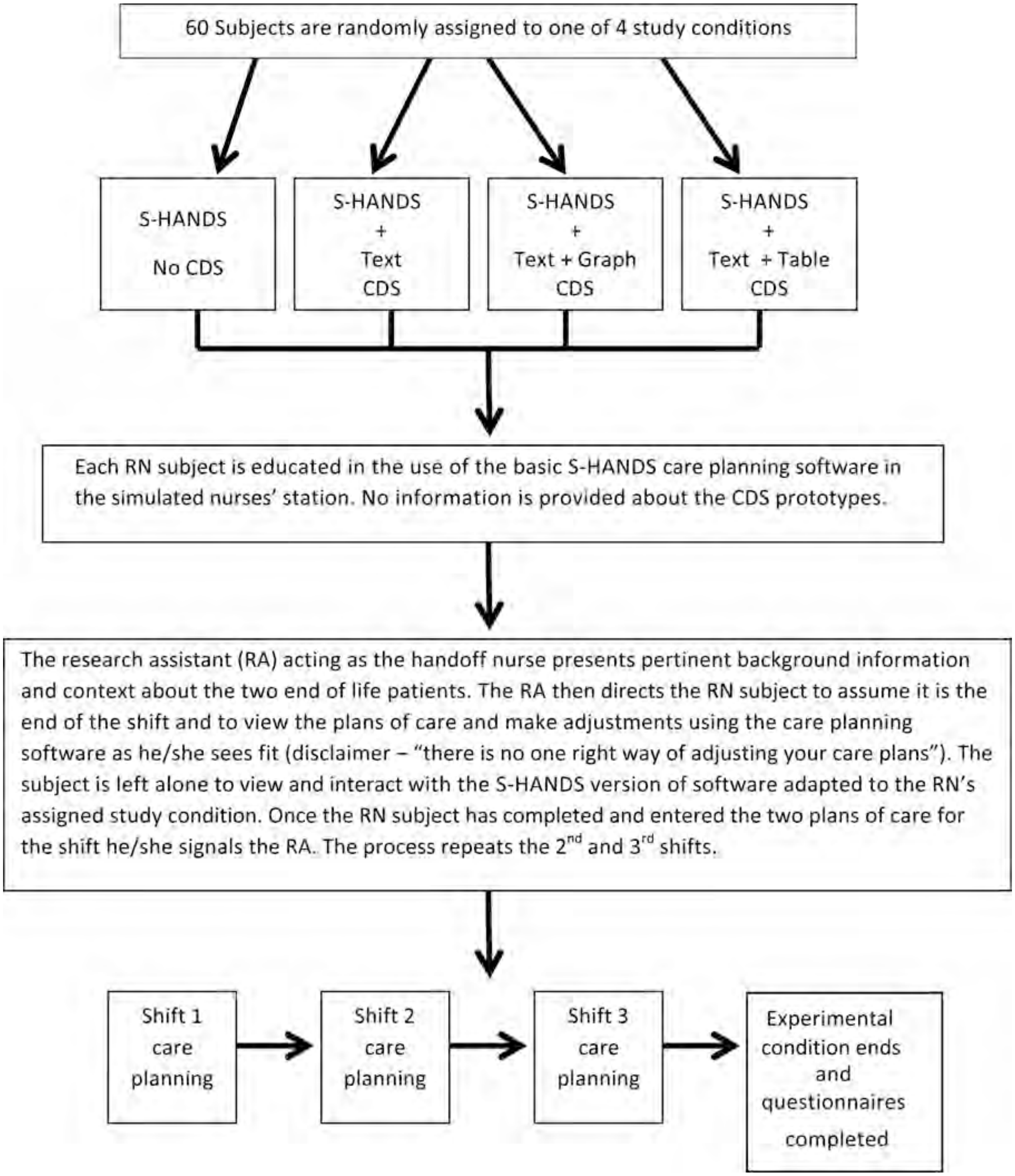

FIGURE 2.
Experimental flow.

TABLE 1

Participant Characteristics and Experimental Outcomes

Characteristic	All *n*	All (%)	No CDS *n*	No CDS (%)	Text *n*	Text (%)	Text+Table *n*	Text+Table (%)	Text+Graph *n*	Text+Graph (%)
Gender										
Male	12	(20)	3	(19)	3	(20)	3	(21)	3	(20)
Female	48	(80)	13	(81)	12	(80)	11	(79)	12	(80)
Ethnicity										
Hispanic	5	(8)	1	(6)	0	(0)	2	(14)	2	(13)
non-Hispanic	55	(92)	15	(94)	15	(100)	12	(86)	13	(87)
Race										
White	25	(42)	7	(44)	9	(60)	5	(36)	4	(27)
Black	13	(22)	3	(19)	3	(20)	3	(21)	4	(27)
Asian	16	(27)	5	(31)	3	(20)	3	(21)	5	(33)
Other	6	(10)	1	(6)	0	(0)	3	(21)	2	(13)
Education										
ADN	4	(7)	2	(13)	1	(7)	1	(7)	0	(0)
BSN	42	(70)	10	(63)	9	(60)	10	(71)	13	(87)
MSN or more	14	(23)	4	(25)	5	(33)	3	(21)	2	(13)
	M	**(*SD*)**	***M***	**(*SD*)**	***M***	**(*SD*)**	***M***	**(*SD*)**	***M***	**(*SD*)**
Age	33.7	(10.8)	34.2	(9.6)	32.2	(9.8)	32.1	(11.0)	36.1	(13.3)
Experience	8.1	(9.7)	9.9	(10.3)	7.3	(7.5)	4.6	(6.8)	10.1	(12.8)
Outcome/shift										
Adoption rate (%)										
Shift 1	68	(26)	38	(15)	83	(20)	79	(19)	77	(20)
Shift 2	66	(23)	45	(11)	79	(25)	66	(19)	76	(19)
Shift 3	66	(20)	49	(13)	76	(22)	67	(16)	74	(18)
Time (minutes)										
Shift 1	7.9	(3.6)	8.1	(3.4)	7.6	(3.2)	8.1	(4.5)	7.7	(3.5)

	All		No CDS		Text		Text+Table		Text+Graph	
Characteristic	***n***	**(%)**	***n***	**(%)**	***n***	**(%)**	***n***	**(%)**	***n***	**(%)**
Shift 2	3.0	(1.6)	3.8	(1.3)	2.5	(1.4)	3.0	(1.7)	2.7	(1.6)
Shift 3	2.6	(1.5)	3.3	(1.3)	2.1	(1.4)	2.8	(1.4)	2.2	(1.6)
NANDAs (number)										
Shift 1	8.1	(1.4)	9.1	(1.6)	7.8	(1.3)	7.7	(1.1)	7.9	(1.2)
Shift 2	8.2	(1.5)	9.1	(1.7)	7.8	(1.2)	7.7	(1.7)	7.9	(1.2)
Shift 3	8.1	(1.6)	9.0	(1.5)	7.7	(1.3)	7.6	(1.8)	7.8	(1.4)
NOCs (number)										
Shift 1	9.6	(2.0)	10.6	(2.3)	9.3	(2.3)	8.9	(1.2)	9.5	(1.7)
Shift 2	9.9	(2.3)	11.1	(2.3)	9.5	(2.4)	8.9	(1.9)	9.7	(1.9)
Shift 3	10.2	(2.6)	11.7	(3.0)	10.1	(2.4)	8.8	(2.0)	10.1	(2.4)
NICs (number)										
Shift 1	28.1	(8.0)	30.1	(9.8)	29.2	(8.5)	25.9	(6.7)	26.9	(6.2)
Shift 2	31.6	(10.1)	37.4	(11.0)	32.0	(9.7)	26.4	(8.8)	29.7	(8.3)
Shift 3	33.7	(10.1)	41.1	(9.2)	33.0	(8.9)	28.8	(7.6)	30.9	(10.6)

Note. $N = 60$. CDS = clinical decision support; NANDA-I = North American Nursing Diagnosis-International; NIC = Nursing Interventions Classification; NOC = Nursing Outcomes Classification; *SD* = standard deviation.

TABLE 2

Regression: Adoption Rate on CDS Condition and Shift

Predictor	***b***	**(SE)**	***p***
Group[a]			
Text	0.45	(0.065)	<.001
Text+Table	0.38	(0.066)	<.001
Text+Graph	0.39	(0.065)	<.001
Shift			
No CDS	0.05	(0.015)	.001
Text	−0.04	(0.016)	.03
Text+Table	−0.06	(0.016)	.001
Text+Graph	−0.01	(0.016)	.45

Note. $N = 60$. *SE* = standard error.

[a]Reference group is no CDS.

TABLE 3

Regression: Care-Planning Time on Group and Its Interaction With Shift, Numeracy, and Graph Literacy

Predictor/value	***b***	**(*SE*)**	***p***
Group[a]			
Text+Graph	−0.66	(0.902)	.47
Text+Table	−0.11	(0.891)	.90
Text	−0.62	(0.872)	.48
Shift[b]			
No CDS	−2.37	(0.430)	<.001
Text+Graph	−2.79	(0.444)	<.001
Text+Table	−2.67	(0.460)	<.001
Text	−2.76	(0.444)	<.001
Numeracy[c]			
No CDS	−0.10	(0.510)	.85
Text+Graph	0.23	(0.657)	.73
Text+Table	−1.14	(0.563)	.05
Text	−0.25	(0.652)	.70
Graph literacy[d]			
No CDS	0.34	(0.376)	.37
Text+Graph	−0.79	(0.299)	.01
Text+Table	−0.02	(0.368)	.95
Text	0.28	(0.319)	.39

Note. N = 60. CDS = clinical decision support.

[a]Reference group is No CDS.

[b]The coefficients represent rates of change over shifts (1–3) in the four groups.

[c]The coefficients indicate the association between care-planning time and numeracy in the four groups.

[d]The coefficients indicate the association between care-planning time and graph literacy in the four groups.