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Toward a more robust & efficient usability testing method of clinical decision support for nurses derived from nursing electronic health record data

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Abstract

Purpose—To develop methods for rapid and simultaneous design, testing, and management of multiple clinical decision support (CDS) features to aid nurse decision-making.

Methods—We used quota sampling, think aloud and cognitive interviews, deductive and inductive coding of synchronized audio video data and archival libraries.

Findings—Our methods and organizational tools allowed us to rapidly improve the usability, understandability and usefulness of CDS in a generalizable sample of practicing nurses.

Conclusions—The method outlined allows the rapid integration of nursing terminology based EHR data into routine workflow and holds strong potential for improving patient outcomes.

Implications for nursing practice—The methods and organizational tools for development of multiple CDS system features can be used to translate knowledge into practice.

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AUTHORS CONTRIBUTIONS: Dr. Dunn Lopez drafted the manuscript and collaborated with co-authors on the development of the methods. Mr. Febretti designed the figures and collaborated with co-authors on the development of the methods. Drs. Stifter Johnson, Wilkie and Keenan reviewed and refined the manuscript and collaborated with co-authors on the development of the methods.

STATEMENT ON CONFLICTS OF INTEREST: Dr. Gail Keenan: The HANDS© software, which includes 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 Florida. Dr. Diana J. Wilkie: is Chairman and Founder of eNURSING llc, a company that creates, tests, and sells evidence-based, electronic tools for patient-centered health care; none are related to standardized nursing terminologies.

PURPOSE

Although standardized nursing terminologies were developed over several decades, their adoption and universal use has not yet been achieved. Increased adoption of these terminologies has grown increasingly important in this era of electronic health records (EHRs) where the analysis of nursing data in standardized terminologies has the potential to advance nursing knowledge and nursing practice. One of the methods to achieve this potential is to transform analytic findings to clinical decision support (CDS) that are integrated with the EHR. Clinical decision support (CDS) includes clinical situation-specific information in the form of alerts, reminders, clinical algorithms and best practices provided to clinicians at the point of care during their routine decision-making (Bates et al., 2003). Although there is significant potential for improving care quality and patient outcomes through CDS, recent literature shows evidence of poor adoption and serious unintended consequences from poorly designed and implemented health information technologies (Ash, Berg, & Coiera, 2004; Han et al., 2005; Koppel, Wetterneck, Telles, & Karsh, 2008; Spetz, Burgess, & Phibbs, 2014; Stead & Lin, 2009).

To overcome these potential consequences, rigorous usability testing is imperative for any health information technology including CDS systems. Usability testing is the evaluation of a system or technology that involves tests by a representative group of potential future users of the technology as they perform certain tasks using the system (Kushniruk & Patel, 2004). Usability testing involves repeated cycles with small numbers of testers (6–10) to obtain feedback of future users that is incorporated iteratively to improve the usability. While EHR vendors may describe a wide array of usability engineering processes, a study of this industry revealed that formal usability testing, user-centered design approaches, and employment of usability experts are rare (McDonnell, Werner, & Wendel, 2010). Technology acceptance is also critical to the successful adoption of CDS systems in practice (Holden & Karsh, 2010). Technology acceptance is influenced by users' perceived ease of use, perceived usefulness, and satisfaction (Holden, Brown, Scanlon, & Karsh, 2012; Holden & Karsh, 2010; King & He, 2006; Melas, Zampetakis, Dimopoulou, & Moustakis, 2011). Usefulness, the perception that the technology will enhance job performance (Holden & Karsh, 2010) can be overlooked in traditional usability measures. Yet, usefulness is particularly important for any workplace systems, including a CDS system, because systems perceived as not useful are unlikely to be adopted (Holden et al., 2012). When a decision support system is designed to influence decision-making in a high stakes domain such as health care, the correct interpretation of the system's messages is essential. Testing of CDS systems therefore must employ rigorous methods that incorporate all of these factors: usability (ease of use), satisfaction, usefulness, and correct interpretation.

When applying traditional user interface design and testing approaches (e.g., iterative focus groups, individual interviews, and usability scenario simulations), developing a CDS system presents specific opportunities and challenges. First is an opportunity to incorporate data visualization techniques to transform complex quantitative data or narrative information into parsimonious graphical representations. A key advantage of graphical representation is the ability to display patterns that speed information processing time over traditional textual displays (Staggers & Kobus, 2000). A challenge is the multiple variables in graphical

displays, such as color, brightness, display location, size, amount of whitespace, and use of symbolic icons as well as cognitive strengths of the testers that may determine interpretation accuracy. (Dunn Lopez, Wilkie, Yao, Sousa, Febretti, Stifter, Johnson & Keenan, 2015). There are also multiple ways to convey narrative messages. In addition to testing multiple options of individual features, the evaluation of the CDS system as a whole is also important. Testing one feature using one visual option or narrative option at a time followed by testing the whole system is both time- and resource-consuming and represents a significant barrier to the timely development of effective CDS systems that are needed in today's health care practices.

Methods to accelerate the rapid deployment of CDS are needed to improve care quality. Despite this urgent need, the process of usability testing must follow rigorous methods (Bias, 2011) because conducting tests in a non-systematic way can lead to poor design, implementation failure, or negative consequences for patient care(Han et al., 2005). Given the significant resources needed to create multiple forms of usable and useful CDS systems, and their potential for improving the overall quality of health care, it is critical that the CDS system be developed to deploy in multiple settings. Thus, CDS system testing that is rapid, rigorous, and generalizable must include development of methods for: 1) recruitment of a representative sample; 2) organization, including how to track multiple features of a single function and whole system prototypes as containers of multiple features and their evolution; 3) integration of multiple types of user data, including voice, rapid display changes, and physical movement, through prototypes and 4) establishing usability, usefulness, user satisfaction, and accurate interpretation of single features and the CDS system as a whole.

In this paper, we present our experience in designing and applying evaluation methods for parallel assessment of usability and usefulness of a multi-feature CDS system. We use examples from a study to develop a CDS system for registered nurses (RNs) to improve outcomes for patients at end of life to illustrate how these methods were applied.

DESIGN

Our methods for an EHR-derived CDS system includes four iterative phases: pre-design, design, testing, and analysis. Our testing methods included sampling for generalizability, recruiting representative users, and conducting user interviews with potential future system users. The analytic methods for features and feature combinations included deductive coding and analysis, both of which promote rapid redesign.

Pre-Design Phase

The EHR data used to create our nursing CDS types were extracted from an electronic nursing plan of care documentation system, the Hands-on Automated Nursing Data System (HANDS©), used in over 40,000 hospitalizations (Keenan et al., 2012). The HANDS© database contains variables needed for health outcomes research, including diagnoses, interventions, and outcomes, that are scientifically validated and codified using the American Nurses Association-recognized standardized nursing terminologies: NANDA-International (NANDA-I), (Herdman & Kamitsuru, 2014) Nursing Interventions Classification (NIC),(Bulechek, Butcher, Dochterman, & Wagner, 2012) and Nursing

Outcomes Classification (NOC).(Moorhead, Johnson, Maas, & Swanson, 2012) Data mining and statistical analytic methods were used to extract information from the EHR records that were ready to be "translated" into features suitable for clinician use at point of care.

The process model in Figure 1 depicts the overall "macro-level" method for developing and testing our CDS system (Keenan et al., 2012). The left side of the figure represents the predesign phase. This includes people, structures, content, and processes involved in collection and storage of usable clinical data obtained in prior real-world use of the HANDS© system. The predesign team used a variety of analytic techniques, including data mining algorithms (Al-masalha et al., 2013), to uncover patterns and relationships among nursing diagnoses, interventions, and outcomes. Patterns discovered from the data mining underwent further statistical testing to determine statistical significance.

Design Phase

The design team, depicted on the right side of Figure 1, included health care domain experts and data visualization engineers who worked collaboratively to develop the CDS system features. Their goal was to transform complex analytic findings from our statistical and data mining processes into clear and concise textual, visual, and graphic features that could quickly and accurately convey our evidence derived from EHR data to clinicians. Our strategy was to create 2–4 forms for each CDS system feature. We grouped the features into 3–4 fully interactive prototypes that could perform several CDS systems activities, such as adding, removing and prioritizing interventions.

Prior to testing the CDS system with nurse users, we reviewed an interactive prototype of the CDS system features one-on-one with 2–3 content experts outside the multidisciplinary design team. The benefit of these informal reviews was to expose design and usability weaknesses not evident to the design team members and to elicit alternate design ideas. (Nielsen, 1993a) These in-depth reviews and subsequent discussion generally took approximately 60–90 minutes to complete and often led to design modifications. This step promoted the creation of higher-quality prototypes that were deployed with the volunteer nurse users.

SETTING

We used a small quiet computer lab in a university based college of nursing in an urban areas for the formative testing and development of the CDS.

Testing Phase

SAMPLE—Unlike many EHR features that are customized or developed at the organizational level, (McDonnell et al., 2010) our goals were to create a CDS system that can be used across organizations and be generalizable to a broad group of practicing nurses. To accomplish these goals, we used two recruitment methods to promote inclusion of nurses from multiple institutions and convenience quota sampling. Our first recruitment method involved an e-mail flyer inviting participation sent to all registered nurses (RNs) affiliated with one College of Nursing and two affiliated hospitals. RNs were eligible if they were currently working as a nurse and had prior or current work experience on medical-surgical

hospital units. A $100 honorarium was publicized in the flyer e-mailed to our potential nurse users. This first e-mail resulted in responses from approximately 40 subjects in the first 4 weeks of recruitment. From our initial group of nurse users, we also used a snowball technique (Creswell, 2012) by asking these nurses to share our study recruitment flyer with their friends and co-workers. Both recruitment approaches resulted in responses from nurses from approximately 25 institutions, but only requiring Institutional Review Board approval from the main university.

Eligible nurses who responded to the email invitation or contacted our team based on snowball recruitment methods: completed a screening questionnaire that included (a) age, (b) gender, (c) ethnicity, (d) race, (e) years of experience, (f) highest nursing education level, (g) electronic health record (EHR) system currently using, (h) knowledge of standardized NANDA-I, NIC, and NOC nursing terminology, and (i) current place of employment. Using these categories, we selected eligible nurses from our database to meet our sample quota criteria for each testing iteration.

Because our goal was to create a CDS system that is generalizable to a broad user population (wide range of ethnicities, years of experience, education levels, etc.) practicing nurses, we used quota sampling (Bondmass, 2013; Fouad, Saleh, & Atiya, 2013; Szolnoki & Hoffmann, 2013). Quota sampling is used to reduce bias associated with convenience samples (Bondmass, 2013; Fouad et al., 2013; Szolnoki & Hoffmann, 2013). In order to set the quotas, we used demographic data of the U.S. population of practicing nurses (U.S. Department of Health and Human Services & Administration, 2010) and oversampled underrepresented groups (male and minority nurses) in order to promote representativeness across gender and ethnicities. For example, the national representation of African American nurses is 5 %, (U.S. Department of Health and Human Services & Administration, 2010) so we targeted enrollment of 13% for this group. We also set quotas for other important population attributes (e.g., gender, education, experience, age) to ensure that we adequately captured the diversity within the profession. Given the number of iterations needed to develop and refine a new CDS system, it was both cost- and time-prohibitive to recruit a random stratified sample for each iteration, though randomized sampling might be feasible for the final CDS system testing.

Data Collection

We employed parallel testing of each design of the CDS system feature such that if the feature was to alert a nurse about a potential problem, we would include four different designs of the alert to be tested by each nurse volunteer user. Although somewhat more complex, parallel testing allows researchers to more efficiently determine the most effective design for a particular feature using fewer research subjects than sequential testing. For example (Figure 2), an alert design may include (a) a message with separate “buttons” for actions and rationale information that are accessed using multiple clicks; (b) a single alert “button” with actions and rationale accessed using a single click that displays information together; or (c) the actions may be overlaid directly on the documentation interface without rationale information.

Testing involved two types of user interviews, think-aloud (Nielsen, 1993b) and cognitive interviews (Jha et al., 2010), conducted sequentially over 75–90 minutes. Our interviews were conducted in a university simulation laboratory, separate from each nurse's workplace. For the development of the new CDS system, we chose to use a low-fidelity laboratory that was free from distraction, to engage our users in deeper discussions of their reactions to each feature in the interactive prototypes than might be possible in higher-fidelity laboratories with visual and auditory distractions of real-world hospital environments.

During the first part of the interview, subjects clicked through screens without prompting as they endeavored to interpret the interface cues. Subjects worked through the interface using different navigational styles, including clicking back to earlier viewed screens to reinforce or clarify their emerging understanding of the CDS system. The ability to self-select their own navigational pathway can present a challenge for correct interpretation of audio interview data because a transcribed interview alone would not reveal which feature the subject was commenting on.

To overcome this challenge, our interviews were video- and audio-taped with two synchronous cameras using Morae software (Techsmith). One camera was placed above the computer screen to record the subject's facial expressions, and a second camera embedded with the Morae software recorded the mouse movements, mouse and keyboard input, and the appearance of the prototypes on the computer screen as the subject interacted with them. The audio, video, and computer interaction data were captured digitally and indexed to a single timeline (Techsmith) that could be analyzed immediately following the interview without further data integration efforts.

Our interviews began with a single patient case study shared during a nurse-to-nurse handoff. The interviewer played the role of the off-going nurse, and the nurse user was instructed to play the role of the oncoming nurse. After listening to the handoff information, the nurse users were instructed to read, explore, and interact with CDS systems features in the patient's HANDS© plan of care (POC). Three to four different POC prototypes containing the same handoff scenario-based information but presented with different CDS system features were reviewed and explored by each nurse user. Two elicitation techniques were used with each nurse user during a single interview session. The first part of the interview used the think-aloud technique. Think-aloud interviews involve the users' vocalizing what actions they are taking and the thought process that motivated the action as they are interacting with a product or technology. (Nielsen, 1993b) This interview technique is a simple, well-accepted usability test to elicit users' understanding and misconceptions, to examine expectations, and to identify usability problems. (Makri, Blandford, & Cox, 2011; Rettig, 1994). We discouraged questions and minimized interruptions to their interaction with the prototypes during this part of the interview to facilitate capturing data about where the users encountered problems and troubleshot what to do next. (Nielsen, 1993b) This part of the interview variably took 15–40 minutes per user.

Immediately following the think-aloud interview, we conducted a 20- to 30-minute cognitive interview. This form of interviewing is borrowed from the instrument development field to improve instrument design (Knafl et al., 2007). During our cognitive interviews, the

interviewer assessed the user's understanding and interpretation of the feature content (Jha et al., 2010; Knafl et al., 2007). We specifically asked subjects to verbalize their interpretation of the CDS system text to identify misinterpretations, ambiguities, and poorly worded CDS text. We also systematically, feature-by-feature, probed a user's understanding of the content. This additional interview method was useful to capture interpretations of features that the user may have missed during the think-aloud and to provide additional insights that will contribute to improved wording of the CDS system messages.

We further questioned the users about which features in the prototypes they perceived to be the most valuable to clinicians, as well as which individual features and which collection of features housed in prototypes they preferred for their own use. Finally, time was allotted to answer any questions that the user raised and to solicit suggestions for feature redesign prior to ending the session.

Analytic Phase

Analysis Methods—With overall usability, perceived usefulness, correct interpretation, and subject satisfaction in mind, we developed and applied a deductive coding schema for the interview data to promote comparable data collection across users (Table 1). For each feature, we included a score (positive, negative, and unclear) for four primary categories: (1) ease of use, (2) usefulness, (3) interpretation, and (4) satisfaction. This allowed us to quantify the percent of positive, negative, and unclear experiences that predict technology acceptance. We treated both unclear and negative scores as negative, but found it useful to distinguish between the two categories as we considered whether to modify a feature of which the subject might have had an unclear interpretation, whereas a feature with high negative interpretation scores likely needed to be redesigned.

We used two or three coders for each cycle of data collection; because later cycles contained new iterations of features and messages, we established inter-rater reliability for each cycle (85–96% agreement). During coding, reviewers analyzed the full context of user actions and verbalizations when interacting with each feature. Each specific prototype was coded and given a unique identifier based on the cycle, round, and user interview number. Export of the data into Excel spreadsheets was facilitated by this approach (focusing on coding each feature using the four categories associated with technology acceptance and applying scores of positive, negative, or unclear). We used Excel pivot tables to dynamically control data aggregation, choose aggregation dimensions, and selectively expand portions of interest in the data to focus on specific issues. The aggregated views also supported quantitative comparison of different versions of a prototype, to quickly assess whether a new feature design was more (or less) effective than previous iterations. For instance, aggregating data by interview section along the user identification dimension allowed us to perform a quick assessment of the data quality. Aggregating by feature along the prototype dimension was used to generate a feature "heat map." Heat maps are graphic displays of data using colors that allow for more rapid detection of patterns within the data than can be perceived with displays of numeric values. Heat maps support aggregation along several dimensions (prototype feature, version, score, code category, etc.). For example, in our data we colored positive (correct) interpretations different shades of green (Figure 2). This allowed us to

quickly identify issues with in a long list of specific features with high percentages of negative or unclear scores. Aggregating data by feature along the score dimension provided an overview of score distributions for each feature.

Though our deductive coding method allowed us to compare across subjects and learn which features needed modification for rapid iterations, it did not give us all the insights we needed to help with the redesign, incorporate verbalizations of users' perceived decision support needs, or incorporate useful subject design suggestions. To capture these important insights, our coders listened to and viewed each tape in its entirety, to gather comments that addressed "why" questions (e.g., why the users were confused, not satisfied with a feature, or felt a feature was not useful to clinical practice). These comments were transcribed verbatim, exported into a text file and coded inductively using content analysis procedures (Hsieh & Shannon, 2005). Comments with similar meanings were grouped and given a code, with similar codes aggregated over time into themes that informed future CDS system designs. Because Morae software included a time stamp for each code, we also pinpointed the exact sections of our videos to review, if needed.

Using iterative design and rapid analysis methods allowed us to refine multiple versions much more efficiently. Figure 2 shows the design evolution of a single graphical feature based on analysis of subjects' satisfaction, perceived usability, correct interpretation, and perceived usefulness to practice. In addition to refining features, we were also able to create new features that were responsive to users' suggestions (e.g. suggested patient-specific nursing intervention lists) to improve the usefulness of CDS systems.

Organization Tools

Testing multiple CDS system features comprised of refined messages and designs in parallel presented significant organizational challenges for meaningful analysis. Each cycle consisted of 2 to 3 expert reviews and then two rounds of individual subject interviews with 7 to 8 nurse subjects per round (a total of 15 nurse users). The multiple rounds within cycles allowed iterative redesign of multiple CDS system features and message content up to three times within a cycle. In addition, we continued to refine and test features and message content in subsequent cycles as needed to enhance usability and interpretation, such that features designed in the first cycle could have up to 12 iterations in four cycles of data collection. If feature A had two versions and feature B had two versions within our multiple prototypes, these feature versions were combined differently in each prototype (collection of features that operate together). We learned early on that a subject's interpretation or preference for a single feature did not automatically translate into an understanding or preference for a full prototype. Therefore, it was essential that the versioning of every message and feature be tracked systematically in a format that was easy to access and interpret.

To address these challenges, we developed an interactive feature library, a message library, and a prototype archive. The feature library was a linked visual library with unique identifiers for each version of each feature within a prototype, similarly the message library organized the specific message content of the CDS message iterations. Each message was assigned a number that represented: feature version, prototype number, and cycle. This

allowed tracking over time improvement or deterioration in interpretation. Message content was critically important because incorrectly interpreted messages may lead to poor clinical decisions, which in turn could adversely impact patient outcomes. If a textual message was interpreted incorrectly by more than 20% of participants, we revised the wording and continued testing. Finally, our prototype archive provided an interactive record of how each feature and message were displayed to subjects within each round and cycle of data collection.

Conclusions

In this paper, we present methods developed by our team for the design and rapid usability analysis of CDS systems for nurses. These methods are offered as a set of tools that can be added to an existing CDS system development "toolbox" to promote the rapid evolution of a multiple-feature CDS system derived from standardized EHR nursing data.

It is important to note that, though there are many forms of CDS systems targeted to physicians (e.g., drug-drug interaction, drug dosing), such systems are not widely available for nurses. Future research is needed to determine whether CDS systems will be accepted and incorporated into real-world workflow and lead to better decision-making among nurses. We believe that the methods presented in this paper are applicable to the development of CDS systems that could use the data in EHRs for CDS to promote care quality for multiple professions and patient populations.

IMPLICATIONS FOR NURSING KNOWLEDGE

EHRs, if designed to allow data analysis, have the potential to rapidly advance nursing knowledge about the impact of nursing interventions on patient outcomes. This can only be realized if the EHRs contain standardized nursing terminologies for nursing diagnosis, interventions and outcomes that is analyzable along with design and rigorous usability testing of CDS. While CDS holds great promise to improve nurse decision–making, it also carries potential for harm if CDS are misinterpreted or care is delayed by poorly designed CDS. The methods described in this paper to rapidly and rigorously test multiple CDS features will promote the development of useable, useful and effective nursing CDS.

KNOWLEDGE TRANSLATION

In this era of EHRs, the need for widespread use of standardized nursing terminologies has become more urgent as the primary means to represent nursing decisions and care in an analyzable format. Analysis of EHR standardized nursing data into CDS can directly translate nursing knowledge into practice. To achieve this potential for care transformation, national policies for health data should be expanded to include requirements for nursing standardized terminologies.

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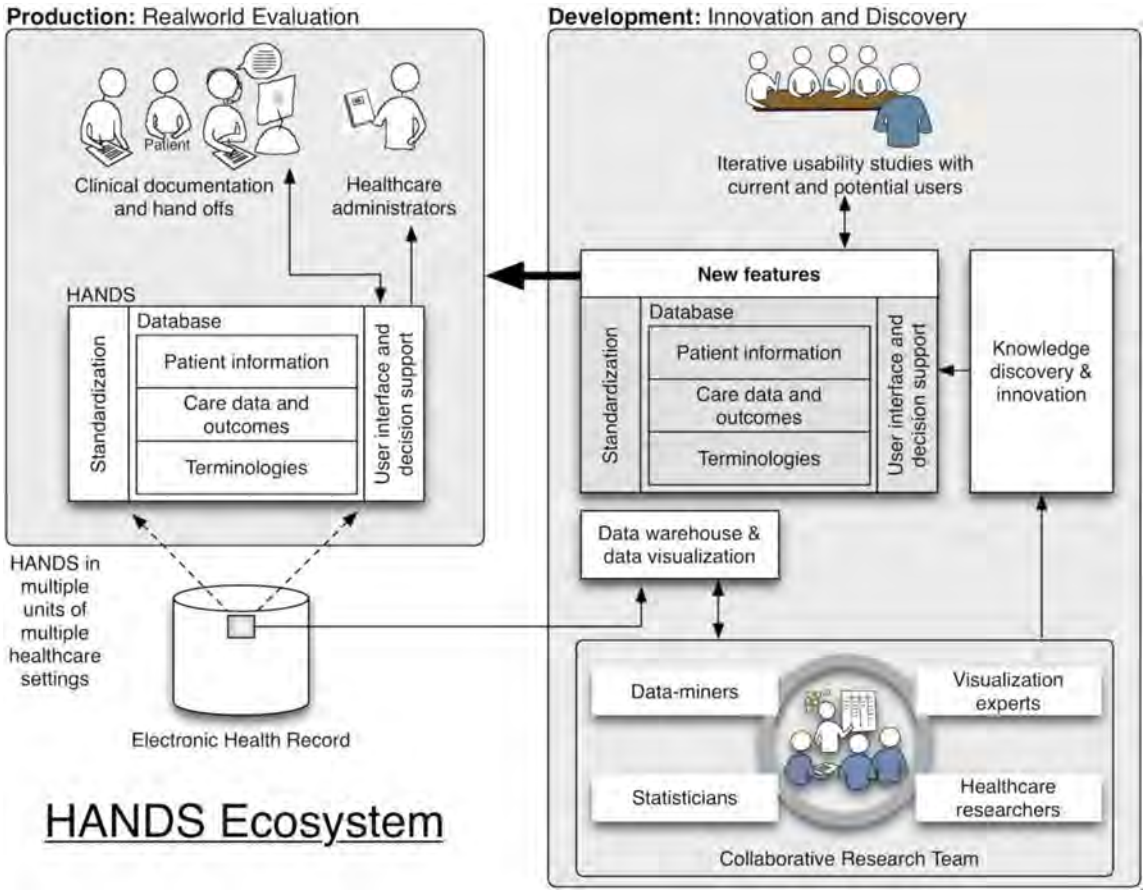

Figure 1. The Hands Ecosystem

The production (left side) represents the predesign phase and development (right side) represents the design phase and the people and processes involved in the usability studies. (Copyright HANDS research Team, 2011)

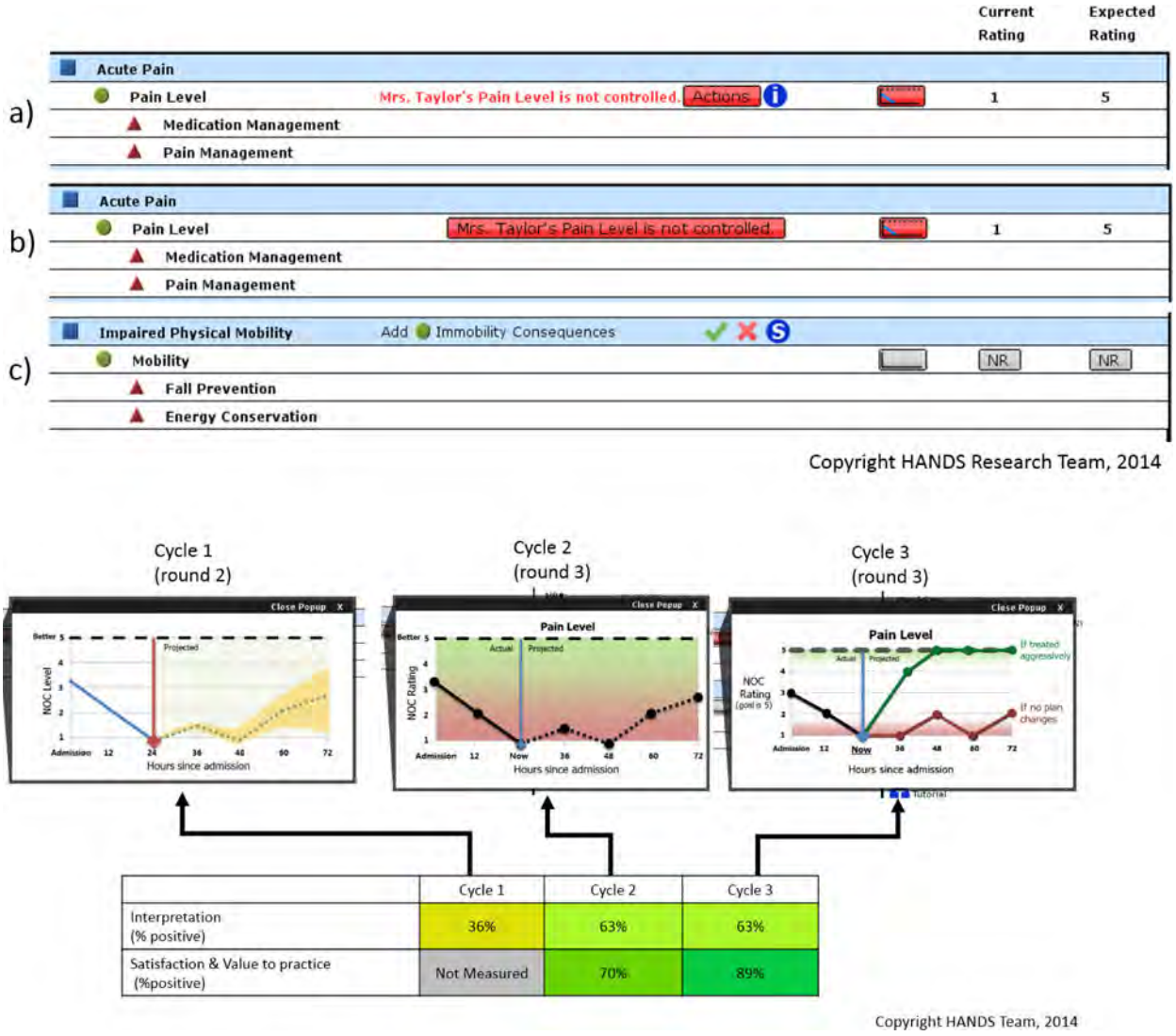

Figure 2.
Alert Features Options and Design Evolution with Heat Map

Table 1

Deductive Coding Schema

Category	Scoring	Definition	Examples
I – Interpretation	0 = correct interpretation 1 = incorrect interpretation 2 = confusion	Does the subject's verbalization of the feature meaning or actions related to use of the feature differ from the design team's intended?	"This red flashing bar means pay attention." "The green check means everything is fine."
U – Usefulness	0 = useful 1 = not useful 2 = neutral	Does the subject verbalize the feature's usefulness to practice?	"It would save me so much time to have the actions listed."
E – Ease of Use	0 = appropriate use 1 = inappropriate use 2 = confusion	Did the feature function and was it used as designed? Must focus on a specific action within the prototype.	Multiple clicking to access; NIC obscured by comment box.
S – Satisfaction	0 = likes 1 = does not like 2 = neutral	Is the feature liked and the preference not related to usefulness to current practice?	"I like that you have a piece of EBI with a corresponding action."