IMPROVING PATIENT SAFETY: INTEGRATING DATA VISUALIZATION AND COMMUNICATION INTO ICU WORKFLOW TO REDUCE COGNITIVE LOAD

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A decade of emerging bedside information-visualization devices and clinical decision-support systems has provided intensive care unit (ICU) clinicians with a range of tools that display and intelligently filter data in ways that support patient diagnosis. There is an absence, however, of research that adequately addresses the need for visualization tools (related to context-sensitive information) that can reduce cognitive strain during decision-making. In response to this issue, Medical Information Visualization Assistant (MIVA) was designed to contextually organize patient longitudinal data with visual-enhancing tools for easy, rapid and more accurate analysis/interpretation of real-time patient data. MIVA was envisioned as an electronic medical record (EMR) visualization dashboard to reduce cognitive load and related diagnostic error. The current design phase will include communication tools to enhance MIVA’s capacity to support ICU team collaboration. In this paper we describe two studies of MIVA that provide insight into its potential as an effective support for clinical work. Quantitative findings show a significant difference in speed and accuracy of MIVA when compared to paper medical charts. Similarly, qualitative outcomes show that participants acknowledge MIVA’s potential to reduce cognitive load, while contributing to a rich social matrix of ICU clinical activity that combines work and information flow.

INTRODUCTION

A hospital’s intensive care unit (ICU) is a complex, data-rich environment that holds critically ill patients and multidisciplinary medical practitioners accessing and interpreting large volumes of data from various sources, both technological (bedside devices, electronic medical records, etc.) and non-technological (paper charts, handwritten notes, etc.) Although ICU patients are the most monitored, tested, and examined of all hospital residents, serious medical conditions and physiological deteriorations are often overlooked (Sutcliffe et al., 2004; Cullen et al., 1997; Patel et al., 2008). ICUs are identified as having the highest annual mortality rate of any hospital unit (12-22%), reaching nearly one-quarter of all admissions (Birkmeyer et al., 2000).

Government and private healthcare entities have noted a critical need for a fundamental redesign of critical care systems, including the expanded use of innovative information visualization systems (iom.edu, 2011). Studies demonstrate that 80% of medical error is attributable to human factors, including cognitive overload, task and workflow management, inadequate team collaboration, and communication breakdown (Winters et al., 2012). Within this 80%, human factors have been linked to the use of bedside visualization systems related to: (1) incorrect use, (2) user error in extracting and analyzing medical data, and (3) poor interface design or interaction sequencing. Studies also point to information loss resulting from workflow interruptions during shift handoffs resulting in cognitive overload and subsequent medical errors (Paas et al., 2003; Nagpal et al., 2012).

While existing ICU bedside device interfaces and electronic medical record (EMR) dashboard interfaces focus on numeric styles, visualization graphics, and color schemes to display patient data (Figure 1, A-D), none address the broader challenges related to (1) their impact on cognitive load (Patel et al., 2015), (2) the transferability of knowledge, and (3) team communication and collaborative work. For instance, the Institute of Medicine (IOM) states that the greatest contributor to cognitive load during data extraction and diagnosis is inadequately designed interfaces of bedside devices (iom.edu, 2011). While other research suggests that team communication failures among clinicians contribute to 91% of medical mishaps (Sutcliffe et al., 2004), largely due to inadequate and inefficient ICU team communication and collaboration, leading to a systemic breakdown of clinical workflow. As such, inadequately designed information visualization systems, as well as breakdowns and disruptions in communication, all add to the complexity of ICU work and information flow.

Moreover, ICU clinicians are inundated (daily) with thousands of independent pieces of information from multiple sources. Patient monitoring in the ICU is labor/time intensive, with cognitive load often exceeding mean expectation. In particular, high “on-call” demands have a tremendous impact on the overall emotional stress and psychological well-being of clinicians, caused primarily from chronic sleep deprivation and extreme and unpredictable workloads. Adding to the complexity of the ICU are the inadequacies of existing health information technology (HIT). Such factors, coupled with alarm fatigue can have a profound impact on the quality of care and patient safety (Bates et al., 2001; Faiola et al., 2012; Blum & Tremper, 2010).

Conversely, HIT that supports ICU distributed clinical intelligence (DCI) (Zins, 2007) could potentially improve the prediction of adverse events and planning courses of action. DCI is a notion suggesting that clinical intelligence is distributed among people and tools as a mutually emergent process of complex problem solving. DCI is further explained as sharable clinical knowledge, often derived from refined clinical experiences of placing unstructured patient data (such as notes, numbers, and diagrams) in meaningful contexts. This knowledge is a driving force for action that gives explicit coherence to rational decisions and the emergence of shared intelligence in the context of clinical work and information flow.
Acquiring, adapting, modifying, and disseminating knowledge provides clinicians with intelligence that is both agile and contextual in coping with unpredictable circumstances. Moreover, the social distribution of knowledge through the use of information visualization tools as a support to decision-making creates a transformative relationship between people and artifacts that impact patient diagnostic outcomes.

Hence, this paper discusses our work in the design and development of an information visualization-communication dashboard, Medical Information Visualization Assistant (MIVA) (Faiola & Hillier, 2014). MIVA offers healthcare practitioners patient data that is intelligently filtered and displayed in ways to enhance diagnosis and team communication as part of a broader clinical work and information flow management system.

Figure 1. Contrary to conventional bedside and EMR displays (illustrated here), without understanding the complexity of work and information flow (and the complex data systems that enable them), designers of visualization systems have been limited in delivering tools that effectively and safely support patient care.

METHODS

The design of MIVA was iterative and spanned over three phases from 2006 to 2014 (Faiola & Hillier 2006; Faiola & Newlon, 2011; Faiola, Srinivas, Karanam, Chartash, & Doebbeling, 2014). See Figure 2. Prior visualization research and elements identified in the context of data delivery from several existing ICU bedside devices formed the basis for the design of static (non-interactive) prototype (phase one). Findings from study one (outlined below) informed the phase two development of a dynamic prototype using Flash Action-Script. Informed by study two (outlined below), phase three included communications tools and a refinement of the icon tray with clinical notes and other longitudinal data tools.

The remainder of this section briefly describes the first two design phases of MIVA, two corresponding empirical studies informing the design process, and a heuristic inspection. Providing greater design details and functionality of MIVA is beyond the scope of this paper.

Figure 2. Static prototype of MIVA interface (1.0) used in study one (Phase 1); Interactive Flash-Based MIVA Interface (2.0) with additional data control tools used for the MIVA study (Phase 2); Current visualization-communication integrated MIVA interface (3.0) that delivers real-time and historic data, with groupware for collaborative clinician teamwork (Phase 3).
Study One. A Comparative study between MIVA (1.0) and conventional paper medical charts

**Design process.** The initial steps to designing MIVA involved discussions centered on several design models based on Tufte’s visualization research (Tufte et al., 1997) and the first known computerized data visualization tool developed by Horn et al. (2001). Two subsequent observational visits to the (Indiana University Riley’s Children’s Hospital) pediatric ICU were made to arrive at a clearer understanding of the complex nature of data accessibility and its interpretation by clinicians. Initial paper prototypes were developed using participatory design methods, followed by evaluative focus groups with medical faculty from the Indiana University School of Medicine and School of Nursing. The focus groups played a significant role in aiding rapid prototyping: helping to identify the placement of data points, size of numeric information, and the location of other biomedical data, tool functionality, and time systems. For instance, a significant component of MIVA designated as the longitudinal data control tool, went through eight iterations of interaction design and analysis. The resulting tool at the end of these iterations led to the completion of initial version of MIVA (1.0). The completion of the first phase of design was followed by an empirical study.

**Participants.** A convenience sample of 12 clinicians that included six physicians and six nurses of mixed gender were recruited from the Indiana University School of Medicine and School of Nursing population. The sample participants were selected due to their easy accessibility and proximity to the researchers. The participants were formed into control and experimental groups of equal number and clinical background, e.g., nurses or physicians. All participants had prior experience in the ICU and or Emergency Room.

**Procedure.** The control group used the paper charts and the experimental group used MIVA (1.0). Both control and experimental groups were provided a five-minute priming session to understand the placement of data on the paper charts and MIVA (1.0) interface. A clinical scenario and corresponding questions were then provided each participant. (See Figure 5 outlining the ICU scenario and sample questions.) Participants responded with answers extracted from their analysis of either the paper charts (Figure 3) or an electronic (static) prototype of MIVA (Figure 2, Phase 1). To arrive at the correct answer, the control group analyzed data extracted from paper medical charts, while the experimental group clicked through the static screens of MIVA 1.0. Two comparative test data points were collected: 1) clinical decision-making related to accuracy and 2) time-on-task related to usability.

**Findings.** Mann-Whitney test using SPSS (v17.0.2) identified the experimental group to be significantly faster in answering two of the eight questions: \( U=7.0, p=.01, r=.66; \) \( U=7.5, p=.01, r=.64 \). The experimental condition tended to be faster than the control condition, although this was not significant across all items. The Chi-squared test identified a significant difference in accuracy between experimental and control groups for question one: \( \chi^2 (1, 16)=6.35, p=.041 \). The experimental group participants were found to respond positively in the post-task survey, with an overall mean score of 3.78 (Likert 1-5), consistent with the acceptance of MIVA in providing a powerful information visualization dashboard and aiding in efficient and effective clinical decision-making. See Figure 4.

**Figure 3.** Paper medical charts used by the control group.

**Figure 4.** Graph of study one shows significant difference in time-on-task between the control and experimental groups. Note significant difference in time-on-task between the experimental and control groups for tasks three and four. Task six was removed from the analysis since each participant from the groups performed tasks incorrectly.

**Figure 5.** Pediatric ICU clinical scenario statement and (three of eight) sample questions used in studies one and two.

PICU Clinical Scenario: A 6-month old infant has undergone repair of an AV Canal. The post-operative course is complicated by pulmonary hypertension, requiring nitric oxide (iNO) to be started on the second postoperative day. On the third postoperative day you are called to the bedside at 14:15 because of an acute deterioration. The bedside nurse states that the patient’s mean arterial pressure (ABP) and mixed venous oxygen saturation (SvO₂) have declined and the mean pulmonary artery pressure (PAP) has increased over the past 15 minutes.

**Scenario Sample Test Questions:**

1. What is the current ventilator (RR)?
2. What is the mixed venous oxygen saturation at 12:00 time did the pulmonary artery pressure begin to increase?
3. When (day and approximate rate (RR)?)
4. A. 16
   B. 18
   C. 24
5. A. 65%
   B. 70%
   C. 80%
6. A. Post op day 1, early afternoon
   B. Post op day 3, late evening
   C. Post op day 3, Noon
7. A. E. 16
   B. E. 18
   C. E. 24

See Figure 4.
Study Two. A Comparative study between MIVA (2.0) and conventional paper medical charts

Design process. Findings from study one informed the design of MIVA 2.0, phase two. Flash ActionScript was used to develop an interactive version of MIVA (2.0). Two key contributions to this phase included: 1) the application of a “time scrubber tool” to control longitudinal data, allowing the user to identify a specific point in time while obtaining readings for all intersecting points at the Y axis (Figure 6) and 2) the dataset tool from which clinicians drag-n-drop the needed dataset parameter into the primary visualization display. Figure 7 shows the drag-n-drop model used to change physiological parameters. The physiological parameter is dragged (Figure 7A) onto the visualization platform to the right (Figure 7B), and the new parameter with its corresponding data populates the visualization platform (Figure 7C).

Following the phase two design process, testing sessions were again conducted, comparing the dynamic prototype of MIVA (2.0) with the same conventional paper medical charts used in study one.

Participants. 12 participants from the same convenient population (but different persons) were recruited to participated in study two. As in study one, the participants were grouped into control and experimental groups of equal numbers and professional backgrounds.

Procedure. A clinical scenario and corresponding questions were used as in study one. The dynamic prototype of MIVA (2.0), which was a SWF file, was rendered for testing on an 11.6” laptop through a web browser. The SWF file had the ability to load sample patient data pre-loaded into the system. To ascertain the correct answer to the eight questions, the control group analyzed data extracted from their paper medical charts, while the experimental group clicked through the necessary menus and controls of the interactive MIVA 2.0 prototype to find and analyze data. Four data points were collected: 1) clinical decision-making accuracy, 2) time-on-task (in min.) usability, 3) context-of-use information through a post-test questionnaire, and 4) close-ended questions and open-ended interviews. Similar to study one, both control and experimental groups were provided a five-minute priming session to understand the placement of data on the paper charts and MIVA (2.0) interface.

Findings. Similar to study one, analysis for study two was performed using SPSS (v21.0). No significant difference in time-on-task was identified between the control (M=1.30, SD=.78) and the experimental groups (M=1.53, SD=.87). However, an independent samples t-test identified that the experimental group participants performed significantly faster than the control group in answering two questions: t(10)=3.11, p=.011, r=.70; t(10)=3.65, p=.004, r=.76. Chi-squared test identified an overall significant difference in accuracy between the experimental and control groups: $\chi^2(1,12)=5.04, p=.03$. Participants noted that MIVA: a) provided added patient data visualization points without the need to review traditional paper charts, b) was consistent with ICU clinical practice, c) provided external representations of activities for clues about ICU team coordination, and d) was a solution to resolve conflicts about interpreting others’ activity (Figure 8).
Study 3. Heuristic inspection of MIVA (2.0)

At the conclusion of study two, a heuristic inspection was conducted to further determine MIVA’s degree of usability.

*Participants.* Three information technology professionals from Indianapolis were recruited to examine the MIVA (2.0) dynamic prototype.

*Procedure.* Five categories of medical heuristics were collated from software and medical design references. See Figure 9 (A - E). Participants inspected and evaluated MIVA (2.0) against these medically relevant heuristics.

*Findings.* The inspection findings suggested no catastrophic errors, but rather that the interface and interaction design of MIVA was well conceived. However, several lower priority improvements were recommended to improve MIVA’s usability, e.g.: (1) the Minutes/Current Data and Date/Time labels must be clarified, (2) the background window of each notation should match the color of that notation’s icon, (3) the background of the current data box should be red if any of the data are out of range, and (4) a pop-up legend should be created, explaining the types of icons. Changes were made immediately or put on the list of items to fix during the next development iteration. See Figure 9.

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### A. Factors Affecting General Usability
1. Keeps display simple and free of clutter
2. Maintains content accuracy
3. Supports content currency
4. Provides orientation cues
5. Supports content accessibility
6. Demonstrates clarity in display of content
7. Provides information sent
8. Supports intuitiveness
9. Grouping is appropriate

### B. Factors Affecting Visibility of Actions and Options
10. Supports user mental model of the system
11. Provides contextual informational "zoom"

### C. Factors Affecting Monitoring of Condition
12. Design reflects clinician cognition
13. Includes appropriate graphics that support / clarify data
14. Graphically condenses data
15. Provides comparisons to references & normal limits
16. Reduces short-term and long-term memory load

### D. Factors Affecting Determination of Diagnosis
17. Provides relevant task information & features to user
18. Displays the level of confidence in information
19. Provides patient data portability and security

### E. Factors Affecting Initiation of a Treatment Plan
20. Eases data entry
21. Supports both overview and details on demand
22. Gives feedback on treatment / diagnosis (task) status
23. Ensures patient safety and care

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**Figure 9.** Using the five categories of medical heuristics, the inspection yielded a summary with the primary areas of error.

**DISCUSSION**

This paper described the design evolution of an ICU EMR (information-visualization) dashboard tool, referred to as MIVA. Two studies and a heuristic inspection were conducted to evaluate MIVA as it advanced over two phases. Participants from both studies noted that MIVA provided a unique analytical perspective and a broader context for real-time ICU experiences, with a rich social matrix of human activity.

Further, there was considerable concurrence among all clinicians that MIVA demonstrated considerable promise as an EMR dashboard system that could impact clinical decision-support and improve work and information flow effectiveness. Notably, 75% of both the control and experimental group participants from study two agreed that current approaches to collecting and presenting ICU critical care data is not sufficient for supporting accurate diagnoses or management of the critically ill. The participants, however, suggested that integrating predictive clinical rules and providing a mechanism for the clinician to customize these to set alerts will lead to better decision support.

One of the participants believed that adhering to clinical practices would help MIVA integrate seamlessly into the current work and information flow (system), providing that MIVA’s visualization paradigm provides a careful balance between being informative and visually distracting. All the participants agreed that MIVA has the potential to change the current clinical practices by emergence of new analyses and reduced time and effort in placing requests for data. It might thus lead to changes in functions of some of the clinical roles.

Limitations of the studies relate primarily to phase one of development of MIVA, i.e., a relatively small sample size, and use of a single clinical problem. As such, the study showed the need to include more advanced computer prototypes, a larger sample size, and a broader range of problems, ideally from several clinical ICU settings that require collaboration with clinicians across teams and physical locations.

Further limitations were also noted by the participants in study two, i.e., a lack of consideration for communication and collaboration between the critical care team members in the ICU. For this reason, communication tools were added in phase three. In support of these recommendations and new design developments, we found that previous research attributed a second major source of workflow error to factors aligned with communication breakdown and team collaboration conflicts (McCaffrey et al., 2010). These findings suggest that 91% of all medical mishaps are due to communication difficulties (e.g., breakdowns, miscommunications) and inefficient team collaboration and decision-making (Cohen et al., 2006). Communication among clinicians, including but not limited to face-to-face interaction, is often interrupted and of poor quality. This leads to inefficiencies and potential error in the ICU, where rapid and accurate communication is essential for delivering safe patient care (Williams et al., 2007). Furthermore, inadequate and inefficient collaboration among nurses and doctors increases the average length of stay of patients, leading to severe inconvenience and greater patient mortality.

Direct verbal communication is one of the chief sources of trust building among ICU clinicians, which fortifies work relationships and cognizance of others’ expertise, leading to increased collaboration (Collins & Currie, 2009). Since nurses and physicians hold significantly different abilities, experiences and expectations of clinical decision-making,
good communication and collaboration between multidisciplinary teams is essential (Maxson et al., 2011). Additionally, it has been found that clinicians using communication technologies improve team relationships, staff satisfaction and patient care (O’Connor et al., 2009). Such technologies can improve communication speed by 92%, communication reliability by 92%, coordination by 88%, reduced staff frustration by 75%, and faster and safer patient care (Silver & Antonow, 2000). Hence, communication among clinical staff should consist of more than face-to-face, but also incorporate the use of synchronous and asynchronous communication technologies (e.g., cell phone, email, text and video conference) in order to optimize and enable bidirectional, rapid, secure, and non-disruptive transmission of content-rich messages and patient data, for purposes of expediting and increasing the accuracy and effectiveness of decision-making (Reader, Flin & Cuthbertson, 2007).

Given the above discussion, MIVA was re-designed to include communication components as shown in Figure 2, phase three, including the: (1) Communication Tool-Set: Consists of communication and collaboration tools for exchanging information about patient status, contacting specialists for diagnostic decisions and emergency management and (2) Clinical Team Network System: Displays the team of clinicians working on the given patient in the network for quick access while using the communication tool-set.

As to future work with MIVA, we are currently executing a comprehensive ICU study in three Indianapolis hospitals. The focus of this study is the next-phase design of MIVA. Details of the study include the need to understand the interoperability of the sociocultural, communication, distributional, and cognitive systems that impact clinical work and information flow. By uncovering ICU error and the affective impact of cognitive load, models will further inform MIVA phase three as a mobile application (for tablet) and its ability to seamlessly integrate with existing EMR, Clinical Physician Order Entry, and communication systems. Also, from these findings, the construction of activity models will comply with IOM recommendations for ICU patient safety and clinical effectiveness and efficiency, including these three measures:

**Keeping ICU patients SAFE from injury and death:**
Information visualization tools should support work and information flow with intuitive interfaces and interaction sequencing, as well as data that are easily transferred among clinicians. ICU workflow should include: (a) the safe use of visualization interfaces that are designed and usability tested and (b) the mitigation of human error, including the effective utilization of visual information that facilitates communication and optimal delivery of clinical data.

**Maintaining EFFECTIVE clinical decision support:**
Work and information flow should be supported by evidence-based medicine drawn from the most accurate and accessible data from bedside information visualization systems. ICU clinical workflow models should provide knowledge that fosters: (a) effective and timely methods of communication and collaboration among clinicians and (b) effective use of visualization systems to support the distribution of clinical intelligence.

**Reducing clinical waste with models that reflect EFFICIENT ICU management and allocation of psychological, physical, and temporal resources:**
To deliver safe and effective care, work and information flow should contribute to the reduction of waste related to clinical resources, including: (a) cognition (e.g., cognitive load, emotional stress), (b) physical fatigue, and (c) time and effort.

**CONCLUSION**

User error in the ICU can be attributed to inadequately designed interfaces and interaction sequencing, which impact cognitive load during diagnosis and caregiving irrespective of using paper charts or electronic displays. Existing visualization systems assist clinicians in analyzing data for multiple parameters. However, such systems do not allow for an immediate recognition of vital sign trends and relationships between co-parameters, while presenting a comprehensive historical representation of other patient data, e.g., lab work, drug compliance, x-rays, clinical notes, etc. Moreover, they do not contribute to mitigating medical mishaps, which are due to inadequate and inefficient ICU team communication.

Moreover, there are 5,724 U.S. hospitals caring for 55,000 ICU patients everyday that are affected by the quality of patient safety. By making available ICU information visualization dashboards (such as MIVA) that aid in clinical decision support, this work could have a significant impact on the greater ICU patient population. As such, we believe millions of ICU patients could be benefited from the transformative science of this strategically designed application by allowing clinicians to overcome the restrictions of data control and physical location.

As to the medical communities impacted by this project, the results will find immediate importance for clinical researchers, physicians, and clinicians specializing in critical care, as well as human-computer interaction scientists increasingly interested in “improving patient outcomes” and the impact of information visualization on clinical work and information flow. In sum, the implication of our work is that a more comprehensive and precise understanding of ICU patient data could significantly improve health and recovery outcomes, while supporting team communication.

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