

Understanding Complex Clinical Decision Tasks for Better Health IT System Design

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1. STRUCTURED ABSTRACT

Purpose: The purpose of this study was to increase the understanding of complexity in clinical decision tasks.

Scope: Understanding the user's interaction with complex decision tasks can lead to the integration of appropriate decision support tools with the electronic health record (EHR) to improve patient safety. **Methods:**

We 1) conducted cognitive task analysis (CTA) interviews; 2) observed clinicians' interactions with complex decision tasks; 3) led the development of the integrated clinical complexity model, including task and patient complexity; 4) identified specific complexity-contributing factors using our model; 5) developed *population information display* by querying a VA clinical database about similar patients; 6) evaluated the visualization display in a pilot study; and 7) used the responses from clinicians to redesign the display. **Results:** Our first study found the cognitive strategies clinicians use to adapt to their information environment and mapped relevant decision support tools. In our second study, using the clinical complexity model, we identified 20 relevant complexity-contributing factors. In our final study, we found that the population information display helped to change 60% of plans positively and that clinical expertise has an effect on how information is processed. **Key Words:** clinical decision support, clinical complexity, population information display.

2. PURPOSE

The widespread adoption of health information technology (IT) by healthcare organizations has mostly been due to the HITECH (The Health Information Technology for Economic and Clinical Health) Act of 2009 [1]. To comply with the act and the criteria set forth by the Office of National Coordinator for meaningful use of health IT, healthcare organizations have focused on implementation within the timeline. Also, health IT design has been more focused on support for billing processes than on better patient safety or improving clinical decision-making. As a result, importance has not been accorded to problems with health IT system design. Poor design and workflow interruptions are causing provider frustrations with and poor adoption of health IT systems. Also, the workflow of a specific organization's socio-technical complexities has largely been ignored [2, 3]. Specifically, most of the systems in healthcare lack user-centered design. Other domains, such as aviation and the military, have adopted user-centered design for better designing their information technology interfaces. In addition to the perils of computerized physician order entry (CPOE) risks identified by Koppel et al., about 81% of health IT events reported in the Pennsylvania Patient Safety study involved medication errors [4]. Most of these errors were related to alert fatigue in decision-support systems. Additional risks include the lack of understanding of clinician preferences for laboratory test results display in electronic health records (EHRs), resulting in the failure of timely follow-up for abnormal test results, which is the third most common EHR-related serious safety event [5, 6]. To address these issues, it is important to understand and design systems based on how users interact with complex decision tasks.

Clinical decision support systems (CDSS) have been shown to improve the quality, safety, and value of healthcare. However, most of the studies demonstrating the benefits of CDSS were done in four healthcare organizations that have homegrown EHR systems and advanced CDSS capabilities [7-9]. Conversely, typical commercial EHR systems, coupled with basic CDSS, have supported primarily low-level reasoning (i.e., drug-drug interaction alerts and preventive reminders). This kind of decision support fails to account for factors that complicate decision-making tasks, resulting in widely reported issues such as alert fatigue and lack of usage uptake. We propose that CDSS should support high-level reasoning, for example, by providing a broad, system-level perspective of the patient and decision alternatives. For example, a visual display supporting high-level reasoning can empower the user to control and customize displays using filtering and retrieval functions to change the aggregation level of patient data from highly detailed to overall summaries [10, 11]. Most studies outside healthcare have found that incorporating decision task complexity in the system design has the potential to improve the quality of decision-making [12]. Therefore, to guide the design of high-level reasoning in CDSS, it is imperative to understand the complex decision-making patterns and factors that contribute to decision task complexity. However, despite substantial prior research on task complexity in other domains, less is known about task complexity in clinical decision-making.

The goals of this study were to 1) investigate clinicians' coping strategies to deal with complexity; 2) identify specific complexity factors to support high-level reasoning; and 3) design, develop, and evaluate a population information display that shows similar complex patients for improved clinical reasoning.

Specific Aims:

Aim 1. Characterize leverage points of complex clinical decision tasks.

Aim 1.A – Conduct Cognitive Task Analysis (CTA) interviews to characterize cognitive strategies to deal with complexity.

Aim 2. Identify factors that contribute to complex decision tasks.

Aim 2.A – Conceptualize an integrated clinical complexity model.

Aim 2.B – Use the complexity-contributing factors from the clinical complexity model to identify specific complexity factors in the infectious diseases (ID) domain.

Aim 3. Design and evaluate a prototypical CDSS that supports high-level reasoning for decision tasks.

Aim 3.A – Design a population information display using similar complex patients.

Aim 3.B – Conduct a pilot simulation study to evaluate the impact of display on clinical reasoning.

Aim 3.C- Redesign the population display based on the qualitative data and iterations.

3. SCOPE

Background:

Complexity refers to the amount of information needed to describe a phenomenon or observation under analysis. The closer the phenomenon is to randomness, the more data are needed until the phenomenon can be described within terms that can be comprehended by the human mind [13]. According to Plesk and Greenhalgh, a complex adaptive system consists of individual agents that are not always predictable and that have actions that are interconnected, and thus the actions of one agent can change the context for another agent [13, 14]. Therefore, the interconnected actions and interactions may provide a better understanding of the complex system to be comprehensible by our minds.

Different domains in medicine deal differently with complexity in patient cases. Thus, the decision-making process cannot be generalized for all areas of medicine. In medicine, the complexity in family medicine may explain the high intra-physician variability in patient management that is observed for general practitioners [15]. Most complex and unique patients do not fit into evidence-based guidelines. However, as we are moving toward evidence-based medicine, it is imperative to define complexity to better support patient care decisions. Physicians and nurses define complexity in patient cases from various perspectives, including task complexity as well as patient complexity. However, researchers have not yet developed a model that describes complexity and decision-making difficulty, especially in the area of infectious disease (ID) where treatment and diagnosis are urgent, and thus an understanding of the complex decision-making process is vital for the safety and quality of outcome for the patient. A group of physicians in the Veterans Administration Medical Center, Birmingham, Alabama, has developed a vector model of complexity. This model takes into account the different forces and their interactions that act on a patient, including biological, socioeconomic, cultural, environmental, and behavioral factors [16]. Still, the model does not focus on explaining the different factors that contribute to task complexity. Grant et al. categorized patient cases into different domains of complexity based on the perceptions of primary care physicians. They were not, however, able to identify characteristics of those domains [17]. De Jonge et al. made a very clear distinction between case and care complexity [18]. However, the issues of understanding the contextual factors of complexity stemming from the interactions between the clinician and tasks they perform have not been well studied.

Context:

Task complexity is well defined in other successful areas of system design, including defense, the humanities, engineering, business, and the social sciences [19-23]. Several studies have found task complexity to be a crucial factor that influences and predicts human behavior and performance. Liu et al. conceptualized decision task complexity in 10 dimensions: size, variety, ambiguity, relationship, variability, unreliability, novelty, incongruity, action complexity, and temporal demand [24]. However, this model has not been applied in the healthcare domain. Our research used these successful approaches from other fields to identify the complexity-contributing factors in clinical decision tasks.

Most CDSS capabilities available in EHR systems (e.g., drug-drug interaction alerts) adopt an oversimplified approach to patient and decision-making tasks. This oversimplification tends to support low-level reasoning, which may lead to problems such as alert fatigue [5, 25]. On the other hand, clinicians reason at higher levels of abstraction. Therefore, the key in decision-support design is to provide the users an overall integrated view without overloading them with information. Systematic reviews have found that an effective CDSS must minimize the effort required by clinicians to process and act on system recommendations [26]. For the sake of a high level of reasoning and better adaptation of CDSS, we need to understand the context of complex decision tasks, the interactions between task attributes, and the complexity-contributing factors of specific decision tasks.

Settings:

The project was coordinated with an experienced multidisciplinary informatics team at the University of Utah and the Salt Lake City Veterans Administration Medical Center. The Institutional Review Board (IRB) of the University of Utah approved the study for both sites.

Participants:

The participants included were infectious disease experts, physicians with different expertise (palliative medicine, geriatric care, and internal medicine), and an ID fellow.

Impact on Health IT:

This project touched on all aspects of a health information technology life cycle (Figure 1). In Aim 1, we investigated the coping strategies clinicians use to deal with the complexity factors for better decision-making. Guided by the findings of Aim 1, in Aim 3 we designed and evaluated a novel information display tool that supports clinicians cognitively to deal with complex clinical tasks. In Aim 2, we developed the first clinical complexity model that includes task complexity and conducted an observational study to identify specific complexity factors (CCF) pertaining to the ID domain. The work done in Aim 2 resulted in identifying specific task complexity factors for better allocation of design for the display in Aim 3. The results and products from this proposal have provided specific decision-support design recommendations that can be used by researchers, designers, vendors, and health IT policy makers for improving patient safety.

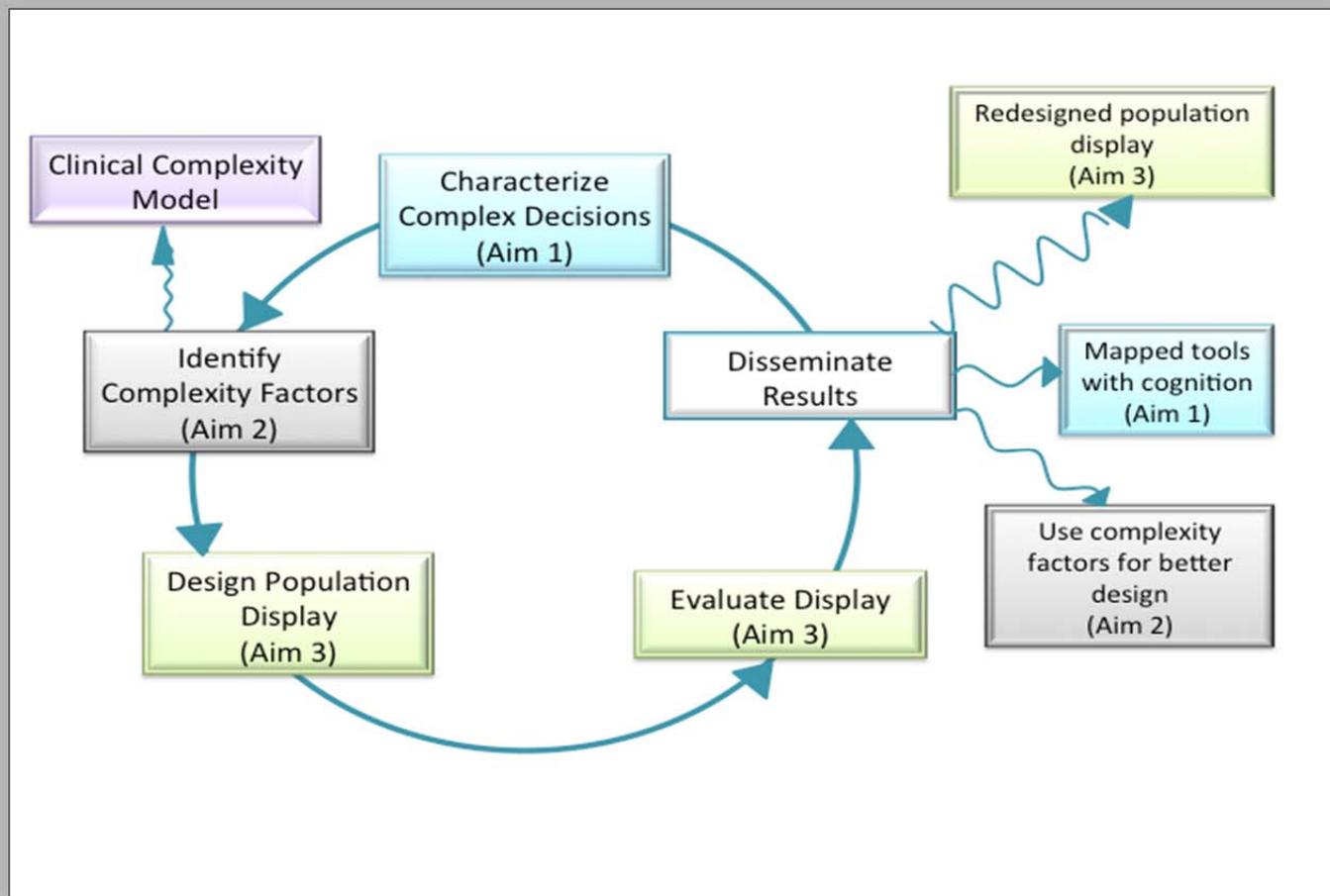


Figure 1 – Health IT innovation life cycle.

4. METHODS

4.1 Aim 1: Characterize leverage points of complex clinical decision tasks

4.1.1 Aim 1.A – Cognitive task analysis interviews to identify cognitive strategies to deal with complexity

Study Design. We conducted semi structured interviews with ID experts using Cognitive Task Analysis (CTA) methodology [27]. CTA is a systematic and scientific method for studying and describing complex reasoning and knowledge that experts use to perform complex tasks [8]. CTA is an effective technique to determine the cognitive skills, strategies, and knowledge required to perform tasks [27]. It is composed of several methods for understanding cognition in natural settings. Previous studies were effective not only in analyzing cognitive challenges but also in eliciting the organizational challenges and environmental ambiguities

of complex, time-pressured, uncertain, and high-risk situations using the technique [28-31]. In this study, we have used “Combinatorics” of CTA, which involved utilizing the Critical Decision Method with critical incident interviews [32-34]. We have used the RATS (Relevance of study question, Appropriateness of qualitative method, Transparency of procedure, and Soundness of interpretive approach) protocol for qualitative data analysis for the transcriptions of the interviews [35]. The RATS protocol provides standardized guidelines for qualitative research methods.

Settings. The study was conducted at the Salt Lake City Veterans Administration Medical Center and the University of Utah Hospital and was approved by the Institutional Review Board (IRB). All participants provided oral informed consent that was approved by the University of Utah central IRB.

Participants. Participants were 10 ID experts who practice at one of the study sites. We defined “clinical expertise in infectious disease” as board certification in ID full-time work for a minimum of five years in a clinical environment, and identification by peers as an expert in the ID domain.

Interventions. Interviews were conducted according to the CDM, a type of CTA [36]. Each ID expert was asked to describe a recent complex case that was challenging in terms of diagnosis and/or treatment. A semi-structured interview script was piloted and refined. The primary author interviewed the participants. At the end of the interviews, participants were asked to provide basic demographic information. The interviews were audio-recorded and transcribed. All identifiers were removed from the transcripts.

Data Analysis. The research team conducted qualitative thematic analysis of the interview narratives [36-38]. The analysis was conducted iteratively, with three of the coauthors (RI, CRW, GDF) independently identifying relevant concepts associated with aspects of complexity, sense-making, cognitive goals, and adaptive strategies. Three researchers conducted the data analysis over multiple sessions. The procedure included detailed and systematic examination of individual interviews and a structured documentation process of coding. Group consensus was sought at the end of each iteration, and the resulting codes were used in the subsequent iterations. Once all transcripts were coded, similar codes were merged based on code frequency and consensus. In turn, codes were consolidated into high-level themes using data-reduction techniques such as category sorting, in which interview segments are grouped according to content similarity [39]. The final step of the data analysis involved the identification of relationships among themes. Interconnected themes emerged from this analysis. Atlas.ti®, a qualitative research software, was used to conduct the data analysis.

Limitations. The CDM relies on clinicians’ memory of previous cases and therefore is prone to recall bias. Also, experts possess tacit knowledge that is difficult to verbalize and articulate [27]. Thus, the CTA method is limited due to knowledge that cannot be verbalized in principle. Also, since the first author conducted the data collections, this researcher may have influenced the way the interview was conducted. To guard against this bias, we piloted and constructed the questionnaire based on the CDM instrument.

4.2 Aim 2: Identify factors that contribute to complex decision tasks

4.2.1 Aim 2.A- Conceptualize an integrated clinical complexity model

Study Design. We used the transcripts of the observational study based on the methods in Aim 2.B to conceptualize an integrated model that includes both patient and task complexity. The settings were two tertiary care hospitals in the United States: the University of Utah Hospital and the Salt Lake City Veterans Administration Medical Center. Observations were conducted with the inpatient ID house staff teams. Our sample size for the observational study was 30 cases over a period of four days. Previous studies have successfully used cases ranging from 16 to 30 [40-42]. Each case observation lasted four days from the initial consultation handed to the ID team. Each clinical team consisted on an ID expert, one ID fellow, a physician’s assistant, and one pharmacy resident. Daily rounds for the entire team were recorded and transcribed.

Procedure. The measurement model was developed by a standardized process to represent and maximize the content domain according to Lynn’s recommendation [43]. Procedures for developing and validating the measurement model were comprised of five steps: 1) Descriptions of initial model revisions, 2) unitizing texts from interview transcripts, 3) expert panel content coding for validation, 4) modification of categories through discussion and assessment of reliability, and 5) iterative recoding and modification of categories.

Data Analysis. The data analysis was based on content analysis [44]. Specifically, we have followed the “emergent coding” process of content analysis [45]. In this process, researchers independently review a subset

of the data and form a checklist for coding. After independently coding, they meet to discuss and reconcile the differences. Once the coding has reached the desired reliability, it is applied to the remainder of the data. Also, we have used the RATS protocol for qualitative data analysis for the transcriptions of the interviews [35]. This protocol provides standardized guidelines for qualitative research methods.

A list of 49 candidate complexity-contributing factors (CCFs) was adapted from the task and patient complexity review by Liu et al. and Schaink et al. [46, 47]. From those, 27 task-related CCFs were identified. Factors not relevant to medical care were removed. In addition, 22 CCFs from the patient complexity perspective were identified. The 49 total CCFs identified from the initial models served as the coding framework for the transcripts from the observational study.

One researcher unitized or parsed the texts to prepare for coding. Each unit consisted of one or more sentences that conveyed one idea. Although content can be unitized in multiple ways, the three investigators reviewed and agreed with the units during the coding process. Fifty unitized sections were used for each iteration. We used ATLAS.ti-7.5 qualitative data analysis software package for unitizing the texts, segmenting the text, attaching the codes to the segments, and merging and combining codes, and for coding and retrieval strategies that facilitated formation of the final codes and the connections between the codes. The other two researchers reviewed the unitized segments for consistency and accuracy. As a result of discussion, codes were merged, deleted, and renamed. This process was repeated four times. For each iteration, the expert panel validated the codes by matching the unitized text with one and only one code. When a text could not be coded, a new category was created and then retested across additional text units.

4.2.2 Aim 2.B - Use the complexity contributing factors from the clinical complexity model to identify specific complexity factors in the infectious diseases domain

Study Design. We conducted an ethnographic study based on observation to prospectively understand the complexity-contributing factors in the ID domain.

Settings. An observational study was conducted in the inpatient ID settings at the University of Utah Hospital and Salt Lake Veterans Administration Medical Center. The University of Utah and VA Salt Lake City Institutional Review Board (IRB) approved the study.

Participants. We observed the rounds of three ID teams. Each team consisted of an ID fellow, one physician assistant and one ID pharmacy resident.

Procedures. Case Selection. Thirty patient cases were observed across the three teams. Each case was observed for four consecutive days. Previous studies have successfully used 16 to 30 cases for conducting similar studies [40-42]. The only inclusion criterion for a case was the referral to the ID team for consultation from the primary care team in the hospital.

Observation Events. The ID physicians contacted the first author when they were ready to do rounds for the patient cases. The rounds were audiotaped and transcribed. All patient identifiers were removed. The transcription and notes were organized for data analysis.

Complexity Ratings. After the rounds on day 1 for each new case, the ID experts were asked to rate the overall perceived complexity based on the criteria explained in Table 1. The four constituents of perceived complexity, i.e., diagnostic uncertainty, perceived difficulty, treatment unpredictability, and similarity, were obtained from the Liu et al. task complexity model [21, 25].

Table 1: Perceived complexity: Definition and questions asked after rounds on day 1

Perceived Complexity	Criteria**	Question
	Diagnostic Uncertainty	How uncertain are you about the diagnosis of this patient? (1=very certain; 7=very uncertain).
	Perceived Difficulty	How difficult does this case seem to you? (1=not difficult; 7=very difficult).
	Treatment Unpredictability	How confident are you about the treatment outcome? (1=very predictable; 7=very unpredictable).
	Case Similarity	How similar is this patient compared with your previous patients? (1=very similar 7=very unique)

**Obtained from the conceptual framework of task complexity by Liu et al. [46]

Data Analysis. A total of 252 pages of transcripts were coded. The first author organized the transcripts according to the sequence of cases and progression of days observed. The first author also unitized the transcripts into one or more sentences that conveyed one idea. Units were then refined through team consensus. Subsequently, two of the authors (CRW and GDF) independently and iteratively coded the unitized sections using the 24 CCFs from the patient and task complexity models. After each coding iteration, the three researchers met for recoding and modification of the categories, selecting one CCF for each unit of text. Cohen's kappa was calculated after each revision of 50 unitized statements. The final inter-rater reliability reached a Cohen's kappa of 0.8. We defined objective complexity for this study based on the coding by the three researchers. The coding frequencies were then correlated with the ratings of the perceived complexity for statistical analysis. We used Atlas.ti 7.0 for coding purposes.

We conducted statistical analysis on the coding frequencies of the CCFs listed in Table 2. First, we organized the data using a data reduction technique. Since the data were collected in their natural setting during routine patient care rounds, with one physician evaluating the complexity of each patient, there were no data available to assess the inter-rater reliability among the physicians. One-way analysis of variance (ANOVA) was used to assess physician effect on average complexity scores. Levene's homogeneity of variance test was used to assess physician effect on the variability of complexity scores. We conducted principal component analysis (PCA) (with varimax rotation) to group the CCFs. The internal consistency of the variables of each factor was determined using Cronbach's alpha. We used linear regression analysis to assess the correlation between perceived complexity and each factor identified in the PCA. We used STATA 13.1 to perform the statistical analysis.

Limitations. The coding of the complexity factors involved the transcription of conversations among ID team members during rounds. However, there are other potential sources of complexity data such as patient-provider interactions, patient-caregiver interactions, and provider-provider interactions regarding patient cases. Capturing these interactions could improve understanding of complexity. Also, the study design was susceptible to observer bias. However, all conversations were recorded, transcribed, and analyzed by three independent reviewers with clinical background. Generalizability may be limited due to the focus on the ID domain. However, as infection is prevalent in most clinical domains, the design recommendations may be generalizable. Further studies are needed to assess CCFs in different clinical domains.

4.3 Aim 3: Design and evaluate a prototypical CDSS that supports high-level reasoning for decision tasks

4.3.1 Aim 3.A. Design a population information display using similar complex patients

First, we designed a complex case pertaining to the ID domain. Then, we identified similar patients based on our complex case. We designed a population information display based on our findings from Aim 1 and Aim 2. We included all the similar complex patients we queried from the VA clinical database. As a result, we found 19 patients from the database who matched the similarity profile of the complex case we designed.

Design Guideline. The two main goals for the design process were the presentation of similar complex patients in one display and support of an "if-then" relationship. The idea behind the information display was to show the aggregated patient information to represent the data and provide a better understanding of certain outcomes for similar patients. The "if-then" heuristics supports the mental model for simple decision logic. We designed the display in such a way that the time-oriented data are graphically displayed for individual patients.

4.3.2 Aim 3.B - Conduct a pilot simulation study to evaluate the impact of display on clinical reasoning

Study Design. The design of the experiment was mixed-methods including 2 between (level of expertise) X 2 within (pre-/post presentation of population-based display) simulation study.

Participants. Ten volunteer physicians participated in the study (five ID experts and five non-ID experts).

Procedures. The participants were first asked to read the patient chart, including patient background information and lab data. Then, they were asked to write down a plan for the case and to rank each item of the plan according to their priorities. After the participants wrote down the ranked plans, they were shown the population display of similar patients. Once they examined the display, they were asked to make modifications to the plan as deemed necessary. The first author observed the mouse movement and noted specific pauses

while participants were looking through the population display. The reasons for the pauses were explored in probing questions by the interviewer. Finally, the first author conducted post study in-depth interviews, probing into each pause to gauge the subject's mental models and asking follow-up questions. An expert panel (EP) consisting of two ID experts and a clinical pharmacist reviewed the case and constructed the criteria for an appropriate plan. All experts had clinical experience greater than 5 years.

Outcome Measures. *Preference for population information display* (qualitative content analysis to find themes for the preferences), *time looking at the population display* (Quick Time player to record the amount of time), *time to read the chart* (Quick Time player to record the amount of time), and *appropriateness of plans* (as judged by expert panel pre-/post presentation of population information display).

Data Analysis. Content analysis and appropriate qualitative methods were used to generate themes for the preferences for population display. We used Atlas ti for coding the post study interviews regarding the preferences for population display. Two researchers (RI and JM) independently reviewed the transcripts and later met face to face to discuss their perceptions for multiple rounds. After several iterations, themes emerged about the clinicians' preferences for ideal population information display.

We conducted quantitative analysis to explore the perceptions for population information displays and the impact of population display on cognitive outcomes. We used a t-test to explore the expertise effect on the perceptions for population information display. We operationalized cognitive outcomes by measuring the percentage of subjects who changed their treatment plans after being exposed to the population display. We used a paired sampled t-test to understand the significance of changed (appropriate versus not appropriate) plans before and after the population information display was shown. We used the t-test to detect expertise effects on reading the chart. The level of significance was set at $\alpha=0.05$ (two-tailed) a priori. A sample size of five in each group makes this analysis exploratory. Previous exploratory pilot studies successfully used 4 to 10 participants for similar study designs [48-50].

4.3.3 Aim 3.C - Redesign the population display based on the qualitative data and iterations

The results from Aim 3.B provided us with rich qualitative data regarding the preferences for population information display design. We applied the findings from the qualitative data and our aims for the final redesign of the display.

5. RESULTS

5.1 Aim 1: Characterize leverage points of complex clinical decision tasks

5.1.1 Aim 1.A – Cognitive task analysis interviews to identify cognitive strategies to deal with complexity

Principal Findings. The following themes were identified from the factors contributing to decision-making complexity: 1) the *overall clinical picture does not match the pattern*, 2) a *lack of comprehension of the situation*, and 3) *dealing with social and emotional pressures*. These themes included several associated factors. For example, the *overall clinical picture does not match pattern* consisted of *unexpected outcome*, *risky patient characteristics*, and *unusual case*. All these factors refer to situations in which the clinical manifestations of the patient do not match the recognized mental pattern of the clinician. This mismatch in the pattern matching may be the reason for increased uncertainty. In naturalistic decision-making (NDM) environments, the human mind looks for patterns that may help individuals select optimal courses of action and predict outcomes [51]. The complexity of the situation seems to be higher when clinicians cannot recognize a pattern that matches the patient's case from their previous experience or training. A *lack of comprehension of the situation* includes the complexity factors of *lack of and/or conflicting indicator data*, *lack of evidence about treatment effectiveness*, *lack of diagnosis*, and *gaps in physician's knowledge*. These factors refer to the scarcity of information with clinical utility, which compromises situational awareness. The last theme of *social and emotional pressures* includes the factors *frustration/regret*, *liability and/or fear*, and *multiple care provider conflict*. These factors contribute to clinicians' anxiety with the decision-making process and the patient's care. Emotions such as anxiety, fear, or conflicts can also positively help clinicians evaluate better treatment options for the patient. Not all fear or anxiety is negative [52]. Fear and anxiety for the betterment of patients can motivate clinicians to improve clinical decision-making.

Five broad themes emerged from the data analysis for the strategies ID clinicians use to deal with complexity: 1) *watchful waiting instead of prescribing antibiotics: less is more*; 2) *theory of mind: projection and simulation of other practitioners' perspectives*; 3) *heuristics: using shortcut mental model to simplify problems*; 4) *anticipatory thinking: planning and re-planning for future events*; and 5) *seeking help: consultation with other experts for their opinions*.

Discussion. Dual process theory (DPT) may provide a framework to interpret the results [53]. The DPT postulates two systems of reasoning: System 1 (automatic, nonanalytic, intuitive) and System 2 (effortful, analytic, abstract and logical thinking) cognitive processes [54][55, 56]. System 2 is activated in situations associated with a high level of novelty and uncertainty, such as when complex patients are encountered. As a result, System 2 imposes significantly higher requirements for attention and cognitive effort than System 1. The cognitive mechanisms identified in this study can be interpreted as reflecting involvement of both System 1 and System 2. In fact, clinicians transition between System 1 and System 2 to efficiently adapt to the environment to deal with complexity. The mechanism of *theory of mind* requires minimal cognitive capacity and therefore is more System 1 than System 2, whereas *anticipatory thinking*, *seeking help*, and *watchful waiting* are more aligned with the System 2 approach due to their effortful nature. Similarly, *heuristics*, which is a more automated process and thus System 1, can help when the *overall clinical picture does not match the pattern* by a short-cut mental model to fit clinicians' patients based on prior experiences [57, 58].

Significance. This is the first cognitive task analysis that has mapped different decision support tools based on the cognitive strategies used by clinicians. This study motivates future research and decision-support designers to employ a similar approach for developing better designs to help with cognition to improve patient safety.

Implications for Decision Support Current and future innovative informatics tools such as patient monitoring, better documentation, better visualization, and population-based decision support embedded in EHR systems can facilitate clinicians' high-level reasoning.

Patient monitoring tools such as therapeutic antibiotic monitors and adverse drug event monitors embedded in the EHR have the potential to support System 2 and reduce experts' mental anxiety in *watchful waiting*. These tools also provide valuable information for *anticipatory thinking* [41, 59, 60]. For example, teleconsultation and monitoring models, such as the ECHO (Extension for Community Healthcare Outcomes) program in New Mexico, include remote patient monitoring features that may guard against or forestall potential future threats [61].

Documenting decision trade-offs can reduce the fear of liability or the *social and emotional pressures* of *watchful waiting*. Also, better documentation tools that convey the rationale to support treatment decisions can make it easy for providers to understand previous decisions and goals to promote the notion of shared cognition, thereby supporting the *theory of mind* theme found in our research. Our results also suggest that supporting cognitive switching between System 1 and System 2 helps clinicians effectively manage complex clinical reasoning. For example, "Smart Forms," a documentation-based clinical decision support system developed at Partners Healthcare, has been shown to improve decision quality and management of patients [62].

Integrated visual displays can provide clinicians with information that matches the *heuristics* or the high-level mental models. In current EHR systems, information is often presented in a fragmented fashion, splitting a single patient record across multiple screens and modules in different formats. The disjointed records, redundancy of information, and sheer volume of shifting data in multiple displays add a significant challenge to clinicians' sense-making process [63-67]. Integrated displays automatically retrieve and process information from disparate modules within the EHR to provide information overview, while preserving the option of in-depth exploration on demand [68-70].

Also, population-based decision support embedded in EHR systems has the potential to support System 2 with cognitive support for *seeking help* and *watchful waiting* [71]. Cognitive support to clinicians refers to maximizing clinicians' cognitive abilities to improve clinical reasoning and decision-making with the aid of information technology [72].

Implications for Practice. The results of this study suggest a way to rework the paradigm of evidence-based medicine to enhance management of complex clinical tasks. Practice guidelines derived from reviews of evidence typically assume that an experienced clinician is making an assessment of the patient, which is to say that leeway for clinical judgment is allowed. However, when guidelines are incorporated into clinical decision-support systems, the usual focus is to induce clinicians to accept rule-based recommendations. The role of judgment may be acknowledged, but resources are not made available to aid clinicians in reasoning

through complex problems. Our hypothesis is that decision-support systems should be matched to the cognitive mechanisms that clinicians use when managing complex patients. Information displays should facilitate exploration of what-if scenarios in order to improve anticipatory thinking. Better framing of the decision space would help clinicians search for appropriate heuristics and gain confidence from the experience of other clinicians.

Implications for Research. Overuse of antibiotics has been a concern with respect to drug resistance and public health [73, 74]. The notion that doing less in medicine sometimes can mean more has been an important discussion in the ID community [75-77]. More research is needed for innovative decision-support systems that can help clinicians by easing the social pressure that results from the active decision to not prescribe antibiotics.

Conclusions. The cognitive factors that may contribute to decision complexity include 1) *overall clinical picture does not match the pattern*, 2) *lack of comprehension of the situation*, and 3) *social and emotional pressures*. ID experts use the following mechanisms to deal with decision complexity: 1) *watchful waiting instead of prescribing antibiotics: less is more*; 2) *theory of mind: projection and simulation of other practitioners' perspectives*; 3) *heuristics: using shortcut mental models to simplify problems*; 4) *anticipatory thinking: planning and re-planning for future events*; and 5) *seeking help: consultation with other experts for their opinions*. Future and innovative decision support tools in the EHR may facilitate the cognitive switching from System 1 to System 2 to match experts' high-level reasoning. CDSS and EHR designers can incorporate the cognitive mechanisms found in our study to inform the design of innovative solutions.

5.2 Identify factors that contribute to complex decision tasks

5.2.1 Aim 2.A- Conceptualize an integrated clinical complexity model

Principal Findings. Overall, of the 49 CCFs, 13 task CCFs and 11 patient CCFs were identified as relevant to healthcare. Detailed descriptions of each CCF are in Table 1. A total of six CCFs (five patient CCF and one task CCF) remained unchanged from the initial 49 CCFs including *polypharmacy, addictions/substance abuse, older age, heavy utilization of healthcare resources, difficulty with healthcare system navigation and time pressure*.

Significance. Complex patients lead to information overload and decision uncertainty even for expert clinicians [24, 29, 78-80]. As a result, clinicians tend to overlook important information cues, resulting in diagnostic and therapeutic errors [81-86]. Understanding the factors underlying complex clinical decision-making can be used to guide future EHR and clinical decision-support designers. For example, if unclear goals are more prominent in the first few days of inpatient admissions, then decision-support design should incorporate a goal-directed and task-centered approach. This approach provides a shared sense of situation awareness among team members. Thus, by adopting such an approach, system designers can help mitigate communication errors and improve clinical workflow efficiency. Goal-directed task analysis, when incorporated into visual interface design, has shown to improve group decision-making in other domains, such as aviation and the military [87-89]. The complexity factors that are identified for certain domains using this measurement model may help guide the design of EHR functionality to help clinicians cope with complexity.

Implications. Most complex patients do not fall under simple guidelines due to issues such as multi-morbidity and chronic conditions. Recent estimates indicate that more than 75 million persons in the United States have two or more concurrent chronic conditions [90]. Moreover, the aging population will contribute to increasing the complexity of patient presentations. Thus, managing these complex patients requires extra effort for the clinicians from both healthcare and non-healthcare resources. On the other hand, the standard quality of measures in the study population often excludes complex patients and thus applying inappropriate quality measures can be a distraction for clinicians while taking care of the unmet, high-priority needs of complex patients [91-93]. As a result, clinicians have the option to select healthier patients and may reject the chronic complex patients if not properly incentivized [94]. Therefore, a model to objectively measure clinical complexity may be necessary in the coming era of pay-for-performance.

Conclusion. This study proposes a systematic understanding of complexity in medicine. The resulting clinical complexity model consists of 24 clinical complexity-contributing factors, including both patient and task factors, organized into 12 dimensions. The model can help researchers in academia and industry develop and evaluate healthcare systems. Also, the proposed model can be useful for system design, task design, work

organization, human-system interaction, human performance and behavior, system safety, and many other applications.

Table 2: Complexity-contributing factors in the clinical complexity model

Task Complexity-Contributing Factors	Patient Complexity-Contributing Factors
Unclear goals	Poly-pharmacy
Large number of goals	Significant physical illness
Conflicting goals	Mental anxiety
Confusing information	Psychological illness
Unnecessary information	Addiction/substance abuse
Changing information	Older age
Urgent information	Health disparity
Multiple decision-making options	Noncompliant patient
Large number of decision steps	Poverty and low social support
Decision conflict	Heavy utilization of healthcare resources
Lack of expertise	Difficulty with healthcare system navigation
Lack of team coordination	
Time pressure	

5.2.2 Aim 2.B - Use the complexity contributing factors from the clinical complexity model to identify specific complexity factors in the infectious diseases domain

Principal Findings. After the final iteration, 20 CCFs (13 task and 7 patient CCFs) emerged. The principal components factor analysis resulted in three factors (eigenvalue>2.0) that explained over 47% of the total pooled variance (Table 3). The internal consistency (Cronbach's alpha) among Factors 1, 2, and 3 was, respectively, 0.87, 0.67, and 0.55. These factors explain, respectively, 26%, 11%, and 10% of the overall variance.

We found no physician effect on ratings of perceived complexity. The one-way analysis of variance showed no significant difference in means of perceived complexity scores among the three physicians (means of three physicians' scores: 3.6, 3.2, 4.0; $p = .33$). Similarly, the Levene's test of homogeneity of variance showed no significant difference in the variability of perceived complexity scores between the three physicians (standard deviations of three physicians' scores: 1.2, 1.2, 1.4; $p = .94$).

Perceived complexity ratings ranged from 6 to 26, and the average across all patients was 14.3 (SD=5.1). A perceived complexity scale summing the four items was created. The Cronbach's alpha for internal consistency of the scale was 0.76. These results show that the four items were correlated strongly with each other and are important constituents of perceived complexity. The regression analysis showed that the relationship between objective and perceived complexity was not significant (multiple R-squared=0.13; $p=0.61$).

Discussion. In this study, we aimed to identify the factors that contribute to complexity within the ID domain and to assess the relationship between objective and physicians' perceived complexity. Previous studies on complexity in healthcare did not consider task CCFs. The main contribution of this study is the finding that task complexity significantly contributes to overall complexity, explaining 26% of the variance in the complexity model. Also, we have used the clinical complexity model to identify the specific complexity factors relevant in the ID domain.

The three dimensions, i.e., *task interaction and goals*, *urgency and acuity*, and *psychosocial behavior*, contain 20 CCFs. Our results indicate that perceived complexity factors were not correlated with objective complexity factors. This finding suggests that physicians may consider other factors for assessing decision-making complexity beyond the objective factors included in the study. Our results regarding patient CCFs resonate with previous studies that identified patient-specific CCFs, such as frailty and psychosocial behaviors [15, 24, 47, 80, 95]. Other studies focused on assessing clinicians' perceived complexity found similar patient complexity factors [17, 29, 96].

Significance. This study demonstrated that it is possible to extract specific complexity contributing factors in the clinical domain. These complexity factors can provide design and task allocation recommendation for decision support design.

Implications for Design. The factors found through factor analysis (i.e., *task interactions and goals*, *urgency and acuity*, and *psychosocial behavior*) can benefit future researchers and health IT system designers. Decision-support tools such as integrated visual display, better documentation tools, InfoButtons, task visualization of clinical workflow, connected patient health records (PHR), specialized decision-support tools designed to manage unique and chronic patients, and informatics tools using machine learning algorithms may have the potential to help clinicians cope with the CCFs found in this study.

Providing an integrated visualization of the overall patient situation may help reduce task complexity factors such as *unclear goals* and *unnecessary information*. A visual analytic display that provides an overview of the patient status while enabling exploration of details on demand can help clinicians focus on the right information and prioritize goals.

Better documentation tools can enhance communication through shared cognition and thus may reduce *lack of team coordination*. Conflict arises when trade-offs are not clear or the correct choice cannot be determined. Thus, clinicians may also use documentation tools to document the rationale supporting their decisions and trade-offs and thus reduce complexity factors such as *conflicting goals* and *decision conflicts* [62, 67].

Clinicians often raise information needs when managing their patients that could be met with online evidence resources [97, 98]. Yet, barriers compromise the efficient use of these resources. Tools such as InfoButtons have been demonstrated to be effective in helping clinicians find evidence at the point of care [99, 100]. Seamless access to evidence-based information at the point of care can reduce cognitive overload associated with information seeking and reduce the *confusing information* factor. Also, access to evidence-based information may address physicians' knowledge gaps, reducing the *lack of expertise* factor.

Task visualization in clinical workflows may reduce complexity factors related to the size of the tasks such as *large number of goals*, *multiple decision-making options*, and *large number of decision steps*. Workflow fragmentation assessment, pattern recognition, and task flow visualization may support prioritization of tasks in acute situations and help reduce complexity caused by *urgent information*, *changing information*, and *time pressure*. Clinical task visualization can reduce communication problems between teams and improve the distributed shared cognition.

Personal health record (PHR) systems, tethered to the EHR, have the potential to reduce the complexity associated with patient factors such as *noncompliant patient* and *poverty and low social support*. PHRs integrated with EHRs may reduce communication gaps between patients and providers and improve clinicians' understanding of the patient's social and compliance issues.

Specialized decision support tools such as medical dosing for patients with renal impairment and for older patients can help clinicians cope with the complexity associated with *significant physical illness*, *older age*, and *heavy utilization of healthcare*.

Innovative interventions that use data extracted from social media also have the potential to reduce complexity factors such as *mental anxiety and psychological illness*.

Conclusions. In this observational study in the ID domain, we found that task complexity contributes significantly to overall complexity. Thus, future research on complexity in healthcare should include task complexity factors. Our results suggest that objective CCFs are not predictors of complexity as perceived by clinicians. Thus, clinicians may consider other unknown factors in their assessment of complexity. Future studies are needed to elicit these factors. The CCFs identified in our study may be used to guide the design of health IT to provide better cognitive support.

5.3 Aim 3: Design and evaluate a prototypical CDSS that supports high-level reasoning for decision tasks

5.3.1 Aim 3.A. Design a population information display using similar complex patients

Outcome: Figure 2 shows a screen shot of the display that we have designed.

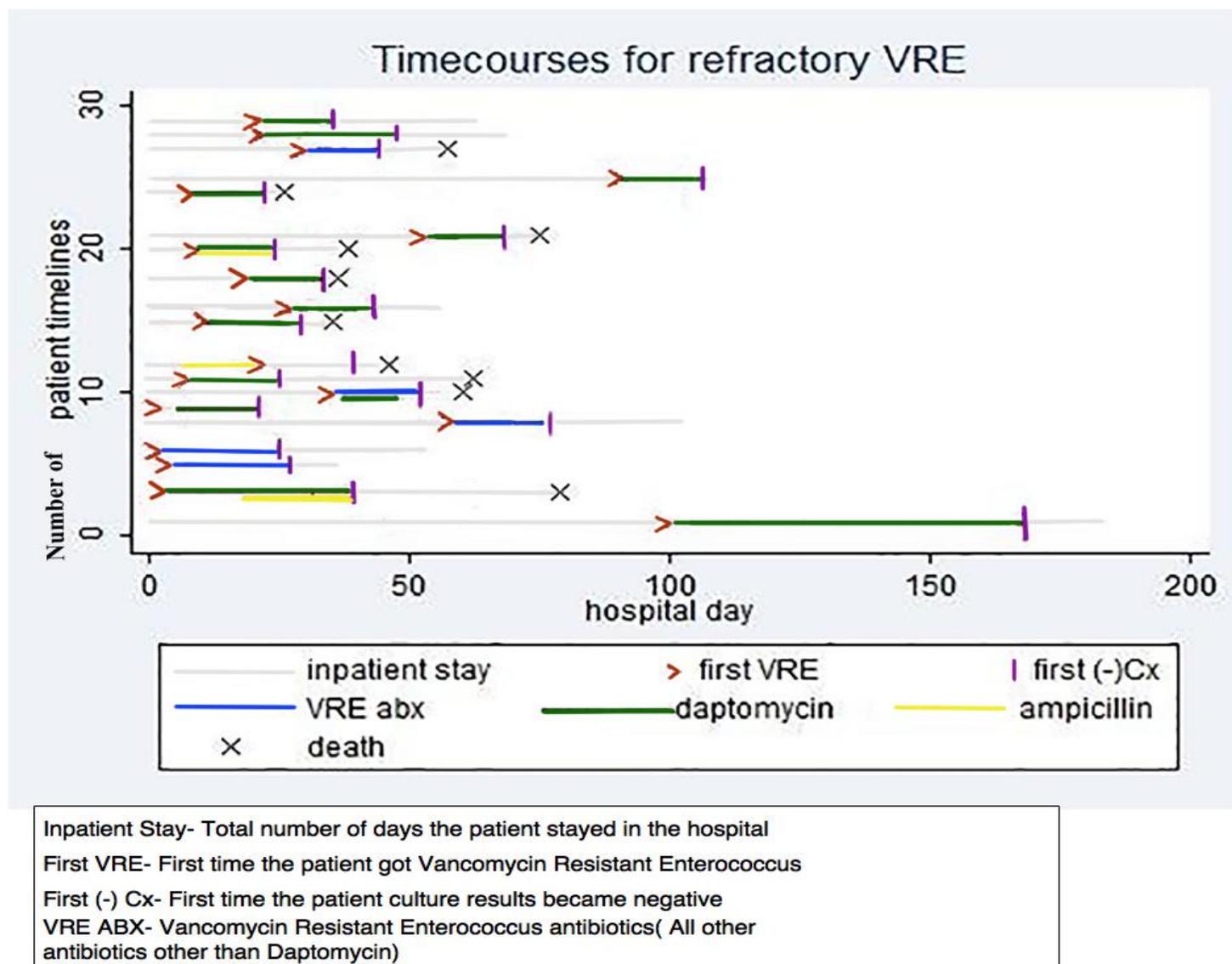


Figure 2: Population information display

5.3.2 Aim 3.B - Conduct a pilot simulation study to evaluate the impact of display on clinical reasoning

Principal Findings. The content analysis revealed the following four themes that emerged as preferences for population information display: 1) trusting population data can be an issue, 2) embedded analytics is necessary to explore patient similarities providers would like to understand more about the similarities, 3) tools are needed to control the view (overview, zoom, and filter) and 4) different presentations of the population display can be beneficial.

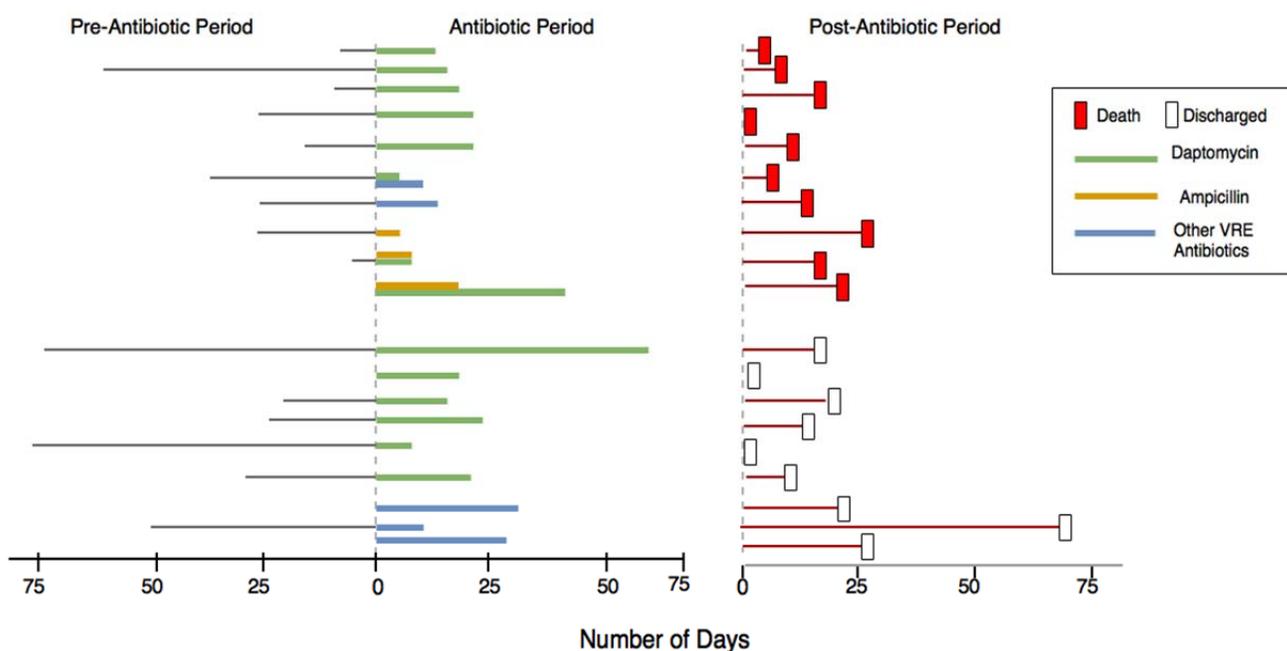
Viewing time for the population graph did differ ($t_8 = 2.3, p = 0.04$) between groups, with experts taking significantly less time than nonexperts (2.3 ± 0.86 minutes versus 3.636 ± 0.91 minutes, respectively). Clinicians' appropriateness of plans (cognitive outcomes) was relatively low (60% of plans being appropriate) and not statistically significant ($t_9 = -1.9; p = 0.08$). For the expert group, the average time to read the chart was 4.9 ± 0.48

minutes and for the nonexpert group 5.5 ± 0.79 minutes. This difference was also not significant ($t_6 = -1.3, p = 0.22$).

Discussion. In this study, we have successfully used an actual clinical database to extract information from patients who are similar to the complex simulated case and designed a population information display. We have used ICD-9 CM codes to find similar patients from the VA clinical database and displayed the information in a single display. Extracting similar patients is difficult and would depend on the size of the database and the efficacy of the search tools. The parameters chosen for extraction may be the key to finding the desired outcome from similar patients' profiles for better cognitive support. Further work is needed to make such queries automatic and efficient, but first, we needed to know if providing that information makes a difference in decision-making and what preferences users might have. We found that the display did have a marginal effect on the quality of the plan in pre-/post assessments. We also found that experts processed the population-based information faster than nonexperts, giving validity to the display content.

5.3.3 Aim 3.C - Redesign the population display based on the qualitative data and iterations

Outcome. The improved design is in Figure 3.



Summary

	Daptomycin 	Other than Daptomycin 	% Total
Died 	8	2	52%
Did not die 	6	3	48%
% Total	74%	26%	

Figure 3: Redesigned population-based information display. Each line represents a patient who was treated with Daptomycin, Ampicillin, or Other Vancomycin-Resistant Enterococcus (VRE) antibiotics such as Linezolid, Tigecycline, Synercid, Gentamycin, or Streptomycin. These patients were found from querying the VA clinical database. The guidelines for VRE neutropenic patients mandate Daptomycin use. The display provides outcome information for patients who were treated with Daptomycin, Ampicillin, and other VRE antibiotics.

6. LIST OF PUBLICATIONS AND PRODUCTS

6.1. Publications

1. Islam R, Weir CR, Del Fiol G. Clinical complexity in medicine: a measurement model of task and patient complexity. *Methods Inf Med* 2015. <http://dx.doi.org/10.3414/ME15-01-0031>
2. Islam R, Weir CR, Del Fiol G. Heuristics in managing complex clinical decision tasks in experts' decision making. *IEEE Healthcare Inform (ICHI)* Sep 2014; 186-193. DOI: 10.1109/ICHI.2014.32
3. Islam R, Weir CR, Jones M, Del Fiol G, Samore MW. Understanding complex clinical reasoning in infectious diseases for better electronic health record cognitive support. *BMC Med Inform and Decis Making* 2015. Online only publication, DOI: 10.1186/s12911-015-0221-z
4. Islam R, Weir CR, Del Fiol G, et al. Role of population decision support in complex clinical reasoning: system design perspective. *Health Inform J* (Under review)
5. Islam R, Weir CR, Samore MW, et al., Identifying complexity in infectious diseases domain for healthcare information technology system design and better cognitive support. *Int J Med Inform* . (Under review)
6. Islam R, Mayer JM, Clutter J. Supporting novice clinician's cognitive strategies: a system design perspective. *IEEE Int Conference on Biomed and Health Inform*. (Under review)
7. Islam R, Del Fiol G, Mayer JM, et al. Feasibility of population health analytics and data visualization for decision support in the infectious diseases domain: a pilot simulation study. *J Biomed Inform* (In preparation)
8. Islam R, Weir C, Del Fiol G, et al. Implication of heuristics in health information technology system design. *J Am Med Inform*. (In preparation)

6.2. Professional Poster Presentation:

1. Islam R, Weir CR, Del Fiol G. Heuristics in dealing with complex clinical decision tasks: a pilot study. Poster presentation at National Library of Medicine Conference in July 2014. Bethesda, MD.
2. Islam R, Hurdle JH, Weir CR, et al. Heuristics in managing complex clinical decision tasks. Poster presentation at IEEE Conference on Healthcare Informatics in Sept. 2014. Verona, Italy.

6.3. Professional Presentations:

1. Understanding complex clinical decision tasks for a better health IT system design, presented in the doctoral consortium at **IEEE Conference on Healthcare Informatics (ICHI)**, Verona, Italy in Sept. 2014
2. Understanding complex clinical decision tasks for a better health IT system design, presented in front of audience at the **University of Minnesota**, Twin Cities, MN, in Feb. 2015
3. Understanding complex clinical decision tasks for a better health IT system design, presented in front of audience at the **University of Nebraska**, Omaha, NE, in April 2015
4. Understanding complex clinical decision tasks for a better health IT system design, presented in front of audience at the **Houston VA Medical Center**, Houston, TX, in May 2015
5. Understanding complex clinical decision tasks for a better health IT system design, presented in front of audience at the **University of Pittsburg**, Pittsburg, PA, in June 2015
6. Understanding complex clinical decision tasks for a better health IT system design, presented in the doctoral defense at the **University of Utah**, Salt Lake City, UT, in July 2015