UNDERSTANDING COMPLEX CINICAL DECISION TASKS FOR BETTER HEALTH INFORMATION TECHNOLOGY SYSTEM DESIGN

by

Roosan Islam

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STATEMENT OF DISSERTATION APPROVAL

The dissertation of **Roosan Islam**

has been approved by the following supervisory committee members:

Guilherme Del Fiol	, Chair	**10/09/2015** Date Approved
John Hurdle	, Member	Date Approved
Charlene Weir	, Member	**10/12/2015** Date Approved
Matthew Samore	, Member	**10/08/2015** Date Approved
Yarden Livnat	, Member	**10/12/2015** Date Approved

and by **Wendy Chapman**, Chair/Dean of

the Department/College/School of **Biomedical Informatics**

and by David B. Kieda, Dean of The Graduate School.

ABSTRACT

Clinical decision support systems (CDSS) and electronic health records (EHR) have been widely adopted but do not support a high level of reasoning for the clinician. As a result, workflow incongruity and provider frustrations lead to more errors in reasoning. Other successful fields such as defense, aviation, and the military have used task complexity as a key factor in decision support system development. Task complexity arises during the interaction of the user and the tasks. Therefore, in this dissertation I have utilized different human factor methods to explore task complexity factors to understand their utility in health information technology system design.

The first study addresses the question of generalizing complexity through a clinical complexity model. In this study, we integrated and validated a patient and task complexity model into a clinical complexity model tailored towards healthcare to serve as the initial framework for data analysis in our subsequent studies.

The second study addresses the question of the coping strategies of infectious disease (ID) clinicians while dealing with complex decision tasks. The study concluded that clinicians use multiple cognitive strategies that help them to switch between automatic cognitive processes and analytical processes.

The third study identified the complexity contributing factors from the transcripts of the observations conducted in the ID domain. The clinical complexity model developed in the first study guided the research for identifying the prominent complexity

factors to recommend innovative healthcare technology system design.

The fourth study, a pilot exploratory study, demonstrated the feasibility of developing a population information display from querying real complex patient information from an actual clinical database as well as identifying the ideal features of population information display.

In summary, this dissertation adds to the knowledge about how clinicians adapt their information environment to deal with complexity. First, it contributes by developing a clinical complexity model that integrates both patient and task complexity. Second, it provides specific design recommendations for future innovative health information technology systems. Last, this dissertation also suggests that understanding task complexity in the healthcare team domain may help to better design of interface system.

To my parents, Nurul Islam and Rokeya Islam

my brothers, Rijwane and Roomman

my sister in Law, Sanjida Khair

my nephews Areeb and Neil, and many more to come

and

my wife, Mumtahena Roosan

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CHAPTER 1

INTRODUCTION

Objectives and Research Questions

The overall goal of this dissertation is to increase the understanding of complexity in clinical decision tasks. Complexity of a system is defined as the amount of information needed to describe its behavior [1]. Complexity also includes cognitive complexity, which focuses on the contents of the information flowing, and relational complexity, the relevant information flow among agents [2]. Also, any measure of complexity must be accounted for by the range of inputs and variations of personal traits of the task performer [3]. Therefore, the agent's interactions with the tasks and goals are key to understanding the complexity of the domain. For the clinical domain, comprehension of overall complexity depends on an understanding of the clinician's interactions with task complexity as well as the complexity of patient care. The main hypothesis of this study is that understanding the user's interaction with complex decision tasks may lead to the integration of decision support tools with the electronic health record (EHR) to improve patient safety. For our studies, we explored how clinical experts interact with complex tasks to better understand the aspects of task complexity.

First, we have conceptualized and validated a clinical complexity model (Chapter 3) that includes both the patient and task complexity variables. This clinical complexity model also helped us to explore and identify complexity-contributing factors in the ID domain (Chapter 5). Then, we conducted three studies to answer the following research questions:

1. What are the specific constituents of complexity and the coping strategies for dealing with the complexity in the infectious diseases (ID) domain (Chapter 4)?
2. What specific complexity-contributing factors are relevant in the ID domain, and what is their relationship to perceived complexity (Chapter 5)?
3. Is it feasible to extract and display population-based information from a clinical database to support complex decision-making (Chapter 6)? What design features of population display may help with complex clinical decision-making?

Rationale for Analysis

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 [4]. To comply with the act and the criteria set forth by the Office of National Coordinator (ONC) 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 rather than on better patient safety or improving clinical decision-making. As a result, importance has not been accorded to issues 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 [5]. Specifically, most of the systems in healthcare lack user-centered design. Other domains, such as aviation and 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. [6], about 81% of health information technology events reported in the Pennsylvania Patient Safety study involved medication errors. 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 [7]. To address these issues, it is important to understand how users interact with complex tasks and design systems based on the findings of users' interactions with task complexity [8, 9].

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 electronic health record (EHR) systems and advanced CDSS capabilities [10]. 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 [11-13]. We propose that CDSS should support high-level reasoning, for example, by providing a broad, system-level perspective of the patient and decision alternatives [14]. 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 [15]. 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 [8, 16, 17]. 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 [14, 18-20].

In this dissertation, we propose that the study results will help guide the design and allocation of innovative decision support tools to be embedded into the EHR or CDSS for better cognitive support. In Chapter 3, we develop the first clinical complexity model that includes both the task and patient complexity-contributing factors that guided our research to identify specific complexity-contributing factors in the ID domain. The specific coping strategies found in the cognitive task analysis (Chapter 4), the domain-specific, complexity-contributing factors found in the observation study (Chapter 5), and the feasibility of designing a population information display and identifying ideal features (Chapter 6) provide a better understanding for innovative healthcare system design.

Our research was guided by a theoretical framework of task complexity developed in other successful fields and proposed by Liu et al. and Schaink et al. [21] [22]. The framework conceptualizes 10 dimensions of task complexity, including size, ambiguity, and novelty. The research was conducted in the domain of ID due to its dynamic complexity and importance for public health [23].

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.

Significant Contributions

The dissertation provides a better understanding of task complexity for intuitive and improved healthcare information technology system design.

In the first study (Chapter 3), we developed a clinical complexity model from the task complexity framework proposed by Liu et al. and the patient complexity framework of Schaink et al. [21, 22]. Other domains of medicine can use this measurement model to identify domain-specific, complexity-contributing factors. Such complexity-contributing factors, once identified, can then help researchers and designers focus on these factors for better task allocation in the interface system or better usability.

The constituents of complexity and the coping strategies in the second study (Chapter 4) provided the basis for a mental model of experts' clinical complex decision-making process. Understanding the coping strategies helped to guide the features necessary for decision-support design recommendations for better cognitive support for clinicians.

The third study (Chapter 5), the observation study, revealed features of designing population information display for complex decision tasks and the complexity-contributing factors specific to the ID domain. We used the clinical complexity model from our first study and its complexity-contributing factors to identify the specific complexity-contributing factors for the ID domain. Finding these complexity-contributing factors led to better design recommendations for different types of decision support to be embedded in the EHR. Also, this study helped us understand the relationship between perceived and objective complexity.

The fourth study (Chapter 6) was an exploratory simulation study. This study demonstrated the feasibility of querying and extracting similar patient features to show in a single population information display. Also, we were able to identify specific design features for ideal population information display through the poststudy interview. This study paved the way for larger studies including more participants and complex cases with better and fine-tuned population information visualization display.

Finally, the dissertation demonstrates the need to understand experts' heuristics management and different goal representations of clinical tasks. Heuristics plays a major role in how information is stored and retrieved from a user's memory for decision-making [24]. Heuristics management by clinical experts can shed more light on which information is ignored and the foci of attention cues while taking care of complex patients. Goal representation depends on how the tasks are aligned with the different levels of expertise and motivation of clinical experts [25]. Understanding these different levels of goals may help us better design CDSS and EHR specifications based on clinicians' different levels of expertise.

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CHAPTER 2

BACKGROUND

Complexity From the Clinical Decision-Making Perspective

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 comprehensible by the mind [1]. Something is complex when it contains a large amount of important information that surpasses our ability to process. However, if something contains a large amount of useless and meaningless information, our mind simply ignores the information [2]. 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 [3, 4]. Therefore, the interconnected actions and interactions may provide 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 intraphysician variability in patient management that is observed for general practitioners [5]. Therefore, physicians adjust the care they provide based on the complexity of the clinical situation or case [6]. As a result, the feedback loop of learning is not very strong in practicing medicine due to the existing uncertainty and complexity. Most complex and unique patients do not fit into evidence-based guidelines. However, as we are moving towards 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 [7-10]. However, researchers have not yet developed a model that describes complexity and decision-making difficulty, especially in the area of infectious disease 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 [11]. 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 [7]. De Jonge et al. made a very clear distinction between case and care complexity [12]. 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.

Identifying Task Complexity Can Help With Design

Task complexity is well defined in other successful areas of system design, including defense, the humanities, engineering, business, and the social sciences [13-18]. Several studies have found task complexity to be a crucial factor that influences and predicts human behavior and performance [13, 19-23]. Liu et al. conceptualized decision task complexity in 10 dimensions: size, variety, ambiguity, relationship, variability, unreliability, novelty, incongruity, action complexity, and temporal demand [20]. 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.

The Value of Perceived Complexity

Several studies have found task complexity to be a crucial factor that influences and predicts human behavior and performance [13, 19-23]. Even though there is no clear definition of task complexity, it can be better understood by dividing it into objective task complexity and perceived task complexity. Objective task complexity refers to the characteristics of the task model. In other words, it is the manipulation and quantitative assessment of task complexity based on the task model [20]. Perceived task complexity considers the task performer's characteristics and the perceived difficulties of performing the task. Subjective task complexity is the complexity of the 'state of mind' of the individual who performs the task [24, 25]. Thus, subjective or perceived task complexity can shed light on why the task performer perceives the task at hand to be difficult. No research has been done on the factors that identify the features or domains contributing to the perceived complexity factors for ID experts' decision-making process. In this research, we adopted the perceived complexity constituents from the literature review of Liu et al. that were used in other domains outside healthcare [20]. The four constituents we used for measuring perceived complexity are *diagnostic uncertainty*, *treatment unpredictability*, *perceived difficulty,* and *similarity* of the cases.

Contextual Factors of Patient/Case Complexity

Currently, there are few methods for estimating complexity in either ambulatory care or specialties in medicine [4, 7, 26-28]. One study tried to define complexity from the perspective of "complexity theory," but it did not take into account the different characteristics of patient complexity [29]. This study included some related measures of risk adjustment, such as case-mix measures, that are used to compare patients seen by primary care physicians and patients seen by specialty services. However, the study did not capture the dimensions of health status, demographics, health behavior, psychosocial issues or health behavior [30]. Another system, called ambulatory diagnostic groups (ADGs), uses a prediction system based on 51 ambulatory care groups and combined patients' age and sex to create a risk score mechanism [31]. Another similar approach, Ambulatory Severity Index (ASI), combines biophysical and behavioral dimensions with a complexity severity index. This index also includes complexity based on urgency, complications, and communication [32]. Other systems, such as the diagnostic-related groups (DRGs) and case mix groups (CMGs), are based solely on medical diagnoses. However, these systems include too many patient groups, and their predictive power is limited. Their usefulness in defining case complexity is limited by the large differences within the diagnosis-based groups [12]. The same DRG and CMG group developed a Complexity Prediction Instrument (COMPRI) using 117 items, including patient's admission status, severity of illness ratings, living/working situation, stress, social support, activities of daily living, health status, previous healthcare use, compliance, drug abuse, and emotional status [33, 34]. Another group of researchers developed a new method for estimating the relative complexity of clinical encounters based on the care provided weighted by diversity and variability [26]. In another study, a theory-driven approach for case complexity assessment revealed three dimensions: frailty, neuroticism and metabolic syndrome [12]. All these different methods have focused on risk assessment and assigning a value of severity. However, the specific contextual factors for each disease state are different due to the nature of the disease state and the complex attributes of specific patient cases. On the other hand, our study was focused on the contextual factors of simple as well as complex cases (Chapter 5) in the infectious disease domain.

Context of Complex Decision Task in CDS Design

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 [35-41]. 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 [42]. Systematic reviews have found that an effective CDSS must minimize the effort required by clinicians to process and act on system recommendations [36]. 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 [21].

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CHAPTER 3

CLINICAL COMPLEXITY IN MEDICINE: A MEASUREMENT MODEL OF TASK AND PATIENT COMPLEXITY

R. Islam, C. Weir, G. Del Fiol

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Clinical Complexity in Medicine: A Measurement Model of Task and Patient Complexity

R. Islam[1]; C. Weir[1]; G. Del Fiol[2]

[1]University of Utah, Biomedical Informatics, School of Medicine, Salt Lake City, Utah, USA;
[2]University of Utah, Biomedical Informatics, Salt Lake City, Utah, USA

Keywords

Decision Complexity, Decision Support Systems, Clinical/Utilization, Social Medicine/Methods, Humans, Quality Assurance, Health Care/methods, Software Design, Information Technology

Summary

Background: Complexity in medicine needs to be reduced to simple components in a way that is comprehensible to researchers and clinicians. Few studies in the current literature propose a measurement model that addresses both task and patient complexity in medicine.

Objective: The objective of this paper is to develop an integrated approach to understand and measure clinical complexity by incorporating both task and patient complexity components focusing on the infectious disease domain. The measurement model was adapted and modified for the healthcare domain.

Methods: Three clinical infectious disease teams were observed, audio-recorded and transcribed. Each team included an infectious diseases expert, one infectious diseases fellow, one physician assistant and one pharmacy resident fellow. The transcripts were parsed and the authors independently coded complexity attributes. This baseline measurement model of clinical complexity was modified in an initial set of coding processes and further validated in a consensus-based iterative process that included several meetings and email discussions by three clinical experts from diverse backgrounds from the Department of Biomedical Informatics at the University of Utah. Inter-rater reliability was calculated using Cohen's kappa.

Results: The proposed clinical complexity model consists of two separate components. The first is a clinical task complexity model with 13 clinical complexity-contributing factors and 7 dimensions. The second is the patient complexity model with 11 complexity-contributing factors and 5 dimensions.

Conclusion: The measurement model for complexity encompassing both task and patient complexity will be a valuable resource for future researchers and industry to measure and understand complexity in healthcare.

Correspondence to:
Roosan Islam, PharmD
University of Utah
Department of Biomedical Informatics
421 Wakara Way, Ste 140
Salt Lake City, UT 84108-3514
USA
E-mail: roosan.islam@utah.edu

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1. Introduction

The degree of complexity involved in medical decision-making has been increasing exponentially and has been a topic of interest for the last several decades [1–9]. With each new clinical discovery, the complexity of diagnostic, therapeutic and preventive decision-making increases. The advent of genomic medicine and the explosion of translational data are making clinical decision-related tasks more complex and dynamic [10, 11]. Fields such as cybernetics, general systems theory, chaos theory, game theory, artificial life and some aspects of artificial intelligence provide a good theoretical background for designing methods to measure complexity, but may not be directly translatable to medical decision-making. Being able to model complexity in medical contexts would be useful for many purposes, including decision-support design, workflow modeling and communication interventions. Many fields have found that using models to reduce complexity helps clarify the domain cognitively [5, 7].

Previous studies focused on patient factors that contribute to complexity [12, 13]. For example, the concepts of multi-morbidity, psychosocial factors and frailty have helped our understanding by reducing patient complexity to specific dimensions. These factors are mostly derived from the subjective experience of the providers or from the literature review. However, measuring and reducing complex decisions to its objective properties have not been studied as extensively in medicine as it has in other fields [14–20]. In this study, we adapted two models of complexity from other successful fields such as aviation and

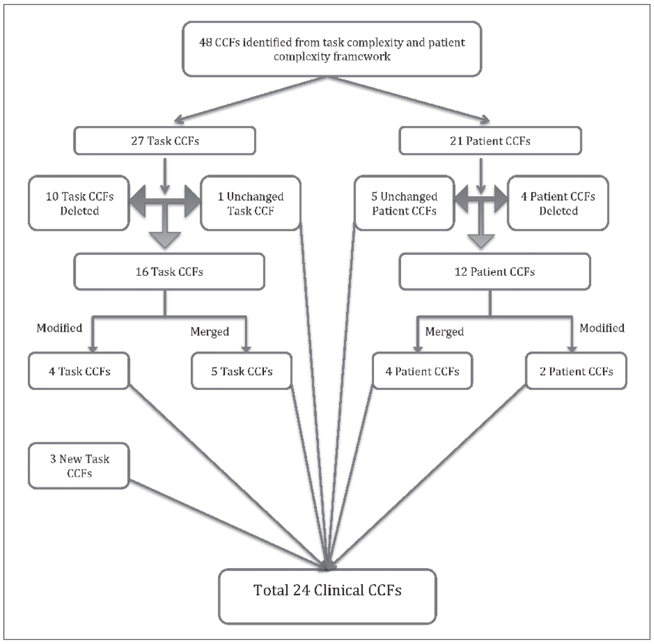

Figure 1 Complexity-contributing factors (CCFs) selection process

military to form the basis for a new, more integrated and targeted taxonomy that can be generalized in medicine. We are integrating the two perspectives, patient and task complexity.

Liu et al. have successfully conceptualized the theoretical foundation for a task complexity model from different fields and have provided a clear-cut and in-depth taxonomy of decision task complexity [21]. Schaink et al. have addressed the medical domain and have done research to create a simplified model of patient complexity [22]. The Schaink model also captures the vector models of patient complexity from Safford et al. [23]. However, this model has not been validated. Both models were synthesized from a description of the objective properties of decision task and patient complexity from a review of the literature. However, although the task complexity framework has been developed by a careful study of many different domains including aviation, the military, nuclear power plants, etc., it did not include healthcare. As a result, some of the domains identified in this framework might not be congruent with the medical domain. Therefore, to address this gap, we propose to adapt the measurement models of Schaink et al. and Liu et al. as a general initial framework of clinical complexity and to identify and validate the relevant complexity-contributing factors and dimensions within the context of healthcare using human judgment.

Although our assumption is that the proposed model may help to understand the complexity factors in different domains of medicine, we are specifically focusing on the infectious disease (ID) domain because the interplay among the disease (which is often changing), the patient's response (which is not always predictable) and population-based issues of immunity and resistance often results in difficult cases [24–26]. Future electronic health records need to be designed to deal effectively with emerging infections and population health data [27–30]. Therefore, we have used the infectious disease domain for validating our proposed model.

Table 1 Examples of de-identified unitized texts and associated codes

Unitized texts	Associated Codes
It can cause a purulent infection so I don't know. These were cultures that were done and everyone has got coag-negative Staph. So, I don't know if that even counts for this. We just don't have any culture results.	Lack of Expertise
So I think actually, if you were to follow the guidelines in him, I don't think Vancomycin is usually a go-to medication, it might be Unasyn. But we will start both medications.	Decision Conflict
There are other options as well. For example, Ciprofloxacin or clindamycin. I think it is fine for right now.	Multiple Decision Making Options
The guy is telling me that his toe is worse now on Unasyn and Vancomycin. So, it would be nice to get better gram- negative coverage but really what I think the question is if there is a little fluid collection in there or not.	Confusing Information
But the toe is getting worse and that is more what I would be worried about. I don't know if it is from his bruising it or not.	Changing Information

2. Methods

2.1 Settings

The settings were two tertiary care hospitals in the United States: the University of Utah Hospital and the Salt Lake City Veterans Affairs (VA) Hospital. The University of Utah Institutional Review Board approved the study and all participants consented with a verbal waiver.

2.2 Description of Observations

Observations were conducted with the inpatient infectious disease house staff teams. Our sample size for the observation study was 30 cases. Previous studies have successfully used cases ranging from 16 to 30 [31–33]. Each case observation lasted four days from the initial consultation handed to the ID team. Each clinical team consisted of an ID expert, one ID fellow, a physician's assistant and one pharmacy resident. Daily rounds for the entire team were recorded and transcribed. All transcripts were de-identified and then analyzed for developing and validating the measurement model.

2.3 Description of Reviewers

The three authors conducted the analysis. All three are researchers and represent the diverse healthcare backgrounds of nursing, pharmacy and medicine. Each researcher has more than five years of clinical experience and an extensive research background in healthcare and informatics, especially in clinical decision-making.

2.4 Procedures

The measurement model was developed by a standardized process to represent and maximize the content domain according to Lynn's recommendation [34]. The procedure for developing and validating the measurement model included 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.

This overall process is described in ► Figure 1.

2.4.1 Data Analysis

The data analysis was based on content analysis [35]. Specifically, we have followed the "emergent coding" process of content analysis [36]. 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, then it is applied to the remainder of the data.

Also, 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 [37]. This protocol provides standardized guidelines for qualitative research methods.

Table 2 All candidate task and patient complexity contributing factors

Task complexity		Patient complexity	
Dimensions	**Complexity Factors**	**Dimensions**	**Complexity Factors**
Goal/Output	Clarity	Medical/physical health	Loss of physical functioning
	Quantity		Polypharmacy
	Conflict		Limited application of clinical practice guidelines
	Redundancy		Multimorbidity
	Change	Mental health	Psychological distress
Input	Clarity		Psychiatric illness
	Quantity		Cognitive impairment
	Diversity		Addictions/substance abuse
	Inaccuracy	Demographics	Older age
	Rate of change		Frailty
	Redundancy		Female gender
	Conflict		Ethnic disparities
	Unstructured guidance		Lower education
	Mismatch	Social capital	Negatively affected relationships
	Non-routine events		Caregiver strain and burnout
Process	Clarity		Low socio-economic status and poverty
	Quantity of paths		Poor social support
	Quantity of actions/steps	Health and social experiences	Heavy utilization of healthcare resources
	Conflict		Costly care
	Repetitiveness		Self-management challenges
	Cognitive requirements by an action		Poor quality of life
	Physical requirement by an action		Difficulty with healthcare system navigation
Time	Concurrency		
	Pressure		
Presentation	Format		
	Heterogeneity		
	Compatibility		

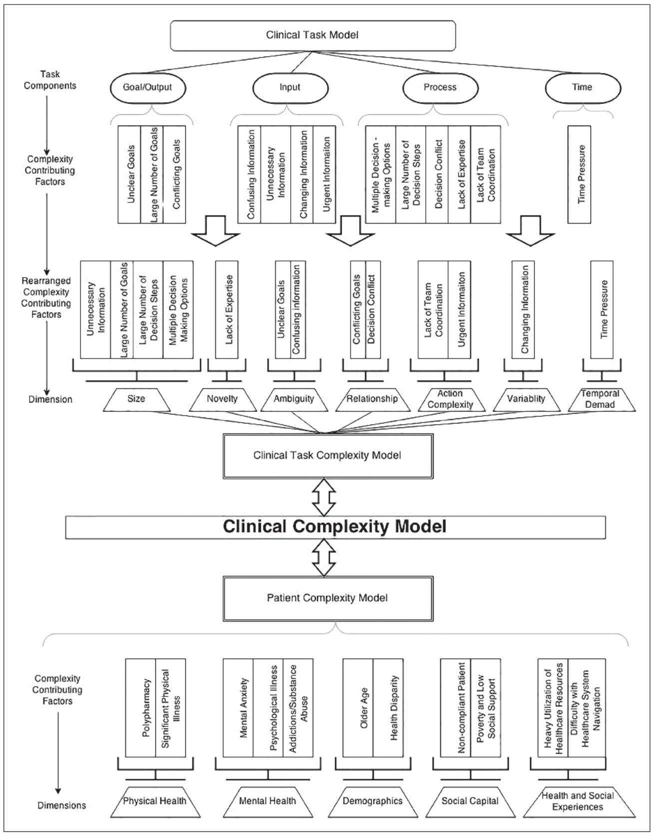

Figure 2 Clinical Complexity Model

2.4.2 Description of Initial Model Revisions

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. [21, 22]. 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 observation study.

2.4.3 Unitizing Texts from Interview Transcripts

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 the ATLAS.ti-7.5 qualitative data analysis software package for unitizing the texts, text segmentations, attaching the codes to the segments, merging and combining codes and for coding and retrieval strategies that facilitated forming the final codes and the connections among the codes. The other two researchers reviewed the unitized segments for consistency and accuracy. In ► Table 1, we provide some de-identified unitized texts and the associated codes.

2.4.4 Expert Panel (EP) Content Coding for Validation

One researcher unitized the texts and the other two researchers independently coded each unitized text based on the 49 CCFs. In ► Table 2, we have included all the initial candidate factors.

2.4.5 Modification of Categories through Discussion and Assessment of Reliability

After each coding session, the three researchers met to examine coding disagreements and to revise codes and code definitions. Cohen's kappa was calculated after each revision. The final inter-rater reliability of Cohen's kappa was 0.8.

2.4.6 Iterative Recoding and Modification of Categories

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.

3. Results

The results are organized into two sections. In the first section, the formation of the clinical task and patient CCFs is described. In the second section, we integrated the CCFs into higher-order dimensions. The conceptualized framework for clinical complexity is shown in ► Figure 2.

3.1 Clinical Task and Patient Complexity-contributing Factors

Overall, out of the 49 CCFs, 13 task CCFs and 11 patient CCFs were identified as rel-

Table 3 Clinical complexity-contributing factors (CCFs) and specific definitions

	CCFs	Definitions
Task complexity contributing factors	Unclear goals	Objective is unclear or vague, less clear or specific goals
	Large number of goals	Multiple goal elements, higher or larger number of goals
	Conflicting goals	Achieving one goal has negative effect or outcome on another goal
	Confusing information	Unclear, missing, ambiguous or contradictory information cues
	Unnecessary information	Large quantity of not useful information
	Changing information	Unpredictable events, high rate of information change
	Urgent information	Information about very acute patient situation
	Multiple decision-making options	Large number of options to make a decision
	Large number of decision steps	More than two steps or actions to attain the objective
	Decision conflict	Two or more actions that are incompatible or competing, conflict between task components
	Lack of expertise	Unique situation requiring additional knowledge, novel and non-routine decisions, treatment or disease uncertainty
	Lack of team coordination	Coordinating activities and creating shared decision-making within and between healthcare teams
	Time pressure	Situations that need immediate attention due to scarcity of time
Patient complexity contributing factors	Polypharmacy	Patient receiving medications from more than one pharmacy
	Significant physical illness	Multiple chronic conditions, loss of physical functioning
	Mental anxiety	External factors creating cognitive stress (e.g., job, culture, family)
	Psychological illness	Depression, mood disorders, loosing self-consciousness
	Addiction/substance abuse	Drug or substance abuse in the past or present
	Older age	Patient age 75 and older
	Health disparity	Patients with different ethnic background and cultural barrier with limited access to healthcare
	Non-compliant patient	Patient not following medication or treatment regimen, difficulty communicating with providers
	Poverty and low social support	Poor social support, low quality of life due to economic strains and lower social status
	Heavy utilization of healthcare resources	Complex chronic patients with multiple care providers and institutions require more resources
	Difficulty with healthcare system navigation	Low understanding of healthcare system, limited healthcare literacy

evant to healthcare. Detailed descriptions of each CCF are in ▶ Table 3.

A total of 6 CCFs (5 patient CCFs and 1 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.*

The selection of the CCFs consisted of three types of activities:

i) relevant items modified,
ii) items removed as not relevant and
iii) new items generated. The overall process is described in ▶ Figure 3.

3.1.1 Relevant Items Modified

Overall, the EP modified and merged 16 task CCFs into 9 task CCFs. The *goal clarity* and *goal change* CCFs were merged into *unclear goals.* The EP merged *input conflict, clarity* and *inaccuracy* into a general category called *confusing information.* Also, the *input non-routine information* and *input rate of change* were merged into one category, called *changing information. Input quantity* and *input diversity were merged into a new category, called unnecessary information. Process clarity, process conflict and process cognitive requirement by an action were merged* into *decision conflict. Process quantity of paths* and *process quantity of action/steps* were respectively renamed *multiple decision-making options* and *large number of decision steps.*

The EP also modified and merged the13 patient CCFs into a final set of 6 patient CCFs.

Loss of physical function leading to chronic disease, *multimorbidity* and *frailty* were merged into *significant physical illness.*

Cognitive impairment was merged into the definition of psychological illness. *Psychological distress and negative affected relationship* were modified, respectively, to *mental anxiety and non-compliant patient*. *Ethnic disparity* and *lower education* were merged into a broader definition of *health disparity*. Then, *caregiver strain and burnout, low socio-economic status* and *poverty, poor social support* and poor quality of life were merged into *poverty and low social support*.

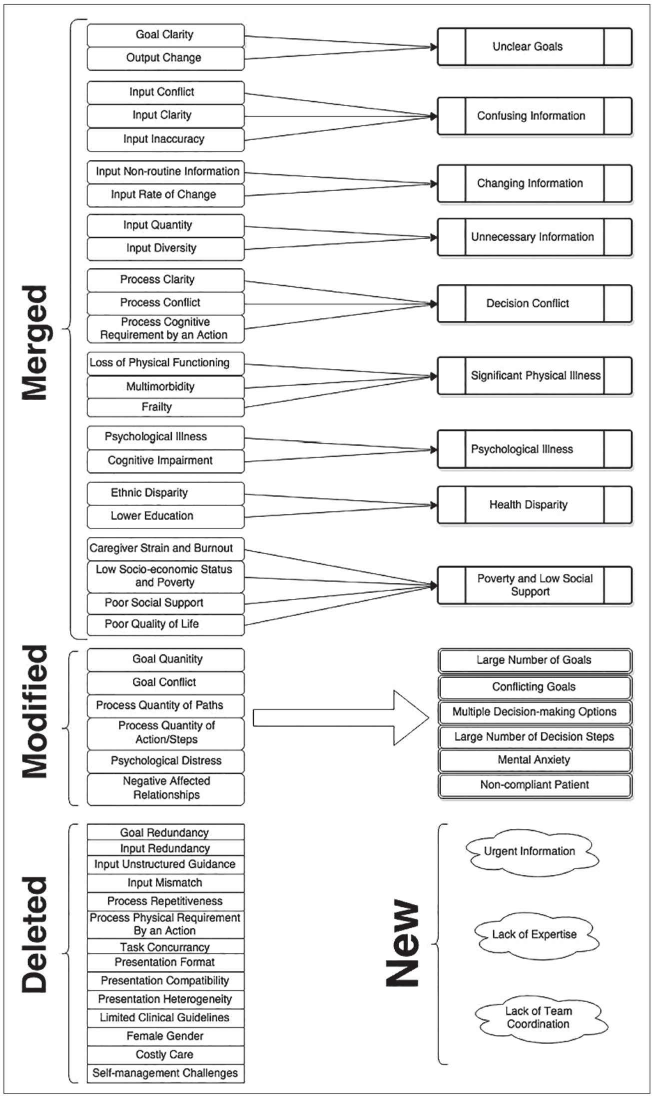

Figure 3 Overview of the merged, modified, deleted and new clinical complexity-contributing factors (CCFs)

3.1.2 Items Removed as Not Relevant

Overall, a total of 14 complexity-contributing factors including both task (10 CCFs) and patient (4 CCFs) complexity-contributing factors were not used for coding the transcripts and were removed: *Goal redundancy, input unstructured guidance, input mismatch, input redundancy, process repetitiveness, process physical requirement by an action, task concurrency, presentation format, presentation heterogeneity, presentation compatibility, limited clinical guidelines, female gender, costly care and self-management challenges.*

3.1.3 New Items Generated

Overall, three new task CCFs were added: *urgent information, lack of expertise* and *lack of team coordination.*

3.2 The Formation of Dimensions from Complexity-contributing Factors (CCFs)

Seven clinical task complexity dimensions were grouped together from the 13 clinical task CCFs. Then, the 11 patient CCFs were grouped into 5 patient complexity dimensions. ►Table 4 includes a short description of the clinical task complexity and patient complexity dimensions and the criteria we used to group them. We have adapted the dimensions from the conceptualizations by Liu et al. and Schaink et al. [21, 22].

4. Discussion

In this paper, we have conceptualized and validated a clinical complexity model that includes both task complexity and patient complexity-contributing factors, and groups these factors into higher-level dimensions. To our knowledge, this is the first research that has integrated a clinical task complexity model with a patient com-

Table 4 Dimensions, criteria and specific definitions

	Dimensions	Criteria	Definition
Clinical task complexity	Size	Number, quantity	Large number of clinical tasks
	Novelty	Uniqueness	Novel, non-routine tasks, clinical tasks dealing with treatment or diagnostic uncertainty
	Ambiguity	Not clear or specific information	Unclear, vague, less-specific clinical task components
	Relationship	Connection	Incompatible, conflicting or competing clinical tasks
	Action complexity	Shared attention	Shared cognition for task execution, acuity of the clinical task
	Variability	Changing information	Unpredictable, high rate of changing clinical task components
	Temporal demand	Time constraints	Clinical tasks requiring immediate action or attention due to time pressure
Patient complexity	Physical health	Physical attributes	Multimorbidity, polypharmacy, chronic conditions, loss of physical functioning
	Mental health	Psychological domains	Psychological, cultural stress leading to mental pressure, depression, mood disorders, addictions/substance abuse
	Demographics	Background information	Age, gender ethnicities for the patient
	Social capital	Behavior and social support	Non-compliant patient, loss of social support, low quality of life and social status
	Health and social experiences	Chronicity and impaired cognition	Complex chronic patients requiring more healthcare resources, poor understanding of overall healthcare system

plexity model for a better understanding of overall complexity in medicine.

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 [39]. 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 [40 – 42]. As a result, clinicians have the option to select healthier patients and may reject the chronic complex patients if not properly incentivized [43]. Therefore, a model to objectively measure clinical complexity may be necessary in the coming era of pay-for-performance. The proposed model can fill that gap and objectively measure clinical complexity for the daily practice of medicine.

Moreover, complex patients lead to information overload and decision uncertainty even for expert clinicians [1, 3, 13, 44, 45]. As a result, clinicians tend to overlook important information cues, resulting in diagnostic and therapeutic errors [46 –51]. Understanding the factors underlying complex clinical decision-making can be used to guide future electronic health record 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 to mitigate communication errors and improve clinical workflow efficiency. Goal-directed task analysis, when incorporated into visual interface design, has been shown to improve group decision-making in other domains, such as aviation and the military [52–54]. 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.

In this study, we adopted models from non-healthcare fields and applied them to healthcare. In the process, we added new complexity contributing-factors and more specifically, the integration of task and patient complexity factors including expert review. Future studies may address this initial reference model with other reference models for comparison by using physicians' subjective judgment. Also, future studies in different clinical domains may validate whether the proposed model can adequately capture all components of complexity.

5. Limitations

A limitation might be the generalizability to other clinical domains. Infectious disease is a very complex and dynamic domain. Thus, the complexity it entails is likely to give a reasonable representation of the complexity in healthcare. However, other clinical domains might present some diverse and unique complexity-contributing factors. Therefore, future research can probe into other clinical domains by using our framework. Additional findings of complexity-contributing factors from different domains of medicine can help simplify complexity even further. The fact that all the investigators were involved in the coding process may have introduced some bias. However, the researchers had different clinical and scientific backgrounds that may have helped to reduce any coding biases. Also, this study was conducted in only two hospitals in Utah. Thus, it is unknown whether the results can be generalized to other settings. Nevertheless, the patients, clinicians, and study sites are typical representations of academic medical centers in the US. Another limitation of this study is that the clinical complexity captured in this study was limited to conversations among the ID clinical team. Other complexity factors may arise from interactions between patients and providers, between physicians and other types of providers who did not participate in the rounds, and as part of other care coordination activities.

6. 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 to 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.

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CHAPTER 4

COGNITIVE TASK ANALYSIS TO UNDERSTAND COMPLEX CLINICAL REASONING IN INFECTIOUS DISEASES FOR BETTER ELECTRONIC HEALTH RECORD COGNITIVE SUPPORT

Roosan Islam , Charlene R. Weir , Makoto Jones , Guilherme Del Fiol, Matthew H. Samore

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Abstract

Clinical experts' cognitive mechanisms for managing complexity have implications for the design of future innovative healthcare systems. The purpose of the study is to examine the constituents of decision complexity and explore the coping strategies clinicians use to control and adapt to their information environment.

We used Cognitive Task Analysis (CTA) methods to interview 10 Infectious Disease (ID) experts at the University of Utah and Salt Lake City Veteran's Administration Medical Center. Participants were asked to recall a complex, critical and vivid antibiotic-prescribing incident using Critical Decision Method (CDM), a type of Cognitive Task Analysis (CTA). Using the four iterations of the Critical Decision

Method, questions were posed to fully explore the incident, focusing in depth on the clinical components underlying the complexity. Probes were included to assess cognitive and decision strategies used by participants.

The following three themes emerged as the constituents of decision complexity experienced by the Infectious Diseases experts: 1) *the overall clinical picture does not match the pattern, 2) A lack of comprehension of the situation* and dealing with 3) *social and emotional pressures* such as fear and anxiety. All these factors contribute to the decision complexity. These factors almost always occurred together, creating unexpected events and uncertainty in clinical reasoning. Five themes emerged in analyses of how experts cope with the complexity. Expert clinicians frequently used 1) *watchful waiting* instead of over prescribing antibiotics, engaged in 2) *theory of mind* to project and simulate other practitioners' perspectives, reduced very complex cases into simple 3) *heuristics*, employed 4) *anticipatory thinking* to plan and replan events, and consulted with peers to share knowledge, solicit opinions and 5) *seeking help* on patient cases.

The cognitive switching of reasoning to deal with decision complexity found in this study has important implications to design future decision support systems for the management of complex patients.

Background

Electronic Health Record (EHR) systems hold great promise for the development of Clinical Decision Support Systems (CDS) [1]. CDS provides intelligently filtered, patient-centered information to clinicians, potentially leading to improved performance and patient outcomes [2-7]. However, current CDS tools in EHR systems may not be particularly suitable to assist with complex reasoning because they do not support both the automatic pattern matching of experts and high-level deliberative reasoning required in complex cases [8, 9]. Most CDS capabilities available in commercial EHR systems (e.g., drug-drug interaction alerts) address low-level cognitive functions, such as reminding or alerting. On the other hand, superior expert performance is mediated by highly structured and domain-specific knowledge that allows new pieces of information to be absorbed efficiently [10-13]. Cognitive support that accounts for this dual approach is largely missing in CDS design [12, 14-16].

Advances in CDS are particularly necessary in the field of infectious diseases (ID). Despite some early success of seminal CDS interventions for ID, little progress has been made to assist decision-making in this area [17-25]. Understanding the complex decision process by ID experts may help design advanced CDS tools to help with tasks such early infection detection and treatment monitoring [26-29]. In addition, given the public health importance of ID, improvements in the understanding of cognitive strategies in ID decision-making have larger population-based implications. The overall goal for this study is to identify the constituents of decision complexity and the coping strategies to inform the design of health information technology that provide high-level cognitive support to clinicians. Our study is focused on the following research questions: (1) What are the factors associated with decision-making complexity experienced by ID experts? (2) What cognitive strategies do ID experts use to cope with complexity?

Methods

Study Design

We conducted semistructured interviews with ID experts using Cognitive Task Analysis (CTA) methodology [30]. CTA is a systematic and scientific method used for studying and describing complex reasoning and knowledge that experts use to perform complex tasks [31]. 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 [32]. The RATS protocol provides standardized guidelines for qualitative research methods.

Settings

The study was conducted at the Salt Lake City Veteran's 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 IRB.

Participants

Participants were 10 infectious disease experts who practice at one of the study sites. We defined "clinical expertise in infectious disease" as board certification in infectious disease, full-time work for a minimum of 5 years in a clinical environment and the identification by peers as an expert in the infectious disease domain. The first author contacted the participants through email and participation was voluntary. The interviews were conducted at the participants' private offices.

Procedure

Interviews were conducted according to the Critical Decision Method (CDM), a type of CTA. The CDM procedure is described in Table 4.1. Each ID expert was asked to describe a recent complex case that was challenging in terms of diagnosis and/or treatment. A semistructured 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 interview narratives [33-35]. The analysis was conducted iteratively with three of the co-authors (RI, CRW, GDF) independently identifying relevant concepts associated with aspects of complexity, sense-making, cognitive goals and adaptive strategies. 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 [36]. The final step of the data analysis involved the identification of relationships among themes. Interconnected themes emerged from this analysis. Atlast.ti®, a qualitative research software, was used to conduct the data analysis.

Results

The ID experts had an average of 18.5 years of experience. Of the 10 ID experts, 2 were female and 8 were male.

Factors Associated With Decision-Making Complexity

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 dealing with *3) social and emotional pressures.* These themes consisted of 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 where 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 cognitive complexity. 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*. All these factors refer to the scarcity of information with clinical utility, which compromise 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. Table 4.2 presents a detailed explanation of the constituents of complexity and example quotations from the interview.

Strategies Used to Cope With Complexity

Five broad themes emerged from the data analysis: 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 replanning for future events;* and 5) *seeking help: consultation with other experts for their opinions*.

Watchful waiting instead of prescribing antibiotics: less is more. In general, expert ID physicians attempt to minimize antibiotic overuse. In this process, they use their clinical expertise and consensus among the team members as a means of seeking support for conservative treatment, such as avoiding overuse of antibiotics or watchful waiting to see if patients improve on their own. Experts engage the principle of "less is more" in clinical reasoning. For example,

> *There was nothing that I needed to do today on that patient. Now, again, if I really thought that the risk of endocarditis was high based on the fact that she had a murmur, any other signs or stigmata of endocarditis, then we would have gotten three blood cultures before starting antibiotics.*

Theory of mind: projection and simulation of other practitioners' perspectives. Theory of mind refers to the cognitive ability or capacity that can attribute mental states to self and others[37]. Experts project and simulate what other practitioners might think in terms of the course of treatment for the patient in order to simplify the problem for better communications. As a result, experts mentally "simulate" possible scenarios of how other clinicians might view past decisions. For example,

> *Someone will complain about everything you do. So if we'd treated her with antibiotics then someone would be like, 'Why are you treating her with antibiotics? She doesn't need them at this point.' So someone will find something to complain about.*

Heuristics: using shortcut mental model to simplify the problem. Experts construct heuristics to deal with complex cases in order to spare attention resources and to cope with information overload. For example,

> *I think usually we would consider stopping therapy in a patient who's had six months of therapy total, IV and oral for vertebra osteomyelitis in the absence of retained prosthetic material. However, this is his second about to near death with the same pathogen and a very similar infection. He is tolerating the antibiotic very well. So, we're considering now leaving him on oral suppressive antibiotics indefinitely.*

Anticipatory thinking: planning and replanning for future events. Anticipatory thinking is the mental projection or simulation of potential events that may affect future decisions and outcomes; it is the "what if" component of deliberative thought [38]. The ID experts also use a chronological method to understand the patient history in depth to predict the trajectory of the disease state. This form of sense-making of looking forward rather than retrospectively is part of the macrocognitive process of anticipatory thinking [38]. For example,

> *The risk/benefit analysis then would I think favor continuing him on antibiotics because the risk of the antibiotics themselves are very low once he's tolerated them for a certain amount of time. And the potential consequence is if he relapses from off course then it is very severe. So in this circumstance, I suspect I'll probably leave him on antibiotics for quite some time.*

Seeking help: consultation with other experts for their opinions. Our analysis found that experts strongly rely and seek case consultation with other experts they trust. For example,

> *We have a weekly conference for the immune-compromised ID docs. We discussed his case in that conference and just reviewed everything, sought out any other opinions, any advice as to what other people might consider for evaluation or duration of therapy and tried to come up with kind of a consensus, which I think was very valuable.*

Discussion

Previous studies on complexity in medicine have focused on patient factors related to complexity [39-45]. Different patient complexity measures have been developed based on the amount of care provided weighted by the diversity and variability of the patient [46-48]. Unlike previous research, the present study contributes to the understanding of complexity from the decision-making perspective. Our results reflect the deep cognitive mechanisms of ID experts to cope with complexity from well-established qualitative methods [30, 49-53]. The cognitive mechanisms found in our study have also been described in the context of the cognitive and decision science literature including naturalistic decision-making, clinical reasoning, heuristics and mental simulation [10, 37, 54-57]. The coping strategies used by ID experts may help them reduce the identified complexity factors in several ways. These strategies resonate with the findings of Patterson and Woods for individuals dealing with information overload [58]. For example, *anticipatory thinking*, *theory of mind and seeking help* can support *lack of comprehension of the situation*. Risk assessment by using *anticipatory thinking* helps clinicians prioritize tasks for the best outcome for the patient [59, 60]. Also, *heuristics* can help when the *overall clinical picture does not match the pattern by* a short-cut mental model to fit their patients based on prior experiences [10, 54]. Moreover, w*atchful waiting* provides clinicians the time to comprehend the situation better and reduce the complexity factor of *lack of comprehension of the situation*. *Theory of mind* may reduce *social and emotional pressures* by group conformity and social validation. However, *social and emotional pressures* make it harder to follow a *watchful waiting*. The relationships of the coping strategies with the sources of decision-making complexity are shown in Figure 4.1.

Dual process theory (DPT) may provide a framework to interpret the results. The DPT postulates two systems of reasoning: System 1 (automatic, nonanalytic, intuitive) and System 2 (effortful, analytic, abstract and logical thinking) cognitive processes [15, 61, 62]. System 2 is activated in situations that are 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 both System 1 and System 2 for efficient clinical reasoning to cope 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 their patients based on prior experiences [10, 54].

All the complexity coping mechanisms help to deal with constituents of complexity. Only social and peer pressures make dealing with watchful waiting challenging.

Implications for Decision Support

Current and future innovative informatics tools such as patient monitoring, better documentation, better visualization and population decision support embedded in EHR systems can better facilitate clinicians' high-level reasoning. The mapping of these tools with the coping strategies is illustrated in Figure 4.2. 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* [63-65]. 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 [66]. The planning and the ability to monitor the patients may help with better sensemaking and planning for the future to aid *anticipatory thinking*. In addition, these features may improve providers' confidence on their decisions, reduce *social and emotional pressures,* and as a result implement *watchful waiting.*

All these CDS tools embedded in the EHR can support both System 1 and System 2 of Dual-Process Theory. Please note that just one kind of CDS tool may not be sufficient to help with the cognitive switching.

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 decision support recommendations for medication orders, laboratory tests, future appointments and tailored patient educational material [67].

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 the sheer volume of shifting data in multiple displays add a significant challenge to clinicians' sense-making process [68-72]. Integrated displays automatically retrieve and process information from disparate modules within the EHR to provide information overview, while preserving the option of indepth exploration on demand [73-75]. For example, a quick overview of a white board display of care coordination has been shown to improve and standardize communication in a care team in an acute care hospital [76]. By presenting information aligned with users' workflow, "Smart Forms" help clinicians with the automatic (System 1) thought process. At the same time, the system allows users to switch to analytical (System 2) thought process through noninterruptive decision support recommendations for medication orders, laboratory tests, future appointments and tailored patient educational material.

Also, population decision support embedded into EHR systems has the potential to support System 2 with cognitive support for *seeking help* and *watchful waiting* [77]. Population-based decision support is a systematic application for analyzing population databases to improve the health of groups of individuals [77]. Such decision support can work as a "cognitive extension" for clinicians by providing information about treatment response for similar patients and interventions by other clinical experts. This information can help the clinician locate peer consultants who have experience with similar patients. Also, the decision not to prescribe antibiotics by other clinicians in the database can support the coping strategy of *watchful waiting* and reduce the associated *social and emotional* pressure.

The sociotechnical barriers that exist in our health information technology infrastructure can benefit from a better understanding of cognitive switching from System 1 to System 2 [26-29]. For example, in October 2014, a patient with Ebola virus came to a hospital in Dallas, Texas with classical symptoms of viral fever. Even though the nursing notes included travel history, it was ignored. However, an intelligently designed CDS that could encompass local and population data could have detected the travel history as a potential threat and warned the clinicians [78]. Thus, future informatics tools that incorporate the coping strategies into the system design may incorporate the *heuristics* (System 1) of expert clinicians and act as a cognitive extension to notify (System 2) clinicians about travel history when appropriate.

Implications for Research and Practice

Overuse of antibiotics has been a concern with respect to drug resistance and public health [79, 80]. The notion that doing less in medicine sometimes can mean more has been an important discussion in the infectious disease community [22, 81, 82]. 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.

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 there is leeway for clinical judgment . 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.

Limitations

The Critical Decision Method (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 [30]. Thus, the CTA method is limited due to knowledge that cannot be verbalized in principle. Also, since the first author conducted the data collections, there is the potential that this researcher influenced the way the interview was conducted. To guard against this bias, we piloted and constructed the questionnaire based on the CDM instrument. Also, our results reflect the opinions and deep cognitive processes of ID experts, which may have influenced the generalizability of the results. However, as infection is prevalent in all aspects of medicine, these results can be translated for broader impact in all areas of clinical medicine.

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 cope 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 replanning for future events and 5) Seeking help: consultation with other experts for their opinions*. Future and innovative decision support tools in the EHR may support the cognitive switching from System 1 to System 2 to match experts' high-level reasoning. CDS and EHR designers can incorporate the cognitive mechanisms found in our study to inform the design of innovative solutions.

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Table 4.1. Critical Decision Method phases

Phases	**Description**
Incident identification and selection	The first step of the CDM process. The participant selects an appropriate incident for probing. The participant is asked to give a detailed description of the incident from the beginning to end. For example, in this study, the ID experts identified a recent case that seemed complex to solve cognitively.
Timeline verification and decision point identification	The second step is to get a clear and refined overview of the incident structure, key events and segments. For each of the key events, the participants were asked for goals at that point. For example, in this study, the timeline verification started from the very moment the ID expert got involved with the case or was referred to the case.
Progressive deepening	The third step refers to points in the timeline where the interviewer probes the participants for additional details. As a result, more details about decision points, judgments and the decision-making process are revealed. This particular phase makes sure that the participants are probed for specific and detailed information regarding cognitive skills, experiences and expertise. For example, in this study the experts were asked specific questions about their gut feelings and how they knew the information that suddenly occurred to them.
"What If" queries	In this final phase, the participants are asked hypothetical questions regarding their incidents that further help to illuminate the implicit decision-making process of the experts. For example, the interviewer asked, "If the patient had contracted a different type of pathogen, how would you have responded?"

Table 4.2. Constituents of complexity with example quotations

Themes	Factors	Example quotations
Overall clinical picture does not match the pattern	Unexpected outcome	“So he was started on Cefotaxime. And about five days went by and he did not improve; he became more encephalopathic. He had trouble recalling not the city but the state and the country he was residing in”
	Risky patient characteristics	“So he’s on antiretroviral for his HIV. He is on two psychotropic medicines. He was in a car accident ten years ago and had brain trauma at the time and he’s on one of the medications for improving memory”
	Unusual case	“I’ve never seen a case of Brucellae, that was my first one. I think I may have ordered a Brucellae culture once in the past and it was negative. But I thought that the case was just very strong for that. TB of course is a common thing and that would be something that it could have been as well”
Lack of comprehension of the situation	Lack of and/or conflicting indicator data	“You start to get a trend, and when you get 20 minutes of data and you have a fever in a guy with pan-resistant drugs it’s scary. When you have three days of the same guy going down for a smoke break, relaxing, chilling in his room, watching TV, you’re a lot more comfortable with the plan”
	Lack of evidence about treatment effectiveness	“We knew he had stuff everywhere at one point. He was sort of stalled in his clinical improvement. We were having some slight to moderate suspicion that there’s another pocket of infection, and what was the best imaging study to get. The problem is if you asked 10 radiologists you might have gotten 10 different answers. And what really happened is he probably got a very expensive, non-specific test that then led us to do a CAT scan”
	Lack of diagnosis	“Could he have candida endocarditis, or could he have some occult viscous rupture, like a ruptured diverticulum; something that would let all the candida in the GI tract suffuse into the peritoneal fluid where then it would grow like in a bath of mycology broth?”

Table 4.2. Continued

Themes	Factors	Example Quotations
Lack of comprehension of the situation	Gaps in physicians' knowledge	"We looked at some review papers on vertebra osteomyelitis and we looked for guidelines. There's guidelines about to be published but they've not yet been published so we looked for clinical trials but didn't find much except for some vague low-grade recommendations that you should treat until epidural collection was resolved – but that was not specified what that meant, absolutely disappear versus no longer abscess versus no longer bone involvement. So that wasn't very helpful"
Social and emotional pressures	Frustration/regret	"I also see sometimes there's a nervousness or an anxiety about stopping so they continue but they never make clear in their own minds or in the medical record why they're anxious, why they believe their patient deserves a longer duration of therapy than standard. And I think it's an important exercise to at least be able to clarify in your own mind why you're doing things differently and be able to express that and argue that"
	Liability and/or fear	"This is a guy who had in the past, recent past, been critically ill on various occasions, and when you look at his microbiology it's terrifying frankly the number of bugs he has and the various resistance"
	Multiple care providers/conflict	"But the cardiology and the transplant team is very aware of all of these because anytime anything happens to the kidney all of their other medicines get screwed up including all the anti-rejection drugs. So they're watching it like a hawk, you know"

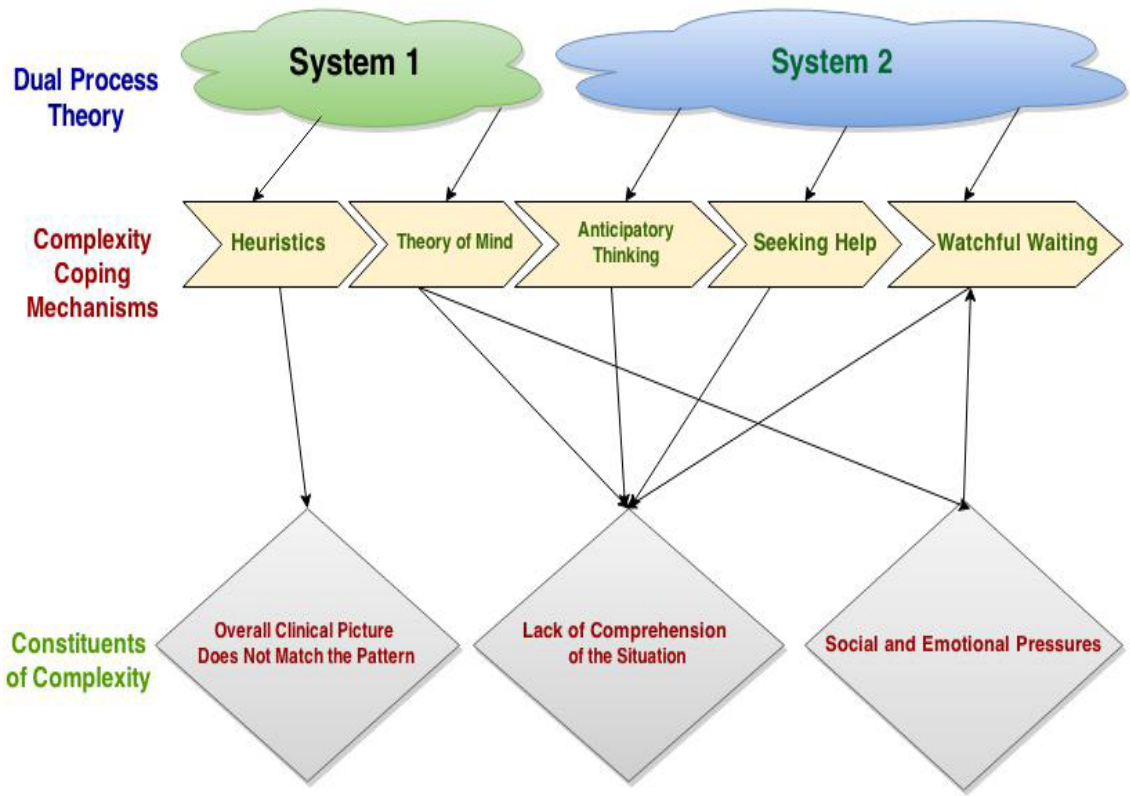

Figure 4.1. Relationship between coping strategies with cognitive factors of complexity

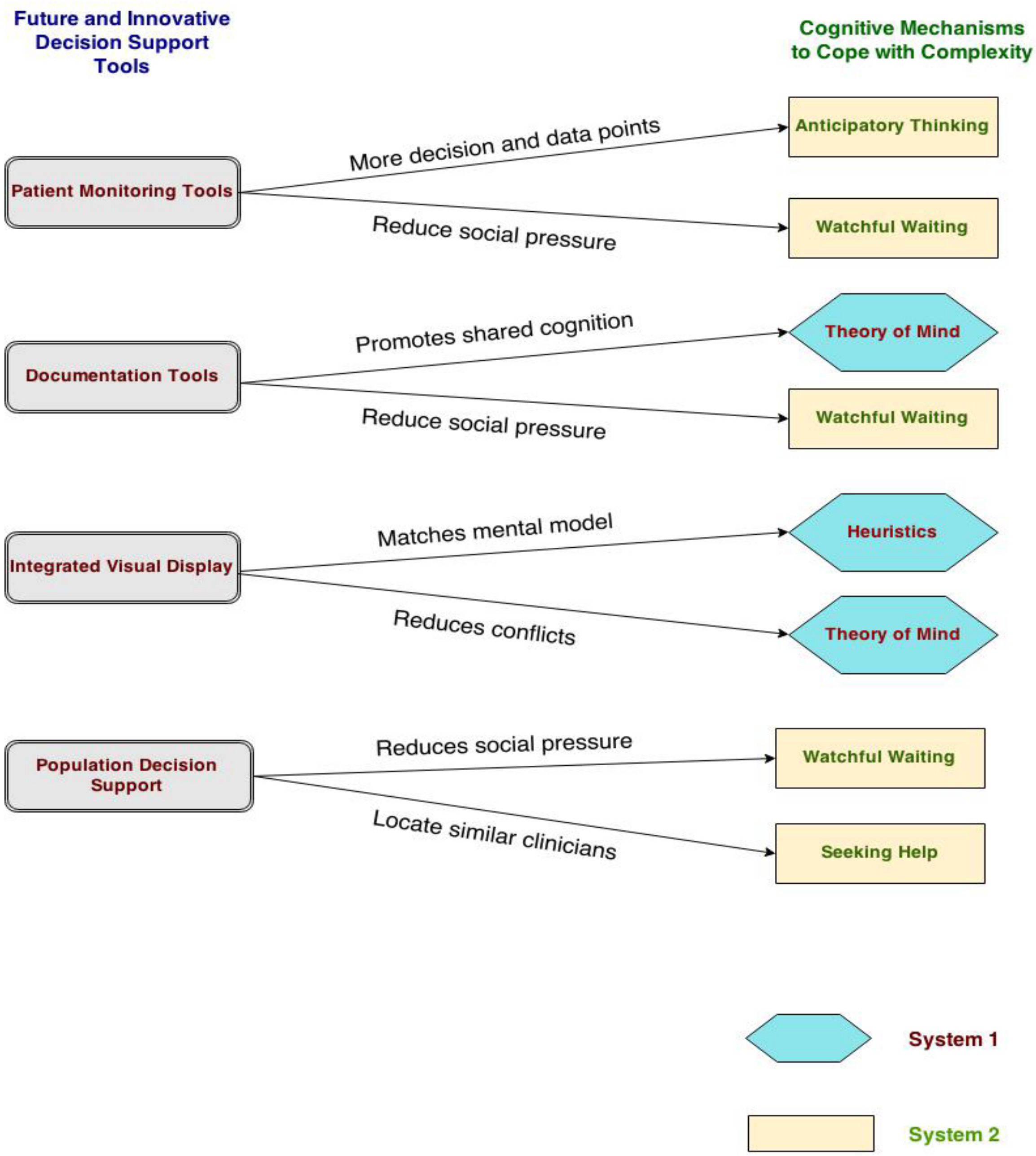

Figure 4.2. Mapping of the CDS tools with cognitive mechanisms and dual process theory

CHAPTER 5

COMPLEXITY IN THE INFECTIOUS DISEASE DOMAIN: GUIDING INFORMATION TECHNOLOGY DESIGN FOR IMPROVED COGNITION SUPPORT

Roosan Islam, PharmD., Makoto Jones, M.S, MD., Gregory Stoddard, MS., Charlene Weir, RN, PhD., Guilherme Del Fiol, MD, PhD *(In review in International Journal of Medical Informatics)*

Abstract

Understanding complexity in healthcare has the potential to reduce decision and treatment uncertainty. Therefore, identifying both patient and task complexity-contributing factors may provide a better task allocation and design recommendation for next generation health information technology system design.

The objective is to identify the specific complexity-contributing factors in the infectious disease domain and the relationship with the complexity perceived by the clinicians.

We observed and audio-recorded the clinical rounds of three infectious disease teams. Thirty cases were observed for a period of 4 consecutive days. Transcripts were coded based on the clinical complexity contributing factors from the clinical complexity

model. Ratings of complexity on day 1 for each cases were collected. We then used statistical methods to identify complexity contributing factors and their relationship with perceived complexity of clinicians.

A factor analysis (principal component extracts with verimax rotation) of specific items revealed three factors (Eigenvalues>2.0) explaining 47% of total variance, namely task interaction and goals (10 items, 26%, Cronbach's Alpha=0.87), urgency and acuity (6 items, 11%, Cronbach's Alpha=0.67), and psychosocial behavior (4 items, 10%, Cronbach's Alpha=0.55). The regression analysis showed no statistical significance between perceived and objective complexity (Multiple R-squared=0.13, p=0.61). There were no physician effects on the rating of perceived complexity.

Task complexity contributes significantly to overall complexity in the infectious disease domain. The different complexity contributing factors found in this study can help health information technology system designers and researchers with intuitive design. Different types of decision support tools can help to reduce the specific complexity contributing factors found in this study. Future studies aimed at understanding clinical domain-specific complexity contributing factors can ultimately help healthcare system designers with better task allocation and management.

Introduction

The characteristics of infectious diseases (ID) set this domain apart from other areas of clinical care due to their complexity, unpredictability, and potential for global effects [1-4]. The complexity surrounding newly emerging infections, environmentally persistent organisms and increasing antibiotic resistance interacts with patient acuity to create a significant decision-making burden [4, 5]. Understanding the scope of factors contributing to complexity would help improve the design of clinical decision support systems, electronic health record (EHR) systems, educational interventions, and risk assessment.

Other domains in medicine such as general ambulatory care have methods to estimate complexity considering diversity, variability, volume, and time limitations as complexity factors [6]. However, few methods take into account characteristics of both patient and decision tasks to assess complexity. Most of the complexity features in the Ambulatory Diagnostics Groups (ADGs) and Case Mix Groups (CMGs) consist of medical diagnosis and other patient-related complexity factors, but exclude decision task complexity [7-10].

To understand complexity, it is important to assess the factors related to both objective properties of the task and perceived task complexity. The objective properties of task complexity involve specific task characteristics, such as the number of decision steps or competing goals [11, 12]. On the other hand, perceived task complexity refers to the conjunct property of the task and task performer characteristics [13, 14]. When the task overcomes the cognitive capacity of the task performer, the task is perceived to be complex by the task performer. Models of task complexity have been created in other research domains such as aviation and military to influence and predict human performance and behavior [15-20]. Liu et al. have developed a task complexity conceptualization framework from a literature review [21]. In this model, task complexity is represented in 10 dimensions (e.g., size, variety, ambiguity, relationship) and 27 complexity-contributing factors (CCFs). However, this model has not been validated or applied in clinical settings. In a previous study, we developed and validated a clinical complexity measurement model that includes both patient and task complexity contributing factors [22]. In the present study, we conducted provider observations to identify the specific CCFs in the ID domain and their relationship to perceived complexity. Our findings can be used to guide the design of health information technology solutions that help clinicians cope with complex decision-making.

Methods

Settings

An observational study was conducted in the inpatient ID settings at the University of Utah and Veterans Affairs Salt Lake City 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 infectious disease teams. Each team consisted of an ID fellow, one physician assistant, and one ID pharmacy resident.

Description of Procedures

Case selection

Thirty patient cases were observed across the three teams. Each case was observed for 4 consecutive days. Previous studies have successfully used cases ranging from 16 to 30 [23-25]. 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 5.1. 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.

Development of the Clinical Complexity Model

In a previous study, we developed an integrated clinical complexity measurement model that includes both patient and task CCFs [22]. Three of the co-authors (RI, CRW, GDF) used the transcripts from the present observational study to iteratively constructed the measurement model. This model integrates the patient CCFs proposed by Schaink et al. and task CCFs outlined by Liu et al. [21, 26]. A list of CCFs used in the model is available in Table 5.2. The CCFs in this model were used to code the transcripts of the present observational study.

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 interrater reliability reached a Cohen's kappa of 0.8. We used Atlas. Ti for coding purposes.

Statistical Analysis

We conducted statistical analysis on the coding frequencies of the CCFs listed in Table 5.2. 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 interrater 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. Cronbach's alpha was computed among the components of perceived complexity to assess the internal consistency. We conducted principal component analysis (PCA) (with verimax rotation) to group the CCFs. The internal consistency of the variables of each factor was determined using Cronbach's alpha. We used regression analysis to assess the correlation between perceived complexity and each factor found in the PCA. The changes in complexity factors over time were assessed using a standardized score (Z-score). We used STATA 13.1 to perform the statistical analysis.

Results

Physician Effect

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; $p = .94$).

Internal Consistency of Perceived (Subjective) Complexity

Perceived complexity ratings ranged from 6 to 26, and the average across all patients was 14.3 (SD=5.11). 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.

Factor Analysis of the Objective Complexity Variables

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 5.3). 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.

The complexity factors found in Factors 1, 2, and 3 represent the following dimensions: task interactions and goals, urgency and acuity, and psychosocial behavior. Ten task complexity variables represent the task interaction and goals dimension. *Confusing information* and *unclear goals* represent ambiguity or unspecific clinical task components in making efficient decisions. *Decision conflict* and *conflicting goals* represent competing or incompatible clinical tasks. *Large number of goals, large number of decision steps,* and *multiple decision-making options* refer to the size or increased number of task specifications, requiring the task performer to perform more steps. *Lack of expertise* refers to the novelty of the situation because of the uniqueness of the patient, treatment or decision uncertainty, or less experience of the provider. *Lack of team coordination* represents deficiency in shared mental cognition and inefficient clinical workflows. Factor 2 represents total of six complexity variables representing acute situational awareness and urgent nature of the patient's situation. *Urgent information, changing information,* and *time pressure* represent the temporal demand and variability associated with the patient's situation. *Significant physical illness* and *older age* are patient CCFs and represent the acuity of the patient's situation. *Heavy utilization of healthcare* represents patients with chronic conditions and multimorbidity. Factor 3 refers to four patient CCFs represented in

Table 5.2. This dimension represents the patient's overall well-being. *Psychological illness* and *mental anxiety* refer to the mental health of the patient. *Noncompliant patients* refer to patients when they do not follow the prescribed regiment of treatment. *Poverty and low social supports* add the intricacies of social capital dimension.

Relationship Between Objective and 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). The different correlation factors are presented in Figure 5.1.

Changes in Complexity Over Time

The complexity factors were most prominent in day 1, decreased significantly in day 2, increased again in day 3, and decreased in day 4 (Figure 5.2). However, no clear pattern emerged from the assessment of complexity over time.

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 health care 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.

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 [7, 10, 26-28]. Other studies focused on assessing clinicians' perceived complexity found similar patient complexity factors [8, 9, 29]. Also, the total changes of complexity over the course of care and time shows the variability of complexity.

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 information technology 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 [30-32]. For example, LifeLine2 allows users to drill down into details and filter *unnecessary information* [33]. LifeFlow allows visualization of millions of patient records in one single page. This feature can provide better situational awareness and helps clinicians set clear goals [33].

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* [34, 35]. For example, at Partners Healthcare, "Smart Forms," a documentation-based clinical decision support tool, has been shown to improve decision quality and management of patients [35]. This tool can organize and highlight clinical data in a disease-focused manner and thus help with focusing on correct choices to reduce decision conflicts.

Clinicians often raise information needs when managing their patients that could be met with online evidence resources [31, 36]. Yet, barriers compromise the efficient use of these resources. Tools such as infobuttons have demonstrated to be effective in helping clinicians find evidence at the point of care [32]. Seamless access to evidence-based information at the point of care can reduce cognitive overload associated with information seeking and reduce the c*onfusing 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. For example, a timeline belt visualization exhibiting workflow fragmentation of tasks helped during the implementation of computerized provider entry (CPOE). These kinds of tools can identify patterns and prioritize tasks for clinicians, thereby leading to optimal management of clinical operations [37]. This kind of task visualization for optimizing workflow has been successfully used in the design of decision support tools in aviation and military systems.

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. For example, the complementary patient information (CPI) model developed by Puentes et al. can be integrated with the EHR and can provide valuable information about the patient's social and treatment adherence issues for better outcomes [38].

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.* For example, Nephros, a renal dosing application, takes into account patient age, gender, creatinine, and weight to accurately predict the renal clearance of the patient [39]. This tool also can suggest new renal dosing for the patient. Thus, this kind of decision support tool can improve clinical reasoning by providing patient-specific recommendations about dosing regimens for the older and chronic complex patients. We have mapped the complexity factors with different tools that can support EHR in Figure 5.3.

Innovative interventions that use data extracted from social media also have the potential to reduce complexity factors such as *mental anxiety and psychological illness.* For example, Choudhry et al. built a machine-learning model from Tweeter feeds that predicts the onset and the likelihood of depression [40]. Tools leveraging such algorithms could be integrated with EHR to help clinicians cope with psychosocial complexity.

Limitations

The coding of the complexity factors involved the transcripts 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.

Conclusion

In this observational study in the ID domain, we found that task complexity contributes significantly to overall complexity. Thus, future research on complexity in health care 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 information technology to provide better cognitive support.

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Table 5.1. Perceived complexity: Definition and questions asked after rounds on Day 1

	Criteria**	**Question**
Perceived Complexity	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. [21]

Table 5.2. Complexity contributing factors (CCFs)

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	

Table 5.3. Principal components factor analysis with the objective complexity variables

Complexity Variables	**Factor 1**	**Factor 2**	**Factor 3**
Task Interactions and Goals			
Confusing information	0.42	-0.07	0.12
Decision conflict	0.38	-0.01	0.23
Lack of team coordination	0.33	0.06	0.1
Multiple decision making options	0.33	-0.02	-0.09
Lack of expertise	0.33	0.01	-0.05
Unnecessary Information	0.30	-0.12	-0.11
Conflicting goals	0.31	0.2	0.02
Unclear goals	0.23	-0.12	-0.26
Large number of goals	0.19	0.1	-0.16
Large number of decision steps	0.18	-0.01	-0.24
Urgency and Acuity			
Urgent information	-0.04	0.45	-0.05
Older age	0.06	0.44	0.06
Heavy utilization of healthcare	-0.05	0.41	-0.19
Changing information	0.12	0.36	-0.1
Significant physical illness	0.02	0.17	-0.18
Time pressure	0.07	-0.44	-0.21
Psychosocial Behaviors			
Noncompliant patient	0.1	-0.03	0.53
Psychological illness	0.03	-0.01	0.42
Mental anxiety	-0.08	0.06	0.33
Poverty and low social support	0.05	0.09	0.23
Eigenvalues 5.25 2.25 2.01			
Proportion of variance explained (%) 26 11 10			

**The Eigenvalues are with the proportions of variance explained by each factor. The 20 CCFs are relevant to the ID domain from the 24 CCFs from

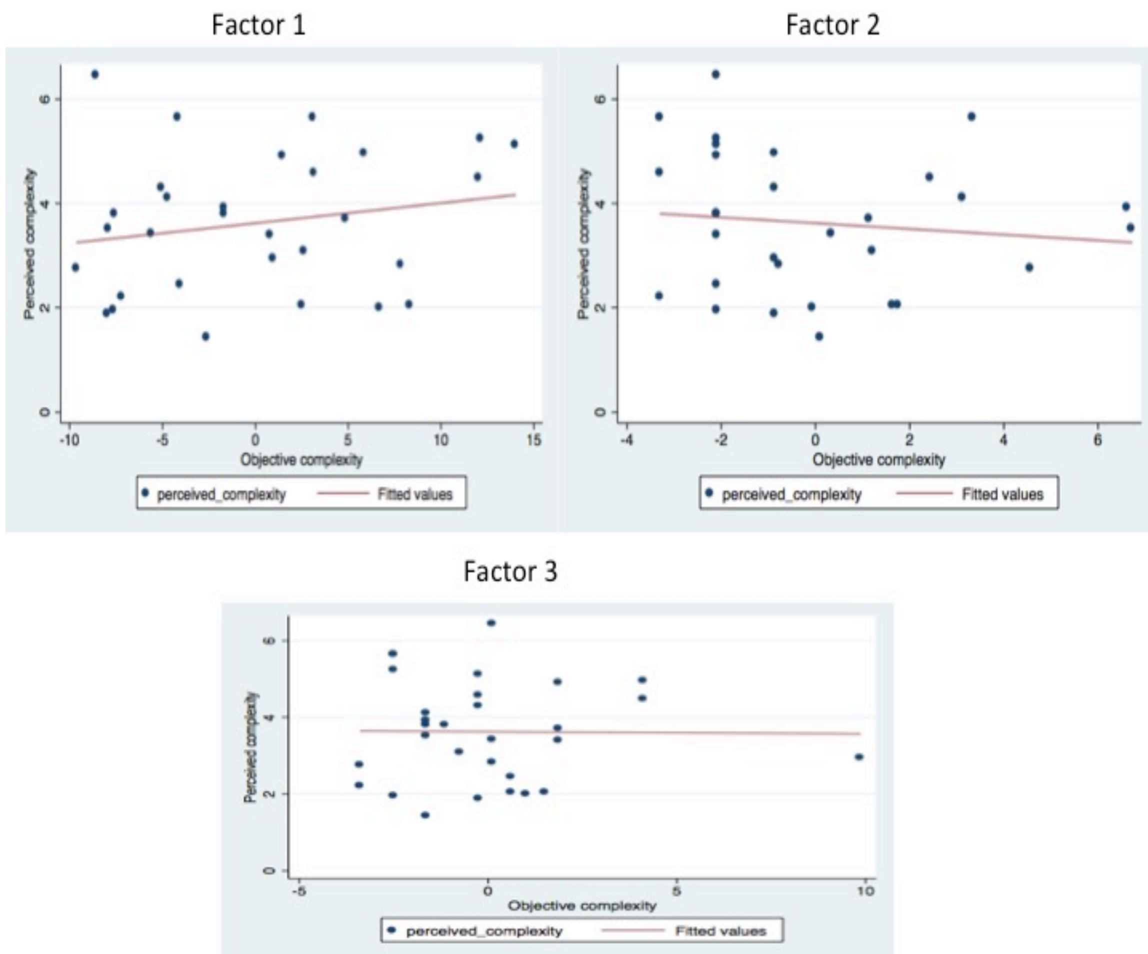

Figure 5.1. Correlation between perceived complexity and Factor 1, Factor 2, and Factor 3

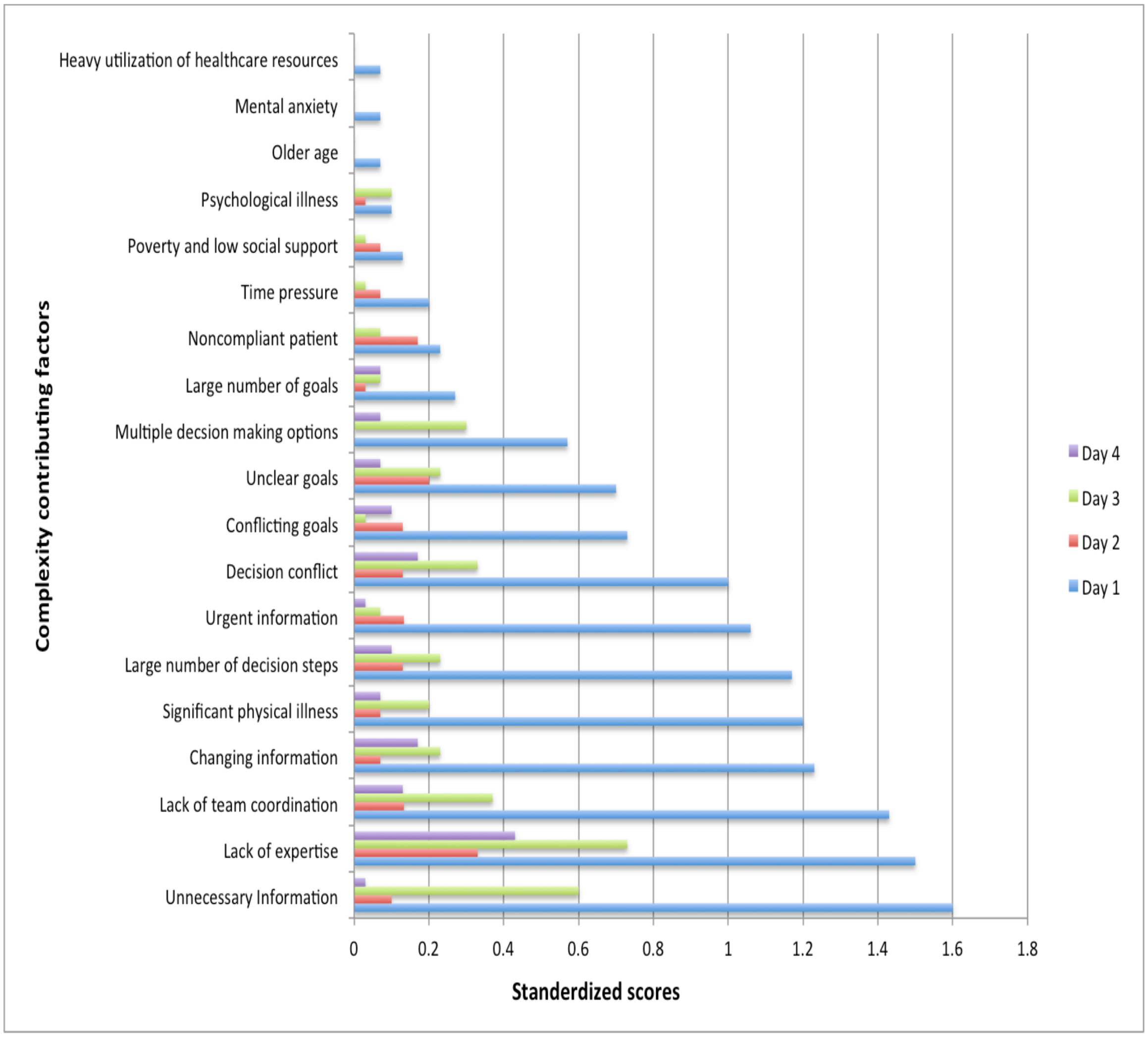

Figure 5.2. Complexity contributing factors over 4 days.

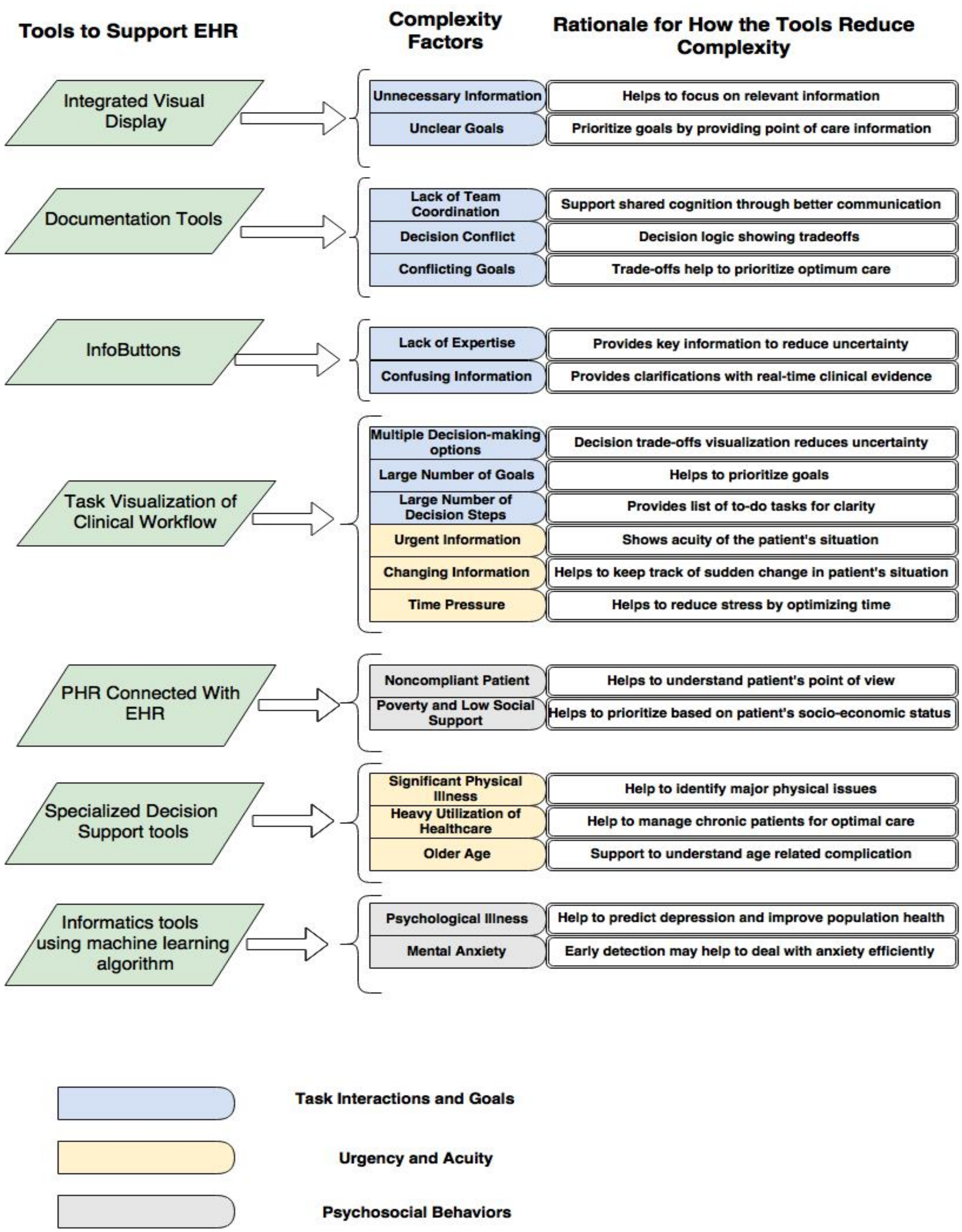

Figure 5.3. Mapping of decision support tools that can help to reduce complexity

CHAPTER 6

FEASIBILITY OF POPULATION HEALTH ANALYTICS AND DATA VISUALIZATION FOR DECISION SUPPORT IN THE INFECTIOUS DISEASES DOMAIN: A PILOT SIMULATION STUDY

Introduction

Most visualization displays address simple problems by categorizing tasks into simple or smaller steps [1]. The goal is often to minimize cognitive load or analytical thinking while maximizing pattern matching. However, when dealing with complex problems, displays should also give support for more intense and deliberate thinking by providing a rich source of information that matches the needs of the decision-maker. If the information is difficult to comprehend and does not match the decision task, there is a risk of increasing cognitive load and a higher chance of diagnostic errors. Therefore, easy-to-understand presentations of the aggregated patient information from a population database are equally important alongside individual data for effective clinical decision-making. Especially in the infectious diseases (ID) domain, due to emerging and resistant infections, the changing morphology of pathogens, and public health implications, a high level of uncertainty makes it more difficult for ID clinicians to focus on early goals. Therefore, a high-level display that can help ID clinicians focus on prioritizing information can help clarify the goals.

Few studies have addressed the feasibility of extracting and displaying population-based information from clinical records. In this study, we have designed a complex case in the ID domain and assessed the feasibility of population-based analytical algorithms to extract similar patients in a "live" patient database electronic warehouse. To test design components for a population information display, we created a simulated computerized visualization display that presents data on similar patient cases. Finally, we performed an exploratory mixed-method study to assess the impact of population health analytics and data visualization on cognitive outcomes.

The objectives of this study were:

1. To explore the feasibility of extracting and displaying population-based information from a large clinical database.
2. To identify specific features of population display that may help with complex clinical decision-making.
3. To explore perceptions for population information displays.
4. To explore the impact of a population information display on cognitive outcomes.

Literature Review of Healthcare Data Display

The rapid expansion of electronic health data has increased the potential for knowledge discovery given that the data are managed in innovative and effective ways [1]. A systematic review by West et al. investigated the use of visualization techniques reported between 1996 and 2013 and evaluated innovative approaches to information visualization of EHR data for knowledge discovery. The systematic review found that healthcare data visualization studies since 2010 have focused on multiple-patient data visualization [1]. Uncertainty in medicine arises due to treatment variations and unique aspects of complex patients. Therefore, understanding the patient with respect to other multiple similar patients can help clinicians reduce uncertainty and increase confidence in their decisions. Our project involved visualizing multiple complex patient records in a single display to support patient care decision-making. Therefore, in this literature review, we discuss similar systems that provide visual displays for multiple similar patients. In the following paragraphs, we discuss some of the most advanced visualization tools that exist, including Lifeline2, VISITORS, DICON, CommonGround, and SIMILAN. These systems have the ability to emphasize querying, sorting, aggregating, and clustering multiple patients' data.

LifeLines2, developed by researchers at the University of Maryland, is one of the most advanced applications for both numerical and categorical data visualizations [1]. The purpose of this tool is to enable discovery and exploration of patterns across multiple records to support hypothesis generation and find cause-and effect relationships in a population to support research. Initially, this tool was developed only to support pattern discovery for research purposes. Eventually, motivated by the advent of EHRs, this tool was introduced to the clinical practice domain for pattern discovery to understand patient responses. One of the unique features of this tool is the interactive visualization designed to search and explore different event sequences in multiple records of temporal categorical data. The distinguishing design for LifeLines2 is alignment. Users can align the records by any specific event type (for example, stroke). However, in this design, the system cannot visualize numerical data (for example, high/normal/low blood pressure).

The ability to drill down into details when looking into patient records as well as to see trends and explore data for patterns is the strength of this tool [2]. Also, this tool allows the groups to be compared with parallel temporal summaries. It also allows a temporal sequence search including absence of events. As a result, users can select patients based on similar patterns. LifeLines2 also has the ability to aggregate patients based on similar event sequences in histograms. The i2b2 clinical research platform from Partners HealthCare has adopted LifeLines2 in over 50 research sites [3].

Another innovative visualization tool called VISITORS, or Visualization of Time-Oriented Records, has also gained attention [4]. The purpose of this system is to analyze the results of large amounts of time-oriented multiple patient data from multiple sources such as clinical trials. This system can also show numerical data as a combination of point plots and line charts, and categorical abstractions are shown as size- and color-coded rectangles using the same timeline. VISITORS offers an impressive query language that allows users to search for both raw and abstracted data in groups of patients. This system can accommodate diverse temporal data from multiple records as well as form-based user interfaces to search and filter. The users can use both dynamic query as well as a threshold indicator to perform filtering without temporal constraints. One of the unique features of this system is adaptability. For example, the color-coded rectangles in the display can change to a bar chart and then into a line chart to show different presentations of the same data. One of the issues this system faces, based on the usability study, is the fairly complex user interface that requires lengthy training time for the users [4]. The features of VISITORS are commercially available from MediLogos [5].

Among other notable visualization tools, Dynamic Icons (DICON), by Gotz et al., has shown promise. DICON applies machine-learning algorithms to cluster similar patients and visualize the information as a tree map [6]. The main purpose of this tool is to help clinical domain experts visualize similar patient cohorts for better understanding of population-wide statistical data. Clinicians can use DICON for large and complex data and high-level statistical information to evaluate cluster quality, and a detailed display of multidimensional attributes of the data helps clinicians understand the meaning of the clusters. Users can rapidly analyze the data from the icons and the timeline to make sense of the data as well as embed statistical information into a multiattribute display to facilitate cluster interpretation, evaluation, and comparison. Its unique features include visualization of the clustered EHR records as composite icons that have parts representing the features of all EHRs in a cluster. Finally, this system can provide different spatial arrangements such as scatter plots and manual refinement of the clusters. Another unique feature of this system is that it uses color saturation to depict data variance and diversity. An evaluation study, which was a case study in the healthcare domain to visualize a dataset containing more than 10,000 patient records to find patterns of prominent disease over age groups and geographic locations, found a limitation that the system cannot overlay statistical measures of quality onto the visualization. This system was finally implemented as part of the DaVinci system and has been used with both traditional displays and on touch screen devices.

The CommonGround Infectious Disease Weather Map interface is another sophisticated tool that was developed by Livnat et al. at the University of Utah [7]. The purpose of this system is to create a visual paradigm using visual correlation of multidimensional epidemiologic data that can serve as an infectious disease weather map for public surveillance. The system offers a 'common ground' for detection, monitoring, exploration, and discovery of infectious diseases. This dynamic display provides a novel visualization that facilitates situational awareness. This prototype also provides the first iteration of an integrated infectious disease weather map that can be used by public health professionals. The use and visualization of tags from independent data sources are organized in a methodical manner. The tag clouds give users an impression of the overall situation. The unique features of the dynamic tag visualization show how the authors creatively used it rather than displaying only an alphabetically sorted list. Moreover, the display shows a systematic identification of trends in chronological order. The system was developed for helping the public health epidemiologist. However, it can be modified for other settings such as situational awareness in acute care hospitals.

The purpose of the Similan visualization system is to enable discovery and exploration of similar patient records in temporal categorical datasets to support both clinicians and researchers [8]. The color-coded categorical variables are represented by icons on a zoomable timeline and can focus on point events as opposed to intervals. Many similarity measures exist for numerical time series, but temporal categorical records are different. In Similan, M&M measures (match and mismatch) were included based on the concept of aligning records by sentinel events and then matching events between the target and the compared records. In most traditional search systems, records that do not fit the search criteria are removed from the users' sight. However, in Similan, users can better refine their searches as well as see such results. Also, users can specify a time range of interest (absolute or relative) for searching similar patient records. The unique feature of Similan is that it can sort patients by similarity to target a temporal pattern. This system has been evaluated by case studies. One of the limitations of this system is the complex user interface. As a result, participants have had difficulty learning the M&M measures.

The goal of analyzing single patient records is different from analyzing multiple patients' records. Most systems support tasks for analyzing either a single patient or multiple patients. However, transitioning from multiple patients' analysis to single patient analysis or vice versa has not been widely studied.

Most of these systems were developed to visualize multiple patients' records. However, there has not been any system that can select only complex attributes of patients and then visualize the patients. In the ID domain, clinicians face significant challenges when dealing with unique and complex patients. Therefore, understanding the key features and attributes that make the patient complex is important before visualizing the information. In addition, previous visualization tools have focused on discovery and exploration of similar patients to help with research and epidemiology. This study addresses the need for tools to deal with complex patients providing cognitive support to improve clinicians' decision-making. Also, what information needs to be visualized depends on the clinical questions raised at the point of care. In this study, we have addressed these gaps by focusing on the key attributes of the complexity. Then, we have used the VA clinical database to query only similar complex patients to visualize the data. This study adds to the science of visualization by designing a visual display based on the attributes of the complexity of previously seen patients.

Methods

Study Design

The design of the experiment was a mixed-methods 2 between (level of expertise) X 2 within (pre-/postpresentation of population-based display) simulation study. In other words, we blocked on expertise through our selection of two defined groups and exposed all participants to both forms of the display, collecting data pre-/postexposure to the population-based display. The design included both qualitative and quantitative components.

Participants

Ten volunteer physicians participated in the study (five infectious disease, or ID, experts and five non-ID experts). Expertise was defined by board certification in ID. The "experts" were selected based on ID board certification and ID faculty role. The nonexperts were board certified in areas outside ID. Both were required to have a minimum of 5 years of clinical experience. The experts had an average experience of 15.6 years and a range of 10 to 24 years. The five nonexpert participants had an average experience of 17 years with a range of 7 to 38 years. The clinicians were contacted by email and participation was voluntary. All participants provided verbal consent. The participants did not receive any compensation for this voluntary participation. The experiment was conducted in private offices and conference rooms at the University of Utah Hospital and Veterans Affairs (VA) Hospital in Salt Lake City. The study was approved by the IRB (Institutional Review Board) at the University of Utah.

Development of Stimulus Materials

In this study, we have used two types of materials: 1) simulated case and 2) display forms. Three of the authors (YL, RI, and MJ), including an ID clinician (MJ), were involved with the design of the materials.

Simulated Case

A simulated case was created to mimic realistic diagnostic uncertainty in the ID domain. A real patient was selected by two of the authors, one ID expert and one clinical pharmacist (MJ and RI), and the patient's deidentified data were used to form the backbone of the simulation. The case was presented in "ChartReview," an artificial electronic chart. We asked all participants to rate the complexity of the case based on high (8-10/10), medium (5-7/10), and low complexity (1-4/10) scores. The summary of the overall case is described in Table 6.1.

Display Forms

Two forms of case display were created. The first emulated the usual narrative, patient-based medical record. The second included both the case narrative and a population-based information display. The design process for the population display involved two steps. First, we used several search criteria for finding similar patients from the VA clinical data repository. Then, we designed the display based on the information of similar patients found from the database. The process is described below.

Search Criteria From Population Database

We first identified the most important clinical question for the complex patient (Table 6.1). For our complex case, the patient's deteriorating condition and comorbidities did not fit any evidence-based guideline. Moreover, the use of Daptomycin was recommended per clinical guidelines for Vancomycin-resistant *Enterococcus* (VRE) neutropenia patients [9]. However, using this agent did not improve the patient's overall clinical status. On the contrary, the patient's overall clinical and functional status declined rapidly. As a result, the clinician had to deal with the uncertainty of using other medications without knowing the consequences due to a lack of evidence. This uncertainty adds to the cognitive complexity. Therefore, to reduce the cognitive complexity, the goal was to find treatment outcomes regarding other therapeutic agents from practice-based information from the VA clinical database. We first defined parameters for finding similar patients.

To investigate the treatment of refractory VRE bacteraemia, we initially focused our search within admissions with combinations of the following ICD-9-CM codes: neutropenia (204) and acute myelogenous leukemia (208, 288), the presence of fever (780.6, 790.7), bacteraemia (038.0, 038.9), bacterial infection (041, 599), or other general infection codes (771.8, 785.2, 995.92, 995.91). Refractory VRE bacteraemia was defined as the inpatient isolation of an enterococcal species from blood, where the first and last positives were more than 5 days apart, but positive cultures in the series were separated by no more than 14 days.

Initial examination of the potential cohort revealed that the matched group of patients was quite small; therefore, all individuals with refractory VRE bacteraemia were included, regardless of their comorbidities, which resulted in a cohort of a few hundred patients. We measured the administration of antibiotics with potential activity against VRE alone or in combination with other antibiotics, i.e., Quinupristin / Dalfopristin, Daptomycin, Ampicillin, Gentamicin, Streptomycin, Linezolid, or Tigecycline. We defined courses as consecutive antibiotics where gaps between doses were no longer than two hospital days apart. As a result, we found 19 patients from the database who matched the similarity profile of the complex case we designed. A summary of these patients is described in Table 6.2.

<u>Population Display and Design Rationale</u>

The population information display includes the number of hospital days in the X-axis and individual patients in the Y-axis (Figure 6.1). The antibiotics administered to each patient are represented by different colored lines (Daptomycin as green, Ampicillin as yellow, and other antibiotics as blue). The gray line represents the total stay for the patient in the hospital. The first culture for positive VRE is represented by a red arrow, and the first negative culture is represented by a straight purple line. The X represents the time of death for each patient.

We utilized our findings from Chapter 4 and Chapter 5 for innovative design of the population display. Specifically, we incorporated anticipatory thinking, heuristics, and theory of mind coping strategies from Chapter 4 in this design. For example, the timeline view supports the trajectory of patient responses and thus helps clinicians to anticipate the future outcome depending on the treatment selected. The one single view of all previous patients with different therapies and outcomes helps clinicians build their mental model about the current patient, treatment alternatives, and expected outcomes. Moreover, the "if-then" heuristics supports the mental model for simple decision logic. For example, in this display, we were interested in the outcome (i.e., number of deaths) of Daptomycin or a combination drug including Daptomycin versus other antibiotics. We laid out the outcomes (deaths versus not death) of therapeutic agents in a timeline view, which supports formulation of "if-then" (if patient used drug X, then death happened or did not happen) relationships. Finally, the different treatment strategies used by different providers may help to promote theory of mind. The design aims to encourage the clinician to consider options for treatment previously used by clinicians with different patients. Thinking about other options helps reduce the focus on only one alternative, otherwise called the anchor bias. Thus, the design in turn aims to reduce anchor bias and help the clinician evaluate different treatment strategies.

The population display design aims to reduce the complexity-contributing factors of *unnecessary information, unclear goals* and *lack of expertise* found in Chapter 5. Complex patients have many different attributes and information cues. For example, by focusing the display on antibiotic treatment and survival, we aimed to reduce the number of *unnecessary information* cues to help the clinician to focus on relevant information. Focusing on relevant information may help the clinician prioritize goals and reduce *unclear goals.*

Finally, the display utilizes population information from the VA clinical database. This information includes the collective experiences of other clinicians with similar patients. For most complex and unique cases, clinicians do not have enough experience because such problems may be outside the clinician's domain of expertise or have unusual presentation or response to therapy. Therefore, the information display aims to address clinicians' *lack of expertise* with a given situation.

The longitudinal view provides the patient-specific outcome represented in a timeline view. Figure 6.1 depicts the different features of the display. The population graph and the patient electronic information were embedded into an artificial electronic chart, "ChartReview," developed by Duvall et al. [10]

Population Information Display Validation

To validate the display content, we asked two ID clinicians to evaluate whether the population information display represented similar patient characteristics of the complex patient described in Table 6.1. The first author presented the case and the population information display to both ID clinicians in "ChartReview." The inclusion criteria for the ID clinicians were the same as for the study participants. However, these clinicians did not participate in the study. They volunteered only for the purpose of validation. The clinicians first checked the parameters of finding similar patients and confirmed the appropriateness of the parameters based on their clinical experience. They then explored the visualization of the population information in depth, making sure that the legends and data points cognitively made sense. They checked to make sure if the outcomes (death or no death) from the therapeutic agents for similar patients added any clinical value to reduce uncertainty. They verbally confirmed that the population information display contained similar matched patient characteristics representing the complex case. They also confirmed the validity of the clinical utility of the population display for helping with clinical decisions for this very complex case.

Procedures and Manipulation of Variables

The clinicians consented to participate and were provided an explanation of the study purpose. Clinicians were first shown “ChartReview” with a mock patient to understand the functionalities and get acquainted with the electronic chart. They were asked to verbally confirm that they understood the functionalities of “ChartReview” before the study started. Training took approximately 5-10 minutes. During this training, participants could ask questions and receive any support they needed. A separate window in the chart had the guideline information of patients with VRE neutropenia related to the complex patient case. Once the study started, participants were asked to move the mouse where they were focusing their eyes while reading the chart. The steps are as described below:

1. Participants were first asked to read the patient chart, including patient background information and lab data.
2. Then, they were asked to write down a plan for the case and rank each item of the plan according to their priorities.
3. After participants wrote down the ranked plan, 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.
4. 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.
5. Finally, the first author conducted poststudy, in-depth interviews, probing into each pause to gauge the subject’s mental models and asking follow-up questions. Demographic information was collected at the end of the study.

Study Outcome Measures

The measured outcomes for the objectives were

1. *Preference for population information display* (qualitative content analysis to find themes for the preferences)
2. *Time looking at the population display* (Quick Time player to record the amount of time
3. *Time to read the chart* (Quick Time player to record the amount of time) and
4. *Appropriateness of plans* (as judged by expert panel) pre-/postpresentation of population information display.

The preferences for population information display provided design guidelines for future population-based visual displays. The time to read the chart and time looking at the population graph shed better light on the effect of expertise on reading or interpreting information. Changes in appropriateness of plans before and after seeing the population information display helped in understanding if the display had any impact on the cognitive outcome. The measured outcomes and the procedures for data collection are described in Table 6.3.

Criteria for the Review of Appropriateness of Plans

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. They first decided on different appropriate plans for ID experts and non-ID experts. Then, they reviewed the plans from the study and rated them as appropriate or not appropriate per group consensus. The EP developed the basis for the appropriate plan described in Table 6.4. Any plans that did not meet the criteria were rated as not appropriate. As long as the clinicians mentioned one of the plans included in the table, the plan was determined to be appropriate. For example, if the clinicians wrote down "start Linezolid" and mentioned other actions to be taken for the patient, the plan was termed as appropriate. Therefore, as long as one of the plans in Table 6.4 was mentioned, the plan was considered to be appropriate by the EP.

The rationale for developing the criteria for the ID group included the fact that the patient's clinical and functional status was declining using Daptomycin. Therefore, it was necessary to start other antibiotics. For the non-ID group, the EP decided that nonexperts do not have the necessary training for making decisions on domain-specific complex cases. As our case was developed to be an ID specific complex case, the EP decided that the plan was appropriate as long as the clinicians plan to consult an ID expert. Therefore, for the non-ID group, all the other criteria remained the same with an extra criterion for consulting ID experts.

When faced with uncertainty and lack of evidence, it is often difficult for clinicians to judge plans as right or wrong. Complex patients oftentimes have several comorbidities that can be responsible for their demise. Therefore, it is hard to predict or judge the right or wrong course of treatment even retrospectively. The expert panel reached consensus to categorize the plans as appropriate and not appropriate from their years of clinical practice.

Data Analysis

The data analysis involved both qualitative and quantitative analysis.

Qualitative 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 poststudy 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 used the RATS (Relevance of study question, Appropriateness of qualitative method, Transparency of procedure and Soundness of interpretive approach) protocol for the content analysis [11].

Quantitative Analysis

We conducted quantitative analysis to explore the perceptions for population information display 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 [12-14].

Results

We successfully extracted similar patient information from the VA database and designed a population information display incorporating the similar patients. The results are organized in two sections: qualitative and quantitative analysis. All clinicians rated the case as highly complex except one who rated the case as medium complex.

Qualitative Analysis

The qualitative section is further subdivided into two sections. In the first section, we discuss criteria for the review of appropriateness of plans. In the second section, we discuss the content analysis of the transcripts.

Results of Appropriateness of Plans

The EP reviewed all the cases based on the appropriateness of the plans in Table 6.4. Of the 10 clinicians, 5 clinicians changed their plans after being shown the population display. The overall appropriateness of plans before and after the display is explained in Figure 6.2.

In the ID group, of the 5 clinicians, 3 did not change their plans after seeing the population display. Two changed plans after seeing the display, but only one of the plans was appropriate and one was not appropriate. Four of the five clinicians kept Daptomycin in the regimen, and thus their plans were reviewed as not appropriate. One clinician added Linezolid and considered changing therapy to Tigecycline; that plan was reviewed as appropriate. The specific changes after showing the population display for the two ID clinicians were as follows.

<u>ID clinician 1</u>

- Start Linezolid and stop Daptomycin.
- Look into synergistic therapy with Ampicillin, Ceftriaxone or other beta-lactam less toxic then Gentamycin.
- Continue Gentamycin.
- Boost cells for possible surgical intervention.

<u>ID clinician 2</u>

- Look for improved outcomes for VRE bacteraemia with Daptomycin + Ampicillin.
- Explore options with newly approved antimicrobials including Oritavancin.

For the non-ID group, all 5 clinicians' plans were reviewed as appropriate by the EP before showing the display. Of the 5, 2 clinicians did not change their plans after seeing the display. The other 3 clinicians who changed their plans kept the "Consult ID" option in the treatment plan, and thus their plans were considered appropriate. The specific changes after showing the population display for the 3 non-ID clinicians were:

Non-ID clinician 1

- More inclined to use Linezolid.
- Consult ID.

Non-ID clinician 2

- Consider switching to other antibiotics based on possible better survival.
- Consult ID.

Non-ID clinician 3

- Consider changing to other VRE antibiotics.
- Consult ID.

Content Analysis of the Transcripts

The content analysis revealed 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). 4) Different presentations of the population display can be beneficial. The themes are described in the following sections.

Theme 1: Trusting the Population Data Can Be an Issue

Clinicians appear to be concerned about the validity and trustworthiness of the data. Even though the patients found through the population database search are similar to a certain extent, they are not identical. Therefore, clinicians are cautious about using the information to infer cause-effect relationships. Also, the practice-based information may differ significantly due to different formulary management or culture of practice in a particular hospital, resulting in potential decision conflicts rather than reducing such conflicts. Therefore, establishing clinician trust in the population data is crucial. For example,

> *Exactly, so I would narrow it down and go this way and see how many patients we have here actually. So I would want to know that because just glancing at this, I don't know if it really is the same patient population.*

Theme 2: Embedded Analytics Is Necessary to Explore Patient Similarities

Clinicians would like to see the similarities and differences among patients in an aggregated summarized view or through analytical functions. It is important to understand the differences between the matched similar patients and the patient at hand. For example,

> *So I think a complex display is fine. There's some learning curve for it but once I got used to it, it could be useful. But I have to think about how to show that better. The similarity profile of the match patients may help. Or you can also show the data of matched profile as percentage of similarity.*

Theme 3: Tools Are Needed to Control the View (Overview, Zoom, and Filter)

Features such as overview, zoom, and filter embedded in the display may reduce confusion. Therefore, clinicians prefer an overview function to explore the patient profiles first for an integrated view; to zoom if necessary to look into specific details (lab results and different days of results); and filter the data based on specific patient features or outcomes, such as time of death or time for negative culture results. For example,

> *And by that have a filter panel with full control over those comorbidities. I'm saying I want to include or exclude diabetics, the heart failures, the surgical abscesses, the by sight infection. And if I could tweak this and knowing that the VA probably has a few thousand patients that potentially could be like this then as soon as it gets a few thousand patients, then you're starting to have to display this differently; summarizing is better. So, this is the individual case review and you almost would say that I want a summary viewed first. Then, sort of overviewed, filter and zoom kind of thing. I think that's relevant. The overview is of the, you know, the four, five antibiotics choices, some sort of heat map of how well you did and then drilling in to individual cases like this being able to filter in or out, the ones that you think are closest to the patient.*

Theme 4: Different Presentations of the Population Display

Can Be Beneficial

Different presentations of the same information can help make sense of the data cognitively [15-17]. Depending on the question related to the problem, the searching criteria are set to find similar patients from the population database. Therefore, few patients can be found for very rare or complex cases, and many patients can be found regarding comparative outcomes of certain treatments. Therefore, different presentations depending on the number of patients available may be necessary. For example,

> *I don't know about pie chart for very small number of patients but that might work for large numbers of patients. But, yeah, I mean when you're dealing with all those cases and you want to give the data, showing individual level patient's data is a good way to do it I think.*

Quantitative Analysis

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 3.63.6±0.91 minutes, respectively). The viewing time for the population display is shown in a box plot in Figure 6.3.

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 that is similar to the complex simulated case. We then designed a population information display. Previous studies also developed similar visualizations by extracting information from EHRs or population databases [18-20]. We have used ICD-9 CM codes to find similar patients from the VA clinical database and presented the information in a single display. Extracting similar patients is difficult and depends 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. Most complex patients do not fit into the evidence-based guidelines [21-25]. Therefore, clinicians need more point-of-care information without information overload for reducing cognitive complexity. Also, the data can be better represented by visualization in a single display. Visualization of population information has the potential to support "if-then" heuristics for improved and informed clinical reasoning [26-28]. Most decision support systems do not take heuristics into consideration in the design due to the associated biases [26, 29]. However, intuitive design for future innovative population decision-support systems should match the higher cognitive reasoning and mental models of clinicians [30-32]. Showing treatment or diagnostic outcome data leveraged from population or EHR database may nudge the clinician positively and provide cognitive support when the clinician is dealing with unique and complex patients. The visualization design principles used in our study can help future researchers and designers with better task allocation and intuitive display features. Future work is needed in the area of visual presentation that can match clinicians' mental models to effectively show similar complex patients in a single display The discussion is further subdivided into the following three sections: implications for healthcare system design from the qualitative analysis, implications of the quantitative analysis, and improved design of the population information display.

Implications for Healthcare System Design From the Qualitative Analysis

The themes that emerged based on the preferences for information display may help future researchers and designers. Our results resonate with those of previous studies on understanding clinicians' preferences for information display design in healthcare [33-38]. However, our findings that providers are concerned with data trustworthiness, that they need to have more meta-information about the display and that they want to explore the similarity profile of the patients are unique to this kind of display. In the following paragraphs, we discuss the results from the perspective of the implications for design.

Improving the Trust in Population Data

Practice-based information may provide a glimpse of what can be done when the case at hand is complex and evidence is scarce. However, data pulled from a population database may reveal wide variations in clinical practice, leading to more confusion for the clinician, or at least much more uncertainty as compared to a clinical guideline. Also, the snapshot view may lead to attribution errors regarding the cause and effect of different choices [39]. For example, if providers can assume from the data that 50 patients receiving drug A had a positive outcome, then their patients at hand may also benefit from it. However, the treatment outcomes of the matched patients may not be the same for the patient at hand due to the unique characteristics of each patient's clinical and functional presentation. Therefore, embedding different types of analytics to verify the data may be a solution. For example, different patient-matching algorithms, temporal patterns, or predictive analytics within the population decision-support systems may help clinicians to understand the data [40-43]. This problem needs to be addressed before making the data available in real-time to clinicians. Many current applications for providing population data assume that real-time information can be shown without validation [18]. Our findings suggest that clinicians are worried about the validity of real-time population data and would prefer that data validation by a domain expert be done before the data are used to guide decisions for a specific patient.

Analytical Complexities of Finding Similar Patients

It is sometimes difficult to explore a large number of similar patients when the patient at hand has complex and very unique characteristics. Therefore, defining similarity measures for temporal categorical data is important for understanding the results of the population inquiry. Features for showing the results of similar patients in terms of natural frequencies rather than probabilities may reduce cognitive biases due to the misapplication of probabilities [28]. For example, a similarity measure of temporal categorical data called M&M (Match and Mismatch) developed by researchers at the University of Maryland finds similar patients by ranking scores [8]. This tool has the capability of comparing different features of a patient's characteristics by using filters as well as visualizing the similarities in a scatter plot. Tools such as M&M may be embedded in the population information display to provide a better measurement of the matched similar patients.

<u>Better Tools to Control Display</u>

The need for tools to control the view of the display can include overview, zoom, and filter functions. Such functionalities have worked well in many other domains as well as in medicine [43-48]. An overall view gives a better understanding and helps with the clinician's situational awareness. Then, zoom and filter options help the clinician to focus on the important information by filtering out the unnecessary information and allowing him or her to pay particular attention to details [49]. For example, LifeFlow has an analytic function to show the overall view. In addition, users can zoom and filter as needed to obtain the relevant information from the EHR [50]. From our study, it is clear that clinicians want to explore in detail particular information from a display. Therefore, the analytical capabilities for control over the display will empower clinicians to obtain a better understanding of the similar matched patients from the population database.

Multiple Representations of the Population Display

Different visualizations of the same information can help researchers make better sense of the data. Infographics researchers in other domains, such as information or computer science, have established design guidelines (e.g., space/time resource optimization, attention management, consistency, etc.) [51-54]. However, the particular problem of finding and displaying similar patients is new, and guidelines have not been established. Information presented in a timeline view for individual patients may help when the case is very complex and only a few patients can be found through a database search. However, if the number of similar patients found is large, then pie charts or bar graphs with aggregate information may be a better option. A systematic review of innovative visualization of EHR data has shown pie charts, bar charts, line graphs, and scatter plots may reveal important information in an aggregated view for representing a larger number of patients [1]. However, for a very small number of patients, a longitudinal view may be better [4]. For example, researchers from IBM Research developed an interactive clinical pattern technique that can visualize and change the visualization display based on the pattern of the data [55].

Implications From Quantitative Analysis

The quantitative results from this exploratory study offer insights into the effect of a population display on cognitive processes. We found that the display did have a marginal effect on the quality of the plan in pre-/postassessments. We also found that experts processed the population-based information faster than nonexperts, giving validity to the display content. This finding is congruent with similar findings about experts' ability to process information in search, perception and reasoning components of the task faster when compared with nonexperts [56-60].

Improved Design of the Population Information Display

The literature review of healthcare information visualization highlights important design features. Also, the results of this study provided us with rich qualitative data regarding the preferences for population information display design. In the following paragraphs, we discuss how the new design supports the themes raised from clinicians concern in this study.

Improving Trust in Population Data

Clinicians raised concern about the quality of the data and the need to understand how similar their patients were to the cases we found by querying the VA database. Visualization approaches may help clinicians feel more confident about the similarity of the patients presented. In our previous design, we did not separate the antibiotics period explicitly by pre-post and current antibiotic timeline, which caused confusion. Clinicians also raised concern in the previous display about the position of the legends, as they had to search what each legend represented due to its position at the bottom of the display. Therefore, in this new design, we have placed the legends on the right side of the display for convenience. Showing the antibiotics period as three different timeframes side by side provides a better picture to compare the patient in hand. The differentiation of the timeline can improve the comprehensibility of the display. However, analytics-based information display can improve confidence and trust overall. Future enhancements to address clinicians' lack of trust on the data include approaches to explain the logic that can determine two patients to be similar as well as helping clinicians visualize the differences and similarities between patients.

Better Cluster to Understand Similarity of the Patients

The patients were not clustered by deaths or antibiotic type in our previous display. Clinicians raised concerns as they had to find similar groups of patients. Therefore, in this present display, we have clustered the patients by deaths and by the types of antibiotics used. These clusters provide a better representation of the population information and help to make better cognitive sense of the display by reducing search time.

Supporting Possible Analytical Capabilities for Improved Control of the Display

Clinicians want to be able to zoom, filter, and sort patients based on different attributes. Even though the design for the current display is static, different analytical capabilities such as zoom to patient information based on the antibiotic period can be achieved. In this display, we have separated patients by different timeline periods and deaths. In our previous display, it was not possible to zoom into pre-, current, and post-antibiotic timelines and explore similarities. However, in the current display, it is possible to add those analytical capabilities due to the separate timeline view.

Support Multiple Representations of the Population Display

Clinicians recommended different presentations of data for better comprehensibility in this study. Our previous design included only a visual display.

However, in this new design, we have added a summary table for a different presentation of the data through numerical variables. The summary table inside Figure 6.4 provides a quick overview of the patients who died after using Daptomycin versus non-Daptomycin medications. The different presentation of the population data promotes better understanding and improved comprehensibility of the population-based information.

Limitations and Future Work

The main limitation of our study was the small sample size. As an exploratory study, the results will guide future larger studies with visualization displays showing population information. There were also biases with regard to the appropriateness of plans for experts versus nonexperts. The expert panel decided that as long as the nonexperts consulted ID clinicians, the plan was appropriate. However, this was not the case for experts' evaluations of the plans. It is difficult to judge an appropriate plan for very complex cases. Last, this study was focused on the ID domain. Future studies in other domains are needed to assess generalizability. Also, in this study, we have used a static population information display without analytical capabilities. Future work may include better population information displays incorporating the preferences for design found in this pilot exploratory study.

Conclusion

In this study, we have successfully extracted similar complex patient information from an actual clinical database and presented the information in a population information display. Future studies may use our methodology for finding similar complex attributes of patients based on the clinical question to reduce uncertainty and cognitive complexity. In addition, the content analysis of the qualitative data on preferences for population display revealed the following four themes: 1) trusting population data can be an issue, 2) embedded analytics is necessary to explore patient similarities, 3) tools are needed to control the view (overview zoom and filter), and 4) different presentations of the population display can be beneficial. The results suggest that ID experts processed the population information visualization faster than nonexperts. Future studies with a large number of participants and a more fine-tuned visualization population display may validate the results of this exploratory study.

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Table 6.1. Complex case summary

Patient is a 60-year-old man with AML s/p induction with 7+3 day+35 now s/p re-induction who has had sustained neutropenia and now fever for the past 7 days. Initial blood cultures revealed Vancomycin-resistant *Enterococcus.* Infectious diseases was consulted the day after the fever spike and recommended Daptomycin given history of the same during previous admissions. Routine susceptibility report demonstrated susceptibility to Daptomycin, but after 2 days of sustained bacteraemia and worsening picture, gentamicin was added and his PICC line was discontinued. The patient remains on the floor, but has been persistently febrile. Transthoracic echocardiogram shows new tricuspid-valve regurgitation and a 3 cm vegetation.
He endorses subjective fevers and chills but does not otherwise localize his symptoms. He reports feeling depressed about his outlook.
VRE TV endocarditis currently failing or with delayed response to Daptomycin + Gentamicin and removal of the PICC line. Worsening on therapy. Creatinine now 1.6 from 1.3. Currently neutropenic, precluding surgical intervention. Daptomycin etest 4, Linezolid 2. Susceptibility on the VRE from 2 days ago was rechecked and was the same as the original.
Instructions: Please write down a plan about how will you manage the patient therapeutically and rank the plans

Table 6.2. Information from similar patients

	Patients with Daptomycin and/or combination therapy including Daptomycin	**Patients with any antibiotic other than Daptomycin**	**Total**	**Percentage of total patients**
Died	8	2	10	52%
Did not die	6	3	9	48%
Total	14	5	19	
Percentage of total patients	74%	26%		

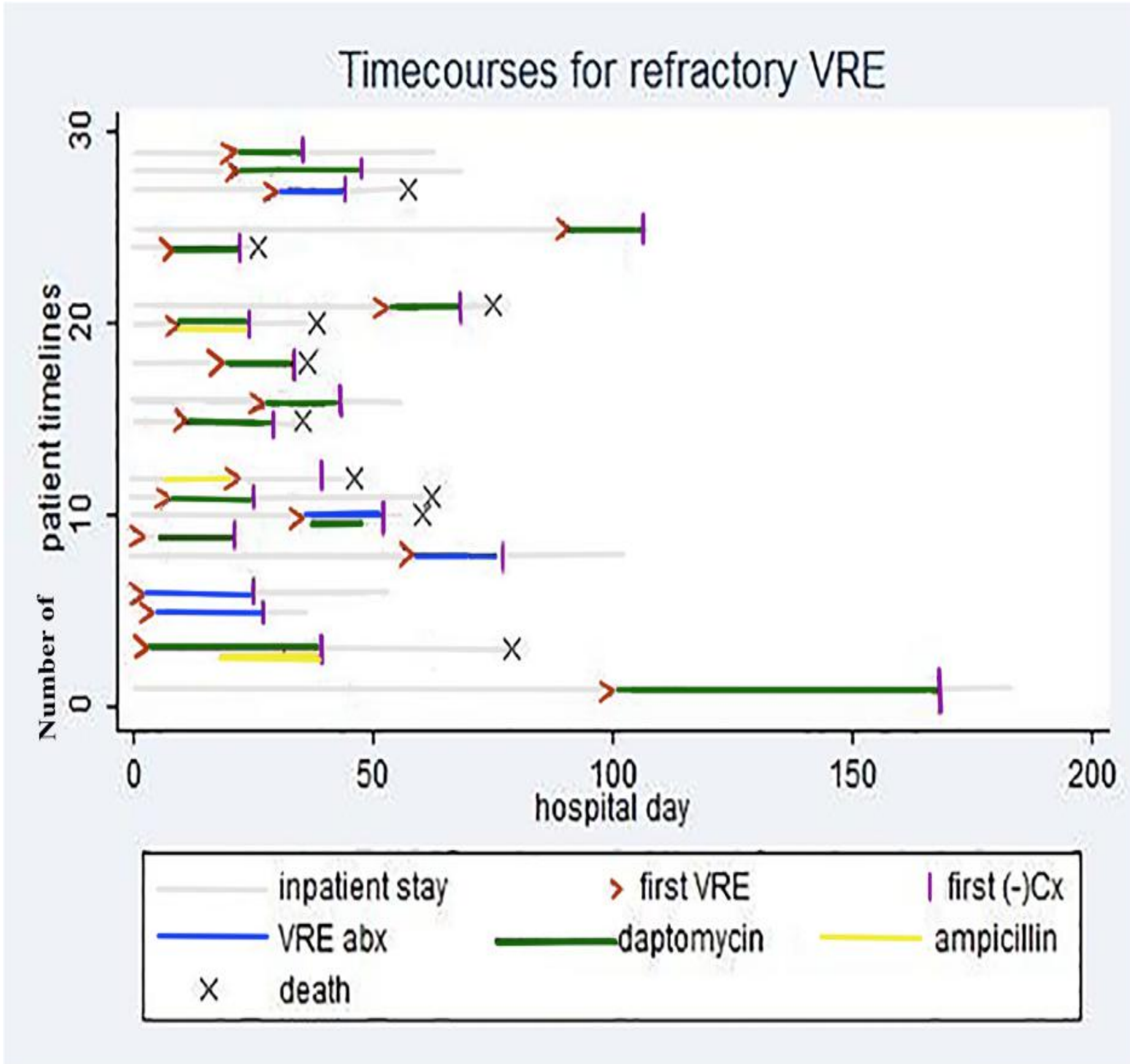
**More patients died on treatment therapy containing Daptomycin than other therapeutics alternatives. Also, the guideline does suggest using Daptomycin as an initial therapeutic agent.

Table 6.3. Measured outcomes and data collection

Independent variables	**Data collection procedure**
Preferences for information display	The first author audio recorded and transcribed the post-study, in-depth interview with the participants
Time looking at the population information display	Quick Time player screen capture recorded the total time each participant spent looking and exploring the population information display
Time to read the chart	Quick Time player screen capture recorded the total time each participant spent reading the patient chart
Appropriateness of plans	Participants wrote down the treatment plan in word-processing software and ranked the plan. They wrote down the plan twice: once after reading the chart and then again after seeing the population information display

Table 6.4. Criteria for appropriate plans (if participants mentioned at least one of the treatment strategies such as start Linezolid or Tigecycline or consult ID, the plan was termed appropriate).

	Appropriate Plan
Infectious diseases group	1. Start Linezolid or 2. Start Tigecycline or 3. Start very high dose of Ampicillin + Ceftriaxone
Noninfectious diseases group	4. Consult ID or 5. Start Linezolid or 6. Start Tigecycline or 7. Start very high dose of Ampicillin + Ceftriaxone



Inpatient Stay- Total number of days the patient stayed in the hospital

First VRE- First time the patient got Vancomycin Resistant Enterococcus

First (-) Cx- First time the patient culture results became negative

VRE ABX- Vancomycin Resistant Enterococcus antibiotics(All other antibiotics other than Daptomycin)

Figure 6.1. Population information display.

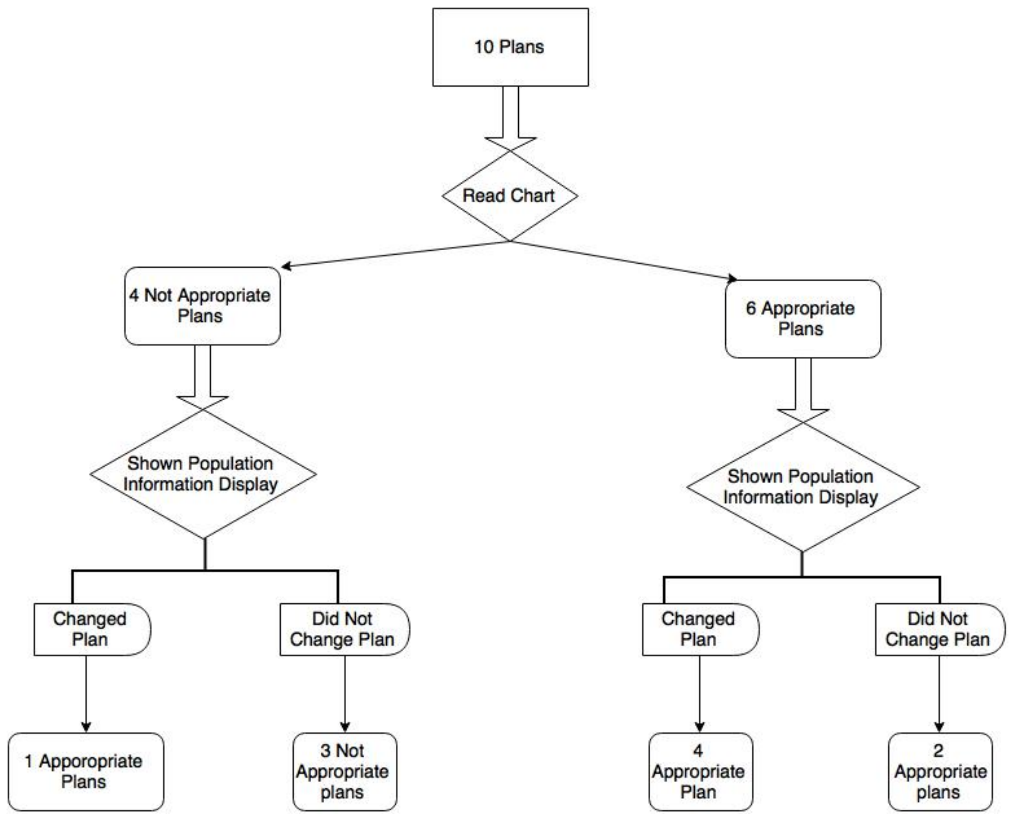


Figure 6.2. Appropriateness of plans before and after showing the display.

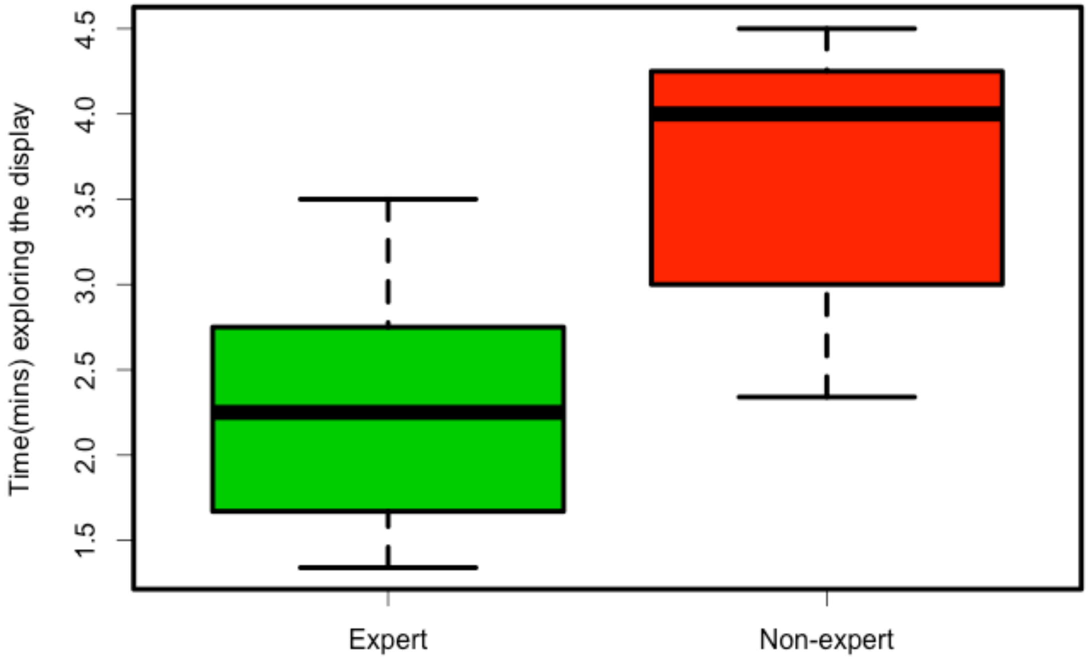
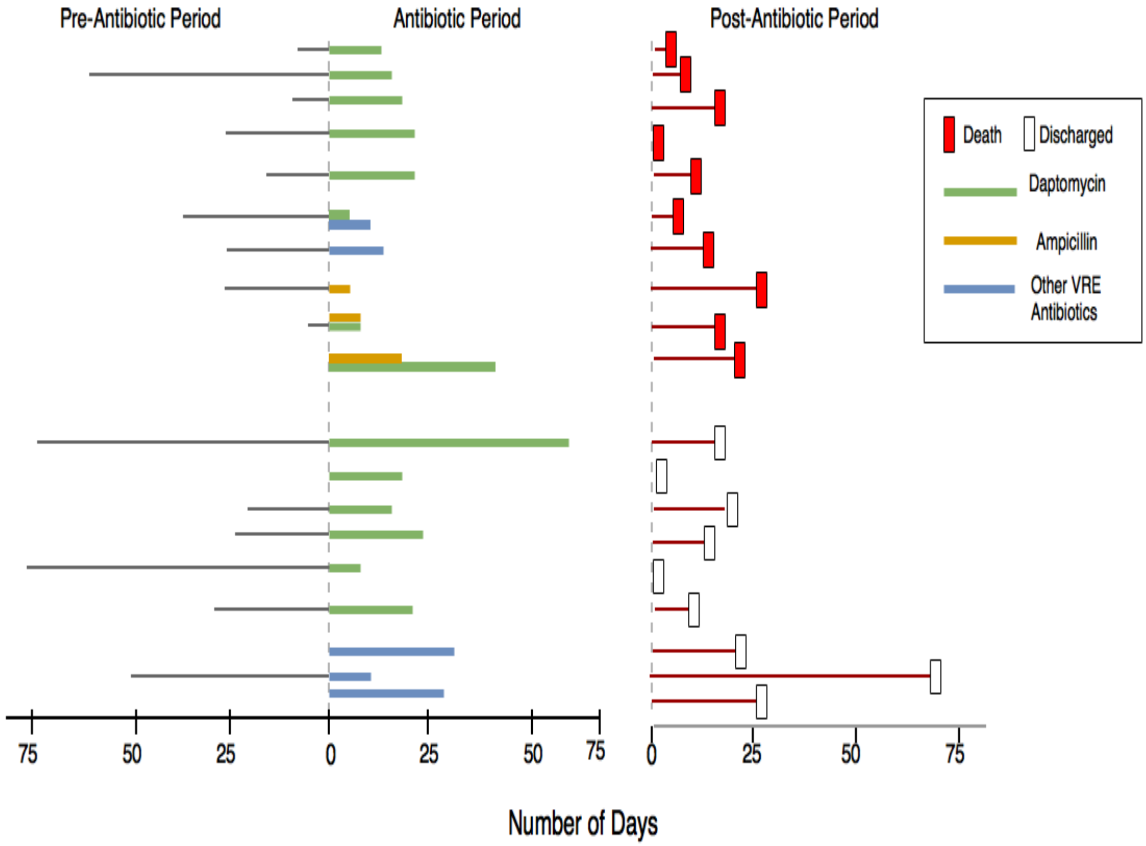


Figure 6.3. Viewing time for the population display (expert versus nonexpert)



Summary

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

Figure 6.4. 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.

CHAPTER 7

DISCUSSION

Summary

In this dissertation, we explored task complexity for a better understanding of the design principles for next generation health IT systems. Previous research on complexity in healthcare lacked a clinical complexity model that included both patient and task complexity variables. Our main hypothesis was that understanding the user's interaction with complex decision tasks may lead to improved recommendations for the design of decision support tools integrated with EHR systems to improve patient safety. To achieve this, we created the first integrated clinical complexity model (Chapter 3) that includes both patient and task complexity. Then, we successfully identified specific decision support tools tied with cognitive mechanisms (Chapter 4) and specific complexity-contributing factors (Chapter 5). Our findings (Chapter 4 and Chapter 5) from this dissertation have successfully led to the recommendation of different decision support tools based on the cognitive mechanisms and complexity-contributing factors.

To improve the understanding of complex tasks in the healthcare domain, we have conducted four studies focused on the following topics. First, we have merged and adopted a patient and task complexity model from previous studies [1, 2] for a healthcare-specific clinical complexity model (Chapter 3). However, this model was not validated in the infectious diseases (ID) domain. To make sure that this model represents clinical complexity, we used it for the data analysis in the observation study (Chapter 5). As a result, we found that 20 of 24 complexity-contributing factors in the clinical complexity model were relevant for the ID domain. Identifying these complexity-contributing factors led to better design recommendations for different decision support tools. Moreover, the cognitive task analysis (Chapter 4) of ID clinicians helped us understand the constituents of complexity and the coping strategies expert clinicians use to deal with complexity. These coping strategies provide a better understanding of specific design recommendations to incorporate different decision support tools for better cognitive support for our clinicians. The final pilot study (Chapter 6) demonstrated the feasibility of extracting and displaying population-based information from an actual clinical population's database records. Also, the specific preferences (Chapter 6) for population information display may guide future design recommendations for population-based decision support systems. These studies demonstrated aspects of different task complexity factors and provided specific design recommendations for future innovative and safer health IT systems.

Our research has focused on task complexity in the ID domain. Most of our participants were clinical experts who manage uncertainty and complexity in their daily practice using their experiences. This research has delved into the interaction of task characteristics and individual differences (e.g., experience, cognitive capabilities). Our results suggest that the problem-solving process can best contribute to effective and efficient problem-solving outcomes when individuals' mental models accurately represent the complex tasks. Previous research for understanding clinical complexity lacked a measurement for understanding factors related to objectively characterize complex tasks. As a result, complexity in medicine was more of an abstract concept. The clinical complexity model (Chapter 3) developed in this dissertation can objectively measure complexity and reduce the abstraction. Moreover, the design recommendation by understanding the coping strategies (Chapter 4) for dealing with complex tasks and identified complexity-contributing factors (Chapter 5) will guide the informatics community, health services researchers, and system designers for safer and better information technology platforms.

For example, the cognitive mechanisms (Chapter 4) for dealing with complex decision tasks may help with the design of decision support tools that can be integrated with EHR systems for better clinical reasoning. The different patient monitoring tools to support *watchful waiting* may provide better task allocation for interface design for decision support systems. Also, the complexity-contributing factors (Chapter 5) found in the observation study yielded specific design guidelines. For example, the *unnecessary information* and *unclear goals* can be reduced by integrated displays in the ID domain. These findings can greatly help informatics researchers and health IT designers for specific task allocation for future innovative interface design. All these complexity factors are related to tasks, and thus they can help with task allocation features for designing systems.

Also, we found that information presented in spatial format (e.g., population information display in Chapter 6) contributed to faster processing of information for domain experts when compared with nonexpert clinicians. The preferences for ideal population display (Chapter 6) have led to better design principles for improving and incorporating big data for better clinical decision-making. These results also imply that complex information presented in specific visualization formats (such as different time views) may reduce cognitive load. Overall, this dissertation suggests that better understanding of task complexity can provide informatics solutions for safer and improved technological designs to enhance the clinical reasoning of clinicians and thereby improve patient safety.

Finally, the studies from this dissertation suggest that task complexity is an important and crucial factor to be considered in healthcare information technology system design. Future studies of how complexity in medicine can validate our clinical complexity model in different clinical domains and identify domain-specific task complexity factors may provide a better understanding of task allocation and design specifications in future innovative interface systems. The results of our studies can help future researchers and designers build systems for our clinicians for the way they behave and not the way we want them to behave.

Limitations

The research described in this dissertation has several limitations. Several human factors methods elicit the decision-making process, such as hierarchical task analysis (HTA) and cognitive work analysis (CWA). In this research, we have used one form of cognitive task analysis, as well as observation and simulation, to understand the overall clinical reasoning process. Other methodologies, including HTA (Hierarchical Task Analysis) and CWA (Cognitive Work Analysis,) could also be used to understand the task interactions. However, the methods that we have used are very robust and have been employed in many different fields to understand the decision-making process.

Another limitation is the sample size for the observation study (Chapter 5) and the exploratory study (Chapter 6). The results of the observation study suggest that a greater number of cases may help researchers predict the relationship between perceived and objective complexity. Also, we conducted the pilot study (Chapter 6) with 10 participants only. Therefore, more participants could have provided a significant relationship among the outcomes of the study measures.

The main limitation of this overall study is generalizability to other clinical domains. All the studies have been done in the ID domain. Among all other clinical domains, ID is challenging due to the resistant and emerging organisms causing infections and the concomitant public health implications [3-5]. An avenue for future research is the examination of the research questions in different clinical domains.

Finally, understanding task complexity is just one of the many but important steps to understand user-centered design. Understanding different task allocations and the requirements for interface system design is important. However, there are many other methods, such as cognitive work analysis, timeline analysis, and event analysis of systemic work. These methods also can help us to understand the overall design process from the human-computer interaction point of view. The alternative methods may generate more decision points and complexity-contributing factors that can add important knowledge for the problem on which we are focused. Also, task complexity may reside in the cognitive complexity of the user. Therefore, understanding socio-technical complexities such as teamwork, workflow analysis, and social network analysis is also an important part of the process. In this study, we did not explore the other relevant human-factor methodologies. Therefore, future studies may shed light on task complexity by integrating other robust human-factor methodologies.

Future Directions

Our findings can help future decision support designers in medication management in different clinical domains. For example, our mapping of decision support tools based on cognitive mechanisms can be applied in other clinical areas such as managing patients with high blood pressure or psychiatric use of antidepressants. In all domains, clinicians experience complexity. However, little has been done to manage the complexity by presenting information in innovative visualization. Our second design clearly shows the outcome of different therapeutic agents in a longitudinal manner. Other clinical domains such as primary care or psychiatry can use such displays to provide outcomes of different therapeutic agents and provide guidance to clinicians for managing optimal treatment regimens.

The research described in this dissertation may lead to such future research directions as task complexity to understand clinical workflow, heuristics management for intuitive system design, and action identification to differentiate between high- and low-level tasks for better cognitive support.

Task Complexity to Understand Clinical Workflow

In our work, we found that the complexity lies not only between the clinician and the artifacts (display, computers, etc.) but also within and between the actor and the environment (other factors such as teams, patients). Therefore, understanding task complexity in a team environment can shed better light on clinical workflow from a design perspective.

The complexity and importance of tasks likely affect how decisions are made at the level of communication and coordination required among team members. The complexity of the task determines the time and effort team members invest in the collaborative problem-solving process. Understanding task complexity can shed light on clinical workflow variations and effective management of the patient. It may be possible to create a framework to map clinical workflow based on the task information-social network approach to understand the macro-cognition of teams. Understanding task complexity among clinical teams may help us to develop a generalizable framework for mapping clinical workflow for health information technology system (re)-design.

Heuristics Management for Intuitive System Design

In our results from Chapter 4, we found that heuristics or a short-cut mental model plays a very important role in overall clinical reasoning. However, most decision support design does not take the principle of "less is more" seriously. On the contrary, it is assumed that more information will lead to better decision-making. Therefore, understanding the short-cut mental model is important for intuitive design.

Heuristics plays an important role in overall clinical reasoning. Due to cognitive limitations, we cannot process information beyond our cognitive capacity. As a result, the brain filters out unnecessary information and focuses only on pertinent information. Although generally effective, this process may lead to cognitive bias and errors. However, if heuristics management is not optimized, information overload will confuse the user and make him or her more prone to errors. For example, by identifying the ignored information during clinical reasoning, decision logic built into the system may provide cognitive support for clinicians not to miss pertinent and important information. Future studies may look into these ignored factors to reduce the bias that comes with heuristics. Therefore, future intuitive systems can match the higher cognitive ability of the clinician by focusing on the important information in order to convey only relevant point-of-care information to the clinician to reduce cognitive bias and errors.

Action Identification to Differentiate Between High- and Low-Level Tasks

In our research from Chapter 3 and Chapter 5, we found that complexity-contributing factors can vary based on time and the situation of the patient. Therefore, to identify these factors in clinical domains, it may be helpful to understand how these tasks are represented in the clinician's mental workflow.

The task complexity factors discussed in this dissertation were domain specific. However, tasks are represented in the expert's mind with respect to different levels of goals and expectations. As a result, the same task may not be in the same level of representation in the nonexpert's mind as in the expert's mind. Therefore, understanding these different representations of high- and low-level tasks may help with future design and task allocation in the interface system.

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