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Identifying Complexity in Infectious Diseases Inpatient Settings: An Observation Study

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Abstract

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

Objective—To identify the specific complexity-contributing factors in the infectious disease domain and the relationship with the complexity perceived by clinicians.

Method—We observed and audio recorded the clinical rounds of three infectious disease teams. Thirty cases were observed for a period of four 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 case were collected. We then used statistical methods to identify complexity-contributing factors in relationship to perceived complexity of clinicians.

Results—A factor analysis (principal component extraction with varimax 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). A linear regression analysis showed no statistically significant association between complexity perceived by the physicians and objective complexity, which was measured from coded transcript by three clinicians (Multiple R-squared=0.13, p=0.61). There were no physician effects on the rating of perceived complexity.

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Authors' Contributions

Conceived and designed the experiments: DR, GDF, and CW. Performed the experiments: DR. Analyzed the data: DR, GDF, MR, MJ, GJS, and CW. Wrote the paper: DR. Manuscript Review: DR, GDF, MR, MS, MJ, GJS, and CW.

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Conclusion—Task complexity contributes significantly to overall complexity in the infectious disease domain. The different complexity-contributing factors found in this study can guide health information technology system designers and researchers for 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 improve task allocation and design for intuitive clinical reasoning.

Keywords

Clinical complexity; Uncertainty; Health information technology; Infectious disease; Medical informatics; clinical decision support

1. Introduction

The characteristics of infectious diseases (ID) set this domain apart from other areas of clinical care due to its 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. In the following background section, we discussed about the importance to understand complexity in medicine.

1.1 Background

Complexity refers to the amount of information needed to describe a phenomenon or observation under analysis. The closer the phenomenon is to randomness, the more data are needed until the phenomenon can be described within terms comprehensible by the mind.[6] Something is complex when it contains a large amount of important information that surpasses our ability to process. The degree to which we can process information is a function of expertise and experience.[7] An expert can process a great deal of information if it matches their mental models. However, if something contains a large amount of useless and meaningless information, our mind has to expend a great deal of effort or simply ignores the information.

Different domains in medicine deal differently with complexity in patient cases. Thus, the decision-making process cannot be generalized for all areas of medicine. In medicine, the complexity in family medicine may explain the high intra-physician variability in patient management that is observed for general practitioners. Therefore, physicians adjust the care they provide based on the complexity of the clinical situation or case.[8] Kannapalli and Patel studied different complex systems by conducting a functional decomposition of a complex system as a whole.[9] The degree of interrelatedness between system components was an indicator of system complexity. However, we are dealing with the provider, the patient and their context from the more psychological point of view. From this perspective, it is important to focus in on specific clinical domains.

Currently, there are few methods for estimating complexity in either ambulatory or specialty medical care. 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.[10] 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 behaviour, psychosocial issues or cultural background. 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.[11] Another similar approach, Ambulatory Severity Index (ASI), combines biophysical and behavioural dimensions with a complexity severity index.[12] This index also includes complexity based on urgency, complications, and communication. Other systems, such as the diagnostic-related groups (DRGs) and case mix groups (CMGs), are based solely on medical diagnoses.[13] 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. 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.[14] 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.[15] 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. The different risk assessment parameters from all different research groups did not take into considerations of the perceived or subjective complexity of the task performer. Understanding the different factors that can get influenced by perceived complexity can provider better understanding of the objective properties of such parameters.

Physicians and nurses define complexity in patient cases from various perspectives, including task complexity as well as patient complexity. Task complexity is well defined in other successful areas of system design, including the Defence, the humanities, engineering, business, and the social sciences. Several studies have found task complexity to be a crucial component of the environment that influences and predicts human behaviour and performance.[16–21] Even though there is no clear definition of task complexity, it can be better understood by parsing it into objective task complexity and perceived task complexity. Objective task complexity refers to the characteristics of the task model.[22] In other words, it is the manipulation and quantitative assessment of task complexity based on the task model. It is the inherent complexity that exists regardless the perceived notion of the level of complexity by the task performer. Perceived task complexity considers the task performer's characteristics and the perceived difficulties of performing the task.[23] Subjective task complexity is the complexity of the 'state of mind' of the individual who performs the task. 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 study, we adopted the perceived complexity constituents from the literature review of Liu et al. and used in other domains outside healthcare.[23] The four constituents we used for measuring perceived complexity are *diagnostic uncertainty, treatment unpredictability, perceived difficulty*, and *similarity* of the cases.

Objective complexity has an important and direct relationship with subjective or perceived complexity.[24] As the complexity of a task increases, the task becomes more difficult to the performer and greater effort is needed to manage the complexity. Therefore, to understand the overall complexity, it is vital to take both perceived and objective complexity into consideration.

1.2 Objective

In this study, we are not trying to understand the system complexity. Our goal is to better understand the physiological processes of humans coping with complexity. Therefore, understanding both patient and task complexity factors are crucial for identifying the specific factors contributing to complexity.

In a previous study, we developed and validated a clinical complexity measurement model that includes both patient and task complexity-contributing factors.[25] In the present study, we conducted provider observations to identify the specific CCFs in the ID domain and their relationship to perceived complexity.

In medicine, it is important for the clinician to have a good idea about how complex the situation of the patient is for improving overall care quality. Currently, there are no automated objective measurement quality indicators or software systems that can indicate the level of complexity for a difficult patient. Therefore, it is based mostly on the subjective or perceived complexity of the clinician to decide the difficulty or complexity level of the patient case. In this study, we seek to understand if the perceived complexity is correlated with the inherent or objective complexity of patient cases. Our findings can have important implications for future health IT system design that can support clinicians to reduce cognitive complexity and information overload. For example, systems that can classify different complexity level of patients based on the information entered could objectively identify complexity. As human perception can be flawed, future smart systems can work as a cognitive extension for clinicians to correctly understand complexity in medicine. Identifying overall complexity objectively that is not based on perception of a provider, may be helpful to assess the patient case and get an unbiased opinion. Future decision-support tools or software providing such expertise can be great benefit for treating complex patients with more care as well as help insurance companies to focus on patients for preventive care.

2. Methods

2.1 Settings

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

2.2 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.

2.3 Description of Procedures

2.3.1 Case Selection—Thirty patient cases were observed across the three teams. Each case was observed for four consecutive days. Previous studies have successfully used 16 to 30 cases for conducting similar studies.[26–28] The only inclusion criterion for a case was the referral to the ID team for consultation from the primary care team in the hospital.

2.3.2 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.

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

2.4 Development of the Clinical Complexity Measurement Model

Previously, we developed an integrated clinical complexity measurement model that includes both patient and task CCFs.[29] Three of the co-authors (DR, CRW, GDF) used the transcripts from the present observational study to iteratively construct the measurement model. This model integrates the patient CCFs proposed by Schaink et al. and task CCFs outlined by Liu et al.[23, 30] A list of CCFs used in the model is available in Table 2. The CCFs in this model were used to code the transcripts of the present observational study.

2.5 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. In this study, we unitized sentences based on clinical tasks related to the treatment or intervention for improving patients' well-being. Various aspects of clinical tasks can increase cognitive complexity and thus, may be perceived to be complex tasks. We defined clinical tasks as activities that involve actionable components to achieve goals.[31] Units were then refined through team consensus. Subsequently, two of the authors (CRW and GDF) independently and iteratively coded the unitized sections using the 24 CCFs from the patient and task complexity models. After each coding iteration, the three researchers met for recoding and modification of the categories, selecting one CCF for each unit of text. Cohen's kappa was calculated after each revision of 50 unitized statements. The final inter-rater reliability reached a Cohen's kappa of 0.8. We followed a standard unitization process. To establish proper context, the coders considered previous and subsequent units when coding a specific unit.

We only unitized the texts that are related to clinical decision-making for the patient. There were residents and ID fellows present in the rounds. Therefore, the transcript contained a large portion of sentences related to teaching, such as rhetorical questions. We excluded these sentences from the transcript and from further analysis. For example, the following excerpt was removed due to its teaching focus:

Well, the issue is there is always a balance, right? So what we need to do is like screening for anything. You want high sensitivity. But what that means is you get some false positives, right? So there are always two stages to these types of screening things. So, what you don't want to do is think someone doesn't have an allergy. You think they are fine, and they are not, right? We want to catch 100% of those people but when you try to catch everybody who might have an allergy you are going to catch a few who don't have the allergy. And in this case, most of the people don't have an allergy. So our specificity to having a positive test, the likelihood of that being a false positive is very, very high.

Here we provide an example for the following excerpt that has been coded as *lack of team coordination*

You are probably going to want her to be seen by an ortho team STAT and she probably doesn't want to go back to get washed out. I don't know. We wouldn't want to get involved in that case but, then again, she's the primary responsibility for ortho team. Now, you are PICC lined, they treat you and then send you back to the room. In that respect, I kind of want the burden of proof from ortho.

We defined objective complexity for this study based on the coding by the three researchers. The coding frequencies were then correlated with the ratings of the perceived complexity for statistical analysis. We used Atlas.ti 7.0 for coding purposes.

2.6 Statistical Analysis

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

3. Results

3.1 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; $p = .94$).

3.2 Internal Consistency of Perceived (Subjective) Complexity

Perceived complexity ratings ranged from 6 to 26, and the average across all patients was 14.3 (SD=5.1). A perceived complexity scale summing the four items was created. The Cronbach's alpha for internal consistency of the scale was 0.76. These results show that the four items were correlated strongly with each other and are important constituents of perceived complexity.

3.3 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 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 principal component analysis results clustered around the three main component factors based on strong internal consistency among the three factors indicating that adding or deleting a component to the three component solution would not change the total amount of explained 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 (Factor 1). *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 includes 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 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 do* not follow the prescribed regiment of treatment. P*overty and low social supports* add the intricacies of the social capital dimension.

3.4 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 correlation between objective and perceived complexity for Factors 1, 2 and 3 were not significant (r=0.29, 0.31, 0.29 and p=0.5, 0.44 and 0.48 respectively).

3.5 Changes in Complexity Factor Over Time

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

4. Discussion

In this study, we aimed to identify the factors that contribute to complexity within the ID domain and to assess the relationship between objective and physicians' perceived complexity. Previous studies on complexity in healthcare did not consider task CCFs. Task complexity has been proven to be an important factor to understand workflow processes and overall system design allocation features in other successful fields.[20, 32] The task complexity factors explained more than half (26% out of 47%) of the total variance. Therefore, this study provides a unique perspective about the importance of task complexity factors for identifying overall complexity in medicine. Also, we have used the clinical complexity model to identify the specific complexity factors relevant in the ID domain. The observation data from this study was partially used to modify and create the conceptual model of patient and task complexity, which is described in more detail in *Methods of Information in Medicine* [25]. This conceptual model consists of patient and task complexity contributing factors (Table 2) that were used to code the transcripts.

Our results indicate no significant correlation between perceived and objective complexity factors. It is possible that clinicians' perceptions of patient complexity may not be accurate. Moreover, the small sample size of 30 cases probably was not sufficient enough to find statistically significant results. Also, the criteria we used in our study to understand perceived complexity consisted of four factors from literature review.[23] Perceived complexity is not very well understood as clinicians' emotions such as fear and anxiety also play an important role in characterizing a patient's overall well-being. In the field of affective computing, no extant or projected computing system can simulate all aspects of human emotional interactions. However, significant research is underway to understand the underlying neurophysiology of the brain to mimic smart systems to read and ultimately support human cognition.[33]

The three dimensions, i.e., *task interaction and goals, urgency and acuity*, and *psychosocial behavior*, contain 20 CCFs. Our results regarding patient CCFs resonate with previous studies that identified patient-specific CCFs, such as frailty and psychosocial behaviors.[15, 30, 34–36] Other studies focused on assessing clinicians' perceived complexity found similar patient complexity factors.[37–39] The complexity contributing factors in Table 2 provides unique constituents of task and patient complexity factors. We found 20 complexity factors that are relevant to the ID domain out of the 24 complexity factors from Table 2. The results of this study helped to cluster the complexity factors in the three major components. The cluster of factors that explained most of the complexity factors (26% out of 47% of variance) included the task interaction and goals (mostly task complexity factors). Research on complexity in medicine often did not include task complexity factors and focused only patient related complexity. The findings from this study may encourage future research to including task complexity for better understanding of the overall complexity.

Also, the total changes of complexity over the course of care and time in Figure 1 show the variability of complexity. Our results indicate the objective complexity standardized scores are highest for Day 1 for most of our complexity factors. Day 1 of a clinical consult for ID would empirically seem to be more complex due to "newness" of a situation. Therefore, the amount of complexity is very high on Day 1. Eventually, the complexity goes down on Day 2. However, on Day 3, for most complexity factors we found a sharp increase. It is our assumption that this phenomenon is unique to the ID domain. Most clinical practice in ID domain is highly dependent on the pending culture results from microbiology laboratory. It takes 24–48 hours and even 72 hours for some culture results to be back from the laboratory to confirm diagnosis. As most susceptibility results come back around Day 3, there is much more discussion about possible course to narrow treatment therapy or intervention. Therefore, the sharp rise of complexity in Day 3 presents an intriguing implication for system design. For example, future interfaces can adapt to display the microbiology, source and contact information of the responsible source in laboratory personnel on Day 3 oppose to Day 1. In that way, the task allocation for different display features may change based on days and become more intuitive for clinicians. Currently, system design assumes that interface display should remain constant during the course of treatment. However, in this research, we found that complexity-contributing factors change over the course of time based on the patient's situation. Future research may identify and validate more of the complexity-contributing factors for task allocation of display, and the display may change to reflect the expertise of clinicians.

4.1 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. There are many different types of decision-support tools that can be integrated with current EHRs. In figure 2, we illustrate examples of available decision support tools that can be used to mitigate each of the complexity factors uncovered in our research by reducing cognitive overload. Moreover, future advanced decision support tools may be designed deliberatively to address those complexity factors.

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.[40–42] For example, LifeLine2, a visualization tool, allows users to drill down into details and filter *unnecessary information*.[43] LifeFlow allows visualization of millions of patient records in one single page. This feature can provide better situational awareness and help clinicians to set clear goals.[43]

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*.[44, 45] 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.[45] 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.[41, 46] Yet, barriers compromise the efficient use of these resources. Tools such as InfoButtons have been demonstrated to be effective in helping clinicians find evidence at the point of care.[42, 47] 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-based visualization exhibiting workflow fragmentation of tasks helped during the implementation of computerized provider entry (CPOE). Such tools can identify patterns and prioritize tasks for clinicians, thereby leading to optimal management of clinical operations.[48]

This kind of task visualization for optimizing workflow has been successfully used in the design of decision support tools in aviation and military systems.[49]

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.[50]

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.[51] 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 chronically complex patients.

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 likelihood of depression.[52] Tools leveraging such algorithms could be integrated with EHR to help clinicians cope with psychosocial complexity.

5. Limitations

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

Although content validity was somewhat established by the factor analysis and Chronbach's alpha analysis, predictive validity of the complexity factors was not established because the factors did not correlate with the physicians' perceived complexity. It is not known whether this is a shortcoming of the complexity factors, a shortcoming of the physicians' ability to accurately subjectively assess complexity, or whether the two are simply measures of something different. Future research with more complex cases may answer some of the questions from this research.

The number of cases studied in this study was small. However, the sample size on which the factor analysis is computed is on the number of coded elements (n=24), making the sample less of an issue. Of course, there were few interviewees, but there were 30 patients distributed across the interviews, again making the sample size less of an issue and more fully within recommended guidelines for qualitative research.

Another limitation was that the study was conducted in an academic inpatient setting. However, most very complex medical cases are referred to tertiary care academic medical centers.

6. 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 healthcare should include task complexity factors. Our results suggest that objective CCFs are not predictors of complexity as perceived by clinicians. Thus, clinicians may consider other unknown factors in their assessment of complexity. Future studies are needed to elicit these factors. The CCFs identified in our study may be used to guide the design of health information technology to provide better cognitive support.

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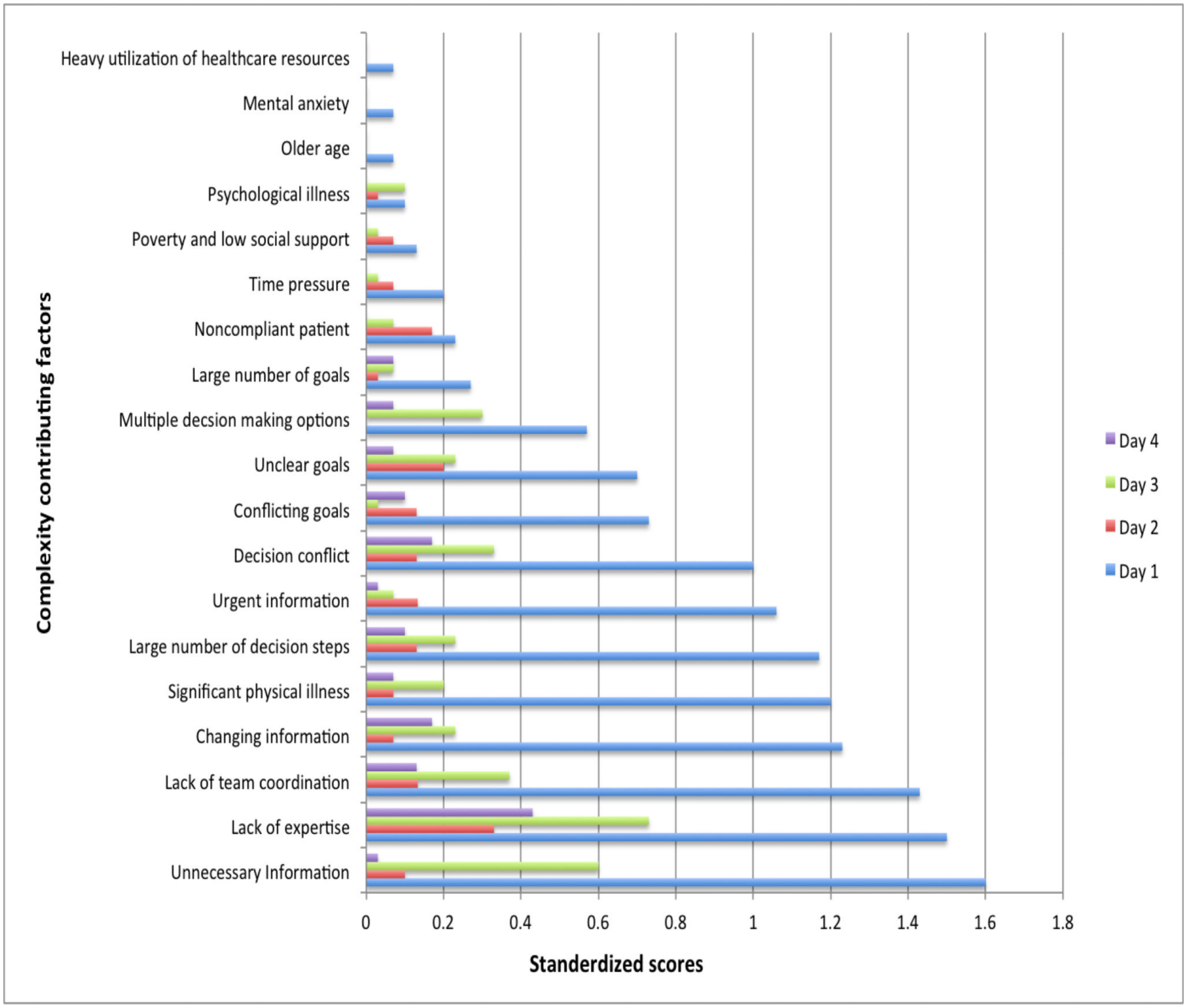

Figure 1.

Complexity contributing factors over four days. The X-axis denotes the z (standardized) scores of the objective complexity factors and Y-axis is all the complexity contributing factors. Here, most complexity factors are higher on day 1 and day 3.

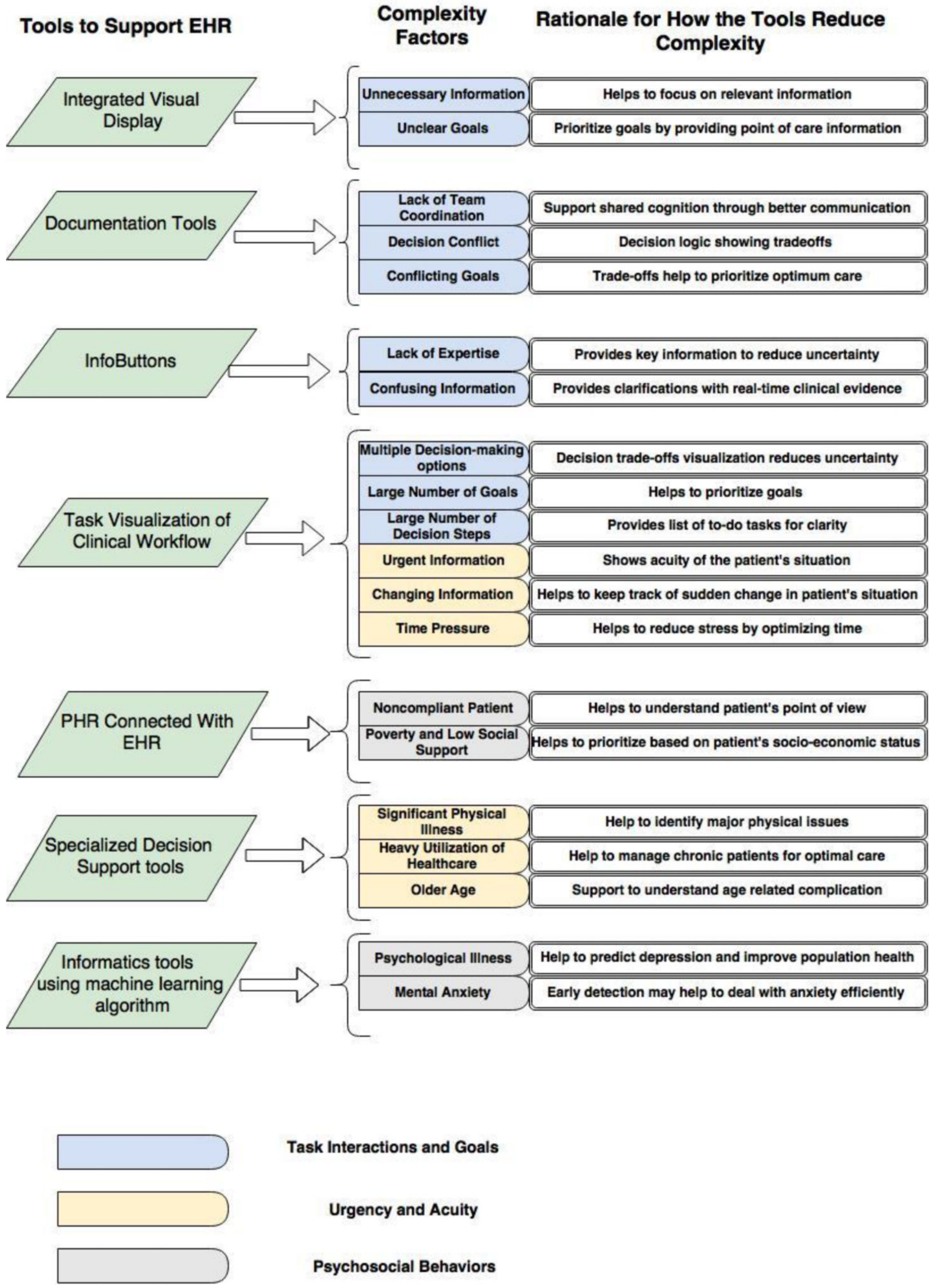

Figure 2.

Mapping of decision support tools that can help reduce complexity with rationale

Table 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.[23]

Table 2

Complexity Contributing Factors

Task Complexity-Contributing Factors	**Brief Descriptions**
Unclear goals	Lack of clarity in the degree of specified goals
Large number of goals	Multiple goal elements with multiple outcome characteristics.
Conflicting goals	Degree of attaining one goal negates or subverts attaining other
Confusing information	Unclear, contradictory, conflicting and ambiguous information cues
Unnecessary information	Large amount of unnecessary information that does not help with decision-making
Changing information	Unpredictable or sudden change of information cues
Urgent information	Refers to acuity of the patient's situation. A lack of control over the overall situation
Multiple decision-making options	Decisions that have too many alternatives and multiple tasks require significant coordination between tasks/actors
Large number of decision steps	More than two steps or actions to attain the goal
Decision conflict	Incompatible or conflicting task components for making a decision
Lack of expertise	Requiring additional knowledge for treatment or diagnosis uncertainty in novel and unique situations
Lack of team coordination	Inadequate communication, lack of aligned activities and lack of shared cognition
Time pressure	Situations requiring immediate or quick action
Patient Complexity-Contributing Factors	**Brief Descriptions**
Poly-pharmacy	The use of multiple medications
Significant physical illness	Multiple chronic disease or loss of physical functions
Mental anxiety	External factors such as social and economic creating mental stress
Psychological illness	Mood disorders, clinical depression
Addiction/substance abuse	Use of illicit substances with negative consequences
Older age	Patients 75 and older
Health disparity	Patients with disadvantageous economic, social, or ethnic background
Noncompliant patient	Patients who do not follow therapeutic or medical regimen
Poverty and low social support	Financially challenged, disadvantaged economic and poor social support
Heavy utilization of healthcare resources	Patients with multiple complex and chronic conditions who utilize more health care resources
Difficulty with healthcare system navigation	Limited health care system knowledge and literacy

Table 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 Table 2. The complexity contributing variables in Factor 1 include task complexity variables. Factors 2 and 3 include patient complexity variables. The complexity variables are hierarchically organized by correlation level. The total variance explained from the analysis was 47%.