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

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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.

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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 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 complex-

ity [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.

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.
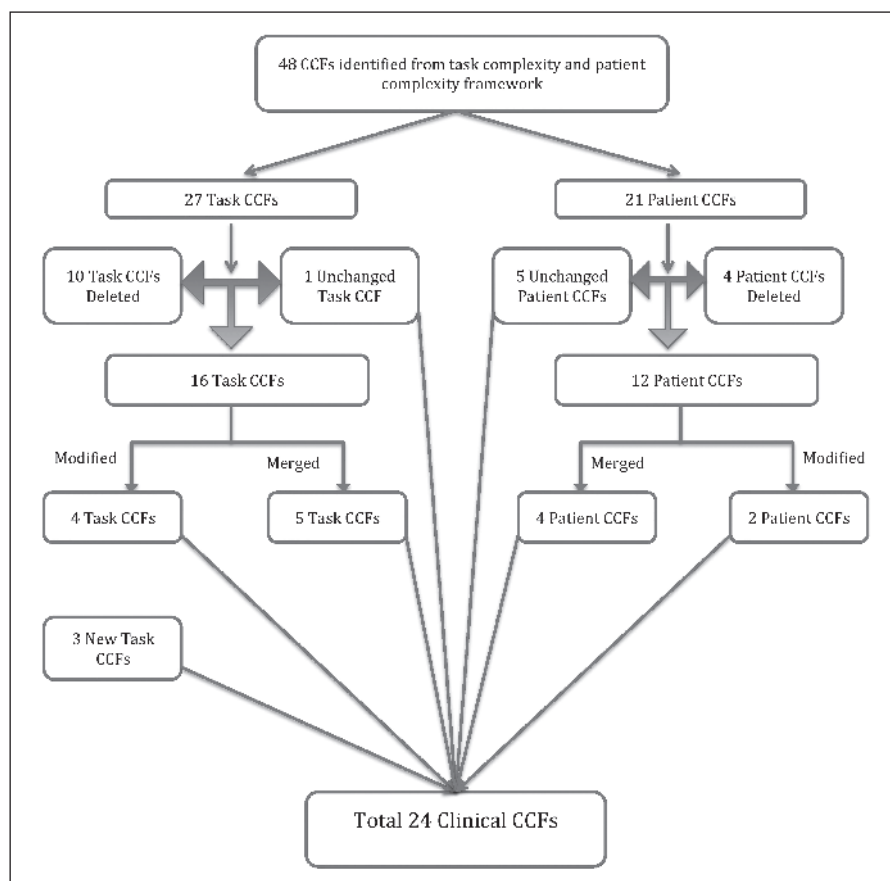
Figure 1   Complexity-contributing factors (CCFs) selection process

2.2 Description of Observations

Observations were conducted with the in-patient 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

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

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.

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.

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		

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.
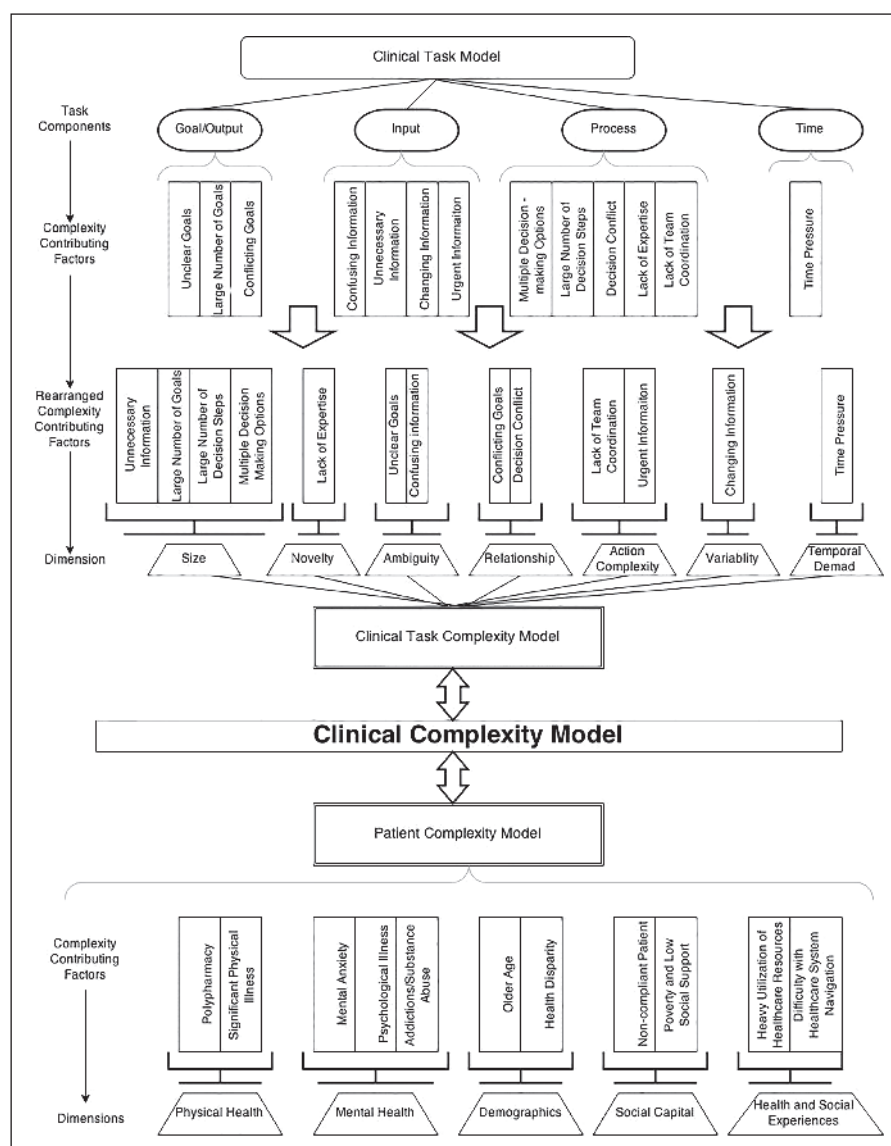

Figure 2   Clinical Complexity Model

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-

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.

	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

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

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 the 13 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*.

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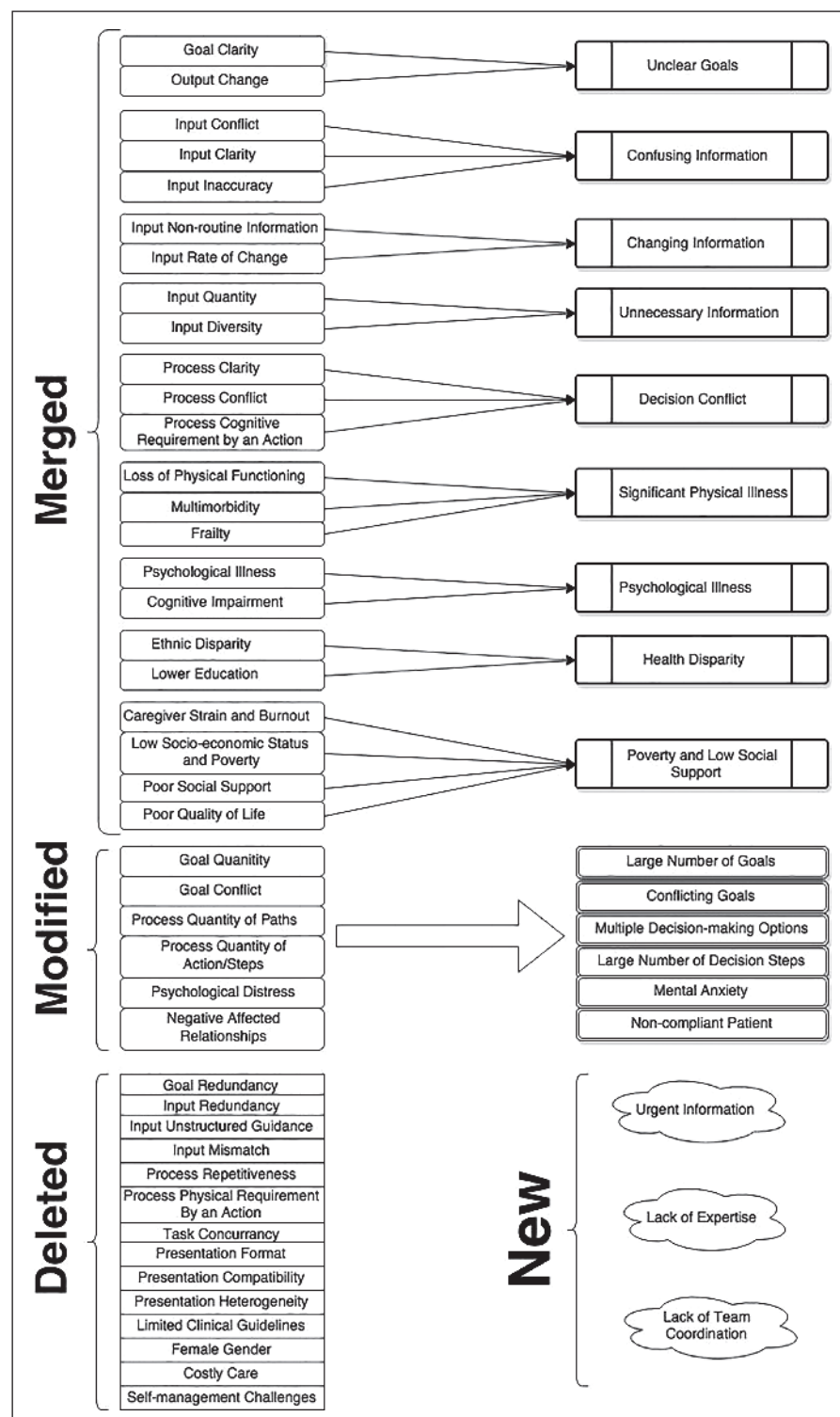
Figure 3   Overview of the merged, modified, deleted and new clinical complexity-contributing factors (CCFs)

creasing 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

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

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.

Acknowledgment

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