ABSTRACT

MCKENZIE, KENDALL ELAINE. Toward a Convergence Research Framework for Hospital Interface Design: Integrating User Needs, Big Data, and Specialized Knowledge into Complex Decisions (Under the direction of co-chairs Dr. Sharon M. B. Joines and Dr. Maria E. Mayorga).

In order to support the growing operational activities of hospital systems and their unique complexities, there has been an increased focus in recent years on research related to healthcare operations, as well as the associated technologies used to support hospital processes. A common thread within healthcare research is the idea of decision support (e.g. clinical decision support), which facilitates the collection, processing, and/or display of relevant information to a decision-maker, often in real time. The end-use artifact of decision-related research is broadly called a decision support tool or a decision support system (DSS). A DSS receives information as input, processes this information in some way, and then displays it. Information is often displayed to the decision-maker through a user interface, which we have termed a decision support interface (DSI). Hospital environments are permeated with DSIs to assist with complex clinical decisions during daily operations and must be created by a developer or programmer. Regardless of who develops a given interface, it is clear that the hospital DSI design process is usually approached with only a partial perspective, which is not reflective of the holistic convergence research approach. The primary contribution of this design research dissertation is creating a process framework, founded in convergence research practices, to guide the hospital DSI design process. The chapters that follow analyze various aspects of the hospital DSI design process, in an effort to propose an initial structure for a process framework, based on convergence research principles, to guide the design of hospital decision support interfaces. The framework aims to integrate knowledge from various disciplines into a comprehensive set of straightforward steps,

so that they can be easily understood and implemented in developer practices. Further research is required before the framework can be used.

Toward a Convergence Research Framework for Hospital Interface Design:
Integrating User Needs, Big Data, and Specialized Knowledge
into Complex Decisions

by
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DEDICATION

This work is dedicated to all my family and friends who have supported me at various points throughout my career as a PhD student. Special thanks to my parents and brother for their consistent encouragement, my graduate school peers for their fellowship, and the members of my household for their patience and love.

BIOGRAPHY

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CHAPTER 1: Problem Context & Motivation

This chapter serves as an introduction, providing the reader with problem context and background information that might be helpful in understanding this body of dissertation research. First, we describe the current state of hospital decision support, in general, and then we narrow our focus to decision support interfaces. Next, we discuss the contribution of this investigation. Finally, we explain how the document is organized and define some key concepts for the reader.

1.1. A Reflection on the Current State of Hospital Decision Support

The healthcare industry has experienced dramatic changes in recent decades, due to a variety of factors. First, with the largest aging population to-date, the demand placed on healthcare delivery systems has been increasing steadily and is projected to continue until at least 2050 [1] [2]. Second, with the passing of the Affordable Care Act of 2010, the government became a primary stakeholder in the United States healthcare industry [3]. The incorporation of governmental objectives (which often compete with the objectives of other stakeholders) into healthcare delivery has resulted in increased focus on (and funding for) (i) the improvement of healthcare metrics, (ii) the reduction of healthcare costs, and (iii) the utilization of technology to support safe and efficient healthcare [4] [5]. Third, as technological advancement has exploded in recent years, the healthcare domain has received increased attention from researchers in all fields to support such technologies. As a result, healthcare facilities and workflows have become more complex, permeated with more devices, more displays, more machines, and more data than ever before [6]. Finally, there has been significant diversification of the healthcare workforce (e.g. more non-physician clinicians, more support staff, more administrators), resulting in additional communication challenges and knowledge barriers during the care delivery process [7] [8].

The changes in the healthcare industry as a whole have led to new dynamics within the daily operations of healthcare facilities, especially hospitals [9]. Years ago, healthcare was provided almost entirely by one's primary care provider, and hospitals were used almost exclusively as temporary surgery locations; today however, healthcare is provided by a variety of different doctors and facilities over the course of a patient's lifetime (often dependent upon specific patient needs), and visits to the hospital are far more common [10]. Hospitals have become massive, multi-department systems that provide a wealth of services to patients around the clock [11]. From a patient's perspective, hospitals are healthcare facilities that deliver safety-critical services to patients. From an executive's perspective, hospitals are seen as transactional businesses that staff many different types of people to manage their complex operations. From a researcher's perspective, hospitals are viewed as massive data and research hubs that should be utilized to advance scientific knowledge [12].

Regardless of the manner in which hospitals are perceived, however, common challenges usually surface in their daily operations. First, patients need to be treated and kept safe, but important health details sometimes get lost among the many moving pieces of a hospital environment [5]. Second, healthcare providers want (and need) to spend time with their patients in order to properly evaluate and treat them, but workflow and documentation requirements often mean that at least half of their time is spent in their offices, summarizing their decisions and looking at screens [11]. Third, hospitals require an extremely wide variety of personnel (from administrators to surgeons, with varying levels of education) in order to run their daily operations; however, communicating complex healthcare concepts across employees with such different bases of knowledge often results in misunderstandings or errors [7]. Clearly, hospital environments are becoming increasingly complex systems, and in an era of big data and competing stakeholder objectives, they are currently experiencing more pressure than ever to leverage available information to provide healthcare that is better, faster, safer, and cheaper.

In order to support the growing operational activities of hospital systems and their unique complexities, there has been an increased focus in recent years on research related to healthcare operations [12]. Additionally, the majority of this research relates to some sort of technology that will be used in hospitals [13]. Published research that investigates topics related to technology use in hospital operations spans a wide variety of disciplines, including engineering, computer science, operations research, psychology, ergonomics, informatics, and design [14] [15] [16] [17] [18] [19] [20]. However, this research has only begun to scratch the surface of investigating healthcare delivery-related problems, since technology is constantly developing, and a wealth of complex healthcare issues remain to be explored.

A common thread within healthcare research is the idea of decision support (e.g. clinical decision support), which facilitates the collection, processing, and/or display of relevant information to a decision-maker, often in real time [21]. In general, many researchers (including those in healthcare operations) can often connect their work, at least loosely, to the idea of "supporting" a specific decision point in some way or another. The end-use artifact of decision-related research is broadly called a decision support tool or, when it involves automation, a decision support system (DSS). A DSS receives information as input, processes this information in some way, and then displays a set of relevant information for a given decision. Information is often displayed to the decision-maker through a user interface [21], which we have termed a decision support interface (DSI). Hospital environments are permeated with DSIs to assist with complex clinical decisions during daily operations [22].

The increased prevalence of DSIs in hospitals has attracted the attention of researchers who want to inform the design and development of such decision support artifacts. Research questions related to DSIs include: How can we help a doctor make the best decision? What information does the decision-maker need to see in order to make a decision, and in what format? How can DSIs be augmented to reduce errors and poor decisions? How can we use machine learning to make DSIs smarter? How can the design of a DSI be used to incentivize consideration of all possible outcomes of a decision? When is the optimal timing for a recommendation to be displayed on a DSI?

All of these research questions are valuable in informing hospital DSI design and development, but there are challenges with translating this disjointed evidence-based research into practice. First, hospital DSI research investigations are often reported only in disciplinary silos with limited communication of findings to other domains [5]. Second, DSI-related research findings are often not applied in practice due to challenges with the hospital DSI development process (described further in the next section). Recent advocacy for convergence research suggests that improved solutions can be found when complex problems, such as supporting hospital operational decisions, are approached in a way that utilizes findings from multiple disciplines [23].

1.2. Practical Challenges of Hospital DSI Development

In practice, the request to develop a new hospital DSI will likely come from management and be directed either to an in-house information technology (IT) department or an in-house design department (although some hospitals are able to outsource to large software companies). When translating hospital DSI-related research into practice, various challenges arise that do not necessarily foster a convergent development process.

First, hospital DSI design and development is heavily limited by the knowledge base of the developer (i.e. the individual (or team of individuals) responsible for designing, developing, and programming a hospital interface). In practice, the developer of a hospital DSI is often just one individual (or very small team of individuals from the same department), whose knowledge pertains only to a single discipline (e.g. computer science). In effect, this means that a single (or heavily limited) disciplinary perspective is taken during the DSI development process.

Some hospitals have the resources to use a team approach to DSI development; but even when this is the case, the team is often small, and members do not have an organized method for addressing and integrating the considerations of multiple different disciplines. Additionally, hospital employees who stand to provide valuable input on a DSI development team (usually providers) are often distracted by either (a) patient care or (b) participating on multiple interdisciplinary project teams (e.g. DSI development, facility redesign, quality improvement programs, etc.) at a given time. In the cases where hospital DSIs are outsourced to commercial software companies with dedicated R&D departments, process fidelity, clinical details, and interface customization often fall short.

Regardless of who develops a given interface, it is clear that the hospital DSI design process is usually approached with only a partial perspective, which is not reflective of the holistic convergence research approach. A partial approach might mean that knowledge from all disciplines is not represented or considered, or that only one aspect of the interface (e.g. graphic design/layout) is successful while other important aspects (e.g. predictive capability, patient safety considerations, fidelity to users' mental models) suffer.

However, these risks can be mitigated during the design process by taking a convergence research approach to hospital DSI development. Convergence research is a problem-centric approach to research in complex domains that transcends disciplinary boundaries. A convergent approach is appropriate for informing the DSI development process because of (a) the complexity of hospital operations and clinical decisions and (b) the opportunity to integrate knowledge across a variety of research disciplines. Figure 1 identifies various stakeholder groups whose perspectives might be considered during the DSI design process and lists some specific questions that researchers in different disciplines might strive to investigate.

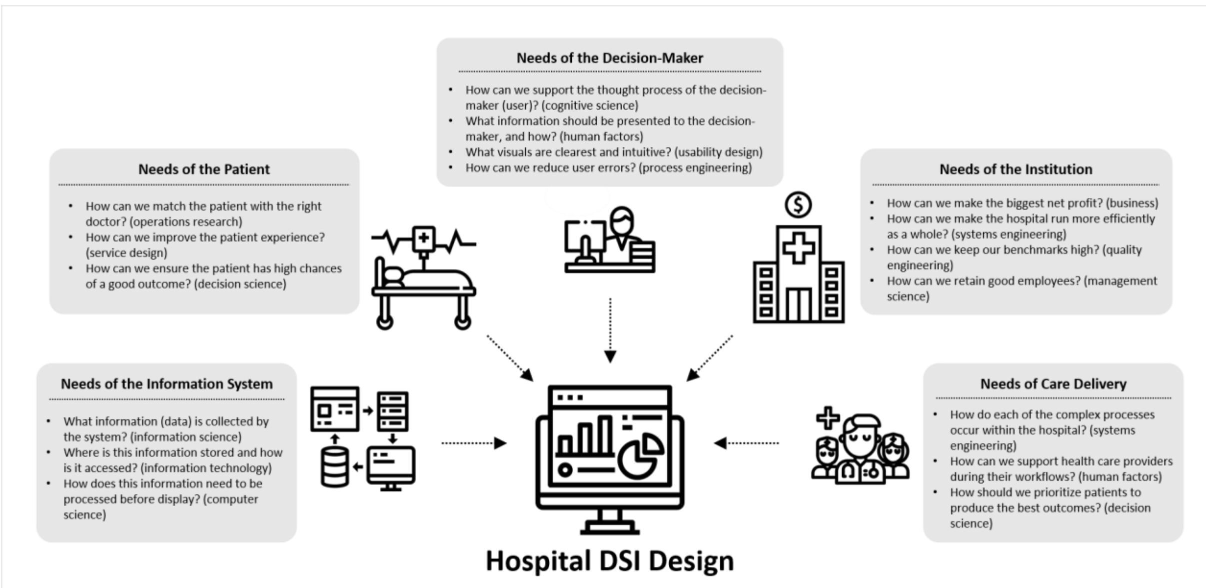

Figure 1. High-level diagram showing convergence of disciplinary expertise to answer research questions that support stakeholder needs in the DSI design process

1.3. Contribution of Current Investigation

The primary contribution of this design research dissertation is creating a process framework, founded in convergence research practices, to guide the hospital DSI design process. A process framework is a model that "specifies steps (stages, phases) in the process of translating research into practice, including the implementation and use of research" [24]. Process frameworks are often represented by diagrams. Examples of some existing process framework diagrams are provided in Appendix A.

While others have created similar frameworks to guide healthcare interface design in the past [25] [26] [27] [28], this research is the first to approach hospital DSI development from a truly convergent (as defined by the Institute of Medicine and other prominent organizations [23]) perspective. By employing convergence research principles in the creation of a framework, we aim to produce an initial framework structure that is broad (i.e. not domain-specific), and thus, easily accessible to any individual (e.g. designer, developer, programmer, engineer, etc.) who might need a "roadmap" that outlines (a) the steps to take during the hospital DSI design process, (b) the important things to consider at each step, and (c) the resources available to the DSI developer for addressing any issues that may arise.

1.4. Document Organization

The remainder of this document is organized into five chapters. Chapter 2 provides an overview of relevant literature, describes the theoretical perspective that serves as the basis of this research, and presents an overview of the research design. Chapters 3, 4, and 5 describe three different investigations (i.e. studies) into hospital DSI design. Chapter 6 presents an initial draft of a design process framework for hospital DSI development, discusses the practical implications of such a framework, and proposes future work.

1.5. Key Terminology

Research that involves multiple disciplines requires interactions between experts in different fields, each of which usually utilizes its own domain-specific vocabulary when communicating about complex ideas. Thus, in order to ensure clarity of understanding for readers across multiple domains, this section provides short explanations of key concepts and terminology employed throughout this document.

- **domains / fields / disciplines:** used interchangeably to refer to areas of study
- **operations / processes:** used interchangeably to refer broadly to general activities involved in the delivery of healthcare service at a hospital
- **decision support tool:** an artifact that provides information to aid a decision-maker, whether manual (e.g. checklist) or automated (e.g. analytics software)
- **decision support system (DSS):** an automated electronic system or tool that provides information to aid a decision-maker
- **decision support interface (DSI):** the portion of the DSS that a decision-maker sees and interacts with, often a displayed on a screen or monitor
- **convergence research:** a transdisciplinary approach to complex problem-solving that often integrates life sciences, physical sciences, engineering, and design [23]
- **provider / clinician:** used interchangeably to refer to any person who provides clinical healthcare services to patients (e.g. nurses, doctors)
- **designer / developer:** used interchangeably to refer to an individual (e.g. graphic designer, software programmer, user experience designer, etc.) who is responsible for ultimately creating a decision support tool, system, or interface artifact
- **design process framework:** a set of general instructions (e.g. roadmap, diagram) to guide designers and developers through appropriate and necessary considerations when creating a decision support artifact

CHAPTER 2: Literature, Theory, and Research Design

This chapter provides a detailed and technical description of the perspective taken throughout this body of research. First, an overview of relevant literature is provided. Next, theoretical perspectives are introduced, and the specific perspective selected as the foundation for this research (i.e. pragmatism) is described. Finally, a conceptual diagram representing the problems investigated in this research is presented, and an overview of the research design is provided.

2.1. Overview of Relevant Literature Categories

The literature relating to this problem falls into the three broad categories: (i) communication and visualization of information (e.g. how is complex information communicated, and what display types are most informative?), (ii) efficient decision-making (e.g. what information is required to make a decision, and what algorithm should be used to make efficient decisions?), and (iii) distribution of workload (e.g. what factors contribute to workload, and how can workload be distributed equitably?). When each of these broad categories is narrowed to focus on this specific problem in healthcare, three smaller bodies of literature result, pertaining to healthcare information visualization, patient allocation decisions, and workload balancing for hospitalists and other healthcare providers. Figure 2 shows the three primary categories and identifies specific articles that fall into each category, as well as category overlaps.

2.1.1. Healthcare Information Visualization

Information visualization principles have been employed in a variety of ways to enhance healthcare processes and operations, and there are multiple approaches that can be used to evaluate such visualizations [29]. Additionally, themes for application of information visualization in healthcare have been identified, including treatment planning, examination of patients' medical records, representation of pedigrees and family history, communication and shared decision making, and life management and health monitoring [30]. Common visualization techniques used with electronic health record data often rely on colors, density, and filters to communicate information [31]. Best practices and standardization for medical data visualizations are likely to become increasingly important, as clinicians continue to work in a cognitively complex environment that is heavily dependent upon data [32]. Unique approaches have been used to visualize information pertaining to clinical guidelines [33] and community health datasets [34], but a visualization for the purpose of equitability between healthcare providers (e.g. workload, patient allocations, capacity, etc.) has not yet been documented. A user-centered framework for redesigning healthcare interfaces exists [25], but it has not yet been applied for the purpose of balancing provider workload.

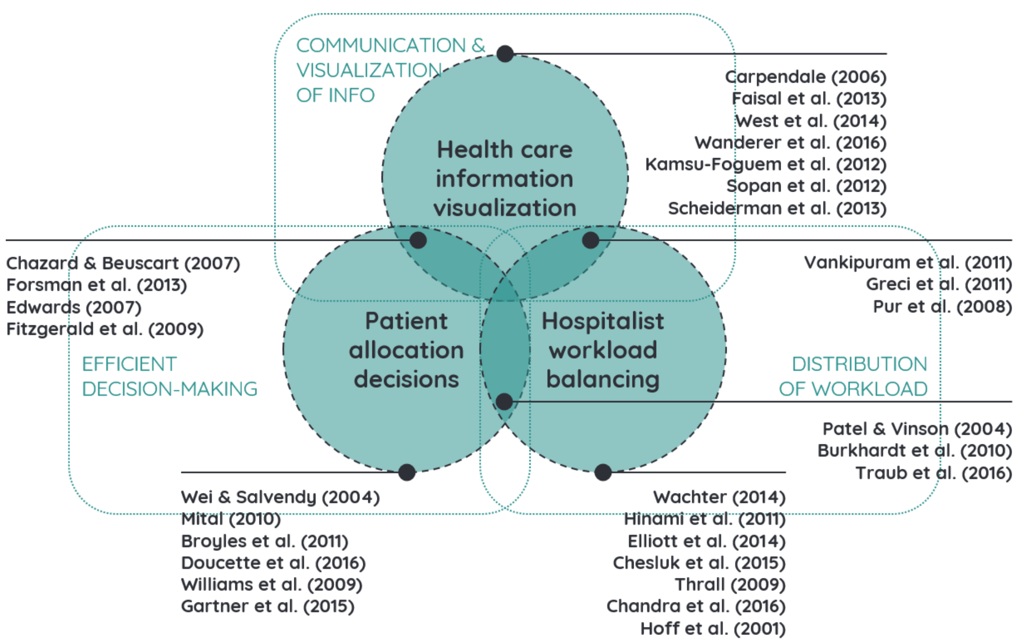

Figure 2. Literature review diagram

2.1.2. Patient Allocation Decision-Making

Systems engineering literature pertaining to patient allocation decisions provides some recommendations for methods that can be used to allocate incoming patients among hospital resources. For example, existing patient allocation models have been based in methods such as machine-learning [35], dynamic multiagent resource allocation [36], queuing analysis [37], dynamic programming [38], and computer simulation [39]. However, none of this research creates an algorithm based on the thought process of the decision-maker who actually allocates patients. Cognitive mapping [40] is one method that can be used to represent the strength of relationships between concepts in a decision-maker's mental model. Cognitive mapping of information can be used to improve the design of tasks because it helps represent the "mental landscapes" of users [41].

2.1.3. Physician Workload Balancing

Workload of healthcare providers is a research topic with several existing investigations, but information about the workload specific to hospitalists is lacking. Understanding, monitoring, and balancing hospitalist workload is important because it correlates directly with certain aspects of patient care quality [42]. One of the first surveys conducted to understand the work that hospitalists do throughout the day identified clinical work, teaching, and research as three of the primary components of hospitalist workload [43]. A more recent survey of hospitalists to understand their job satisfaction found its key predictors to be organizational climate, quality of care, organizational fairness, personal time, compensation, and relationships with leaders and patients [44]. Communication between providers and operational employees is imperative for balancing hospital workload, but hospitals do not typically have much support for effective, interpersonal teamwork [45]. Thus, a communication tool could help bridge this gap and augment or serve as a proxy for communication between hospital staff. Burnout is an issue related to hospitalist workload, as evidenced by studies in which the majority of hospitalists report that they intend to leave the career for either a fellowship program or to work in another specialty, such as primary care [46]. A Hospitalist Morale Index instrument was developed to measure and quantify hospitalist morale, in an attempt to improve hospitalist retention [47].

2.2. Theoretical Perspective

It is important that researchers define their perspective before research begins, and this is often accomplished with the development of a problem-specific framework. The perspective taken in this research is described by two components: a research paradigm (i.e. theoretical perspective) and a conceptual diagram. A research paradigm is an investigator's set of assumptions about the world [48]. A conceptual diagram is a representation of the current state of the problem, its key constructs and factors, and the relationships between its key elements [49]. A researcher's perspective when approaching a given problem can significantly impact the direction of an investigation, especially in dictating which methodologies should be used.

2.2.1. Common Theoretical Perspectives

In the discipline of design research, for which this dissertation is written, we acknowledge there are multiple ways to approach a given investigation, depending on the researcher's perspective of the problem. A researcher's choice of theoretical perspective can significantly impact the course of a study, so it is important to determine this framework before research begins. Four primary perspectives taken by design researchers are positivism/post-positivism, constructivism, transformative, and pragmatism. Important characteristics of each worldview, as described by Creswell [50], are summarized in Table 1. A quick review of the ontological and epistemological viewpoints of these four primary worldviews in research follows, in order to provide context for the theoretical perspective of this research. In general, ontology refers to one's perspective about "the nature of what exists," and epistemology refers to "how one is able to know what exists" [48].

Positivists and post-positivists take an objectivist perspective in their research, focusing on determination, reductionism, and theory verification, usually by employing empirical observation and measurement [51]. This perspective assumes there is a reality that exists "out there" that can be fully and objectively known (or at least known with some probability) [48]. Constructivists take a subjective perspective, focusing on understanding social and historical constructions and generating theories, often by combining multiple participants' perceptions of reality [52]. Naturalistic, qualitative, and interpretive frameworks are often used by constructivists, who believe knowledge emerges as the research and respondents co-create understandings or their "relative" realities [48]. Researchers with a transformative theoretical perspective use collaborative techniques to investigate political problems that are often focused on power and justice issues. Social and advocacy issues are common topics in transformative research [50]. Pragmatists take a problem-centered approach to research, often using pluralistic methods to produce solutions that display results in real-world scenarios [50]. In general, pragmatists assume that the "useful truth" takes precedence over the "factually correct" [48].

Table 1. Creswell's four worldviews of research [50]

Post-positivism	**Constructivism**	**Transformative**	**Pragmatism**
• Determination • Reductionism • Empirical observation and measurement • Theory verification	• Understanding • Multiple participant meanings • Social and historical construction • Theory generation	• Political • Power and justice oriented • Collaborative • Change-oriented	• Consequences of actions • Problem centered • Pluralistic • Real-world practice oriented

The specific methods employed in research investigations are often heavily dependent upon theoretical perspective. The methodology selected for use in a given study should align not only with the theoretical perspective of its investigators, but also with the characteristics of the problem being researched [50]. Eight primary research methodologies include historical, theoretical, qualitative, correlational, experimental/quasi-experimental, simulation/modeling, logical argumentation, case study, and action research. Each research methodology lends itself toward the use of a specific set of tactics for data collection and analysis. Examples of tactics for data collection include direct measurements, focus groups, statistical analyses, observations, interviews, content analysis, and cognitive mapping [48]. Not all methodologies and tactics are appropriate for the overall research objective of a given problem.

2.2.2. A Pragmatic Approach to Healthcare

Traditionally, the majority of research fields take either a positivist/postpositivist (objectivist) perspective, or a constructionist (subjectivist) perspective, and then their methodological choices follow [53]. However, since the unique barriers and limitations on researchers in healthcare settings (e.g. patient privacy policies, safety restrictions, controlled access, geographically-dispersed operations, etc.) can preclude the use of certain methodologies, and since hospitals are often results-driven, research related to hospital DSI design is aptly suited for the pragmatic theoretical perspective.

The ability of pragmatism to merge techniques from different disciplines is particularly valuable in large healthcare facilities like hospitals, since they are aiming to meet the objectives of their many stakeholders, who often have very diverse (sometimes even competing) sets of priorities [54]. Additionally, the pragmatic perspective fosters innovation, since it relaxes rigorous barriers that define “appropriate” approaches to problem-solving and, instead, supports creative thinking. This characteristic of pragmatism is particularly valuable as an approach to healthcare-related research, since healthcare innovations are a primary driving force in the pursuit to balance the objectives of containing healthcare costs and improving healthcare quality [55].

It is important to note that, while the pragmatic perspective values practical and results-oriented investigations, research conducted from this theoretical standpoint is not necessarily applied research. In the context of this dissertation as a whole, pragmatism is identified as the theoretical perspective that aligns most closely with the researcher's viewpoint; and a pragmatic perspective was taken when selecting study methodologies. The integration of the studies into a framework is basic research in the field of design research, since it expands the existing knowledge on approaches to interface development.

2.3. Research Design

By building upon the findings of relevant literature and adopting a pragmatic theoretical perspective, we are able to develop a graphical representation of our problem, define our research questions, and select the methodologies best suited for the objectives of this research.

2.3.1. Conceptual Diagram

The underlying theories described in the previous section can be combined with other concepts to create a conceptual diagram that represents the issues being considered in this research. A conceptual diagram (also called a conceptual framework) is a representation of the current state of the problem, its key constructs and factors, and the relationships between its key elements [49]. Figure 3 provides the conceptual diagram created represent the focus of this dissertation research.

The dotted line in the diagram indicates that the scope of this research considers primarily the perspectives of stakeholders within the hospital system. The perspectives of the patient and the greater social good are not directly considered in this research; however, these perspectives are not entirely ignored, since they are often indirectly influenced by improvements in the efficiency and accuracy of hospital processes. The gray circles represent the needs and objectives of hospital stakeholders in this research. Needs relate to either hospital personnel (e.g. providers, administrators, etc.) or hospital business activities (e.g. processes, efficiency, etc.). Commonalities between these groups include the needs for productivity, employee satisfaction, efficient decision-making, and quality patient care. The striped box communicates that the perspectives of users (i.e. hospital decision-makers), developers (i.e. designers or programmers), and funders (i.e. hospital management) can be integrated into hospital DSI design to help satisfy many needs that are common among hospital stakeholders.

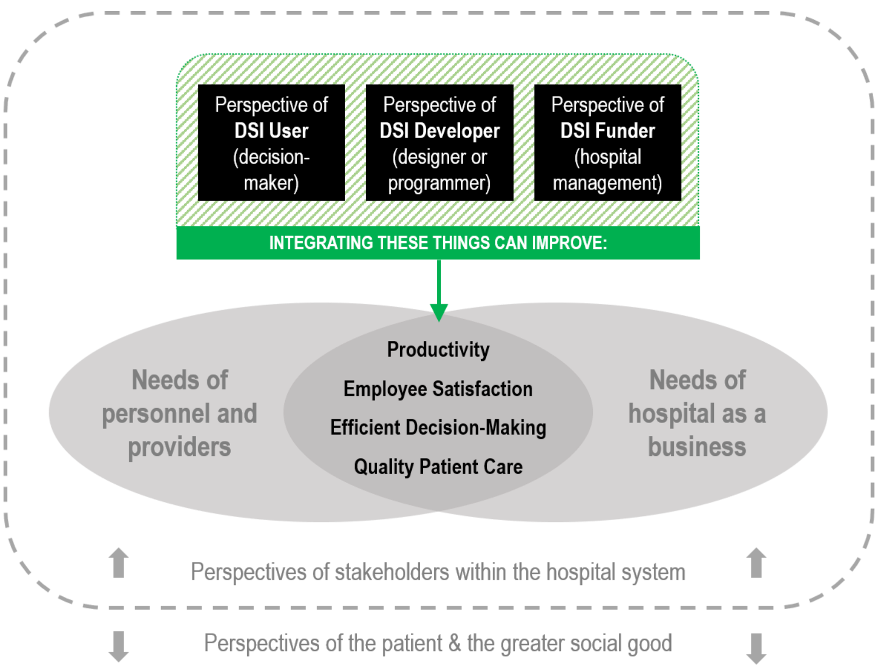

Figure 3. Conceptual diagram representing the problem of interest

2.3.2. Research Questions & Methodology

The research presented in this dissertation ultimately seeks to explore how principles from multiple disciplines can begin to be integrated (i.e. converge) into a design process framework that can guide hospital DSI development. This primary objective is broken into a series of three sub-questions that are investigated in subsequent chapters (listed below). Additional specific research questions are also addressed within each chapter.

1. If we *may want to develop* a DSI to support a complex hospital process (e.g. clinical diagnosis of sepsis), how can we begin to gain understanding of clinician mental models and <u>generate</u> an initial list of candidate interface elements to explore? (Chapter 3)
2. If we *are going to develop* a DSI to support a complex hospital process (e.g. allocation of inpatients to doctors), how can we <u>identify</u> its primary influential concepts and <u>prioritize</u> them into interface elements? (Chapter 4)
3. If we *are developing* a DSI to support a complex hospital process that depends heavily on an abstract element (e.g. provider perception of current workload level), how can we accurately and practically <u>translate</u> this concept into a useful representation? (Chapter 5)

The investigations in this body of research follow a mixed methods experimental design, which supports the pragmatic theoretical perspective. The idea behind this methodology is that a topic of interest (i.e. hospital DSI design) is examined from both quantitative and qualitative perspectives [50]. Figure 4 outlines the broad objectives of each chapter in this dissertation and shows how they relate to each other.

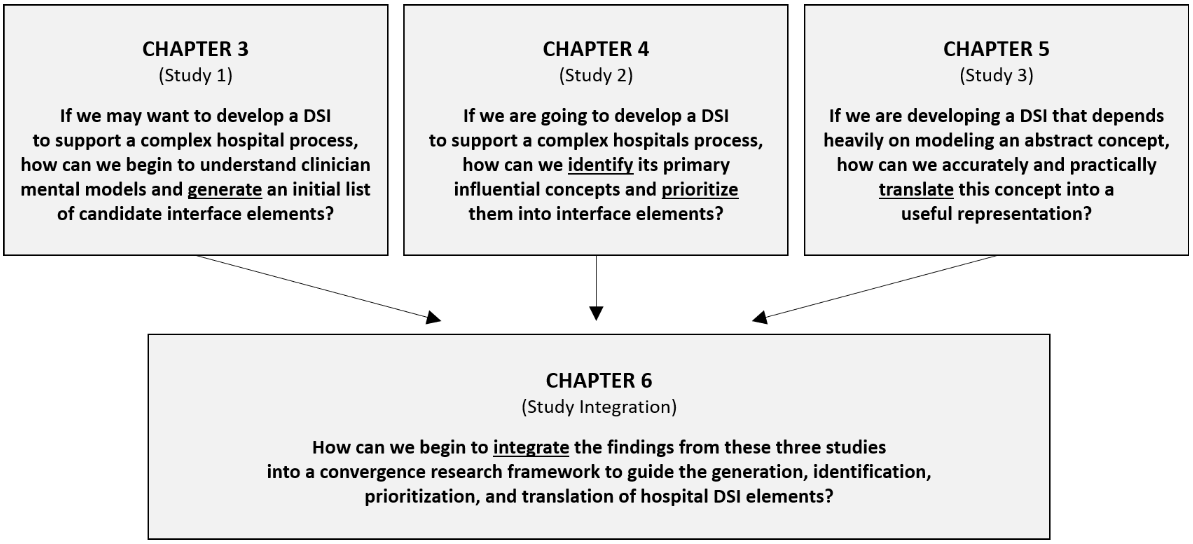

Figure 4. High-level diagram of relationships between dissertation chapters

CHAPTER 3: Understanding Clinician Mental Models in Sepsis Diagnosis: Implications for Decision Support System Development

Sepsis, a deadly physiologic response to an infection, has gained substantial attention from researchers over the past few years as leading sepsis organizations and initiatives – including Surviving Sepsis Campaign, World Health Organization, Centers for Medicaid and Medicare, and Sepsis Alliance – agree that rapid diagnosis and treatment of sepsis are crucial for improved patient outcomes. This study conducts an initial investigation into healthcare providers' mental models related to sepsis diagnosis. We asked clinician participants to perform a word-association exercise to elicit the first 15 words they associate with sepsis diagnosis. We analyzed the words collected from participants by placing them into categories, coding similar responses, and comparing words mentioned by different provider groups. The objective of these comparisons is to provide insight into the differences that may exist across clinician mental models relating to sepsis diagnosis, with the larger goal of informing the design of decision support systems (DSS) that aid this task. Improved understanding of clinician mental models will result in DSS that are more intuitive, easier to implement, and adaptable for different clinical sectors (e.g., emergency medicine, internal medicine). The word-association exercise conducted in this study served to identify a final group of words that will be used in a subsequent study to create fuzzy cognitive maps of clinician mental models for sepsis diagnosis.

3.1. Introduction

Sepsis, defined as an infection with associated acute organ system dysfunction, is a common reason for hospitalization as well as the single most expensive condition treated in U.S. hospitals [56]. Even though this disease accounts for nearly half of all hospital deaths [57], there is currently no gold standard diagnostic test for sepsis, making clinical diagnosis and treatment difficult. Over the past decade, medical guidelines related to sepsis have constantly evolved as the clinical community searches for consensus on the definition, diagnostic criteria, and treatment recommendations pertaining to the disease [58].

The difficulties associated with understanding and diagnosing sepsis are compounded by the complexity of the healthcare system in which clinicians must diagnose the disease. The healthcare system includes clinical practice, business organization, information management, research, education, and professional development, all of which are interdependent and built around interacting systems that have inherently unpredictable attributes [59]. The clinician's autonomy is a "crucial contextual feature" of the complex landscape of any healthcare work environment that must be preserved, since clinical knowledge is increasingly specialized [60]. In particular, clinicians work in complex healthcare work systems and processes and deal with the ambiguities of lived experience on a daily basis [61]. Supporting their diagnostic decision-making using technology that matches the complexity of their mental landscape remains a challenge.

The complexity of the healthcare work environment has attracted the attention of researchers within the fields of engineering, human factors, psychology, design, and computer science, all of whom aim to develop solutions and tools that facilitate clinical diagnosis. Some researchers have attempted to look at the healthcare system through the lens of functional decomposition, a method that separates a complex system into smaller sub-systems to understand how work is distributed across the system as a whole [62]. However, it has become clear that dividing the work of clinicians into independent components is not a simple task. Instead, researchers are challenged to develop solutions for clinical diagnosis that can be integrated naturally into the existing complex healthcare system. As a methodology, cognitive maps were first described in 1976 as decision support tools, serving as visual representation schemes with a computational framework [40]. These maps illustrate knowledge as a network of concepts and their causal relationships. In fuzzy cognitive maps, the relations between elements of a "mental landscape" imitate the way of decision making in humans and resemble human reasoning [41], providing greater utility of the model. These maps provide inexact (fuzzy) linguistic expression of concepts and causal links and allow for comparisons between individuals.

This study is focused on describing healthcare providers' mental models related to sepsis diagnosis through a word-association exercise to elicit the top words they link with sepsis diagnosis. The extensive complexity of the sepsis syndrome and high associated mortality, coupled with its lack of a diagnostic gold standard, makes sepsis an ideal clinical condition to target with this methodology. This exercise is the first step in involving end-users (i.e. clinicians) in the DSS design process by investigating their mental models, and in particular, their vocabulary, related to sepsis diagnosis. Sepsis diagnosis DSS developed to match either individual clinician mental models or shared mental models [63], at least in vocabulary, could promote a better understanding of the similarities and discrepancies in clinical diagnosis processes of different individuals. Consequently, this could inform development and implementation of DSS that are aligned with clinician mental models.

3.2. Data and Methods

The word-association exercise described in this paper served as an initial step in our ultimate goal of creating fuzzy cognitive maps of clinician mental models related to sepsis diagnosis. Cognitive map generation will ultimately utilize a set of no more than 15 words, including two control words (i.e. words unrelated to sepsis diagnosis that share similar clinical presentation). This word-association exercise identified the remaining 13 words that clinicians found most relevant to sepsis diagnosis based on frequency after aggregation and coding. Relevance is defined as the identification of supporting features for reasoning and diagnosis [64]. Methodology is based on expert opinion and represents a novel approach to cognitive mapping [65] and think-aloud approaches [66] [67] that have been used for experts and novices to verbalize their thinking and actions when they process and integrate information with relevant knowledge to performance reasoning and diagnostic tasks.

3.2.1. Participant Selection

Participants for the word-association exercise were selected in a convenience sample from Christiana Care Health System in Newark, Delaware, Mayo Clinic in Rochester, Minnesota, and MedStar Health in Washington, District of Columbia. We recruited different types of clinician participants (i.e. physicians, nurses) across various specialties (i.e. emergency medicine, internal medicine, critical care, research). Participation in the word-association exercise was voluntary. This project has been declared exempt due to its low risk by the MedStar Health Institutional Review Board.

3.2.2. Data Collection Procedure

Each participant was asked, “What are the first 15 words that come to mind when you think of sepsis diagnosis?” Responses were recorded by hand or provided over email, and there was no time limit placed on completion of the word-association task. Participants were encouraged to provide a full set of 15 words, however, when this proved difficult for some participants, we accepted as few as 12 words.

3.2.3. Response Coding and Analysis

We placed each unique word into one of 19 broader word categories, defined by the research team based on the distribution and nature of the words. Word categories included clinical predispositions, subjective physical exam, objective physical exam, systemic inflammatory response syndrome (SIRS), diagnostics, infection, general organ dysfunction, specific organ dysfunctions based on system (neurological dysfunction, renal dysfunction, liver dysfunction, respiratory dysfunction, coagulation dysfunction, cardiovascular dysfunction, hypoperfusion), scoring systems, therapeutics, hospital resources, outcomes, and other. With clinical input, we then created a digital map of all the unique words, positioned according to word category and relatedness.

Using the digital map, we identified and coded words that were essentially synonymous to the words in each set (e.g. fever, febrile, high temperature) and assigned them a primary word to be used in the analysis. We quantified the total number of times that each of the words in this set (using the primary words to aggregate synonyms) were mentioned by respondents and ordered the list of words by this value, from most to least. Starting from the top of this list, we considered each primary word individually for inclusion, excluding any words that were (i) related to therapeutics (to adhere to our objective describing sepsis diagnosis); or (ii) specific types of an already-included word (e.g. bacteremia is a specific type of infection). We stopped this process once 13 words had been identified for inclusion in the final word set.

We assessed for variations in responses between provider type and specialty. The analysis was conducted at the word-category level and among the final set of 13 selected words. To identify statistically significant differences between provider type and clinical specialty with regards to word selection and frequency, we used Fisher exact tests and chi-square tests. Post-hoc corrections for multiple statistical tests were not employed, since this research investigation is exploratory in nature and rooted in behavioral science [68] [69]. All analyses were completed in Excel.

3.3. Theory

A number of methods and theories have been used to inform this body of work, including decision theory in clinical diagnosis, clinical reasoning, and various cognitive strategies (e.g. pattern recognition, the hypothetico-deductive method) that physicians may employ when diagnosing a patient [70] [71]. Because of its complexity, the diagnosis of sepsis comes with unique challenges to clinicians; clinical decision support systems could bridge the gap between the uncertainty of sepsis and the confidence of an appropriate diagnosis and treatment pathway. Decision support systems must integrate seamlessly into the clinical workflow, a challenging but critical characteristic that has a large impact on acceptance by clinicians [72].

Decision theory related to clinical diagnosis seeks to determine how a provider selects a final approach for treating a patient when multiple alternatives for treatment are available [73]. Mental models, a practical application of decision theory, have been used to understand decision making processes across several other disciplines including aviation, engineering, architecture, and law [74] [75]. When applied to healthcare, mental models can reveal decision making processes such as diagnosis and treatment pathways, approximating the clinical gestalt on which providers rely in situations of uncertainty. This insight would be particularly valuable in the context of a heterogeneous and complex disease such as sepsis. By studying mental models among various clinician types and settings, we can begin to understand the differences in decision making processes that influence the DSS's integration into unique clinical workflows, informing compatible design to promote acceptance by providers.

3.4. Results

A total of 34 clinicians participated in the word-association exercise. The distribution of provider types was 16 (47%) attending physicians, 4 (12%) resident physicians, and 14 (41%)

nurses. For our analysis, attending physicians and resident physicians were pooled into a single group of 20 (59%) physicians. The specialty distribution was 16 (47%) emergency medicine, 4 (12%) critical care (intensive care providers), 7 (21%) internal medicine, and 7 (21%) clinicians employed by a hospital research institute. The distribution of employment departments for physicians versus nurses is shown in Figure 5. Since some participants provided fewer than 15 words in the word-association exercise, the total number of words included in this analysis was 490, which is 96% of the potential 510 words that could have been collected.

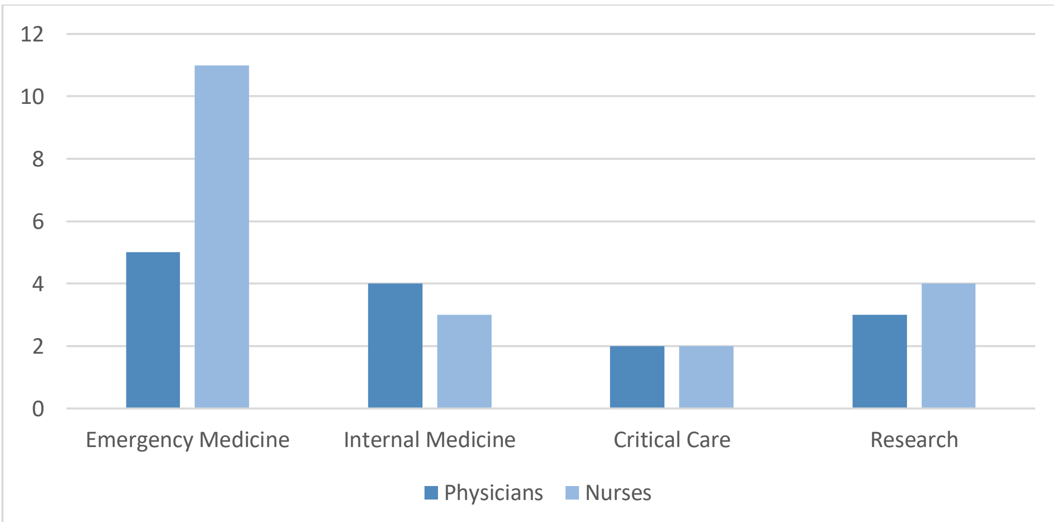

Figure 5. Number of physician and nurse respondents by current department of employment

3.4.1. Digital Map and Final Word Set

Respondents provided 192 unique words that related to sepsis diagnosis, many of which were closely related and could be ultimately categorized into 19 categories. The digital map of these words, which was used to organize all distinct responses by word category and positioned according to relatedness within each category, was extensive; a sample of the digital map is provided in Figure 6. The 19 categories identified from the digital mapping process, and the coding of the distinct words within those categories are presented in Table 2. The distribution of distinct words mentioned by providers across the 19 word categories is shown in Figure 7. The category “other” included descriptive words that did not relate to the broad categories (e.g., tricky, subtle, bad, screening).

Using the selection procedure described in the methodology section, we were able to select a final set of words most related to sepsis diagnosis. The final list of 13 sepsis-related words, along with the total number of times in parentheses they were mentioned by participants in the word-association exercise were included: hypotension (28), fever (27), elevated lactate (25), altered mental status (22), tachycardia (19), infection (19), elevated white blood cells (19), tachypnea (12), shock (11), cultures (11), elderly (9), sick (7), and decreased urine output (7).

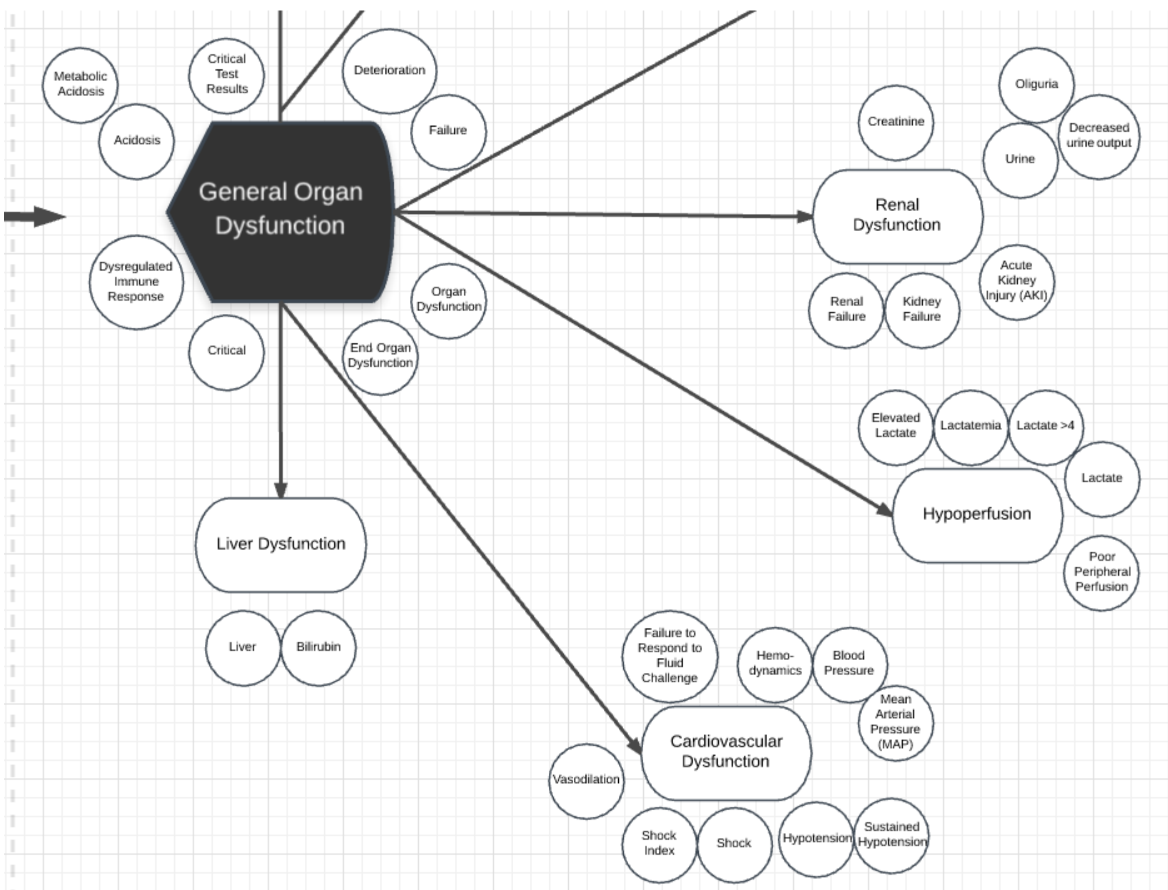

Figure 6. Sample of the digital map of unique words from respondents, organized by word category and positioned according to relatedness.

Table 2. Representative terms selected for each set of synonymous terms, organized by word category

WORD CATEGORY	*REPRESENTATIVE TERM*	*SYNONYMOUS RESPONSES*
Cardiovascular Dysfunction	**Hypotension**	Hypotension, sustained hypotension, blood pressure
Coagulation Dysfunction	**Platelets**	Platelets, thrombocytopenia
Diagnostics	**Cultures**	Cultures, blood culture, urine culture, body fluid cultures
General Organ Dysfunction	**Organ dysfunction/failure**	Organ dysfunction/failure; end organ dysfunction/failure
	Acidosis	Acidosis, metabolic acidosis
	Deterioration	Deterioration, decline
	Serious	Serious, grave, high risk, life-threatening
	Really sick	Really sick, seriously ill
Hospital Resource	**Recent admission/hospital stay**	Recent admission/hospital stay, recent ICU stay, recent surgery/procedure
	Alert	Alert, sepsis alert
	ED volume	ED volume, ED capacity
Hypoperfusion	**Elevated lactate**	Elevated lactate, lactate, lactate > 4, lactatemia
	Hypoperfusion	Hypoperfusion, poor peripheral perfusion
Infection	**Urinary tract infection (UTI)**	UTI, infected urinary catheter
	Bacteremia	Bacteremia, blood poisoning, blood infection
	Source ID/control	Source ID/control, source
	Contamination	Contamination, transmission, spread
	Influenza	Influenza, flu
Liver Dysfunction	**Bilirubin**	Bilirubin; high BILT
Neurological Dysfunction	**Altered mental status**	Altered mental status, change in mental status, mental status, confusion, delirium
	GCS	GCS, decreased GCS
Objective Physical Exam	**Pale**	Pale, ashen, pallor, change in color
	Rash	Rash, mottling
Outcomes	**Death**	Death, mortality
Predisposing Factors	**Elderly**	Elderly, old, nursing home
	Immunosuppression	Immunosuppression, immunocompromised, immunity
Renal Dysfunction	**Decreased urine output**	Decreased urine output, urine output, urine, oliguria
	Kidney failure	Kidney failure, renal failure, kidney
Respiratory Dysfunction	**Respiratory distress**	Respiratory distress, acute respiratory distress syndrome, respiratory
	Oxygen requirement	Oxygen requirement; Sp02/FiO2
Scoring Systems	**qSOFA**	qSOFA, SOFA
	Guidelines	Guidelines, revised guidelines
SIRS	**Fever**	Fever, febrile, temperature, pyrexia
	Tachycardia	Tachycardia, heart rate
	Elevated WBC/leukocytosis	Elevated WBC/leukocytosis, white blood cells, leukopenia, leukocytes
	Tachypnea	Tachypnea, respiratory rate
	Bands	Bands, bandemia
Subjective Physical Exam	**Body aches**	Body aches, myalgia
	Discomfort	Discomfort, malaise
Therapeutics	**Antibiotics**	Antibiotics, antimicrobial treatment, vancomycin, broad spectrum antibiotics
	Fluids	Fluids, IV fluids, fluid resuscitation, saline
	IV	IV, IV access, central line
	Vasopressors	Vasopressors, pressors
	Speed	Speed, fast, timeliness, time
	Bundle	Bundle, surviving sepsis
	Metrics	Metrics, core measure

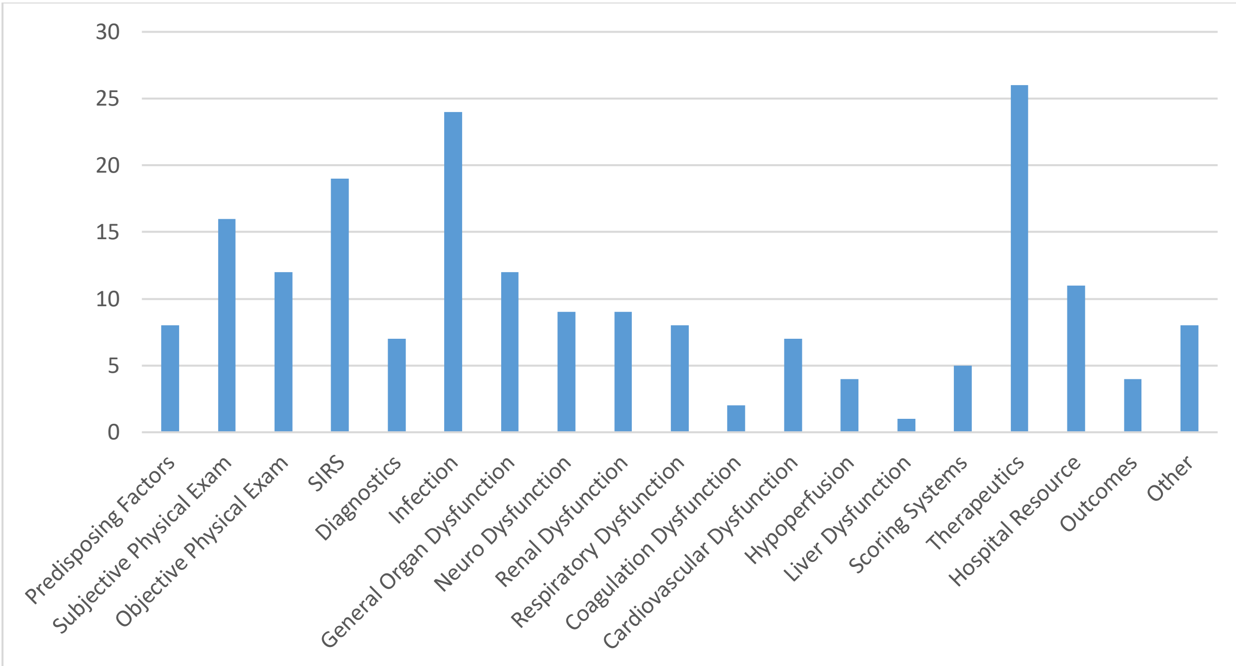

Figure 7. Count of distinct words mentioned by providers in each of the 19 broad categories

3.4.2. Comparisons between Provider Types

Frequency analysis was conducted to understand the differences in responses between provider types (i.e. physicians, nurses). Figure 8 shows the percentages of physician and nurse responses that fell into each of the 19 broader word categories. Physicians mentioned words across all word categories. The top four categories physicians' responses were drawn from were SIRS (19%), cardiovascular dysfunction (15%), hypoperfusion (12%), and infection (10%). Attending physicians mentioned words across all of the broad word categories, whereas resident physicians mentioned words in only 10 of the 19 categories. Nurses mentioned words in all word categories except liver dysfunction. The top four categories nurses' responses were drawn from were SIRS (18%), infection (15%), therapeutics (13%), and subjective physical exam (9%).

In the final set of 13 words, physicians most frequently mentioned hypotension, elevated lactate, fever, and tachycardia. Nurses most frequently mentioned fever, altered mental status, hypotension, tachycardia, and tachypnea.

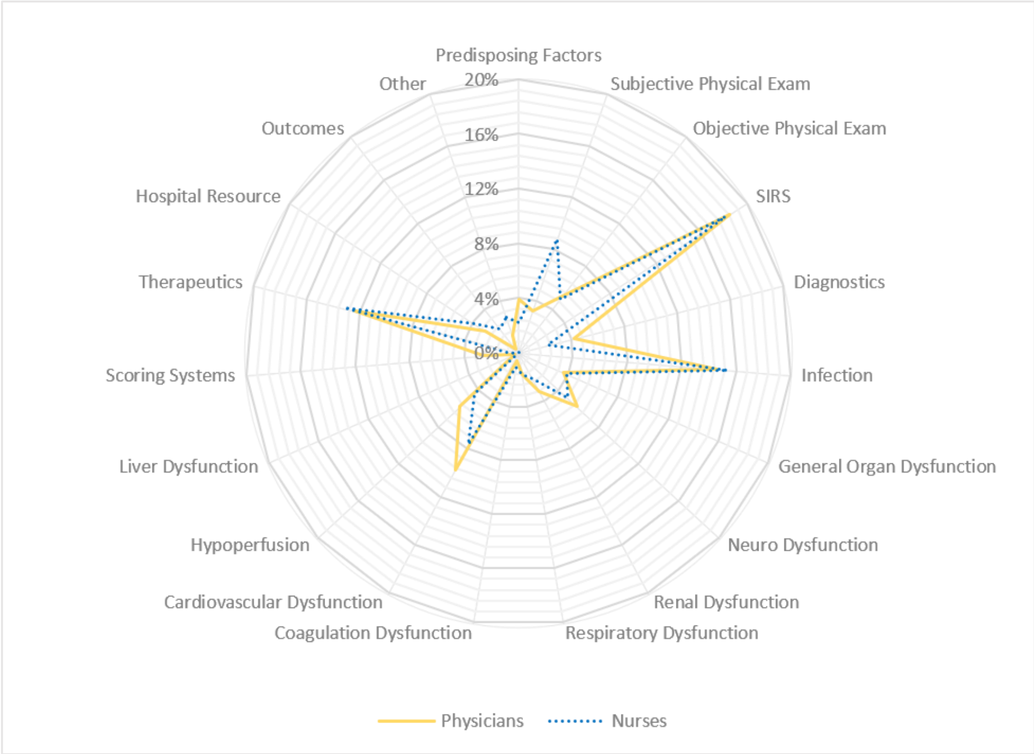

Figure 8. Percentage of responses from each provider type (i.e. physicians, nurses) falling into each of the broader word categories

3.4.3. Comparisons between Specialties

Frequency analysis was conducted to understand the differences in responses between specialties (i.e. emergency medicine, critical care, internal medicine, research). Figure 9 shows the percentages of emergency medicine, critical care, internal medicine, and research institute responses that fell into each of the 19 broader word categories.

Emergency medicine clinicians mentioned words across all word categories, and the top four categories their responses were drawn from were SIRS (20%), therapeutics (14 %), infection (13%), and cardiovascular dysfunction (10%). Critical care clinicians mentioned words across all word categories except outcomes, and the top four categories their responses were drawn from were therapeutics (21%), SIRS (11%), infection (11%), and cardiovascular dysfunction (9%). Internal medicine clinicians mentioned words across all word categories except coagulation dysfunction, liver dysfunction, and other. The top four categories their responses were drawn from were SIRS (23%), infection (18%), subjective physical exam (12%), and therapeutics (10%). Clinicians working at research institutes mentioned words in all categories except liver dysfunction and scoring systems. The top three categories their responses were drawn from were infection (17%), SIRS (15%), and cardiovascular dysfunction (9%).

In the final set of 13 words, emergency clinicians most frequently mentioned hypotension, elevated lactate, fever, and elevated white blood cell count. Critical care clinicians most frequently mentioned infection and shock. Internal medicine clinicians most frequently mentioned fever, altered mental status, hypotension, and tachycardia; general organ dysfunction was never mentioned by internal medicine clinicians. Clinicians currently at research institutes most frequently mentioned fever, hypotension, tachycardia, and altered mental status.

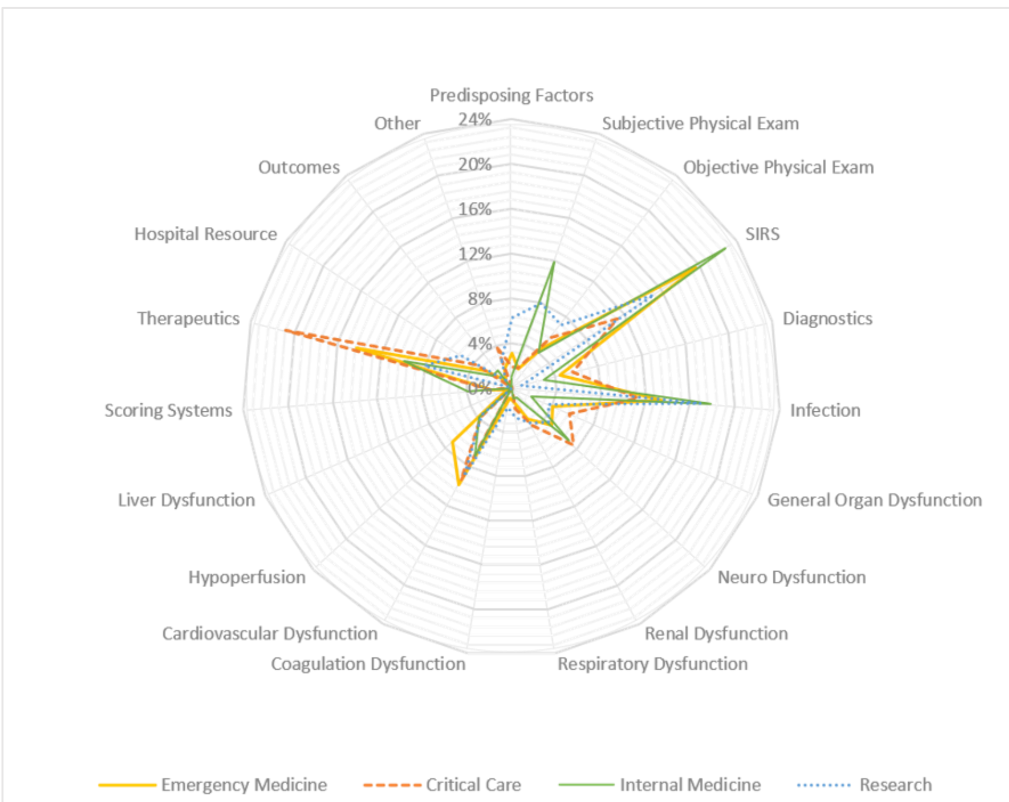

Figure 9. Percentage of responses from each hospital department (i.e. emergency medicine, critical care, internal medicine, research) falling into each of the broader word categories

3.4.4. Statistical Tests

For each word category, we conducted a Fisher exact test using the percentages shown in Figure 8 and Figure 9, to determine whether or not the distribution of words mentioned in that category was independent of each provider's type and specialty. The test results were significant in three word categories—SIRS ($p = 0.0135$), diagnostics ($p = 0.0231$), and neurological dysfunction ($p = 0.0092$)—suggesting that the types of words mentioned in these categories may be dependent upon provider type and specialty. A chi-square test confirmed these results.

3.5. Discussion

Although automated systems may provide significant advantages in clinical decision support for sepsis diagnosis, the development and implementation of a clinical DSS is a complex task. Not only must the DSS effortlessly connect into the massive network of data sources in a single healthcare institution, it must also be intuitive and easy to learn if clinicians are going to accept and adopt it.

This work will inform the design of DSS that aid in the task of sepsis diagnosis. Thus, it has implications for clinicians as well as DSS developers in engineering, operations research, and computer science. For example, we can think of the mental model as a tool for data and knowledge extraction. In a DSS, this information could feed a data/knowledge warehouse linked to a knowledge management [76]. The authors propose a feedback structure whereby the DSS can itself help improve the mental model and ultimately improve decision making. Furthermore, since mental models have been reported as being suitable to analyze unstructured problems (e.g. highly complex, with uncertainty and lack of consensus) [77], the use of such models in DSS increases the likelihood of trust and acceptance of the tools by decision makers.

Applying these results into the process of DSS development will allow for a personalized approach in guided education. The future of DSS is one in which feedback and guidance is provided contextually with awareness as to the location and provider. Recognizing that it is important to deliver the same conceptual message to all providers caring for sepsis, there are opportunities to highlight and augment the decision support environment and to provide education during use of the tool based on performance and trends seen in efforts such as these. For example, there is discrepancy between internal medicine providers and emergency medicine providers in their appreciation of “general organ dysfunction,” which should prompt a more directed education and feedback loop for internal medicine providers. Additionally, emergency physicians describing a high prevalence of “elevated white blood count” associated with sepsis should prompt a directed education on the low sensitivity of this marker in sepsis. However, the low association of respiratory dysfunction and coagulation dysfunction with sepsis across all specialties provides an opportunity for increased attention within DSS development to improve this awareness.

The failure to show significant difference between provider types or specialties within 16 of the 19 word categories in our analysis yields positive gains for DSS development. Knowing that providers share a similar model for diagnosing sepsis allows developers to create a single DSS system that could be tailored to fit a provider’s role and specialty based on available data elements and workflow. Maintaining the balance between standardized care delivery and individualized clinical diagnosis process is particularly challenging in conditions that are complex and lack consensus in definition, such as sepsis. While individual differences in cognitive processing of diagnosis-related information are inherent to clinical decision making, mental models can help identify common patterns in the perception of diagnostic components: (i) relative to each other, and (ii) relative to the condition of interest. Capturing and categorizing common mental elements specific to a clinical condition can inform not only the underlying diagnostic decision making process, but help to measure the association between different information categories and the clinical diagnosis. Comparing mental models based on provider features (such as provider type) over time has implications for the development of interfaces and tools that match the complexity of the mental landscapes that providers in dynamically changing clinical conditions with uncertain trajectories maintain. Further implications for other domains include diagnosis of acute and chronic conditions, and the impact of complexity as well as uncertainty as part of the diagnostic decision making in hospital and ambulatory settings.

Our results support the clinical consensus that neurological dysfunction and altered mental status are important aspects of sepsis diagnosis; however, evidence of these characteristics in electronic health record data is slim. As researchers continue to search for ways to improve sepsis diagnosis, it will become increasingly important for this information to be available as data within a computerized health system.

The primary limitation of this work is the sampling strategy, which was based on convenience. While our results were sufficient to serve our specific purpose, they may not be generalizable to clinicians from other healthcare institutions despite being representative of three unique healthcare systems. In soliciting words from more clinicians, we could potentially identify trends in subcategories (like provider type and specialty) and by soliciting more personal characteristics, could evaluate word choices by elements like years of training and/or expertise. Additionally, there may be bias in our categorization of words into unique categories based on subjective criteria.

A final limitation of this study was the decision to exclude words related to therapeutics when selecting our final set of 13 words. Therapeutics was the broad word category mentioned most often by providers, even though they were asked to provide words related to sepsis diagnosis. These results suggest that providers view diagnosis and therapy as highly intermingled concepts that are difficult to tease apart.

The next phase of this research will use the 13 words identified by this study, along with two control words, to produce fuzzy cognitive maps that show the intensity of relationships between words related to sepsis diagnosis. Visual representations or graphic forms have advantages in representing complex thinking and cognition in flexible ways. Prior studies have indicated that verbal text alone is limited in representing the understanding of complex issues, and a diagram is sometimes worth a thousand words [78]. We will compare cognitive map associations between (i) provider types, (ii) current department of employment, and (iii) level of clinician experience in order to understand how a sepsis diagnosis DSS might be optimally designed and tailored to match the existing mental models of its specific users.

Additional fundamental human factors research relating to the mental models of clinicians would be beneficial to the healthcare domain, a complex setting that relies heavily on the intellect and expertise of its human clinicians. Controlled lab studies with clinicians have the potential to produce more detailed results that can inform DSS developers and others who aim to improve healthcare delivery through support roles.

3.6. Conclusions

This study analyzed the responses of healthcare providers to a word-association exercise that was designed to elicit the terms clinicians most closely associate with sepsis diagnosis. Preliminary results suggest that there may be differences in mental models across provider types and departments of employment, although these remain to be confirmed by future research that will quantify the relationship between the 15 words. The healthcare system, which relies heavily on the valuable human cognition of clinicians, is a complex work environment that merits future cognitive research to support both sepsis diagnosis and intuitive DSS design.

Acknowledgments

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CHAPTER 4: Exploring, Evaluating, and Prioritizing Decision Support Needs for Inpatient Allocation: Characterizing a Common Process Across Multiple Hospitals

As technology continues to advance, hospitals increasingly rely on automated decision support tools to conduct their daily activities. One such activity that is common across hospitals providing inpatient care is allocating each new general medicine admission to a particular internal medicine provider (often a hospitalist) for care. This study aggregates information about inpatient allocation processes from eight different hospitals, in order to (i) characterize these processes and their decision-makers, (ii) evaluate any existing decision support tools being employed, (iii) identify the primary influential concepts in inpatient allocation decisions, and (iv) prioritize these concepts to inform the design and development of future decision support tools.

4.1. Introduction

The integration of automated decision support tools into complex clinical processes is becoming more and more common in hospitals because they can increase patient safety and reduce cognitive workload for the decision-maker [22] [79]. Development of any decision support tool should include evaluation of the activities it will be supporting, as well as identification of key information needed by the decision-maker [21]. In practice, these evaluation and identification steps are often performed at each individual hospital in need of decision support tool development, since clinical process details, data availability, and personnel resources can vary greatly between hospitals [80]. However, for those processes that are common across multiple hospitals (e.g. allocating a newly admitted inpatient to a particular doctor for care), decision support tool development has the potential to be augmented and streamlined by sharing knowledge across these facilities [81].

A first step in sharing knowledge about inpatient allocation processes is to describe general process characteristics and decision-maker needs across hospitals. The objective of this study was to identify and prioritize information needs for inpatient allocation decision-makers, for the larger purpose of informing decision support system design and development in ways that can be applied across multiple hospitals. Data about inpatient allocation processes was collected through interviews and online surveys; data was analyzed in order to (i) characterize these processes and their decision-makers, (ii) evaluate any existing decision support tools being employed, (iii) identify the primary influential concepts in inpatient allocation decisions, and (iv) prioritize these concepts to inform the design and development of future decision support tools.

4.2. Background & Significance

Since this aim of this study is to explore and characterize inpatient allocation processes across multiple hospitals, it is important to first understand the overall purpose and general flow of the process (shown in Figure 10). In any hospital, the process begins when the decision-maker is notified that a new inpatient is arriving for general medicine care. Next, the decision-maker usually investigates the patient's current status and medical notes in some capacity to get an understanding of the case. Based on patient requirements, a set of candidate provider teams is identified as potential matches for the patient, and some communication may occur to help the decision-maker compare these decision-alternatives. Once all information has been gathered and processed, the decision-maker determines which of the candidate provider teams is most appropriate for patient, and this assignment is made in the hospital computer system. The provider team receiving the assignment is notified that they will be receiving a new patient soon. When the patient physically arrives, he or she is admitted (sometimes by the assigned provider team and sometimes by a designated admitter) and the provider team begins care.

At a given hospital, this decision occurs multiple times per day (approximately 10 to 50 times daily, depending on hospital size), so it is important that it is done right. The decisions are complex, requiring many specialized considerations to find appropriate matches between patients and provider teams. Improvements in inpatient allocation decisions have the potential to produce great benefits for a hospital, including increased care efficiency, improved patient outcomes, and enhanced patient and provider experiences.

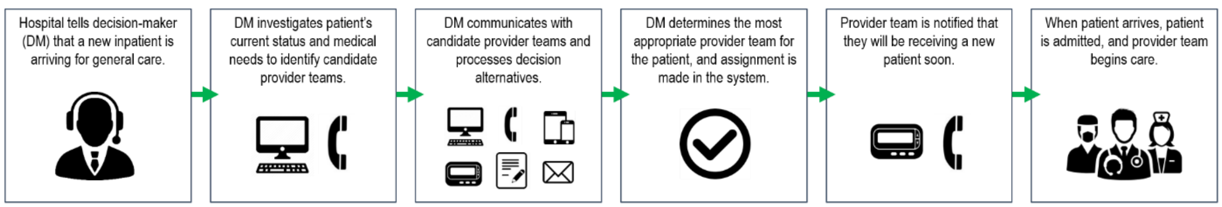


Figure 10. High-level overview of inpatient allocation process

Research investigating patient allocation processes exists across many domains, but rarely does it focus solely on inpatients or relate back to decision support tools. Systems engineering literature pertaining to patient allocation decisions provides some recommendations for methods that can be used to allocate incoming patients among hospital resources. For example, existing patient allocation models have based in methods such as machine-learning [35], dynamic multiagent resource allocation [36], queuing analysis [37], dynamic programming [38], and computer simulation [39]. However, none of this work has deeply explored the processes itself, nor the thought process of the decision-maker who makes these assignments. Additionally, most patient allocation research is not limited to inpatients; it is also rare for a study to characterize a single process across multiple hospitals.

4.3. Methods

A mixed methods study was conducted to explore the inpatient allocation processes (and their associated decision support tools) at eight hospitals across the United States. Between July 2018 and June 2019, semi-structured interviews and online surveys were employed to collect both qualitative and quantitative data from participants. Data from interviews and online surveys were processed and analyzed using multiple methods (described below). Analyses were performed primarily in Microsoft Word and Excel, although some iterative processing occurred by hand. This non-exempt study was approved by the North Carolina State University Institutional Review Board (IRB protocol #12948) in June 2018.

4.3.1. Setting & Participant Sample

Eight tertiary care hospitals (each associated with its own unique healthcare system) in the United States were included in this study: three university hospitals, three community, and two federal. Hospitals that served the public and had direct association with a college of medicine were classified as university; hospitals that served the public yet did not have a direct association with a college of medicine were classified as community; and hospitals that served only a government-specified population were classified as federal. Hospitals were located in four states with an average size of 719 beds (see Table 3).

Participants were identified at each hospital through personal networking and were recruited via email. Any hospital employees directly involved (either currently or previously) in inpatient allocation decisions (i.e. the process of determining specific provider and bed assignments) were eligible for inclusion. Due to the specificity of participant requirements (i.e. direct involvement in one specific hospital process of inpatient allocation), the number of eligible individuals was relatively small, ranging from 2 to 15 per hospital. A total of 18 individuals participated in interviews (at least two from each hospital); and from this participant pool, 11 individuals completed the online survey (at least one from each hospital) (see Table 3). When stratified by hospital role, the total number of participants who were providers, executives, and support personnel were 8, 8, and 2, respectively. When stratified by education type, the total number of participants who had clinical backgrounds versus nonclinical backgrounds were 13 and 5, respectively.

Table 3. Hospital characteristics and number of study participants

Hospital Type	Hospital ID	Ownership Type	For Profit?	Location	Approx. Bed Count	Number of Participants
University	**A**	Nongovernment	Yes	Pennsylvania	500	2
	B	Nongovernment	Yes	North Carolina	950	2
	C	Nongovernment	No	Minnesota	2050	3
Community	**D**	Nongovernment	No	North Carolina	700	2
	E	Government	No	North Carolina	650	2
	F	Nongovernment	No	North Carolina	300	2
Federal	**G**	Government	No	North Carolina	250	3
	H	Government	No	Virginia	350	2

4.3.2. Semi-Structured Interviews

Each participant was interviewed using a semi-structured interview protocol. Interviews were conducted either in person or by phone lasting approximately one hour, during which, qualitative and quantitative data were collected from participants. Notes were captured electronically (typed in a text document) during the interview. Interview questions focused on: the flow of the inpatient allocation process; the personnel involved, the order of events; the information required to make inpatient assignments; common frustrations in the process; and existing tools used to support inpatient allocation decisions. Answers to these questions provided rich qualitative data sets, often referred to as thick descriptions [82]. Quantitative data (i.e. a participant-specified value from 1 to 5) was also collected for three interview questions, which aimed to elicit participants' perceptions of how user-centered design principles manifested through their existing decision support tools. Specific questions used in the interviews are provided in Appendix B.

Qualitative data from interviews (i.e. notes from interview discussions) were synthesized using thematic content analysis [83] [84], in order to identify workflows, primary themes (commonalities across all hospitals and participants), and secondary subthemes (commonalities within a specific hospital or participant type) in the inpatient allocation process. Content analysis was performed by a single researcher who processed (and then re-processed) interview data after each new interview session occurred. This iterative processing, which included coding interview notes (using highlighting) to group similar content, creating tables in Excel for organization and categorization, hand-drawing flow diagrams of each process, and iteratively developing a vocabulary that communicates well across hospitals. Qualitative interview data was reviewed using at least four different processing techniques before convergence was achieved for workflows, themes, and subthemes. This analysis informed the development of the online survey content.

Quantitative data from interviews during three questions were analyzed to gain insight into participants' experiences as tool users. Responses were averaged across all participants to evaluate how useful, usable, and desirable participants perceived their existing inpatient allocation decision support tools [85]. Participants were also asked to comment on their primary decision support tool(s). Themes from these evaluations were aggregated and analyzed using a Strengths, Weaknesses, Opportunities, and Threats (SWOT) approach [86].

4.3.3. Online Surveys

As noted in the qualitative discussion above, the analysis of interview responses produced a set of eight important concepts (i.e. factors) that influence inpatient allocation decision-making processes. This set of concepts (along with two additional control words) was used to create a three-question online survey, requiring no more than 15 minutes to complete.

The survey prompted participants to complete an exercise that asked them to show (visually) the strength of the relationship between each concept (presented in an interactive word bank) and a main concept (i.e. optimal inpatient allocation decisions) by placing each concept onto a bullseye diagram (see Figure 11). The survey was sent to all 18 interview participants, and responses were received from 11 (61%) of them. Qualtrics software allowed participant responses to be securely collected and exported for analysis.

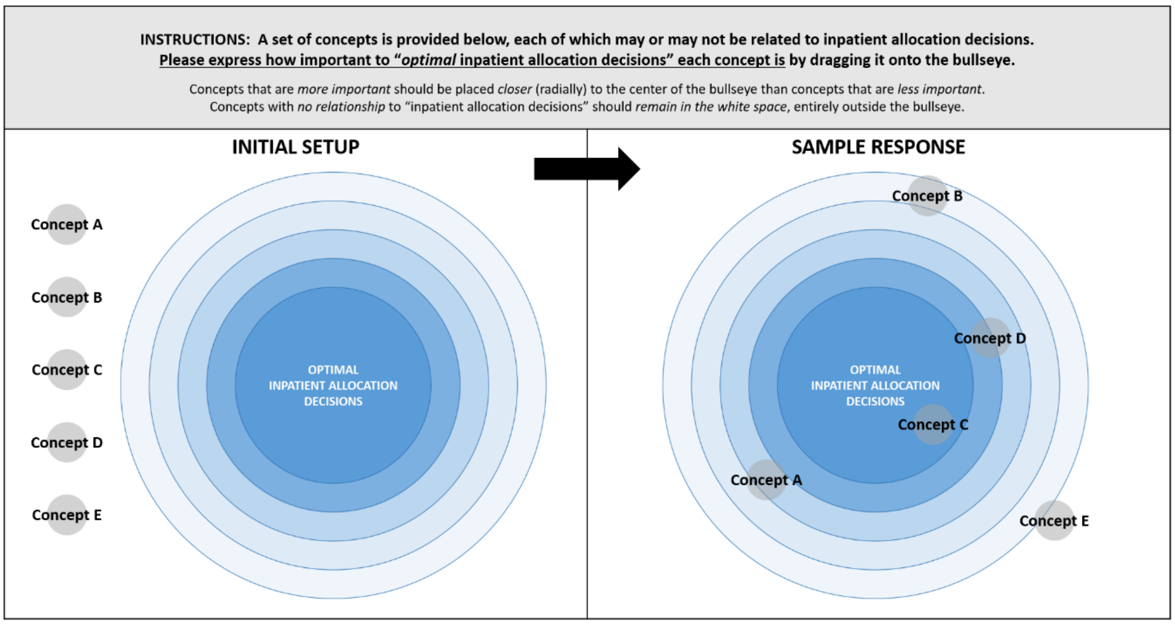


Figure 11. Sample of PowerPoint bullseye exercise uploaded into the online survey

Concept placement on bullseye diagrams was coded into values (higher values were given to concepts placed closer to the center), and an average value was calculated for each concept. These average values were used to prioritize the key concepts (or elements) for decision support tool development. The interactive placement of concepts around the bullseye was accomplished using PowerPoint; the PowerPoint file was uploaded into Qualtrics. Placement of the two control words was also evaluated across all responses, in order to validate that the concepts identified from interviews truly related to inpatient allocation decisions.

4.4. Results

General characteristics of inpatient allocation decision-making processes were aggregated across the eight hospitals, and results are presented in Table 4. Daily inpatient allocation decisions were made by a single individual at 4 hospitals, by a pair at 3, and by a trio at 1, representing 50%, 38%, and 12% of hospitals, respectively. The educational background of decision-makers was primarily clinical at 3 hospitals, primarily nonclinical at 2, and a mixture of clinical and nonclinical at 3, representing approximately 38%, 25%, and 38% of hospitals, respectively. Similarly distributed was the type of primary decision support tool used for inpatient allocation processes, which was physical at 3 hospitals, electronic at 2, and a hybrid of physical and electronic at 3, representing approximately 38%, 25%, and 38% of hospitals, respectively. The number of provider teams (e.g. medical services, hospitalist teams, etc.) at each hospital that were candidates for general medicine inpatient assignment ranged from a minimum of 6 to a maximum of 19.

Table 4. Comparison of inpatient allocation process characteristics across facilities

	Hospital ID	**Decision-maker (DM) characteristics**		**Does DM sit in a command center?**	**Primary decision support tool type**	**Number of candidate teams**
		Number of DM(s) for allocation	DM title(s) (background)			
University Hospitals	**A**	1	Triage resident (clinical)	No	Physical (worksheets with supporting binder)	6
	B	2	Attending (clinical) + APP (clinical)	No	Physical (worksheet)	19
	C	2	Patient placement coordinator (nonclinical) + MOD (clinical)	Yes	Electronic (hospital-specific software)	17
Community Hospitals	**D**	1	Patient placement coordinator (clinical)	Yes	Electronic (commercial software)	18
	E	1	Patient assignment coordinator (nonclinical)	No	Physical (worksheets)	11
	F	1	Patient placement coordinator (nonclinical)	No	Hybrid (worksheets + commercial software)	10
Federal Hospitals	**G**	2	Patient placement coordinator (nonclinical) + Hospitalist (clinical)	No	Hybrid (worksheets + commercial software)	8
	H	3	Bed control (nonclinical) + UM (clinical) + MAA (clinical)	Yes	Hybrid (worksheet + commercial software)	6

*Abbreviations: APP = advanced practice provider; MOD = medical officer of the day; MAA = medical admitting attending; UM = utilization management

4.4.1. Exploring Themes in Inpatient Allocation Processes

Four primary themes (applicable across entire sample) and two secondary subthemes (applicable only to select sample subsets) emerged from the thematic content analysis of semi-structured interview responses.

Theme 1: Inpatient allocation processes were complex and disjointed. Descriptions of inpatient allocation processes at every hospital mentioned the involvement of a wide variety of people (e.g. clinical doctors, nurses, technicians; nonclinical bed management employees, administrators, janitors), activities (e.g. triage, emergency services, transport, placement), tools (e.g. computers, pagers, worksheets, phones), and information (e.g. patient diagnosis, medical history, status of candidate provider teams). Decision-making objectives and protocols were rarely documented. Even when documented, the majority of protocol instructions failed to address all possible decision scenarios (and were thus, incomplete). Communication of complex information relating to inpatient allocation was achieved using multiple modalities, including phone calls, pages, emails, texts, and in-person conversations. Disparate communication channels were a primary bottleneck in process efficiency and created opportunities for errors.

Theme 2: Reliance on paper tools was pervasive. Despite the fact that all hospitals had an electronic medical record (EMR) system that allowed decision-makers to access patient and hospital information, participants from every hospital reported that they also utilized paper tools to support their decisions in some way. Six (80%) of the eight hospital processes were described as incorporating a physical (i.e. paper-based) worksheet as a primary decision support tool.

Theme 3: Decisions required both clinical and non-clinical expertise. As evidenced by the many people and elements involved, inpatient allocation processes at all hospitals involved both clinical and nonclinical components. Six (80%) of the eight hospitals staffed clinical decision-makers. In hospitals staffing only nonclinical decision-makers, inpatient allocation protocols included significant consultation with clinical employees.

Theme 4: The emergency department influenced decisions heavily. All participants mentioned the emergency department (ED) in some capacity in their descriptions of inpatient allocation processes, which indicated that it played an influential role in the decision-making process. Participants described a variety of relationships between inpatient allocation processes and the ED, including regular communications between the decision-maker and ED providers. In almost all hospitals, the ED was the source of the majority of inpatient admissions.

Subtheme 1: Command centers utilized clinical decision-makers. Three hospitals (38%) were described as having a dedicated command center for overseeing all hospital operations. All of these hospitals staffed inpatient allocation decision-makers with clinical backgrounds.

Subtheme 2: Only community hospitals had solely nonclinical decision-makers. Both hospitals that staffed only a single nonclinical decision-maker were community hospitals. In both cases, these decision-makers had heavy communication with providers to support them. Two of the three community hospitals established an order of candidate provider teams each day and assigned patients to them using a simple rotational strategy.

4.4.2. Evaluating Existing Decision Support Tools

Primary decision support tools used for inpatient allocation processes were physical at 3 hospitals, electronic at 2, and a hybrid of physical and electronic at 3, representing approximately 38%, 25%, and 38% of hospitals, respectively. Physical tools included mostly worksheets that assisted with manual organization of information, although other peripheral physical tools (e.g.

binders with reference sheets, bulletin board displays, whiteboards, etc.) were also used. The primary results from the SWOT analysis are presented in Figure 12.

	Helpful to achieving objective	Harmful to achieving objective
Internal origin (attributes of the organization)	**STRENGTHS** In general, most tools are ultimately well-accepted by decision-makers (i.e. users). Tools are usually developed and managed internally by hospital IT staff, making them easy to customize and change, as needed.	**WEAKNESSES** Multiple tools and communication channels are often utilized to make decisions, which can lead to disjointed processes, errors, and loss of information. Decision-makers often have very limited awareness of provider workload when allocating patients.
External origin (attributes of the environment)	**OPPORTUNITIES** Tools could be improved if they were better-aligned with decision-maker workflows. There is opportunity to integrate physical tools into electronic systems. There is a steep learning curve for most processes that could be mitigated with improved protocol instructions.	**THREATS** Associated EMR system(s) may crash. Since the majority of information required for decisions is tied to an EMR, a crash stops or delays the decision-making process.

Figure 12. Results from SWOT analysis of existing inpatient allocation decision support tools

Quantitative questions, which asked participants to provide a rating from 1 (low) to 5 (high) to represent how useful, usable, and desirable they considered their existing tools to be, were averaged across participants. Average user ratings of their existing tools were 4.6, 4.3, and 3.5 for usefulness, usability, and desirability, respectively.

4.4.3. Identifying Key Concepts in Inpatient Allocation Decisions

From the interview themes, eight concepts were identified as being important to optimal inpatient allocation decisions: current location, diagnosis, and medical details (e.g. history, vitals, labs, notes, etc.) of the patient; current location and workload level of each candidate provider team; current availability of inpatient beds and workload level of nurses staffing those beds; and current workload level of the ED. These concepts (along with two control concepts) were used to create the online survey. The two control concepts selected were current workload level of the operating room (which should not apply to most general internal medicine inpatients) and current workload level of the pharmacy (which should affect inpatient allocations minimally, since it is not an integral department in the process).

4.4.4. Prioritizing Concepts to Inform DSS Development

Responses from the online survey placed 11 instances of each concept on the bullseye diagram. Each concept instance was assigned a value based on its placement within the bullseye (outside bullseye=0; inside first ring=1; …; inside center bullseye=5), and an average value was calculated for each. Concepts were then ordered by this value and grouped into high-priority (average value greater than 3), low-priority (average value between 2 and 3), and no-priority (average value less than 1; control words) categories. This created a hierarchy of elements (see Table 5) to be considered for inclusion in a decision support interface. Implications of such a hierarchy are discussed in the next section.

Table 5. Results from bullseye exercise, ordered by average value

Key Concept	Average Value	Priority Level
Patient diagnosis	4	High
Bed availability	3.9	
Patient medical details	3.8	
Workload of candidate providers	3.6	
Patient location	2.6	Low
Workload of the ED	2.5	
Workload of nurses	2.3	
Location of candidate providers	2	
Workload of operating room	1.6	None
Workload of pharmacy	1.1	

4.5. Practical Implications for Decision Support Interface Design

The results from this investigation produced interesting insights into the inpatient allocation processes (and their associated tools and concepts) at eight hospitals, and these insights have implications for future design of a standardized decision support interface.

Processes at all hospitals were found to be complex and disjointed, involving many moving pieces, as well as decision-makers with both clinical and nonclinical backgrounds; thus, the design of a decision support interface would need to be palatable to personnel of various education levels in order to be applicable across multiple hospitals. Decision-makers were clinical at all hospitals with command centers, suggesting that the command center approach might require more efficient clinical expertise. Only community hospitals were able to rely solely on nonclinical decision-makers for inpatient allocation. This may be because, in general, community hospitals often have fewer departments, specialties, services, etc., making appropriate patient-provider matches relatively simple to identify without much clinical interpretation.

Despite the efforts of some hospitals to document them, the protocols and objectives of inpatient allocation decision-making processes were often complex and unclear, especially in hospitals using inpatient allocation strategies that were more complex than a basic rotation through a list. Only one hospital had a tangible objective: to make an assignment decision in five minutes or less. Vague objectives make the design of a decision support tool, as well as the assessment of its performance, more challenging. Additionally, hospitals used a variety of strategies (e.g. rotational, lowest workload first, etc.) to allocate inpatients, which may have positive correlation with hospital size, so designers may want to plan for integration of nonstandard algorithms.

Six hospitals (80%) relied on a physical worksheet as one of their primary decision support tools to support inpatient allocation processes, which seemed surprisingly antiquated in an era of technology advancement. This suggests that a manual component might be facilitating something that is difficult to achieve using electronic modalities. Thus, it may be advantageous to incorporate a physical component into the design of an ideal inpatient allocation decisions support system. The concepts identified as being important to inpatient allocation decisions did not vary greatly across hospitals, which is promising for standardization of tool elements. Also promising for standardization was the theme of strong connection to the ED. The ED was influential in inpatient allocation processes at all hospitals, which presents an opportunity for additional investigation into its ability to inform the design of decision support tools.

Identification and prioritization of the key concepts related to inpatient allocation decisions produced an ordered list of elements (see Table 5) that can be viewed as a list of components that would be helpful if included in a decision support interface. High-priority elements were patient diagnosis, bed availability, patient medical details, and workload of candidate providers; low-priority elements were patient location, workload of the ED, workload of nurses, and location of candidate providers; no-priority elements (i.e. control concepts) were workload of the operating room and workload of the pharmacy. Based on these groups, levels of priority within an interface or display can be assigned. High-priority elements should definitely be included in an interface. Design of high-priority components should be prominent and receive the most effort. These components might be bigger and brighter, with details and visuals that rely on predictive models. Low-priority elements should be considered for inclusion in an interface. Design of low-priority components might be smaller and faded, with fewer details or links to additional resources that support these components. No-priority elements do not relate to the interface and thus would not be included in the design. In general, design efforts should be made in development phases to match concept priorities with visual hierarchy. Investigative efforts can be made by IT or computer science personnel to find data within their systems that represents each concept.

The primary limitation of this study was the small number of participants in interviews and surveys; this was to be expected since the population pool (i.e. hospital employees with intimate knowledge about inpatient allocation decision-making processes) is specialized and limited by nature. However, we considered this a satisfactory sample since, at all hospitals, convergent process descriptions were reached after two to three interviews. Another limitation of this study was the researcher's focus on practical methods for data collection and engagement with often-overloaded hospital employees. While rigor was a priority in methods development, it was secondary to this pragmatic theoretical perspective.

4.6. Conclusion

In this study, we explored inpatient allocation processes (and their associated tools) at eight hospitals, with a goal of identifying and prioritizing a set of elements for an associated decision support system or interface. Concepts central to the process were first identified in interviews, then prioritized using a follow-up online survey. The resulting hierarchy of elements can be used to inform the design of future decision support tools, since it helps us understand the mental models of inpatient allocation decision-makers. Future work that investigates the details of inpatient allocation protocols and their connection with the emergency department would be useful.

CHAPTER 5: Employing Conjoint Analysis in Healthcare: A Practical Approach for Eliciting and Modeling Clinicians' Perceptions of Workload in Complex Hospital Scenarios

Investigations into different aspects of hospital decision support technologies are prevalent in a wide variety of disciplines, and many of these investigations utilize quantitative modeling techniques. Clinician workload is a quantity that is commonly included in models of complex hospital processes, but there is no consensus on the best way to quantify it. In this study, we describe a practical and novel approach for developing a workload quantity (i.e. workload score) to dynamically represent clinician workload based on the characteristics of a given hospital scenario. A case study was used to demonstrate the approach, and case study results indicated that the workload score was a relatively accurate representation of clinician workload.

5.1. Background

In recent decades, the healthcare industry has grown substantially. The growth of the industry is reflected in hospitals, which have become increasingly complex environments [9]. Automated decision support systems (both clinical and nonclinical) have been incorporated into almost every operational process in hospitals, as advancements in technologies have been made [22] [13]. Hospital personnel (i.e. users) rely on these tools to provide them with information (or access to information) so that they can keep patients safe, make activities run more efficiently, and reduce human errors in a large clinical organization [79].

Investigations into different aspects of hospital decision support technologies are prevalent in a wide variety of disciplines, including computer science, systems engineering, human factors, cognitive science, and biomedical informatics [21]. Many of these investigations have employed quantitative modeling techniques, and in an era of big data computing and artificial intelligence, this trend is likely to continue [13]. However, quantitative modeling of hospital processes for decision support purposes remains challenging, since medical scenarios have many complex variables and clinical knowledge is extremely specialized [60] [61]. Relatively recently, the concept of convergence research was introduced as an improved problem-solving approach in complex domains, such as hospital decision support [23]. Convergence research approaches are problem-centric and aim to integrate knowledge from multiple disciplines into solution development. Thus, as utilization of convergence research approaches increases, quantitative modeling will likely need to be made more accessible to researchers from non-quantitative disciplines.

A concept that is commonly incorporated into quantitative models of hospital processes is clinician workload. However, there is no consensus on how this workload should be objectively quantified [87]. In this paper, we describe a practical and computationally simple (in that programs are readily available to facilitate the calculations) approach for developing a customizable quantity (i.e. score) that dynamically represents clinician workload based on the characteristics of a given hospital scenario. The approach is novel because it incorporates conjoint analysis of choice-based surveys [88]. Following the approach description, we present the results of a case study in which our score development process was employed; this case study serves as an example application of score development. Finally, study implications and limitations are discussed.

5.2. Relevant Literature

Relevant literature pertaining to this work falls into two categories. First, we provide some background about conjoint analysis methods and how they have been utilized in healthcare applications. Then we identify and describe existing approaches to workload quantification.

5.2.1. Background on Conjoint Analysis

The analysis method to be applied in a novel way for quantifying clinician workload is called conjoint analysis, which originated in the marketing field and is founded in stated preference theory (i.e. the theory that an individual's inherent preferences for certain alternatives can be elicited and quantified by simply asking the individual to state his or her preference in a structured way) [88] [89]. Traditionally, conjoint analysis has a foundation in the psychology discipline and is a well-known stated preference paradigm that began garnering interest in the 1990s. Conjoint analysis is "principally associated with research dealing with ways to mathematically represent the behavior of rankings observed as an outcome of systematic, factorial manipulation (i.e. known as "factorial designs") of independent factors (also known as "attributes"). If a person ranks a full factorial design, their implied preferences can be represented "as if" they integrate and combine the factor levels in certain algebraic ways, such as "adding" or "multiplying" marginal preferences for each factor level to rank" all possible factor combinations [89]. The use of conjoint analysis methods initially gained traction in the marketing domain as a tool to elicit consumers' preferences for specific product attributes. These preferences could then be used to inform manufacturing decisions, such as what type of new feature to incorporate into next year's model of a car in order to maximally increase the car's value on the consumer market.

In practice, conjoint analysis is often used in conjunction with a particular survey type (called a choice-based survey) that has a special structure and can be analyzed to determine numeric weights (i.e. utility values) representing participants' perceptions of, or the importance they place upon, different attributes of a single object. In this study, we will look at workload as an object that has attributes (e.g. indirect work, interruptions, patient complexity), and attempt to use a conjoint analysis method to elicit a weight that clinicians would attach to each of these attributes. The advantage of using a conjoint analysis approach is that associated choice-based surveys can be relatively short, yet they have the power to produce insightful and accurate results that numerically represent respondents' preferences. The most common applications for conjoint analysis methods have traditionally existed within the fields of marketing and economics, but its use in healthcare applications has grown steadily in recent years.

Most commonly, conjoint analysis in healthcare applications is used to elicit patient preferences for treatment and/or outcomes. For example, one study [91] used conjoint analysis to estimate patient preferences associated with different treatment outcomes for advanced non-small cell lung cancer. Participants in this study's self-administered online survey were systematically presented with pairs of treatment scenarios, and they were asked to choose which of the two scenarios they preferred. Each scenario was described by eight attributes, and conjoint analysis was used to estimate the importance of each attribute and its corresponding levels.

Conjoint analysis has also been used in the medical field as a method for prioritizing patients on surgical waiting lists. For example, one study [92] investigated how three different stakeholder groups would prioritize the patients on a waiting list for elective surgery: patients on the waiting list, laypersons (i.e. patients on other waiting lists), and physicians. To obtain data, each participant was presented with two or three paper cards, each representing a hypothetical patient (described by four attributes). A conjoint analysis of participant responses effectively produced three ranked surgical waiting lists, each based on the preferences of a stakeholder group. The authors were also able to use their results to predict exactly how these rankings might shift if a particular attribute was adjusted. Another study [93] employed conjoint analysis to provide insight into a similar issue, but instead of prioritizing patients on a surgical waiting list, the authors developed weights associated with different disease criteria so that diseases could be ranked in order of their relative severity and prioritized for treatment.

Very few studies have employed conjoint analysis methods to understand the perceptions of healthcare providers. However, one study has started down this research path by examining General Practitioners' "preferences for pecuniary job characteristics (i.e. aspects of a job for which an employee is directly compensated) and non-pecuniary job characteristics in the context of choosing a general practice in which to work" [94]. The aim of this work was to elicit an indirect utility function that represented physician job preferences. A total of seven work characteristics (i.e. attributes) were included in the study, all of which were identified for inclusion through physician surveys and interviews. A key result from the analysis relates to quantifying the trade-offs that general practitioners prefer, reporting that "the extent to which general practitioners trade-off income for other job characteristics gives an estimate of the monetary valuation of those characteristics" [94].

5.2.2. Existing Approaches to Workload Quantification

As stated previously, clinician workload is a concept that is commonly incorporated into quantitative models of hospital processes. Various methods exist for quantifying and modeling workload, in general, but there is no consensus on which approach is most appropriate in for clinicians [87]. Most often, workload is quantified using a linear combination (i.e. weighted average) of influential factors that are weighted by their importance. In general, this is a way to translate any abstract concept into a weighted average of all measurable factors that combine to influence it.

Two of the most common techniques used to quantify workload are the subjective workload assessment technique (SWAT) [95] and the National Aeronautics and Space

Administration Task Load Index (NASA-TLX) [96]. SWAT quantifies workload based on discrete levels of three attributes: time load, effort load, and psychological stress load. In order to perform a SWAT analysis of the workload associated with a specific task, participants must engage in two tedious processes—a card-sorting procedure and a task scoring procedure—that require substantial time and mental effort. Weights are then calculated for each attribute [95]. NASA-TLX is similar to SWAT, but it uses a continuous scale to describe the level associated with each of six factors: mental demand, physical demand, temporal demand, performance, effort, and frustration. In order to develop weights for each of these attributes, task operators / performers are asked to complete choice-based surveys that elicit their individual perceptions of the impact that each attribute has on their workload [96]. The SWAT and NASA-TLX techniques have been used to quantify workload in a wide variety of human activities, including manual control tasks (e.g. flying, driving), visual and auditory monitoring, decision making, and teamwork.

Extensive review of the literature resulted in identification of only one study [97] that has employed conjoint analysis in a workload-related investigation. This work used conjoint analysis to understand the relative influence of different factors on heavy vehicle drivers' perceived workload demands in different driving scenarios. Scenarios were described by their levels (i.e. high versus low) of five different driving conditions that vehicle drivers might experience: traffic density, lighting, road type, visibility, and traction. General consensus was achieved among study participants regarding each attribute's effect on perceived driving workload.

5.3. Research Contribution

Although multiple methods for quantifying clinician workload have been published, the current solutions provided by research theory are not always easily applied in practice, so these methods may not be utilized. Our work focused on bridging this gap between theory and practice. Thus, the primary contribution of this research lies in its practicality for application in real-world scenarios. The secondary contribution of this research is the novel incorporation of choice-based surveys and conjoint analysis as integrated components of workload quantification. Ultimately, the proposed approach can be applied to develop a workload score that is (a) customizable (factors can be included and customized based on scenario and data needs), (b) representative (score development is based on perceptions of the specific clinician population whose workload is being modeled), and (c) implementable (data collection methods and analysis techniques required for score development are integrated from multiple disciplines to keep computations simple and to ensure that the contributions required from the clinician population remained minimal, yet high-value).

5.4. Methodology Description

The remainder of this paper introduces our approach to eliciting and quantifying clinicians' perceptions of workload for the purpose of developing a workload score and demonstrates use of the approach through a case study example (provided in the next section, along with supporting figures). The approach (shown in Figure 13) is comprised of five steps: three expert surveys (steps 1-3), followed by consultations (step 4) and analysis and score creation (step 5). The first four steps require input (via short surveys, interviews, and consultations) from the clinicians whose workload will be represented by the workload score. Once these steps are complete, the score developer can individually conduct the necessarily analysis to create the final score. This approach results in a workload score that is a linear combination of weighted subfactors (i.e. proxies) that represent the larger influential factors. Since workload is heavily dependent on multiple situational factors in a clinician's environment, this workload score is scenario-based. The idea here is that, given a set of specific situation characteristics (i.e. proxy data points representing influential workload factors), a corresponding workload score can be calculated.

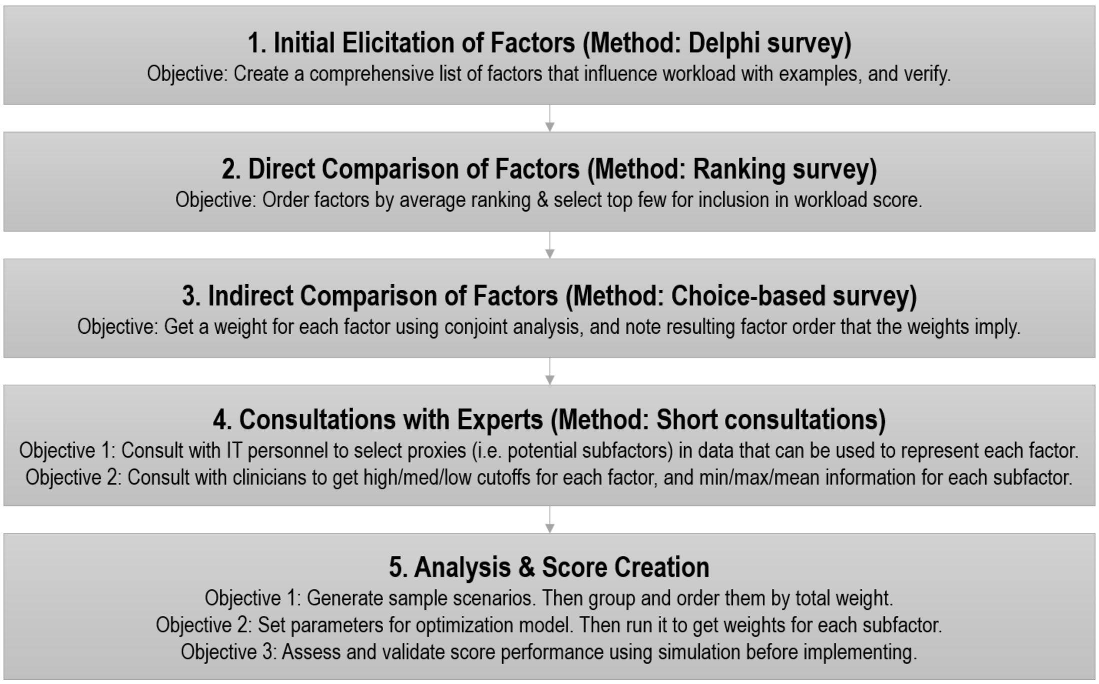


Figure 13. Steps of the proposed workload score development approach

Step 1: Initial Elicitation of Factors from Providers (Delphi survey). The first step is to brainstorm for all possible factors that influence workload by conducting a Delphi survey of the clinician population whose perceptions of workload the score will represent. Once ideas have been collected, the score developer (possibly with expert help) will need to categorize and code common ideas to narrow the list down to 10 or fewer primary factors that influence workload. These will be the factors that ultimately get considered for inclusion in the workload score.

Step 2: Direct Comparison of Factors (Ranking survey). Next, the score developer needs to elicit and compare the relative importance of the primary influential factors identified Step 1. To do this, a second survey of experts will need to be conducted. The survey will directly ask experts to rank the set of factors by their level of influence on perceived workload (with rank

1 representing the most influential factor). After responses have been collected, the score developer will need to calculate an average rank for each factor. Factors should then be ordered (in ascending order) by average rank, and this order should be noted for use in Step 5. Finally, the developer needs to select the subset of factors (approximately 5) that will be included in the workload score. If there is a clear group of "top-tier" influential factors with high average ranks, these factors should be the ones selected.

Step 3: Indirect Comparison of Factors (Choice-based survey). Since direct elicitation can sometimes be inaccurate due to self-reporting bias, it is worthwhile to attempt an indirect comparison of factors, as well. This is done by incorporating a novel approach of a choice-based survey. This survey type is selected because of its ability to be analyzed and output a relative weight for each factor; additionally, it is easy to create automatically with software, can be designed to result in a minimal number of questions (so as not to waste experts' valuable time), and allows experts to indirectly compare factors by comparing scenarios (i.e. combinations of factors) that might be experienced in practice. Conjoint analysis (which can also be conducting using software) should then be employed on aggregated survey results to calculate a utility value for each factor.

Step 4: Consultations with Experts. Before the results of the previous three steps can be brought together to inform a workload score, two types of consultations with experts should occur. First, a consultation should occur to discuss information technology (IT) needs for the workload score. In particular, the score developer needs help identifying specific proxies (i.e. numerical subfactors) that already are (or can be) automatically collected and combined to represent each influential factor. This is necessary so that the score can be programmed and automated, ideally supported with real-time data. Second, a consultation (possibly multiple to gain consensus) should occur to define “levels” for each factor (i.e. high, medium, and low cut-off points), as well “distributions” for each subfactor that will be included in the workload score. These consultations should be with the clinicians whose workload the score will represent; each clinician should be asked to provide (a) a minimum, maximum, and average of “what they ever see” for each factor and numerical data point, and (b) exact numerical “cut offs” for what constitutes high, medium, and low levels of each factor. This information will be used in the scenario generation part of Step 5.

Step 5: Analysis and Score Development. The remaining analysis and score development can be conducted by a single individual, based on the information collected from the previous surveys and consultations with experts. The overall process is first to generate and order sample scenarios, then to use an optimization model to find the weights of each data point that minimize the percentage error within this ordering, and finally to implement the score in a model or in practice and assess its performance. Each of these steps is complex and best-illustrated by an example, so further descriptions are provided in the next section.

5.5. Results of Case Study

The workload score development approach outlined in the previous section was applied in a case study that aimed to balance workload more equitably among hospital internal medicine physicians [97]. The case study was conducted at the request of hospital management, and a customized dynamic workload score was identified as a primary deliverable. Two individuals (with backgrounds in design, systems engineering, and operations research) worked as a team toward score development, which occurred over a three-month period. The score was tested and validated from an operations research perspective and then incorporated into a computer simulation model. Each step taken during the score development process is described below.

Step 1: Initial Elicitation of Factors from Providers (Delphi survey). Clinicians were asked (via email) to brainstorm factors that affected their workload. Responses were collected and combined into categories by a small group of clinicians using Delphi methods. More than 80 unique responses were provided by clinicians. By combining similar responses and creating categories, these responses were reduced to a set of 9 factors that influenced clinician workload (shown in Figure 14). A document listing these 9 influential factors and associated examples was created and distributed. This list was reviewed, discussed, edited, and confirmed at a staff meeting to gain clinician consensus on the definitions of these factors before moving on to the next step.

Patient churn	Lack of autonomy	Work interruptions
Nonclinical responsibilities	Uncertainty about end of day	Complexity of patients
Work inefficiency	Changing team members	Geographical location of patients

Figure 14. Nine factors identified as influential to clinician workload through Delphi methods

Step 2: Direct Comparison of Factors (Ranking survey). Clinicians were asked to complete a short survey (some via email, some handwritten) to rank the 9 influential factors identified in Step 1 by their impact on workload (where rank 1 was high and rank 9 was low). An average rating was calculated for each factor, and the factors were ordered by this value. The resulting list of factors (ordered from most influential to least influential) is presented in Figure 15. This provided a direct ranking of factors. After consultation with clinicians, the top four factors (i.e. patient churn, work interruptions, patient complexity, and work inefficiency) were selected for inclusion in the workload score.

Factor	Factor Priority
Patient churn	1
Work interruptions	2
Patient complexity	3
Work inefficiency	4
Uncertainty about end of day	5
Geographical location of patients	6
Changing team member	7
Nonclinical work	8
Lack of autonomy	9

Figure 15. Factors ordered by average rank

Step 3: Indirect Comparison of Factors (Choice-based survey). The four factors selected in Step 2, were used to design a choice-based survey, so that clinicians' perceptions of influential factors could be assess indirectly (i.e. the clinicians were required to rank scenarios (made up of factors) instead of the factors themselves. The survey was created using Sawtooth software and administered via a secure online survey portal. In order to ensure sufficient statistical strength in analysis of results, conservative estimates were made for required survey parameters (e.g. predicted number of survey participants, number of levels of each factor). The survey consisted of 15 pairwise comparison questions that asked clinicians to identify which of two scenarios was more severe (see Figure 16). Scenarios were described only by the levels (i.e. high, medium, low) of the four workload score factors. The survey was intentionally designed to be short, to increase the likelihood that clinicians would find time to complete them during their busy schedules. Responses to choice-based surveys were aggregated, and conjoint analysis was performed in Excel to obtain a utility value associated with each factor. Specific utility values were recorded for use in future steps.

Which scenario is more severe?	Churn	Patient Complexity	Number of Interruptions	Amount of Indirect Work
Scenario 1:	High	Low	Average	High
Scenario 2:	High	Average	Low	High

Figure 16. Sample question from choice-based survey

Step 4: Consultations with Experts. Before the final step of analysis and score development, two types of consultations with experts occurred. First, two data consultations with hospital IT personnel were used to identify proxy data elements (i.e. subfactors) that could be used to represent each factor within an automated system. With additional clinical assistance, a subset of these elements was selected by the developers for inclusion in the final workload score calculation (see Figure 17). Second, two consultations with clinicians were used to define bounds (i.e. minimums and maximums) and triangular distribution parameters (i.e. minimum, mode, maximum) for all factors and subfactors. Clinicians also provided cutoffs to define the high, medium, and low levels of each factor. This information will be used in Step 5.

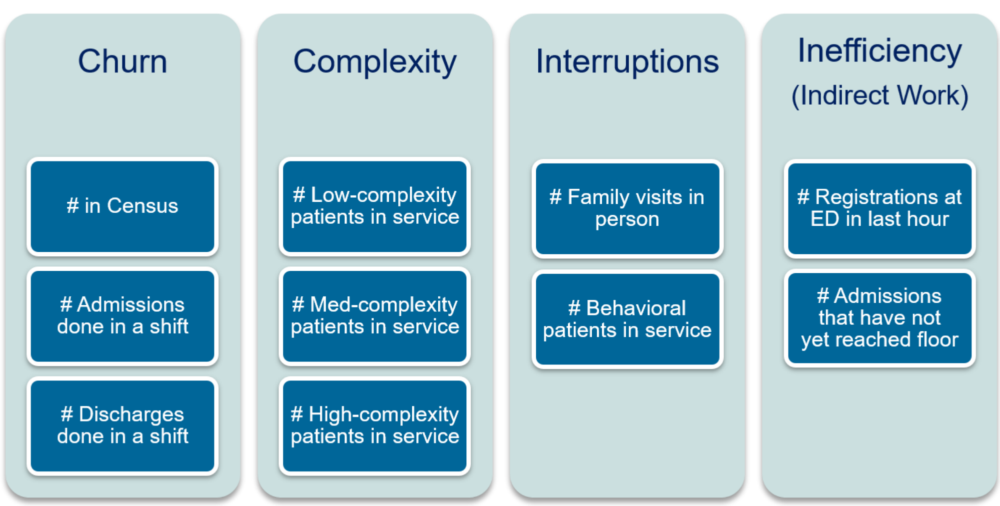


Figure 17. Subfactors (i.e. proxies in the data) identified for inclusion in the workload score

Step 5: Analysis and Score Development. The remaining analysis to inform the workload score was conducted by the two score developers. The information learned in the previous four steps was aggregated for use in this analysis. The overall process was first to (a) generate and order sample scenarios, then to (b) use an optimization model to find the weights of each data point that minimize the percentage error within this ordering, and finally to (c) implement the score in a model or in practice and assess its performance. The results for each of these steps are described below.

(a) Generation and ordering of sample scenarios. Before analysis began, we first generated 1,000 hypothetical scenarios (to be used in subsequent steps). A scenario was fully defined by the 10 subfactors (which represented the primary factors) identified in Step 4; therefore, "generating a scenario" simply meant populating 10 numbers. In order to ensure all scenarios were feasible, the bounds and distribution parameters collected from expert consultations (Step 4) used as inputs for Excel functions with random generation capabilities. Each row of the spreadsheet in Figure 18 represents a different sample scenario.

Admins	Discharges	Current Census	Low Complexity	Med Complexity	High Complexity	Num Families	Needy Patients	ED Registrations	Expected Discharges
0	5	6	0	2	4	4	4	16	2
3	4	12	8	1	3	1	5	9	5
1	1	16	3	6	7	1	6	30	2
3	2	5	3	0	2	0	1	20	3

Figure 18. Screenshot of hypothetical scenarios generated. The red box outlines a single scenario.

Once all scenarios had been generated, an associated hypothetical workload score was calculated for each. For a given scenario, this was accomplished by (1) totaling the subfactor values within each factor, (2) categorizing each factor total as high, medium, or low, based on the factor cutoff values provided in consultations with clinicians, (3) multiplying each factor total by the corresponding utility value for that factor (calculated in Step 2), and (4) adding the utility-weighted factor totals together into a single hypothetical workload score quantity.

Once a workload score had been calculated for each sample scenario, the complete list of hypothetical scenarios was ordered by this value (from highest (severe workload scenario) to lowest (non-severe workload scenario)) for grouping. Grouping was natural since many of the workload scores were identical due to the nature of calculations. This reorganization resulted in k ordered groups.

(b) Use an optimization model to determine the optimal weight for each individual subfactor. An optimization model (created by one of the score developers) was formulated in order to find optimal weights for each subfactor in the workload score. The formulation of this optimization model is presented and described in another paper [97] and is relatively straightforward. The optimization model aimed to identify the weights for the 10 subfactors that, when used to calculate a corresponding workload score for all sample scenarios, caused the fewest sample scenarios (out of the 1,000) to be displaced from their original ordered groups (identified in Step 5(a)), while simultaneously attempting to preserve the order of primary factors (which are simply sums of subfactor values) reported in Step 1. This model was parameterized and solved using CPLEX software. Model output provided optimal weights for each subfactor, as well as an error percentage. The resulting workload score formulation is shown in Figure 19. The associated error percentage (18%) reported in the optimization model output was relatively low.

	Weight		Subfactor to be pulled from real-time data	Primary Factor
+	1.0	x	(# in service census)	
+	3.5	x	(# admissions done today)	Churn
+	2.0	x	(# discharges done today)	
+	1.0	x	(# low-complexity patients)	
+	2.0	x	(# med-complexity patients)	Patient Complexity
+	3.5	x	(# high-complexity patients)	
+	2.5	x	(# families to visit)	Interruptions
+	4.0	x	(# behavioral patients)	
+	1.0	x	(# ED registrations in last hour)	Indirect Work
+	5.5	x	(# admits not yet on floor)	
=	**Real-time Snapshot of Perceived Workload**			

Figure 19. Final customized workload score calculation

(c) Implement the score in practice and assess its performance. Once a workload score had been created, the next step was to implement it somehow and begin to assess its performance. To accomplish this, a detailed discrete-event simulation model of workflow in the hospital internal medicine department was developed and validated using operations research techniques, which are outside the scope of this investigation.

5.6. Discussion & Limitations

The approach we describe for developing a workload score showed great promise in our case study, which was communicated through feedback from hospital management and clinicians. Clinician response rate good for all surveys, indicating that there was motivation to participate. This was likely due to the prominent focus on and regular communication about the project within the internal medicine department.

General implications of the proposed approach are threefold. First, the approach enables us to dynamically quantify the workload level of any given situation that arises, as long as we know a few select details about it. Second, it enables us to represent and quantify the relative workload intensity of complex situations, as perceived by clinicians. And finally, the approach can be easily programmed into a simulation model, so that researchers in quantitative decision support domains (e.g. decision analysis, health systems engineering, operations research) can employ their methods to provide recommendation that are dependent on workload.

The primary limitation of this study was the lack of opportunity for testing and evaluation of this score approach within the case study hospital. Feedback about the performance of a pilot workload score in action could provide additional insights that were not identified through simulation of the workload score.

5.7. Conclusion

In this paper, we described a practical and novel approach for developing a workload score to dynamically represent clinician workload based on the characteristics of a given hospital scenario; a case study was used to demonstrate the approach. Case study results indicated that the workload score was a relatively accurate representation of clinician workload. However, further empirical validation of the approach is required.

CHAPTER 6: Proposal of a Convergence Research Framework to Guide the Design of Hospital Decision Support Interfaces

As stated in Chapter 1, the findings presented throughout this dissertation are meant to be pulled together using convergence research principles, with a larger goal of informing a design process framework for hospital decision support interface (DSI) developers. This chapter serves this purpose. In this chapter, we motivate the need for such a framework, review the relevant literature, propose a framework to guide the hospital DSI design process (based on the findings of previous chapters), and explain the practical implications of the proposed framework.

6.1. Introduction

Hospital environments have become increasingly complex in recent years [6]. They offer multiple services across different departments, all of which depend heavily on integrated technologies (e.g. data, computers, machines, devices, etc.) to support decisions related to providing safe, efficient, high-quality patient care [22]. Hospital employees (i.e. users) interact with such technologies through interfaces, which we have termed decision support interfaces (DSIs), to help them make decisions. Before use, however, a DSI must first be developed, often following some sort of design process framework [24].

The individual (or team of individuals) responsible for the conceptualization, design, and programming of a DSI is referred to as the developer. Developers are often instructed by hospital management to create a specialized system or interface to support a specific hospital decision or process [13]. Depending on a hospital's resources (e.g. staffing levels, size, departments, funding, etc.), the background of a DSI developer might be in computer science, human factors, user interface design, operations research, systems engineering, or other discipline. Since the developer may be the only person (or one of a small set of individuals) involved in all steps of the DSI design process, and since he or she be responsible for creating both the form and function of the DSI, the role of this individual (as well as the specific DSI design process he or she employs) is critical [98].

There are a variety of existing frameworks used by developers to guide their DSI design processes. The developer may follow a generic design thinking process [99], or he or she may utilize a familiar approach from his or her discipline. Existing frameworks that inform interface design in healthcare include: a user-centered framework for redesigning healthcare interfaces [25], a unified framework for electronic health record usability [26], a framework for adaptive user interfaces in eHealth [27], and a framework for evaluating clinical decision support architectures [100]. However, the emergence in recent years of convergence research as an effective approach to complex problem solving suggests that hospital DSIs could be improved if a more integrated, transdisciplinary, problem-centric process was used by developers [23]. Thus, there is a clear opportunity to utilize a convergent research approach for the hospital DSI design process. The remainder of this chapter proposes such a framework and discusses its practical implications.

6.2. Proposed Framework

Approaches used and information learned from the three studies described in this dissertation (Chapters 3-5) were synthesized and incorporated into an initial structure, presented in Figure 20, of a process framework to guide the hospital DSI design. The framework categorizes DSI design process into three stages, each supported by a chapter in this dissertation. The first stage focuses on interface element generation, an exploratory design stage in which a developer determines if a DSI is truly an appropriate solution. The second stage focuses on interface element identification and prioritization, a stage that must occur early in the development process if a DSI solution is deemed appropriate. The third stage focuses on the translation of complex interface elements into useful representation, which is often connected to hospital data; this stage can vary greatly in complexity, depending on the requirements of the hospital process the DSI will support.

	STAGE 1 Generation	STAGE 2 Identification & Prioritization	STAGE 3 Translation
When does this stage apply to a developer?	Early in problem exploration	Early in interface development	Later in interface development
Nature of investigations	Exploratory	Definitive	Creative
What is the developer's objective?	To determine whether or not a DSI is appropriate for supporting a particular process	To select specific elements for inclusion in a DSI and prioritize them to inform interface hierarchy	To translate an abstract interface element into a useful representation for decision support
Connected disciplines, concepts, and methods	Word association exercise Knowledge representation Frequency analysis Statistical analysis Human-centered design Human factors Network diagram Mental models Cognitive science Cognitive mapping	Process mapping Systems engineering Semi-structured interviews Thematic content analysis Cognitive science Bullseye exercise Frequency analysis SWOT analysis Usability evaluation	Choice-based surveys Conjoint analysis Systems engineering Optimization Operations research DELPHI method Simulation modeling Factor analysis Information systems
What is the key takeaway once this stage is complete?	If the elements generated have the potential to represented well in a DSI, then a DSI may be appropriate. Go to Stage 2.	High-priority elements should be included in the interface and possibly investigated further if abstract. Go to Stage 3.	Abstract element representations tailored for a particular hospital decision should tested and validated before use.

Figure 20. Foundational structure of hospital DSI design process framework

In its current state, this framework could be used by a DSI developer to systematically incorporate knowledge from multiple disciplines into various disciplinary; it could also serve as a resource for identifying useful research methods in other domains. As additional investigations are conducted into hospital DSI design processes from the convergence research perspective, this framework should be edited to reflect new knowledge.

6.3. Practical Implications

A convergence research framework (the initial structure of which is presented above) has various practical implications for the design of hospital DSIs. Most importantly, the framework provides an actionable diagram that can be employed in real-world applications, for the purpose of implementing a convergence research approach. Framework information is presented using terminology that is not discipline-specific, in an effort to facilitate understanding across domains. Verbiage should be worded similarly as augmentations to the framework are made.

Another prominent implication of our framework is that there may be a need for the establishment of specializations within the clinical decision support development domain. In this research, various processes were integrated into a single framework structure, but as additional research is conducted, framework information will become increasingly complex. Eventually, this complexity may need to be addressed by dividing the framework into sub-frameworks, each of which informs the DSI design process for a specific hospital activity (e.g. framework for inpatient allocation DSI design, framework for operating room DSI design, etc.). Existing frameworks for hospital interface design, such as the framework for redesigning healthcare interfaces [25], often lack the problem-specific customization that is truly needed to guide developers in supporting a particular complex hospital process.

6.4. Limitations & Future Work

The development of this framework was limited primarily by the relative newness of the convergence research domain. Convergence research has only recently begun to gain attention and traction in academic settings; thus, there are few resources available that describe appropriate study design and analysis techniques for convergence. As knowledge increases in the convergence research domain, more information will be available to inform methodological choices for framework integration.

While the framework presented in this study provides an initial structure for the DSI design process, it clearly requires additional research. Next steps should include further investigation into the different ways that various disciplines influence the DSI design process, with a focus on integration of those into the existing framework structure. Once a framework has been finalized, it will also need to be formally evaluated. A potential study design for this evaluation (already developed and approved by the North Carolina State Institutional Review Board; IRB protocol #17946) is provided in Appendix C.

6.5. Concluding Remarks

This dissertation proposes an initial structure for a framework, based on convergence research principles, to guide the design of hospital decision support interfaces. The framework aims to integrate knowledge from various disciplines into a comprehensive set of straightforward steps, so that they can be easily understood and implemented in developer practices. Further research is required before the framework can be used.

REFERENCES

[1] L. A. Anderson, R. A. Goodman, D. Holtzman, S. F. Posner and M. E. Northridge, "Aging in the United States: Opportunities and Challenges for Public Health," *American Journal of Public Health,* vol. 102, no. 3, pp. 393-395, 2012.

[2] M. Mather, L. A. Jacobsen and K. M. Pollard, "Aging in the United States," *Population Bulletin*, vol. 70, no. 2, 2015.

[3] *Patient Protection and Affordable Care Act,* 2010.

[4] R. F. Vogenberg, "US Healthcare Trends and Contradictions in 2019," *American Health & Drug Benefits,* vol. 12, no. 1, pp. 40-47, 2019.

[5] Institute of Medicine, "Healthcare system complexities, impediments, and failures," in *Engineering a learning healthcare system: A look at the future: Workshop summary*, Washington, DC: The National Academies Press, 2011.

[6] L. A. Lipsitz, "Understanding health care as a complex system," *JAMA,* vol. 308, no. 3, pp. 243-244, July 2012.

[7] S. A. Nancarrow and A. M. Borthwick, "Dynamic Professional Boundaries in the Healthcare Workforce," *Sociology of Health & Illness,* pp. 897-919, November 2005.

[8] R. A. Cooper, "Health care workforce for the twenty-first century: the impact of non-physician clinicians," *Annual Review of Medicine,* vol. 52, pp. 51-61, 2001.

[9] R. Ollivier, E. Hericher and C. Arcos, "The Changing Role of the Hospital," *Health Mangement,* vol. 15, no. 1, 2013.

[10] K. Leonard, "Hospital of Yesterday: The Biggest Changes in Health Care," *U.S. News & World Report,* 15 July 2014.

[11] R. M. Wachter and L. Goldman, "Zero to 50,000 - The 20th Anniversary of the Hospitalist," *The New England Journal of Medicine,* vol. 375, no. 11, pp. 1009-1011, September 2016.

[12] National Academy of Engineering (US) and Institute of Medicine (US) Committee on Engineering and the Health Care, Building a better delivery system: A new engineering/health care partnership, P. P. Reid, W. D. Compton, J. H. Grossman and G. Fanjiang, Eds., Washington, DC: The National Academies Press, 2005.

[13] E. Estopace, "Healthcare IT spending to outpace other industries," *Enterprise Innovation,* 29 November 2016.

[14] R. Kopach-Konrad, M. Lawley, M. Criswell, I. Hasan, S. Chakraborty, J. Pekny and B. N. Doebbeling, "Applying Systems Engineering Principles in Improving Health Care Delivery," *Journal of General Internal Medicine,* vol. 22, no. Suppl 3, pp. 431-437, December 2007.

[15] D. Fone, S. Hollinghurst, M. Temple, A. Round, N. Lester, A. Weightman, K. Roberts, E. Coyle, G. Bevan and S. Palmer, "Systematic review of the use and value of computer simulation modeling in population health and health care delivery," *Journal of Public Health,* vol. 25, no. 4, pp. 325-335, December 2003.

[16] B. T. Denton, A. J. Miller, H. J. Balasubramanian and T. R. Huschka, "Optimal Allocation of Surgery Blocks to Operating Rooms Under Uncertainty," *Operations Research,* vol. 58, no. 4-part-1, 2010.

[17] C. Thompson, N. Cullum, D. McCaughan, T. Sheldon and P. Raynor, "Nurses, information use, and clinical decision making - the real world potential for evidence-based decision in nursing," *Evidence-Based Nursing,* vol. 7, no. 3, pp. 68-72, 2004.

[18] F. Abdollahzade, F. Mohammadi, I. Dianat, E. Asghari, M. Asghari-Jafarabadi and Z. Sokhanvar, "Working posture and its predictors in hospital operating room nurses," *Health Promotion Perspectives,* vol. 6, no. 1, pp. 17-22, 31 March 2016.

[19] E. Rojas, J. Munoz-Gama, M. Sepulveda and D. Capurro, "Process mining in healthcare: A literature review," *Journal of Biomedical Informatics,* vol. 61, pp. 224-236, June 2016.

[20] A. Karahoca, E. Bayraktar, E. Tatoglu and D. Karahoca, "Information system design for a hospital emergency department: A usability analysis of software prototypes," *Journal of Biomedical Informatics,* vol. 43, pp. 224-232, 2010.

[21] E. S. Berner and T. J. La Lande, "Overview of clinical decision support systems," in *Clinical Decision Support Systems: Theory and Practice*, E. S. Berner, Ed., Switzerland, Springer, 2016, pp. 1-17.

[22] E. H. Shortliffe and M. J. Sepulveda, "Clinical decision support in the era of artificial intelligence," *Journal of the American Medical Association,* vol. 320, no. 21, pp. 2199-2220, 2018.

[23] Committee on Key Challenge Areas for Convergence and Health, Board on Life Sciences, Division on Earth and Life Studies, National Research Council, Convergence: Facilitating Transdisciplinary Integration of Life Sciences, Physical Sciences, Engineering, and Beyond, Washington, DC: The National Academies Press, 2014.

[24] P. Nilsen, "Making sense of implementation theories, models and frameworks," *Implementation Science,* vol. 10, p. 53, April 2015.

[25] C. M. Johnson, T. R. Johnson and J. Zhang, "A user-centered framework for redesigning health care interfaces," *Journal of Biomedical Informatics,* vol. 38, no. 1, pp. 75-87, February 2005.

[26] J. Zhang and M. F. Walji, "TURF: Toward a unified framework of EHR usability," *Journal of Biomedical Informatics,* vol. 44, no. 6, pp. 1056-1067, December 2011.

[27] E. Vasilyeva, M. Pechenizkiy and S. Puuronen, "Towards the framework of adaptive user interfaces for eHealth," in *18th IEEE Symposium on Computer-Based Medical Systems (CBMS'05)*, Dublin, 2005.

[28] K. J. Vicente, "Ecological Interface Design: Progress and Challenges," *Human Factors,* vol. 44, no. 1, pp. 62-78, March 2002.

[29] S. Carpendale, "Evaluating Information Visualizations," in *Information Visualization - Lecture Notes in Computer Science*, vol. 4950, A. Kerren, J. T. Stasko, J. D. Fekete and C. North, Eds., Berlin, Springer, 2008.

[30] S. Faisal, A. Blandford and H. W. Potts, "Making sense of personal health information: challenges for information visualization," *Health Informatics Journal,* vol. 19, no. 3, pp. 198-217, September 2013.

[31] V. L. West, D. Borland and W. E. Hammond, "Innovative information visualization of electronic health record data: a systematic review," *Journal of the American Medical Informatics Association*, vol. 22, no. 2, pp. 330-339, March 2015.

[32] J. P. Wanderer, S. E. Nelson, J. M. Ehrenfeld, S. Monahan and S. Park, "Clinical Data Visualization: The Current State and Future Needs," *Journal of Medical Systems,* vol. 40, no. 12, p. 275, December 2016.

[33] B. Kamsu-Foguem, G. Tchuenté-Foguem and C. Foguem, "Using conceptual graphs for clinical guidelines representation and knowledge visualization," *Information Systems Frontiers,* vol. 16, no. 4, pp. 571-589, September 2014.

[34] A. Sopan, A. Song-le No, S. Karol, P. Rosenfeld, G. Lee and B. Shneiderman, "Community Health Map: A Geospatial and Multivariate Data Visualization Tool for Public Health Datasets," *Government Information Quarterly,* vol. 29, no. 2, pp. 223-234, April 2012.

[35] D. Gartner, R. Kolisch, D. B. Neill and R. Padman, "Machine Learning Approaches for Early DRG Classification and Resource Allocation," *INFORMS Journal on Computing,* vol. 27, no. 4, pp. 718-734, 2015.

[36] J. A. Doucette, G. Pinhey and R. Cohen, "Multiagent Resource Allocation for Dynamic Task Arrivals with Preemption," *ACM Transactions on Intelligent Systems and Technology,* vol. 8, no. 1, pp. 1-27, 2016.

[37] K. M. Mital, "Queuing Analysis for Outpatient and Inpatient Services: A Case Study," *Management Decision,* vol. 48, pp. 419-439, 2010.

[38] J. R. Broyles, J. K. Cochran and D. C. Montgomery, "A Markov decision process to dynamically match hospital inpatient staffing to demand," *IIE Transactions on Healthcare Systems Engineering,* vol. 1, no. 2, pp. 116-130, 2011.

[39] P. Williams, G. Tai and Y. Lei, "Simulation Based Analysis of Patient Arrival to Health Care Systems and Evaluation of an Operations Improvement Scheme," *Annals of Operations Research*, vol. 178, no. 1, pp. 263-279, July 2010.

[40] R. Axelrod, Structure of Decision, Princeton, NJ: Princeton University Press, 1976.

[41] B. Kosko, "Fuzzy Cognitive Maps," *International Journal of Man-Machine Studies*, vol. 24, pp. 65-75, 1986.

[42] D. J. Elliott, R. S. Young, J. Brice, R. Aguiar and P. Kolm, "Effect of Hospitalist Workload on the Quality and Efficiency of Care," *JAMA Internal Medicine,* vol. 174, no. 5, pp. 786-793, May 2014.

[43] T. H. Hoff, W. F. Whitcomb, K. Williams, J. R. Nelson and R. A. Cheesman, "Characteristics and Work Experiences of Hospitalists in the United States," *Archives of Internal Medicine,* vol. 161, no. 6, pp. 851-858, 2001.

[44] K. Hinami, C. T. Whelan, R. J. Wolosin, J. A. Miller and T. B. Wetterneck, "Worklife and Satisfaction of Hospitalists: Toward Flourishing Careers," *Journal of General Internal Medicine,* vol. 27, no. 1, pp. 28-36, January 2012.

[45] B. Chesluk, E. Bernabeo, S. Reddy, L. Lynn, B. Hess, T. Odhner and E. Holmboe, "How Hospitalists Work to Pull Healthcare Teams Together," *Journal of Health Organization and Management*, vol. 29, no. 7, pp. 933-947, 2015.

[46] T. H. Thrall, "Encouraging hospitalists to stick with you. Turnover rate cause for concern; workload big reason for leaving a job," *Hospital health & networks,* vol. 83, no. 3, p. 16, March 2009.

[47] S. Chandra, S. M. Wright, S. Ghazarian, G. M. Kargul and E. E. Howell, "Introducing the Hospitalist Morale Index: A new tool that may be relevant for improving provider retention," *Journal of Hospital Medicine*, vol. 11, no. 6, pp. 425-431, June 2016.

[48] L. Groat and D. Wang, "Ch. 2: Systems of inquiry and standards of research quality," in *Architectural Research Methods*, 2 ed., New York, Wiley, 2013, pp. 63-79.

[49] M. B. Miles and A. M. Huberman, "Ch. 2: Focusing and bounding the collection of data," in *Qualitative Data Analysis*, 2 ed., Thousand Oaks, CA: Sage Publications, 1994, pp. 16-26.

[50] J. W. Creswell, "Ch. 10: Mixed methods procedures," in *Research Design: Qualitative, Quantitative, and Mixed Methods Approaches*, 4 ed., Thousand Oaks, CA: Sage Publications, 2013, pp. 215-240.

[51] E. G. Guba, "Criteria for assessing the trustworthiness of naturalistic inquiries," *ECTJ*, vol. 29, p. 75, June 1981.

[52] E. G. Guba and Y. S. Lincoln, "Ch. 6: Competing paradigms in qualitative research," in *The Landscape of Qualitative Research: Theories and Issues*, N. K. Denzin and Y. S. Lincoln, Eds., Thousand Oaks, CA: Sage Publications, 1998, pp. 195-220.

[53] M. Crotty, "Ch. 1: Introduction," in *The Foundations of Social Research: Meaning and Perspective in the Research Process*, London, Sage Publications, 1998, pp. 1-17.

[54] E. G. Guba and Y. S. Lincoln, "Ch. 8: Paradigmatic controversies, contradictions, and emerging confluences," in *The Sage Handbook of Qualitative Research*, 3 ed., N. K. Denzin and Y. S. Lincoln, Eds., Thousand Oaks, CA: Sage Publications, 2005, pp. 191-215.

[55] V. K. Omachonu and N. G. Einspruch, "Innovation in healthcare delivery systems: A conceptual framework," *The Innovation Journal: The public sector innovation journal,* vol. 15, no. 1, p. Article 2, 2010.

[56] A. Elixhauser, B. Friedman and E. Stranges, "HCUP Statistical Brief #122," *Septicemia in U.S. Hospitals, 2009,* October 2011.

[57] V. Liu, G. J. Escobar, J. D. Greene, J. Soule, A. Whippy, D. C. Angus and T. J. Iwashyna, "Hospital deaths in patients with sepsis from 2 independent cohorts," *JAMA,* vol. 312, no. 1, pp. 90-92, 2014.

[58] M. Singer, C. S. Deutschman, C. W. Seymour, M. Shankar-Hari, D. Annane, M. Bauer, R. Bellomo, G. R. Bernard, J. D. Chiche, C. M. Coopersmith, R. S. Hotchkiss, M. M. Levy, J. C. Marshall, G. S. Martin, S. M. Opal, G. D. Rubenfeld, T. van der Poll, T. L. Vincent and D. C. Angus, "The Third International Consensus Definitions for Sepsis and Septic Shock (Sepsis-3)," *JAMA,* vol. 315, no. 8, pp. 801-810, 23 February 2016.

[59] P. Plesk and T. Greenhalgh, "Complexity Science: The Challenge of Complexity in Health Care," *BMJ,* vol. 323, pp. 625-628, 2001.

[60] T. Tenbensel, "Complexity in health and health systems," *Social Science & Medicine,* vol. 93, pp. 181-184, September 2013.

[61] W. E. Doll and D. Trueit, "Complexity and the Health Care Professions," *Journal of Evaluatin in Clinical Practice,* vol. 16, no. 4, pp. 841-848, August 2010.

[62] T. G. Kannampallil, G. F. Schauer, T. Cohen and V. L. Patel, "Considering Complexity in Healthcare Systems," *Journal of Biomedical Informatics,* vol. 44, no. 6, pp. 943-947, December 2011.

[63] L. Mamykina, R. S. Hum and D. R. Kaufman, "Investigating Shared Mental Models in Critical Care," in *Cognitive Informatics in Health and Biomedicine,* V. Patel, D. Kaufman and T. Cohen, Eds., London, Springer, 2014, pp. 291-315.

[64] G. R. Norman, L. R. Brooks, C. L. Colle and R. M. Hatala, "Clinical Reasoning: Experimental Study of an Instructional Intervention for Forward and Backward Reasoning," *Cognition and Instruction,* vol. 17, no. 4, pp. 433-448, 1999.

[65] B. Tyler and D. Gnyawali, "Managerial Collective Cognitions: An Examination of Similarities and Differences of Cultural Organizations," *Journal of Management Studies,* vol. 46, pp. 93-126, 2009.

[66] A. S. Elstein, L. S. Shulman and S. A. Sprafka, Medical Problem Solving: An Analysis of Clinical Reasoning, Cambridge, MA: Harvard University Press, 1978.

[67] H. G. Schmidt and H. P. Boshuizen, "On Acquiring Expertise in Medicine," *Educational Psychology Review,* vol. 5, no. 3, pp. 205-221, September 1993.

[68] L. Garamszegi, "Comparing Effect Sizes Across Variables: Generalization Without the Need for Bonferroni Correction," *Behavioral Ecology,* vol. 17, pp. 682-687, 2006.

[69] S. Nakagawa, "A Farewell to Bonferroni: The Problems of Low Statistical Power and Publication Bias," *Behavioral Ecology,* vol. 15, pp. 1044-1045, 2004.

[70] P. Croskerry, "Achieving Quality in Clinical Decision Making: Cognitive Strategies and Detection Bias," *Academic Emergency Medicine,* vol. 9, no. 11, pp. 1184-1204, November 2002.

[71] A. S. Elstein and A. Schwarz, "Clinical Problem Solving and Diagnostic Decision Making: Selective Review of the Cognitive Literature," *British Medical Journal,* vol. 324, no. 7339, pp. 729-732, March 2002.

[72] D. W. Bates, G. J. Kuperman, S. Wang, T. Gandhi, A. Kittler, L. Volk, C. Spurr, R. Khorasani, M. Tanasijevic and B. Middleton, "Ten commandments for effective clinical decision support: making the practice of evidence-based medicine a reality," *JAMIA,* vol. 10, no. 6, pp. 523-530, 2003.

[73] D. Albert, "Decision Therory in Medicine: A Review and Critique," *The Milbank Memorial Fund Quarterly, Health and Society,* vol. 56, pp. 362-401, 1978.

[74] M. Volkamer and K. Renaud, "Mental Models - General Introduction and Review of their Application to Human-Centred Security," in *Number Theory and Cryptography, Lecture Notes in Computer Science*, vol. 8260, M. Fischlin and S. Katzenbeisser, Eds., Berlin, Heidelberg, Springer, 2013, pp. 255-280.

[75] J. R. Wilson and A. Rutherford, "Mental Models: Theory and Application in Human Factors," *Human Factors,* vol. 31, pp. 617-634, 1989.

[76] H. Nemati, D. Steiger, L. Iyer and R. Herschel, "Knowledge warehouse: An architectural integration of knowledge management, decision support, artificial intelligence and data warehousing," *Decision Support Systems,* vol. 33, pp. 143-161, 2002.

[77] M. J. Kolkman, M. Kok and A. van der Veen, "Mental model mapping as a new tool to analyse the use of information in decision-making in integrated water management," *Physics and Chemistry of the Earth, Parts A/B/C,* vol. 30, no. 4-5, pp. 317-332, 2005.

[78] J. H. Larkin and H. A. Simon, "Why a Diagram is (Sometimes) Worth Ten Thousand Words," *Cognitive Science,* vol. 11, no. 1, pp. 65-100, 1987.

[79] M. B. Buntin, M. F. Burke, M. C. Hoaglin and D. Blumenthal, "The benefits of health information technology: a review of the recent literature shows predominantly positive results," *Health Affairs (Project Hope),* vol. 30, no. 3, pp. 464-471, March 2011.

[80] E. Bernal-Delgado, S. García-Armesto and S. Peiró, "Atlas of variations in medical practice in Spain: the Spanish National Health Service under scrutiny," *Health Policy,* vol. 114, no. 1, pp. 15-30, 2014.

[81] J.-G. Park and J. Lee, "Knowledge sharing in information systems development projects: Explicating the role of dependence and trust," *International Journal of Project Management,* vol. 32, no. 1, pp. 153-165, 2014.

[82] A. J. Mills, G. Durepos and E. Wiebe, Eds., Encyclopedia of case study research, Thousand Oaks, CA: Sage Publications, 2010.

[83] M. Vaismoradi, H. Turunen and T. Bondas, "Content analysis and thematic analysis: Implications for conducting a qualitative descriptive study," *Nursing & Health Sciences,* vol. 15, no. 3, pp. 398-405, 2013.

[84] V. Braun and V. Clarke, "Using thematic analysis in psychology," *Qualitative Research in Psychology,* vol. 3, no. 2, pp. 77-101, 2006.

[85] C. Baird, "Useful, Usable, Desirable: Applying User Experience Design to Your Library," *Journal of Electronic Resources Librarianship,* vol. 27, no. 2, pp. 142-143, 2015.

[86] P. Kotler, Marketing Management: Analysis, Planning, Implementation, and Control, 6 ed., Prentice-Hall International, 1988, p. 776.

[87] D. Fishbein, S. Nambiar, K. McKenzie, M. Mayorga, K. Miller, K. Tran, S. Laura, J. Agor, T. Kim and M. Capan, "Objective Measures of Workload in Healthcare: A Narrative Review," *International Journal of Health Care Quality Assurance,* In-press.

[88] V. R. Rao, Applied Conjoint Analysis, Berlin: Springer-Verlag, 2014.

[89] J. J. Louviere, T. N. Flynn and R. T. Carson, "Discrete Choice Experiments Are Not Conjoint Analysis," *Journal of Choice Modelling,* vol. 3, no. 3, pp. 57-72, 2010.

[90] D. H. Krantz and A. Tversky, "Conjoint-measurement analysis of composition rules in psychology," *Psychological Review,* vol. 78, no. 2, pp. 151-169, 1971.

[91] J. F. Bridges, A. F. Mohamed, H. W. Finnern, A. Woehl and A. B. Hauber, "Patients' preferences for treatment outcomes for advanced non-small cell lung cancer: a conjoint analysis," *Lung Cancer,* vol. 77, no. 1, pp. 224-231, July 2012.

[92] J. P. Oudhoff, D. R. Timmermans, D. L. Knol, A. B. Bijnen and G. Van der Wal, "Prioritising patients on surgical waiting lists: a conjoint analysis study on the priority judgements of patients, surgeons, occupational physicians, and general practitioners," *Social Science Medicine,* vol. 64, no. 9, pp. 1863-1875, 2007.

[93] N. Stebler, G. Schuepbach-Regula, P. Braam and L. C. Falzon, "Weighting of Criteria for Disease Prioritization Using Conjoint Analysis and Based on Health Professional and Student Opinion," *PLoS One,* vol. 11, no. 3, 2016.

[94] A. Scott, "Eliciting GPs' preferences for pecuniary and non-pecuniary job characteristics," *Journal of health economics,* vol. 20, no. 3, pp. 329-347, 2001.

[95] A. Luximon and R. S. Goonetilleke, "Simplified subjective workload assessment technique," *Ergonomics,* vol. 44, no. 3, pp. 229-243, February 2001.

[96] S. G. Hart, "Nasa-Task Load Index (NASA-TLX); 20 Years Later," *Proceedings of the Human Factors and Ergonomics Society Annual Meeting,* vol. 50, no. 9, pp. 904-908, October 2006.

[97] T. E. Nygren, "A Conjoint Analysis of Five Factors Influencing Heavy Vehicle Drivers Perceptions of Workload," *Proceedings of the Human Factors and Ergonomics Society Annual Meeting,* vol. 39, no. 17, pp. 1102-1106, October 1995.

[98] J. H. Park, "Health Care Design: Current and Potential Research and Development," *Design Issues,* vol. 31, no. 1, pp. 63-72, January 2015.

[99] R. Razzouk and V. Shute, "What is design thinking and why is it important?," *Review of Educationa Research,* vol. 82, no. 3, pp. 330-348, 2012.

[100] A. Wright and D. F. Sittig, "A framework and model for evaluating clinical decision support architectures," *Journal of Biomedical Informatics,* vol. 41, no. 6, pp. 982-990, December 2008.

[101] J. G. Schwartz, U. N. Kumar, D. E. Azagury, T. J. Brinton and P. G. Yock, "Needs-Based Innovation in Cardiovascular Medicine," *JACC: Basic to Translational Science,* vol. 1, no. 6, pp. 541-547, October 2016.

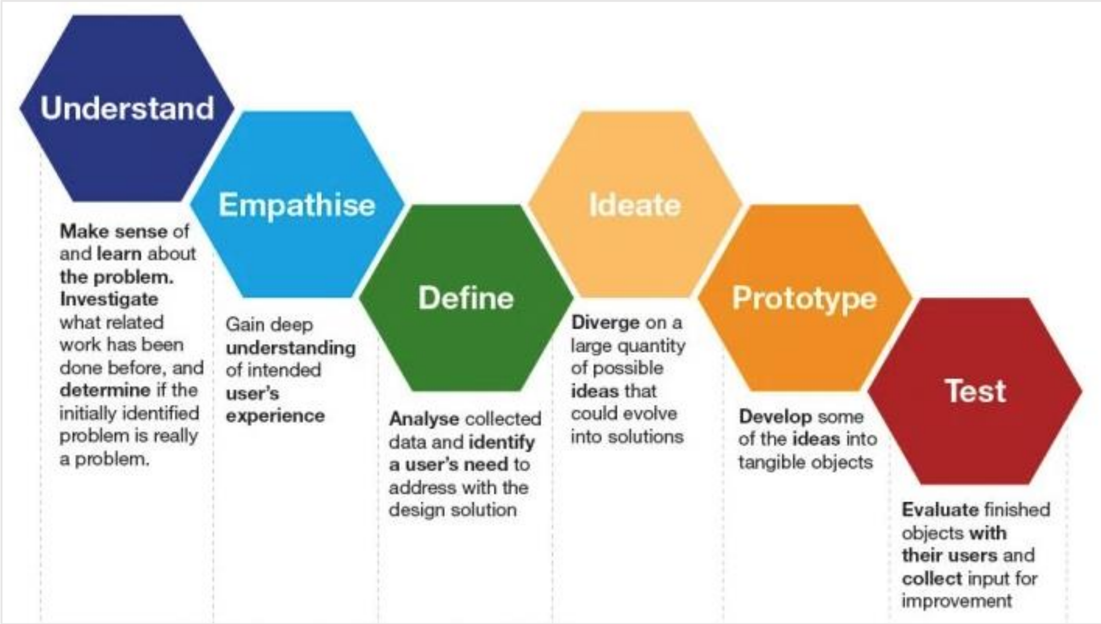
[102] S. Zenios, J. Makower, P. Yock, T. J. Brinton, U. N. Kumar, L. Denend and T. M. Krummel, Biodesign: The Process of Innovating Medical Technologies, Cambridge: Cambridge University Press, 2009.

[103] S. Liu and S. Joines, "Developing a Framework of Guiding Interface Design for Older Adults," *Proceedings of the Human Factors and Ergonomics Society Annual Meeting,* vol. 56, no. 1, pp. 1967-1971, 2012.

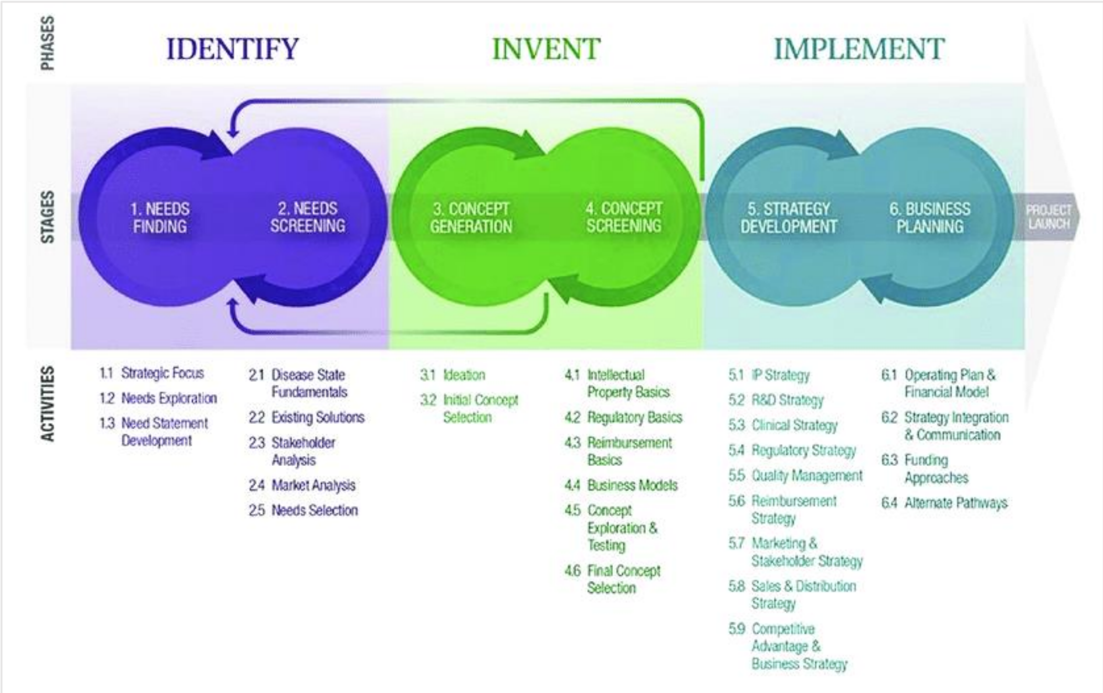
APPENDICES

Appendix A: Example Process Design Frameworks

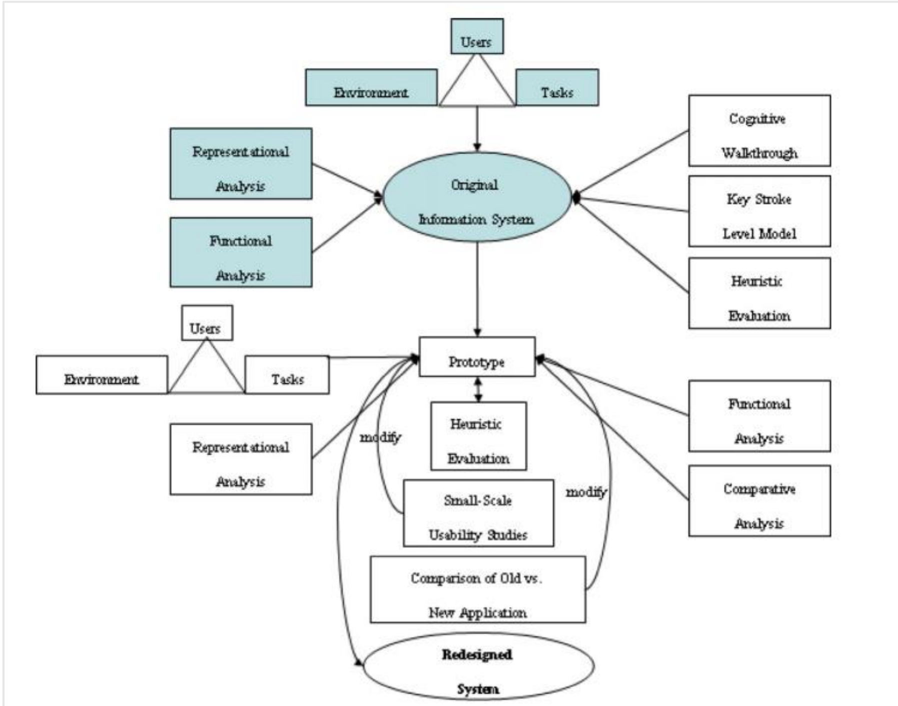
Generic design thinking process for innovation [99]



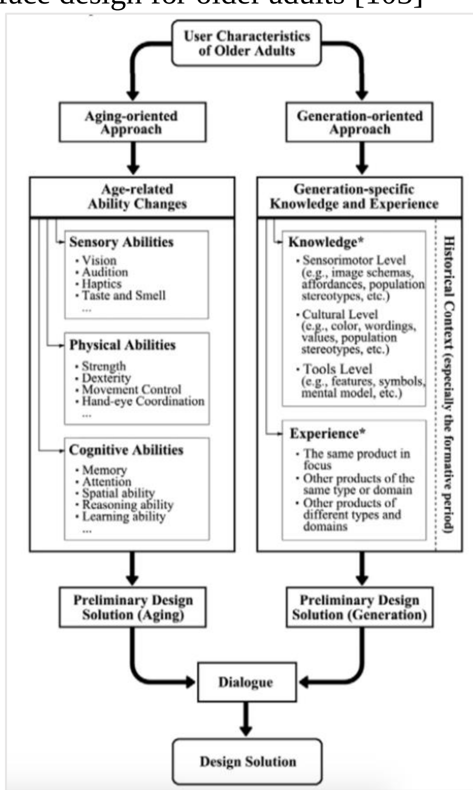
The Stanford Biodesign Process [101] [102]



A user-centered framework for redesigning healthcare interfaces [25]



A framework of guiding interface design for older adults [103]



Appendix B: Semi-structured interview questions

1. What is your job title, and how long have you been working in this role?
2. What are the duties of your job? How would you describe your role in the hospital system?
3. What decision(s) do you help make? Who makes the final decision(s)?
4. What tool(s) do you use to help inform these decisions?
5. Who else in the hospital, if anyone, uses the information provided by the tool(s)?
6. If possible, please show me the tool(s).
7. Please describe the elements of the tool(s). What information does it provide? Where is this information located? How often is this information updated?
8. Please walk me through how you use the tool(s) in your daily work, so I can see your process. Feel free to verbalize your usual thought process as you do this.
9. What pieces of information do you rely on most when using the tool(s)?
10. What are the strengths and weaknesses of the tool(s)?
11. On a scale of 1 to 5, where 1 is "not at all" and 5 is "extremely", how useful would you say your tool is in doing your job?
12. On a scale of 1 to 5, where 1 is "not at all" and 5 is "extremely", how useable would you say your tool is in doing your job?
13. On a scale of 1 to 5, where 1 is "not at all" and 5 is "extremely", how desirable would you say your tool is in doing your job?
14. If you could make changes to the tool(s), what would they be?
15. Is there anything else you'd like to tell me about the tool(s), your process, or your experiences that we haven't already discussed?

Appendix C: Study design template for evaluation of a future framework

Study Title: Evaluation of a proposed framework for designing hospital applications: getting expert and user feedback

Objective: This study aims to get feedback from relevant stakeholders regarding two items: a proposed framework for guiding healthcare application design and an example (sample tool/interface) created using the proposed framework.

Participant Sample: In order to be included in this study, participants must be either (a) subject matter experts in disciplines related to the proposed framework (e.g. cognitive science, human factors, systems engineering, or design) or (b) potential users of the sample tool/interface created using the proposed framework (e.g. patient allocation decision-makers at hospitals). Potential participants will be identified using snowball sampling (starting with initial contacts at various hospitals).

Data Collection: Online surveys will be used to obtain feedback (from subject matter experts and potential application users) about both (a) the proposed framework and (b) the sample tool created using the framework. Survey questions are presented below. Surveys will be conducted using Qualtrics. No identifying information will be collected.

Analysis and Reporting: Data will be reported in aggregate, in order to understand the overall validity of the proposed framework and the example (sample interface/tool) solution. Trends in feedback will be reported, if they are noticed. Direct quotes that are particularly compelling may also be reported, but these will not include any identifying information.

Survey Questions: The survey will present each participant with some subset of the questions below, based on participant characteristics (e.g. some questions may not be asked if they do not apply to a particular participant). Although the survey is still in final stages of refinement, I have provided a list of all potential questions that may be asked of any given participant below. In the final version of the survey: (1) the diagrams will be updated to reflect the most current versions of my framework and the associated sample interface, and (2) the questions below may be presented (or not) in combined or reworded (while retaining meaning) structures. All questions are open-ended (participants will type free-text answers) unless otherwise specified.

1. **Identify your domain(s) of expertise.**
    a. What is your primary domain of expertise? (multiple choice)
    b. If applicable, what is your secondary domain of expertise? (multiple choice)

2. **Describe your educational background.**
    a. What is your highest level of education?
    b. What degrees/certifications do you hold? (e.g. Bachelor’s degree in English)
    c. How would you describe your domain(s) of focus/expertise?
    d. Have you had any medical training or other training related specifically to the field of healthcare? If so, please describe.

e. Is there anything else you want to share about your educational background that might be helpful in understanding your unique perspective in this online survey?
f. Describe your professional experience.
g. What is your current job title?

3. Identify your institution type.

a. Which of the following best describes your institution? (Multiple choice: educational institution, healthcare institution, both (with option to explain), other (with option to explain))
b. What positions have you held that relate to your domain(s) of expertise? Please list titles and provide a brief description, if possible.
c. Is there anything else you want to share about your professional background that might be helpful in understanding your unique perspective in this online survey?

4. Describe any prior experiences you have had with application design/development.

a. Have you ever been involved in the development/design of a software application (e.g. computer programs, decision support tools, interactive displays, data visualizations, user interfaces) in any way? (NOTE: "Involvement" could be as minimal as simply answering questions from a professional software developer.)
    i. If yes, Please provide a brief description (4-8 sentences) of each software application project you have been involved in designing/developing, and explain your specific contribution(s). (Some questions to consider: What was the goal of the application? What were the stages/phases of the design/development process? What was your involvement? Did you get to see the finished product? What were the strengths and weaknesses of the application, in your opinion? How could the application design/development process have been improved?)
    ii. If yes, to the best of your knowledge, who else (please list job titles NOT names) was involved in the design/development of this application? If possible, provide a short (one sentence) description of each person's primary role in the design/development process.

5. Describe your involvement (if any) in the "inpatient allocation" process.

a. Have you ever been involved (in any capacity) in decisions dealing with "inpatient allocation among doctors"? If so, please describe your involvement. (Some questions to consider: What was your role? What were your objectives? Who else did you interact with? How was a new inpatient "assigned" to a particular doctor (or team of doctors) for care?)
b. Would you classify yourself as an "inpatient allocation decision-maker"?

6. EVALUATION OF THE PROPOSED FRAMEWORK

The image shown represents a proposed framework for the integration of knowledge and techniques from multiple disciplines into a single process for the design/development of healthcare applications. Please refer to this image for all questions in this section. (NOTE: An image of the framework will be provided.)

1. Please describe what you think the diagram is showing to you.
2. Who do you think are the potential users of this framework?
3. On a scale of 1 (least) to 5 (most), how likely do you think this framework is to be used by the potential users?
4. What are the barriers to use?
5. Please evaluate the portions of the framework that pertain to your domain(s) of expertise.
6. Do you think the framework includes all the important considerations necessary from your domain? If not, what's missing?
7. What portions of the framework outside your domain(s) resonate most with you? What do you think is most important from the other fields?
8. What opportunities for improvement do you see in this framework?

7. EVALUATION OF AN EXAMPLE INTERFACE

The image shown represents an example of an interface (to be displayed on an interactive screen) that hospital employees could use to support "inpatient allocation decisions." The interface was designed according to the framework presented in the previous question. The image shows a current interface. Please refer to this image for all questions in this section. (NOTE: An image of the interface will be provided.)

1. Please describe your initial thoughts:
    a. Please describe what you see in the example interface.
    b. Do you already use (or are you familiar with) another interface (or other tool like a worksheet) when making inpatient allocation decisions? If so, please describe this tool (What information does it show? How do you interact with it? Who else uses the interface, besides you?
    c. How does the example interface above compare to other interfaces you've seen before?

2. Given the following scenario, please answer the remaining survey questions, using the interface when needed. [NOTE FOR IRB: A description of a possible patient scenario will be inserted here and related to specific content of the final interface image. All information in the description will be completely artificial and will not refer to any private or HIPAA-protected patient information.]
    a. Describe in words what your thought process might be in order to reach a final decision in this scenario. To be clear, you need to determine which doctor will get the new patient.
    b. If you had to make this decision in a real setting, would there have been other steps (e.g. making phone calls, sending emails, checking patient records) in your process?
    c. What information was most important to you in your decision?

d. What information was the least important to you in your decision? Could you have made the decision in absence of this information?

e. Which statement is closest to your opinion of the interface? (Multiple choice answers: This is better than what I've used/seen before, this is relatively equivalent to what I've used/seen before, this is worse than what I've used/seen before, not applicable (I have no prior experience using/seeing patient allocation support tools))

f. How satisfied would you say you were with this interface? (Multiple choice answers: Very satisfied, satisfied, neutral, dissatisfied, very dissatisfied)

g. On a scale of 1 (not likely at all) to 5 (extremely likely), how likely would you be to adopt this interface for consistent use? Please explain.\

8. User-centered design questions:

1. Usability: On a scale of 1 (least) to 5 (most), how usable is the tool?
2. Usefulness: On a scale of 1 (least) to 5 (most), how useful is the tool?
3. Desirability: On a scale of 1 (least) to 5 (most), how desirable is the tool?

9. Questionnaire questions: [NOTE FOR IRB: Questions from the following three previously-published questionnaires will be selected, tailored to reflect our example interface (i.e. meaning will not be changed, but topic wording will be adjusted) , and presented to participants in the online surveys. The published questionnaires from which all questions will be drawn are provided below. When applicable, participants maybe asked to "explain your answer" for these questions.]

- **Technology Interaction questionnaire** (Source: Franke, T., Attig, C., & Wessel, D. (2018). A Personal Resource for Technology Interaction: Development and Validation of the Affinity for Technology Interaction (ATI) Scale. International Journal of Human–Computer Interaction. DOI: 10.1080/10447318.2018.1456150)
- **NASA RTLX Workload questionnaire** (Source: Hart, S. G. (2006). Nasa-Task Load Index (NASA-TLX); 20 Years Later. Proceedings of the Human Factors and Ergonomics Society Annual Meeting, 50(9), 904–908. https://doi.org/10.1177/154193120605000909)
- **Technology acceptance questionnaire** (Sources: Davis, F. (1989). Perceived Usefulness, Perceived Ease of Use, and User Acceptance of Information Technology. MIS Quarterly, 13(3), 319-340. doi:10.2307/249008; Liu, Siwen (2013). Effects of Early Experiences with Interaction Style on Usability and Acceptance of New Technologies by Older Adults: A Generation-Oriented Approach. Dissertation under the direction of Dr. Sharon M. B. Joines.)