Modeling Clinicians’ Cognitive and Collaborative Work in Post-Operative Hospital Care

by

Stephanie Kohli Furniss

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Graduate Supervisory Committee:

David R. Kaufman, Chair
William G. Johnson
M. Adela Grando

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ABSTRACT

Clinicians confront formidable challenges with information management and coordination activities. When not properly integrated into clinical workflow, technologies can further burden clinicians' cognitive resources, which is associated with medical errors and risks to patient safety. An understanding of workflow is necessary to redesign information technologies (IT) that better support clinical processes. This is particularly important in surgical care, which is among the most clinical and resource intensive settings in healthcare, and is associated with a high rate of adverse events. There are a growing number of tools to study workflow; however, few produce the kinds of in-depth analyses needed to understand health IT-mediated workflow. The goals of this research are to: (1) investigate and model workflow and communication processes across technologies and care team members in post-operative hospital care; (2) introduce a mixed-method framework, and (3) demonstrate the framework by examining two health IT-mediated tasks. This research draws on distributed cognition and cognitive engineering theories to develop a micro-analytic strategy in which workflow is broken down into constituent people, artifacts, information, and the interactions between them. It models the interactions that enable information flow across people and artifacts, and identifies dependencies between them. This research found that clinicians manage information in particular ways to facilitate planned and emergent decision-making and coordination processes. Barriers to information flow include frequent information transfers, clinical reasoning absent in documents, conflicting and redundant data across documents and applications, and that clinicians are burdened as information managers.

This research also shows there is enormous variation in how clinicians interact with electronic health records (EHRs) to complete routine tasks. Variation is best evidenced by patterns that occur for only one patient case and patterns that contain repeated events. Variation is associated with the users' experience (EHR and clinical), patient case complexity, and a lack of cognitive support provided by the system to help the user find and synthesize information. The methodology is used to assess how health IT can be improved to better support clinicians' information management and coordination processes (e.g., context-sensitive design), and to inform how resources can best be allocated for clinician observation and training.

DEDICATION

Mum and Dad, you have made many sacrifices to provide me with incredible opportunities for learning and growth. I am forever grateful for your continuous support and encouragement.

These last few years have been the most challenging of my life to date, but also the most joyful. Vanessa, thank you for helping me to find Joy and Peace. God works through you.

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ABBREVIATIONS

CE	Cognitive Engineering
CPOE	Computerized (or Computer-assisted) Provider Order Entry
CRS Rochester	Colon and Rectal Surgery Department at Mayo Clinic in Rochester, MN. The study site for this dissertation work.
DCog	Distributed Cognition Theory
DiCoT	Distributed Cognition for Teamwork method
DiCoT-CL	DiCoT Concentric Layers framework
DRM	Distributed Resources Model
EHR	Electronic Health Record
EMR	Electronic Medical Record
GNP	Gross National Product
H1	Hospitalist participant 1 (others include H2, H3, and H4)
HCI	Human-Computer Interaction
Health IT (or HIT)	Health Information Technology
IOM	Institute of Medicine
ISO	The International Organization for Standardization
MAR	Medication Administration Record
NP	Nurse Practitioner
PA	Physician Assistant
R1	Resident Physician participant 1 (others include R2)
WEM	Workflow Elements Model
WfMC	Workflow Management Coalition

Chapter I

INTRODUCTION

Motivation & Problem Statement

Clinical workflow constitutes a series of tasks performed by the organization of workers supported by processes and tools, for the benefit of the patient. Execution of clinical tasks necessitates collaboration in a complex system where work is knowledge-intensive and organized across many individuals from a range of disciplines who are responsible for different aspects of patient care. Clinicians are challenged with sharing information across members of patients' care teams, managing that information, and performing a series of tasks (e.g., identifying medical problems, entering orders, documenting a daily progress note) for the patients under their care. This can lead to errors and delays in care that risk patient safety. Effective care delivery depends on clinicians' ability to access, recall, and make decisions about their patients' care, and retrieve and share information with other clinicians in a timely manner. Technologies and processes need to support access to and management of relevant patient information, as well as facilitate information sharing to support clinicians' individual and team-based work.

There are over 50 million procedures performed in the United States annually that lead to inpatient hospital stays (CDC/NCHS, 2010). Surgical care is among the most clinical- and resource-intensive settings in health care with multiple care transitions, collaborating specialists, and often involving high acuity patients. Surgical adverse events are second only to adverse drug events (Classen et al., 2011). Surgical adverse events can be reduced through preventative action and timely identification and resolution of post-operative complications. Each of these heavily relies on clinicians' ability to monitor and manage the patients under their care. In addition, post-operative hospital care relies on clinicians from different disciplines to coordinate with each other and use a number of tools over time. Technologies and processes supporting improved information management and coordination processes have potential to yield significant quality and safety enhancements.

Health information technologies (health IT), such as electronic healthcare records (EHRs), are expected to bring significant advancements to healthcare delivery through improved management and availability of patient information. Thus far, there have been mixed results from health IT implementation and use. Problems include EHRs not integrating smoothly into clinical work processes and contributing to unintended consequences, such as decreased efficiency (Horsky, Kuperman, & Patel, 2005) and inadequate support of team-based care (Ash, Berg, & Coiera, 2004), some resulting in adverse events (Koppel et al., 2005) that compromise patient safety and quality of care. Issues with EHRs and health IT contribute to the broader problems in the health care system of high costs, poor safety, and suboptimal outcomes. The productive use of health IT is partly dependent on the degree to which it can provide cognitive support for tasks that comprise clinical workflow. Clinicians' current processes for completing routine clinical tasks, such as information gathering and documentation, involve use of many information sources. Additionally, processes for other associated tasks, such as decision-making and order entry, are too often disconnected due to problems with design and component functionalities. EHR design and use may burden clinicians with cognitive overload. Cognitive load reflects the demands on user's working memory, and is a function of task complexity, user's skill level, and system usability (Kaufman, Kannampallil, & Patel, 2015). A clinician experiencing cognitive overload is more likely to make medical errors and may even endanger patients (Horsky et al., 2005). To address the myriad of challenges to clinical work, health IT needs to address the layers of cognitive, dynamic, interruptive, and collaborative elements of clinical workflow (Hazlehurst, McMullen, Gorman, & Sittig, 2003; Wears & Berg, 2005), which are revealed in the actions, interactions, relationships and dependencies between clinicians and other components of the work system (e.g., patient, information, tools, other clinicians, etc.). A thorough understanding of information management and coordination processes is necessary to redesign health IT systems, processes and policies, toward improved care delivery and enhanced patient safety.

Objective & Aims

The objective of this research is to present a methodological framework that characterizes and evaluates clinical workflow and draws implications for improvements. Cognitive science theories and frameworks are applied to examine how clinicians use information tools to manage and monitor patients, and how information flows in the system of workers and artifacts to support clinicians' decision-making and problem-solving. In particular, the methodology is grounded in two theoretical frameworks, Distributed Cognition (DCog) and Cognitive Engineering (CE). DCog describes how a work system and its components are organized, with a focus on how those components interact in moments and over time, while CE evaluates how users (i.e., clinicians) interact with technologies.

The methodology was applied to a single site, inpatient post-operative hospital care at Mayo Clinic's Colon and Rectal Surgery (CRS) Department in Rochester, Minnesota (CRS Rochester). Post-operative hospital care requires multiple clinicians to coordinate and monitor patient recovery.

To evaluate clinical workflow at CRS Rochester, I collected six kinds of data: interviews, observations, video recordings, participants' think-aloud verbalizations, images of artifacts, and EHR-generated event log files. These data were used to characterize and evaluate: (1) the mechanisms clinicians used to coordinate patient care; (2) how clinicians managed information, as described in two DCog case studies; and (3) the effort required by clinicians to complete health IT-based tasks, as described in two CE task analyses. I specifically focused on two health IT-based tasks, pre-rounds information gathering (InfoGather) and daily progress note documentation (ProgressNote), which are ubiquitous in CRS Rochester clinical workflow and in all in-patient hospital care. Reviewing and gathering patient information, such is the focus of InfoGather, is important for clinicians to understand patient status and care history, helping them actively participate in patient care and make decisions that are then documented in a daily progress note. Additionally, as each patient in a hospital has to have a daily progress note documented in all in-patient clinical settings, understanding how clinicians perform this task is important to developing patient-care solutions nationwide.

The methodology presented here integrates a theoretically robust approach and multifaceted analytic testing that will be an asset to data scientists working in clinical environments. The methodology is also highly transferable and can be applied to characterize and evaluate clinicians' efficiency in a variety of clinical work settings, including perioperative environments and hospital care settings, among others.

The research unfolds over three aims: (1) to investigate and model workflow and communication processes across technologies and care team members in post-operative hospital care; (2) to introduce a mixed-method methodological framework for studying clinical workflow; and (3) to demonstrate the methodological framework with two health IT-mediated tasks (InfoGather and ProgressNote). The long-term objective is to inform future health IT design that facilitates clinicians in managing information and workload for patient care delivery.

The relationship between the theoretical frameworks, the methodological framework, the results (i.e., analyses demonstrated) and conclusions presented in this dissertation document are best understood using Figure 1. The organization of dissertation content varies slightly from the gray boxes in Figure 1; therefore, chapter delineations are marked on the left-hand side of the figure.

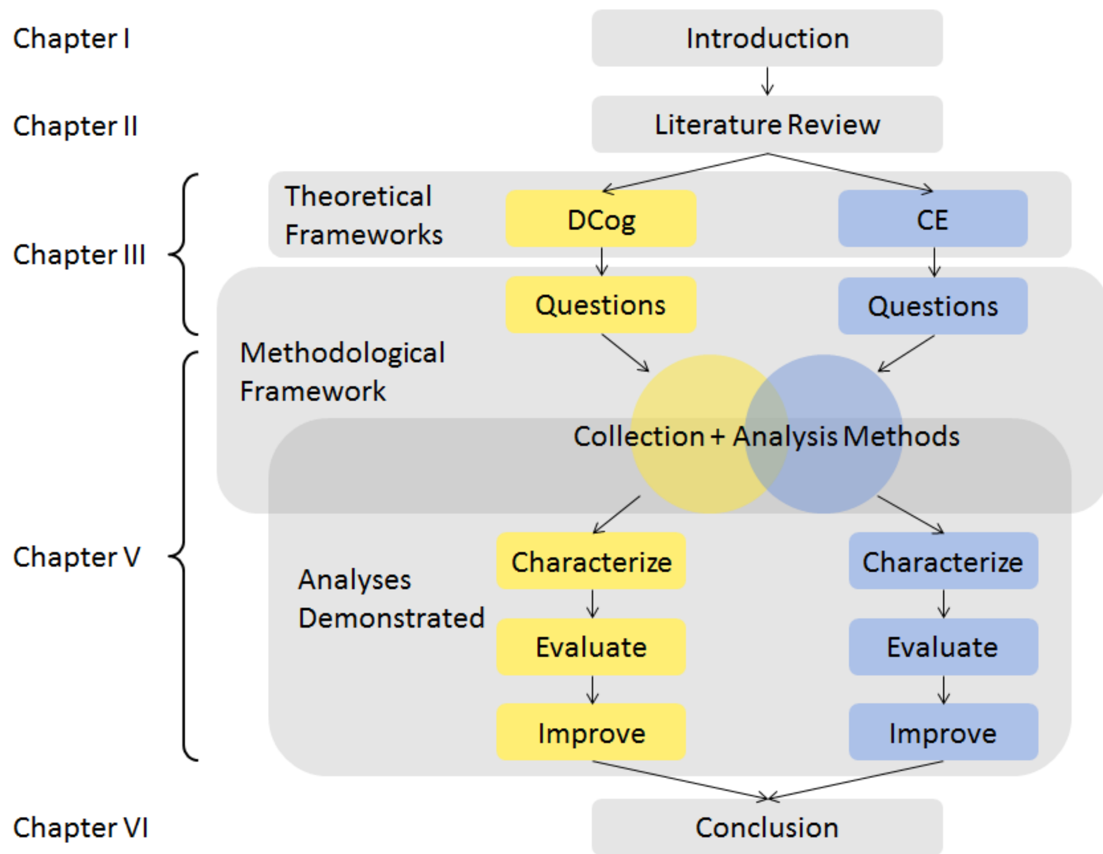


Figure 1. Relationship between the theoretical frameworks, the methodological framework, the results (analyses demonstrated) and conclusions, along with chapter delineations.

Overview of Chapters

Chapter II presents literature reviews on clinical workflow research to include a historical perspective, motivations, and challenges. First, this chapter summarizes three methodological challenges to studying clinical workflow: (1) analytic approaches to workflow studies are not standardized; (2) it is difficult to generalize findings made through workflow studies; and (3) it is difficult to examine multidimensional workflow settings. Second, Chapter II summarizes three key challenges that impede clinicians as they attempt to efficiently complete workflow processes: (1) interface design and system usability; (2) information management processes; and (3) communication and coordination. Together these six challenges served as a springboard for this dissertation.

Chapter III describes the theoretical and methodological frameworks that this research is grounded in: Distributed Cognition theory (DCog) and Cognitive Engineering (CE). It also presents a summary table of the theoretical goals, assumptions, methods and guiding questions that structure the methodological framework presented in Chapter V.

Chapter IV presents the study site and describes its components—participants, tools, tasks, etc. This was separated from the remaining methods to emphasize that the methodological framework can be applied to workflow in any clinical environment.

The methodological framework is presented in Chapter V. First, the data collection methods are explained. Subsequently, the data analysis methods are described and demonstrated using data from the study site. The DCog and CE analyses are discussed separately. The methodological framework is used to characterize and evaluate: (1) the mechanisms clinicians used to coordinate patient care; (2) how clinicians managed information; and (3) the effort required by clinicians to complete health IT-based tasks.

Chapter VI concludes the dissertation. It reviews the strengths of the methodological framework developed and presented in this project. Given the formative nature of this method, this chapter also reviews the work's limitations and its potential to contribute to future studies that aim to improve clinical workflow research.

The methodological framework presented in Chapter V was developed iteratively from review of literature, data collection and analysis. Some of the analysis techniques were developed for and published in two conference papers, which are presented in

Appendices B and C. There is some overlap in content between this dissertation and the publications, but in each case the dissertation presents greater analysis.

Chapter II

REVIEW OF LITERATURE ON CLINICAL WORKFLOW

Introduction & Objective

This chapter provides an overview of workflow research, particularly focused on clinical workflow to include motivation, approaches and challenges to studying clinical workflow, and issues with existing health IT (information technologies). The objective is to convey the breadth of workflow research. To do this, this chapter answers the following questions while highlighting key concepts and papers. The informatics and cognition literature are particularly important. Peer-reviewed journal articles and conference proceedings are relied on most heavily. Because there are significant measures in the United States to improve healthcare safety while lowering costs, committee and agency reports are also referenced.

Questions guiding this chapter:

- What is workflow?
- Why study clinical workflow?
- What approaches are there to studying clinical workflow?
- What are the challenges to studying clinical workflow?
- Based on these challenges, how can clinical workflow research be improved? And what efforts have been made to date on these?
- What are the gaps in our understanding of clinical workflow?
- What are the challenges specifically to health IT-mediated clinical workflow?

- How do these challenges inform needed improvements or approaches to clinical workflow analysis?

Workflow Defined

Workflow research has roots in the industrial engineering discipline, in particular studies related to work processes and patterns. A systematic literature review of peer-reviewed articles published between 1995 through 2007 in an array of disciplines concluded that there is no standard definition of workflow across or within disciplines (Unertl, Novak, Johnson, & Lorenzi, 2010). Though *workflow* lacks a standard definition, there are common attributes that are useful to characterize workflow in most studies: context, temporal factors, aggregate factors (the relationship and interaction among tasks and actors, for example, coordination mechanisms), actors, artifacts, characteristics, actions and outcomes (Unertl et al., 2010). The common attributes describe a system of workers using tools in a given setting and time period to perform processes, to achieve a goal.

Workflow also is a representation of "real work". A report from the International Organization for Standardization (ISO) elaborates on this:

> *"It is a depiction of [related] operations, declared as work of a person, a group of persons, an organization of staff, or one or more simple or complex mechanisms. Workflow may be seen as any abstraction of real work. For control purposes, workflow may be a view on real work under a chosen aspect, thus serving as a virtual representation of actual work." ISO 12052:2006, ISO/TR 16044:2004*

Therefore, *workflow* is a representation of how the work actually gets done rather than the ideal process. Visualization of all the workflows in a setting enables evaluation and improvement of the workflows. In some work, such as clinical work, there is more than one way to complete a task and achieve a goal. Variation can be challenging to capture, quantify and assess in human-technology work. However, workflow evaluation and improvement requires understanding variability in workflows that occur in real work settings.

Motivations for Studying Clinical Workflow

Clinical workflow research is integral to quality improvement (i.e., improving safety and efficiency while controlling costs), health care and system redesign, and technology implementation and integration. The importance of these motivations can be attributed to social, political and economic factors. This section lays out a historical review of these motivations and influencing factors.

The period 1988 to early-1990's is defined by the application of quality improvement concept in health care (Sahney, 1993). Around this time, Leffel and Bumenthal (1989) called for health care organizations to adopt modern industrial quality science theoretical and methodological approaches to improve quality of care (Laffel & Blumenthal, 1989). The increased focus on quality improvement initiatives through the 1980s and 90s was noticeable. For example, the Institute of Medicine (IOM) initiated a series of workshops in the early-1990s to explore specific aspects of healthcare reform, such as measuring and assuring quality of care. To this day, health care organizations take on continuous quality improvement for a variety of reasons, including accreditation requirements, cost control, competitive advantage (e.g., competition for customers), pressure from employers and payers, and true process improvement (Linder, 1991).

The health care industry’s focus on cost control may have first become pertinent in the 1960s. The creation of Medicare and Medicaid programs in 1965 along with advancements in medicine, led to increased utilization of health care services. Increased utilization is evident in the rise of gross national product (GNP) spent on health care services. The total National health expenditures rose from 6.0 percent of GNP in 1965 to 10.5 percent in 1982 (Freeland & Schendler, 1984). They were projected to continue rising and have done so.

The health care system has been plagued with issues of poor safety and suboptimal outcomes, as well as high costs. The IOM report issued in November 1999, *To Err is Human: Building a Safer Health System* (Kohn, Corrigan, & Donaldson, 2000), has been the most influential in drawing national attention to poor safety and outcomes. To improve safety and outcomes while reducing costs, organizations and researchers have sought to address occupational safety issues (e.g., adjacencies of clinicians to patients, other hospital safety design) and clinical management of patients (e.g., integrating care delivery guidelines, best-practices and patient education into practice). In recognition that errors are an indication of a systemic problem (e.g., caused by faulty systems, processes, and conditions) that lead people to make mistakes or fail to prevent them rather than by a careless individual or group (p. 2) (Kohn et al., 2000), much research has focused on clinical work processes. In fact, a fundamental principle of quality improvement is that “*processes, not individuals should be the objects of quality improvement*” (emphasis original, p. 2871) (Laffel & Blumenthal, 1989).

An integral approach to the evaluation of processes toward improved efficiency is to reduce or manage variation in the processes. One application of this in clinical management of patients is the development and implementation of clinical practice guidelines to manage variation in care across clinicians and institutions. For example, the Harvard Community Health Plan (HCHP) launched a major effort of clinical algorithm development in 1986 (Gottlieb, Margolis, & Schoenbaum, 1990). They formulated clinical practice guidelines in the form of algorithms to support clinicians in delivering appropriate care. In another setting, implementation of explicit critical path acute myocardial infarction practice guidelines were associated with improved practice patterns and patient outcomes (Montague et al., 1995). An example from surgical care, adherence to the enhanced recovery after surgery (ERAS) protocol is associated with improved short-term outcomes (Gustafsson et al., 2011) and increased five-year survival (Gustafsson, Oppelstrup, Thorell, Nygren, & Ljungqvist, 2016). Clinical practice guidelines, or protocols, inform best-practice clinical work processes for the management and care of specific procedure or patient characteristics.

To further demonstrate the importance of quality improvement to health care industry's objectives, a 2001 IOM report, *Crossing the Quality Chasm*, defined six categories for health system quality improvement—to be safe, effective, patient-centered, timely, efficient and equitable (Institute of Medicine, 2001). Since then, Unertl and colleagues published a systematic literature review of workflow research, in which they categorized studies' dependent variables to IOM's six categories to describe the purpose and potential impacts of reviewed research studies (Unertl et al., 2010). They found that *efficiency* and *timeliness* were the most common dependent variables. This is not surprising as workflow research originates in the operations research and industrial engineering legacy of Taylor's Scientific Management approach (Taylor, 1911).

Effectiveness and *safety* were also addressed in many studies, which also is not surprising given the important role of workflow in quality improvement research.

Technological advancements became a driving force for changes in the health care industry (Sahney, 1993) and continue to be. Sahney described 1980 to 1988 as a period of management support, most notably influenced by the development of information systems within hospitals and a change to the incentives of the hospital reimbursement system (Sahney, 1993). The coupling of these events perhaps explains why many health IT are described as better facilitating the clinics' billing department in billing for services delivered than facilitating clinicians in care delivery. Still, health IT is increasingly seen and used as a tool for quality improvement initiatives. In particular, *Crossing the Quality Chasm*, argued that improved health IT could lead to significant improvements in patient safety and quality of care delivery (Blumenthal, 2009; Institute of Medicine, 2001), and it may be the most influential publication in making the case. But technical infrastructure can shift the nature of work (Bailey & Barley, 2005). To recognize the challenges of existing systems on clinicians' work, as well as the potential for health IT to bring improvements in clinicians' work, is to acknowledge the influence of health IT on clinical work.

In fact, research has shown that health IT profoundly shapes workflow, to include patterns of work activities (Ash et al., 2004) and clinicians' reasoning (Patel, Kushniruk, Yang, & Yale, 2000). For example, Patel and colleagues examined the effect of an electronic medical record (EMR) system on human cognition by comparing clinicians' information needs and reasoning strategies when they transitioned from paper records to an EMR, and back to paper records. They found that health IT are not merely tools to expedite, facilitate and enable the execution of tasks, these technologies also can impact clinicians' knowledge organization and reasoning strategies (Patel et al., 2000). This suggests that health IT can be designed to burden or facilitate clinicians' work processes. To achieve improved use and design of health IT requires an investment into understanding clinical work processes. Others too have argued that understanding clinical workflow is essential to inform implementation, use and redesign of health IT that effectively supports health care delivery (Berg, 2001; Gorman, Lavelle, & Ash, 2003). The rapid pace of technological change has made the study of workflow even more important.

It is important to note that while there is a shared understanding that the U.S. health care system has problems with safety, quality and costs, long term changes are difficult because the culture of health care is notorious for resisting changes to work processes. One such example is conveyed by Atul Gawande is his book *Better: A Surgeon's Notes on Performance*. Gawande shared a case study of an industrial engineer working to increase medical staff's hand washing behavior in a Pittsburgh hospital in order to reduce the infection rate (Gawande & America, 2007). Initially, infection rates fell almost 90%. However, when the industrial engineer who introduced the changes left, hand washing performance began to slide and the intervention was abandoned (Gawande & America, 2007).

This section introduced social, political and economic factors from 1960s through recent day that have put increasing attention on the need to improve safety and efficiency of health care delivery while controlling costs. While there has been use of health IT in the health care industry since the 1980s, it is more recently that the industry has integrated the cognitive sciences to improve clinicians' use of health IT.

Approaches to Studying Clinical Workflow

There are a number of disciplines that engage in workflow studies, bring improvements to quality and safety while reducing costs, and improve system design. The most notable are applied fields—such as industrial engineering, computer science/engineering—and interdisciplinary fields—such as cognitive science, human factors, systems science/engineering, informatics. Here I compare and contrast several disciplines.

Industrial engineering deals with the optimization of complex systems and processes by eliminating waste. Industrial engineers apply science, mathematics and engineering methods to the design, integration, evaluation and improvement of systems. In particular, industrial engineers work to eliminate waste of time, money, energy and other resources.

In the early 1900's, industrial engineers integrated engineering and scientific management principles to address design of work systems and practices to increase efficiency in factories (Bailey & Barley, 2005). Scientific management took an analytic approach to examine work systems; associated topics included motion, time, and work measurement (Bailey & Barley, 2005). While industrial engineering was primarily applied in manufacturing settings in the early 1900's, there were a few industrial engineers in health care as well (Gilbreth, 1916). From 1910 to 1950, hospital management and clinical professionals also used scientific management to improve operations, but there are relatively few applications in the health sector documented (Sahney, 1993).

In the mid-1900’s, more complicated work settings—such as military operations, transportation, industry—became more prominent than manufacturing settings. Industrial engineers sought to bring improvements to these more complex work settings. For example, during World War II, American military employed operations research teams (teams of mathematicians, physicists and statisticians) to address logistical problems (e.g., optimization, production, decision analysis, etc.) (Trefethen, 1954). A major focus for industrial engineers in the health sector at this time (i.e., 1950 to 1965) was to improve the efficiency at the hospital unit level by addressing both work organization and time spent on work activities (Sahney, 1993). After the war, operations research spread to industry settings and became a focus of research and teaching in academia (Bailey & Barley, 2005). Early history of workflow research shows that more complex work systems are associated with advancements in tools (e.g., digital technologies), processes and worker skills.

A typical industrial engineering approach to examining clinical work relies on Time & Motion analysis (T&M). T&M quantifies clinicians’ time expenditures among different clinical activities. It involves continuous and independent observation of clinicians’ work, which is regarded as a more reliable method than work sampling or time efficiency questionnaires. In studies of clinical workflow, T&M is commonly used to quantify workflow and to assess impact of health IT implementation (Overhage, Perkins, Tierney, & McDonald, 2001; Pizziferri et al., 2005; Zheng, Haftel, Hirschl, O'Reilly, & Hanauer, 2010). For example, Overhage and colleagues conducted a T&M study to assess impact of health IT implementation (Overhage et al., 2001). Specifically, they quantified how clinicians' task duration for order entry was affected by use of a computerized physician order entry system (CPOE) compared to their paper-based process. They found that physicians using the CPOE spent 2.2 minutes more per patients, but, with experience, task time fell by 3.73 minutes per patient (Overhage et al., 2001).

Human factors research emerged in the industrial engineering field during World War II. It has traditionally focused on humans and how we interact with other elements of a system, such as products, devices, procedures, work spaces and the environments we encounter (Sanders & McCormick, 1987). Study of human factors takes into account human strengths and limitations in the design process to design systems that match capabilities and limitations of humans, in order to optimize human performance (Chapanis, Garner, & Morgan, 1949). For example, in health care, human factors research has been applied to designing a patient room to facilitate and support patient care, management training in surgery teams, and implementing an incident analysis system. More generally, human factors research in health care has been applied to the design of medical devices (e.g., infusion pumps, anesthesia equipment) and cognitive interfaces of health IT applications (Zahabi, Kaber, & Swangnetr, 2015), study of medication errors, effects of fatigue on resident's performance, judgmental limitations in medical decision-making, and unintended consequences of automation. It largely developed in high-risk industries such as aviation, chemical processing and nuclear power, where it contributed significant safety advancements.

Human factors work takes a systems approach. Simply defined, "a system is a set of interdependent components interacting to achieve a common specified goal" (Henriksen, Dayton, Keyes, Carayon, & Hughes, 2008). A systems approach emphasizes the need to understand the dynamic interactions between the interdependent system components, and that improvements in quality and safety are "best achieved by attending to and correcting the misalignments among these interdependent levels of care" (Henriksen et al., 2008). The systems approach is useful in examining errors and adverse events. At one time, it was typical in U.S. industries to attribute preventable adverse events to the person "on the front lines." That is, the person closest to the event. However, a systems approach views human error as a consequence of weaknesses or vulnerabilities elsewhere in the system. James Reason, a British psychologist and influential researcher in the patient safety domain, created the "Swiss cheese" model of accident causation to describe how weaknesses, or "holes", in successive components of the system can lead to a preventable adverse event (Reason, 2000). Henriksen and colleagues' Human Factors Framework can aid a healthcare researcher and practitioner in better understanding the components of a system that can contribute to preventable adverse events. The Human Factors Framework describes a five-tier hierarchy with progressively more granular focus on system components—(1) external environment, (2) management, (3) physical environment, human-system interfaces, organizational/social environment, (4) nature of the work, (5) individual characteristics (Henriksen et al., 2008).

The IOM's seminal report, *To Err is Human: Building a Safer Health System* (Kohn et al., 2000) is credited with exposing "a wide audience of health services researchers and practitioners to systems and human factors concepts" that could address the systemic factors which the report argues led to preventable adverse events, while also bringing the health care domain and its problems to the attention of the human factors community

(Henriksen et al., 2008). Other researchers too have noted an increase in human factors and ergonomics research in healthcare quality and patient safety since the IOM report was published (P. Carayon et al., 2015).

Similar to Human Factors, Cognitive Science takes a systems approach where the emphasis is on the components and the interactions or interdependencies among components. But they differ in many ways too. Cognitive Science is the interdisciplinary scientific study of the mind (cognition) and its processes (e.g., perception, memory, attention, reasoning, emotion) (E. Hutchins, 1995). A primary goal is to examine problem-solving and decision-making. In general, cognitive science theories examine cognition in a work system by looking at how information is represented, processed and transformed (E. Hutchins, 1995). This is particularly true for Distributed Cognition theory and methodologies (Blandford & Furniss, 2006; E. Hutchins, 1995; Wright, Fields, & Harrison, 2000), which is discussed in greater detail in the next chapter.

This section briefly compared several disciplines interested in examining clinical workflow. There are a number of challenges that make study of clinical work difficult for researchers from all disciplines. The following section reviews and summarizes literature on these challenges.

Challenges to Studying Clinical Workflow

Challenges to studying clinical workflow can be grouped into three categories: (1) Clinical work is complex and multidimensional, (2) clinical workflow research lacks standardization, and (3) generalizing findings across settings is difficult. Each of these is elaborated on in this section.

Clinical Work is Complex and Multidimensional

Health care delivery is a large, complex work system of people (e.g., clinicians, patients, families, administrative staff), and the processes and technologies used to support them. The dynamic, multi-dimensional view of workflow is apparent in the IOM's definition of the healthcare system:

> *"Health care is composed of a large set of interacting systems—paramedic, and emergency, ambulatory, impatient care, and home health care; testing imaging laboratories; pharmacies; and so forth—that are coupled in loosely connected but intricate network of individuals, teams, procedures, regulations, communications, equipment, and devices that function with diffused management in a variable and uncertain environment. Physicians in community practice may be so tenuously connected that they do not even view themselves as part of the system of care"* (Kohn et al., 2000).

These complex workflows are difficult to capture and model. Therefore, health IT is often designed to support simplified models and, subsequently, clinicians are often trained to use health IT for simplified models. However, in the clinical work setting, the oversimplified model of workflow often fails to address the cognitive, distributed, highly collaborative, and ad hoc nature of clinical workflow (Berg, 2001). Gorman and colleagues contend that problems post-implementation of health IT (i.e., interruptions in workflow) are largely due to a narrow and simplistic workflow model that underlies these systems (Gorman et al., 2003). Effectively implementing IT-related changes in healthcare today requires an understanding of clinical workflow (Berg, 2001; Gorman et al., 2003).

Clinical Workflow Research Lacks Standardization

There now exists wide variation in work systems across and within industries. This variation is evident in the absence of a common definition of workflow (Unertl et al., 2010). Specifically, there is a notable tension between definitions of workflow—

definitions that express a linear, static, sequential work contrast with multi-dimensional, dynamic descriptions. The linear and static view of workflow is apparent in the Workflow Management Coalition's (WfMC's) definition of workflow: "The automation of a business process, in whole or part, during which documents, information or tasks are passed from one participant to another for action, according to a set of procedural rules" (p. 8) (Coalition, 1999). Synonyms include workflow management, workflow computing and case management (Coalition, 1999). The WfMC conceptualizes workflow in the context of Business Process Management (BPM). In this context, a business process is one or more activities that together realize a business objective (Coalition, 1999). Fields that have linear and static workflows (e.g., business, manufacturing) can use workflow management systems to automate repetitive processes. While manufacturing and business processes lend themselves to significant standardization and automation for improved efficiency, complex work environments, such as health care delivery, do not.

Clinical work exemplifies multi-dimensional, dynamic workflow. It has been described as multitasking, cognitive, distributive, collaborative, interpretative, interruptive, responsive, and reactive (Hazlehurst et al., 2003; Wears & Berg, 2005). Further, contrasting the linear workflow definitions, Harrington defined clinical workflow as "the multidimensional, transforming processes clinicians use to achieve patient-centered goals" (p. 49) (Harrington & Harrington, 2014). Unertl and colleagues attribute the complexity of clinical work to health care being an exceptions-driven field. We embrace the definition by Niazkhani and colleagues who define clinical workflow as "the flow of care-related tasks as seen in the management of a patient trajectory: the allocation of multiple tasks of a provider or of co-working providers in the processes of care and the way they collaborate" (p. 540) (Niazkhani, Pirnejad, Berg, & Aarts, 2009). The notion of a "trajectory" in the coordination of patient care and an emphasis on collaboration is central to my approach. Not only is there no standard definition guiding workflow research, there is also no standard approach.

There are a number of methodologies for studying workflow, but there is no standardized approach to studying workflow across or within disciplines (Unertl et al., 2010). For example, to study information flow in a clinical setting, Pennathur and colleagues relied solely on semi-structured interviews (Pennathur, Bisantz, Fairbanks, Drury, & Lin, 2014), Unertl and colleagues employed direct observation and semi-structured interviews (Unertl, Weinger, Johnson, & Lorenzi, 2009), and Tang and colleagues employed direct observation, semi-structured interviews and artifact collection (Tang, Carpendale, & Scott, 2010). In the systematic review of workflow literature, Unertl and colleagues found a majority of studies were descriptive, utilized qualitative or mixed methods. Ethnographic observation and interviews in particular were the most frequently used methods, despite being labor- and time-intensive methods. Across all studies, they identified 18 categories of motivational and methodological approaches to workflow research. There was no consistency linking methods to research motivation; thus, there appears to be no clear relationship between research rationale and method selection (Unertl et al., 2010). The lack of standardization has contributed to the difficulty in integrating and generalizing findings across settings.

Generalizing Findings Across Settings is Difficult

There are other reasons why it is difficult to integrate and generalize findings across settings, to include many studies lack sufficient contextual details, report different workflow measures and vary in quality of research and evidence.

A review of workflow literature found six common attributes of workflow across studies—context, temporal factors, aggregate factors, actors, artifacts, characteristics, actions and outcomes (Unertl et al., 2010). Many studies lacked sufficient detail about these contextual attributes for the given study setting. As a result, it is difficult to generalize findings across studies (Unertl et al., 2010). Consequently, a study's findings cannot be readily extrapolated to other settings. Without contextual overlap, study's findings cannot help shape assumptions for studies in other settings, which delays advancements in workflow research.

In their literature review of workflow research, Carayon and colleagues found much variation in workflow measures (P. Carayon et al., 2010). This is not surprising given that a different review of workflow research identified 18 motivational categories, or research rationales (Unertl et al., 2010). In their review, Carayon et al. specifically focused on proximal measures of workflow, which provide explicit description of how health IT affected work processes (P. Carayon et al., 2010). In contrast, distal measures and outcome measures do not provide enough information about how workflow processes have changed. Proximal measures include efficiency (e.g., time to complete patient documentation), processing time, use patterns (e.g., use of e-prescribing (Schectman, Schorling, Nadkarni, & Voss, 2005), use of electronic laboratory order forms (van Wijk, van der Lei, Mosseveld, Bohnen, & van Bemmel, 2001)), coordination, decision support functioning, decision support adherence, acceptance and system functioning (P. Carayon et al., 2010). Studies of health IT systems on clinical workflow indicated effects with changes to, “for example, communication patterns, treatment adherence, guideline adherence, consultation time, travel time, distribution of tasks, information flow, health IT click patterns, number of visits, waiting time, referral time, or workload.” (p. 85) (P. Carayon et al., 2010). Many possible workflow measures could be impacted by implementation and use of health IT, but each study is likely to only examine small subset of measures (P. Carayon et al., 2010). As a result, each study only reveals a subset of the workflow changes that may have occurred (P. Carayon et al., 2010). They attributed the variation in workflow measures to the absence of a standard definition of workflow (P. Carayon et al., 2010). It is also likely a result of disciplines having differing foci and perspectives of workflow. Whatever the reason, this diversity of workflow measures makes it difficult to compare workflow studies.

Chaudhry and colleagues (2006) conducted a systematic review of literature on the impact of health IT on quality, efficiency and costs of health care (Chaudhry et al., 2006). They reviewed literature published 1995 to April 2005 on broad range of health IT. Based on the 257 studies that met the inclusion criteria, they found most of the higher-quality research regarding multifunctional health IT systems was performed at four benchmark institutions. Studies from these four benchmark institutions demonstrated the usefulness of health IT for improving quality and efficiency. Among this research, six studies discussed the impact of health IT on clinicians’ time, and seven studies discussed how health IT was used as a tool to change practice. From this literature, they determined that health IT had mixed impact on provider time and may be useful for positive practice change. These findings are influential to this dissertation research and are further elaborated on later in this chapter. However, they concluded further research is needed to determine the effectiveness of these technologies in more typical practice settings (i.e., outside the benchmark institutions). Overall, the research performed at non-benchmark institutions that used commercial health IT systems was of poor quality, suggesting that what is published does not sufficiently support decision-making about acquiring and implementing health IT in these settings (Chaudhry et al., 2006).

In 2010, Carayon and colleagues similarly conclude that evidence about the impact of health IT on workflow is still lacking. While they found that some workflow changes associated with implementation to be nearly universal (e.g., the increased workload of physicians in clinics that have an EHR), they also found that others (e.g., a physician's lack of acceptance of a new health IT application) may be specific to the context of one clinic setting. Further, they concluded that "most of the evidence that fills this report is anecdotal, insufficiently supported, or otherwise deficient in terms of scientific rigor" (p. 6-7) (P. Carayon et al., 2010). Variation in quality of research studies makes it difficult to compare workflow studies and generalize findings.

Opportunities to Improve Clinical Workflow Research

Studying clinical workflow is challenging because clinical work consists of complex, multidimensional workflows that are difficult to capture and model. It is further challenged by absence of standardized definitions, terminology, approach and metrics, as well as variability in the quality of research, which make it difficult to generalize findings across settings. This delays research and advancements in clinical workflow. Clearly there is much need for (1) a standardized definition and characteristics of clinical workflow, and (2) a comprehensive approach to examine clinical workflow (Figure 2). The challenges, opportunities, and innovations that direct this dissertation research are summarized in Figure 2. The innovations are presented as existing and needed contributions to acknowledge work other researchers have done to address these challenges and clearly define what this dissertation work addresses. The existing and needed contributions, or efforts, are further explained in this discussion.

Challenges	Opportunities	Innovations
No Standardization	Standardized definition & characteristics	Existing Abstraction of real work; Workflow elements model (Unertl et al.,2010); Conceptual model of clinical workflow (Niazkhani et al., 2009)
Difficult to generalize findings		
Difficult to examine multidimensional work	Comprehensive, theoretically-grounded approach to examine complexities of clinical work	Needed **Comprehensive mixed-method approach**

Figure 2. Summary of the methodological challenges to studying clinical workflow, and related opportunities and innovations.

Standardized Definition and Characteristics of Clinical Workflow

A standardized definition and characteristics of clinical workflow would bring consistent terminology to workflow studies across and within disciplines. Standardized characteristics would ensure studies capture and report sufficient contextual details which would facilitate integration and generalization of findings across settings. The need for a systematic approach with standardized characteristics (e.g., shared terminology, metrics, etc.) to facilitate meta-analyses, systematic reviews, and generalizable or sharable knowledge has been supported by others (Unertl et al., 2010).

Toward this end two separate research teams have developed and introduced a conceptual model or framework for describing contextual elements in a workflow study. Unertl and colleagues developed the Workflow Elements Model (WEM) (Unertl et al., 2010), and Naizkhani and colleagues developed a Conceptual Model of Clinical Workflow (Niazkhani et al., 2009).

The WEM (model shown in Figure 3), which draws on sociotechnical theory, has a pervasive and specific level (Unertl et al., 2010). The pervasive level includes three components that apply throughout: *context*, *temporal factors*, and *aggregate factors*. *Context* serves to constrain and facilitate workflow. *Context* includes a variety of enduring factors, such as physical workspace and organizational policies, and transient factors, such as daily patient load. *Temporal factors* involve scheduling (e.g., patients for surgery), temporal rhythms, and coordination of events (e.g., patient check-in, handoffs), and are important on all levels of analysis. *Aggregate factors* refer to the relationship and interaction among different tasks and actors, including elements of coordination, cooperation, and conflict. The specific level guides description of contextual elements that were common to workflow studies across disciplines. It is composed of the individuals performing actions (e.g., nurses, surgeons, anesthesiologists), tools the actors use (e.g., EHR components, paper checklists), specific details of actions being performed (e.g., patient assessment), factors that describe the actions (e.g., multitasking), and their results (e.g., completion of all documentation, timely patient transfer).

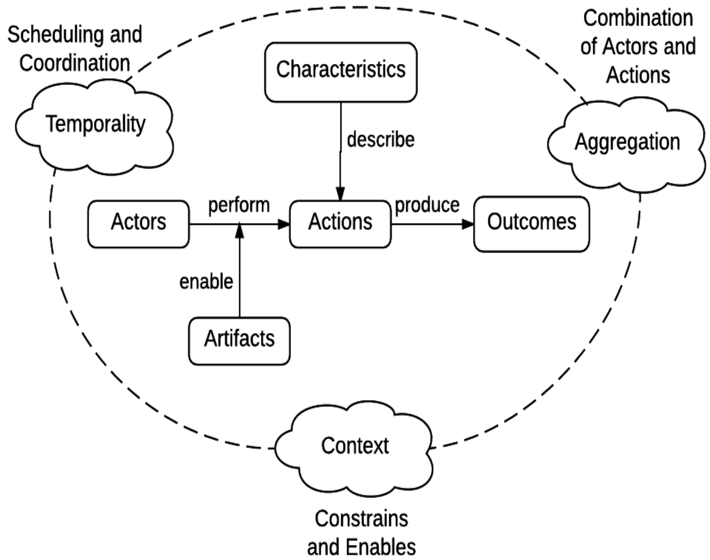


Figure 3. Workflow Elements Model adapted from Unertl et al., 2010, figure 3.

Similarly, Niazkhani and colleagues defined a conceptual model of clinical workflow. To construct the conceptual model, they drew on workflow literature that deals with the modeling of work processes to design information systems that do the work as well as manage the workflow. In particular, they drew on the work of others, notably (Plesums, 2002) and (Ellis, 1999). Based on these, they defined clinical workflow as the flow and allocation of clinical work tasks done for management of a patient trajectory (p. 540) (Niazkhani et al., 2009). It can be described by four inter-related and inter-dependent components: Task Structure, Coordination, Information Flow, and Monitoring (Niazkhani et al., 2009). The conceptual model, as shown in Figure 4, highlights the close connection and interdependencies between these four components.

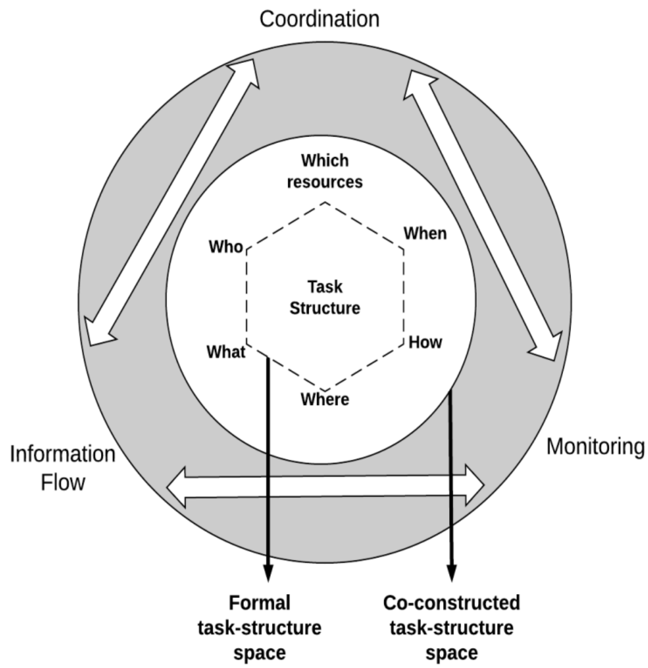


Figure 4. A conceptual model for clinical workflow adapted from Niazkhani et al., 2009, figure 1.

The *formal task-structure space* and *co-constructed task-structure space* shown in Figure 4 are particularly important to relaying the complexities of clinical workflow. In the *formal task-structure space*, work structure describes the relationships and dependencies between tasks, workers, and other resources—the task structure specifies “who” does “what”, “when”, “where”, and “how” by employing “which resources”, and in “what relation” to other tasks and providers, and “serves the core in constructing workflow”. It draws on the integration of organizational knowledge and domain knowledge in healthcare. While task structure defines the core in constructing workflow, the *co-constructed task-structure space* accounts for the inherently ad hoc, contingent and adaptable nature of medical work. In this space, the individual or team has to respond to changing patient state, limitation in information or other ideal resource, etc. As a result, the individual or team are constantly restructuring their work (Strauss, 1988).

The Workflow Elements Model (WEM) is useful in explaining the components of workflow. While it includes or refers to “aggregation” and interactions as a cloud, Niazkhani conceptual model is more useful in addressing the relationships, or coordination mechanisms, of workflow. This dissertation research embraces these definition and components in its effort to create a comprehensive methodology that can capture and examine the complex, multi-dimensional aspects of clinical work, and that would support analysis of many measures across disciplines and foci.

Current State of Health IT-Mediated Workflow Research

Despite efforts to achieve the anticipated benefits of EHRs, there are mixed results as to how well EHRs support tasks related to care coordination and patient management (Bates, 2010). For example, adoption and use of health IT has brought some of the expected improvements, such as improved availability and legibility of patient records. But health IT has not easily integrated into clinical work processes in all settings, leading to unanticipated consequences (Ash et al., 2004; Hammond, Helbig, Benson, & Brathwaite-Sketoe, 2003; Makoul, Curry, & Tang, 2001), to include impacts on workflow such as the sequence in which tasks are performed (Ash et al., 2004), the duration required to complete tasks (Ash et al., 2004), the allocation of tasks among workers (Ash et al., 2004) and development of workarounds (Unertl et al., 2009). These are evidence that embedding technology into complex clinical workflows can have unintended consequences unless integrated properly (Ash et al., 2004; Koppel et al., 2005).

Problems with health IT and its effectiveness for supporting clinical work can be grouped into three themes: (1) interface design and system usability, (2) information-management processes, and (3) communication and coordination. IT systems have a significant impact on users' cognitive processes (Patel et al., 2000) and these themes represent different dimensions of cognitive work that are not supported by health IT. This list is not exhaustive, but serves to structure a review of relevant literature and shape the argument for the proposed research.

Findings from a survey of clinicians reported workflow as the number one EHR usability pain point (Ribitzky, Sterling, & Bradley,). The International Organization for Standardization (ISO) defines usability as:

> *"Usability is the effectiveness, efficiency, and satisfaction with which the intended users can achieve their tasks in the intended context of product use."* (ISO, 1998)

In other words, usability of a system is a measure of its ease of use, learnability and acceptance. Users' interactions with an interface are determined in part by the organization and representation of information and controls (i.e., buttons, scroll bar) on the interface. A user's interactive effort is determined by the physical interactions and mental (cognitive) processing performed to complete work. A poor design is one that increases physical and/or cognitive effort required by the user. A review of literature found seven studies where providers thought EHR/EMR systems were useful (P. Carayon et al., 2010). Among them, four studies reported that customized templates that facilitated retrieval and access to pertinent data had a positive impact of workflow (Babbitt, 2003; Lamberts, 2003; Morrow, 2003; Unertl, Weinger, & Johnson, 2007). In contrast, there was mixed acceptance of CPOE systems—five studies presented that users found the systems useable while three studies presented a decline in satisfaction and perceived usability.

EHR/EMR usability issues included poor navigation (Miller & Sim, 2004), numerous mouse clicks and screen transitions (Rose et al., 2005), crowded screen displays (Rose et al., 2005), difficulties in identifying the correct diagnostic and procedure codes (Gamm et al., 1998), and challenges of health IT learnability (Miller & Sim, 2004). Poor interface usability has been attributed in part "to poor planning for the implementation, vendor restrictions, and/or a lack of sufficient understanding of workflow and information capture (converting paper documents to their electronic equivalent) pre-implementation" (Häkkinen & Korpela, 2007; Unertl, Weinger, & Johnson, 2006; Unertl et al., 2007). EHR/EMR usability issues could lead to new errors (Kuperman & Gibson, 2003) such as typos (Shachak, Hadas-Dayagi, Ziv, & Reis, 2009), selecting the wrong entry from a drop-down list (Shachak et al., 2009), opening the wrong patient's chart (Shachak et al., 2009) or entering information into the wrong patient's chart because two charts were open at the same time (Kaushal, Shojania, & Bates, 2003; Shachak et al., 2009). Improved health IT will be more usable, in particular, they will better support clinicians' physical and cognitive effort.

Health IT that does not fit with clinicians' work processes can also lead clinicians to develop workarounds and, potentially, less efficient processes (Saleem et al., 2009; Unertl et al., 2009; Varpio, Schryer, Lehoux, & Lingard, 2006). For example, a physician experiencing navigation issues developed a workaround that involved keeping multiple displays open. Whereas the workaround reduced the physician's navigation issues, it increased the likelihood of errors in ordering and documentation (Rose et al., 2005). In another study, Embi and colleagues found that both nurses and inpatient practitioners carry paper notes to help manage information for patients under their care. While the availability and transportability of paper notes assist the nurses in information management, they reported recording the same information as many as three times: in paper notes, at the bedside and on a computer. Nurses' paper notes workaround supported their need to continuously collect data, whereas the health IT was designed to support documentation of a care summaries in shift notes (Embi et al., 2013). Workarounds are evidence of a mismatch between health IT's intended use and clinicians' actual work processes.

Paper-based workarounds, in particular, are often created by clinicians to facilitate information management needs, such as the availability and organization of patient information (Embi et al., 2013; Gurses, Xiao, & Hu, 2009; Saleem et al., 2009). For example, Gurses and colleagues, in a study at a trauma hospital, found that nurse coordinators' designed their clipboard (a paper-based information tool) to "[support] mobile nature of clinical work by providing instantaneous access to highly selected information during walkthroughs", "[facilitate] information collection through rapid annotation and dissemination through quick look-ups in meetings, walkthroughs, and opportunistic encounters", "[support] information access under time pressures via data reduction, information organization, and use of visualizations, shorthand symbols, and color highlighters (p. 671) (Gurses et al., 2009). While paper-based workarounds may help some clinicians be more efficient in their work (Saleem et al., 2009), they increase the opportunity for losing clinical information (Saleem et al., 2009) and may create new paths to medical error (Patterson, Rogers, Chapman, & Render, 2006). Improved health

IT may benefit from supporting use of paper in workflow processes where it cannot meet the functionality that paper provides (e.g., availability, mobility, ease of use).

The problems associated with health IT are not solely the product of challenges to individual's work processes, but also how these systems support team-based care coordination processes. Execution of clinical tasks necessitates collaboration in a complex system where work is knowledge-intensive and organized across many clinicians responsible for different aspects of care and from a range of disciplines. Clinicians are challenged with sharing information across members of patients' care teams while also managing information and performing a series of tasks (e.g. identifying medical problems, entering orders, documenting a daily progress note) for the patients under their care. This can lead to errors and delays in care that risk patient safety. Communication errors among clinicians are a key factor in medical errors suggesting the challenges in doing this. Care coordination, as defined by McDonald and colleagues, is the "deliberate organization of patient care activities between two or more members of the patient's care team (stakeholders involved in the patient's care), including the patient, to facilitate the delivery of healthcare services" (McDonald et al., 2007). Coordinating care involves organizing resources (personnel, material, informational, or other) needed to carry out the required patient care activities, and is often managed by the exchange of information (about activities and knowledge) among members of the patient's care team who are responsible for different aspects of care (Reddy, Shabot, & Bradner, 2008).

Coordination among patient care teams relies on shared awareness (Reddy et al., 2008). Shared awareness can be achieved through communication between individuals across synchronous (e.g., face-to-face and phone conversations) and asynchronous (e.g., text page, email, progress note documentation) channels in planned (e.g., daily rounds, shift handoff) and unplanned communication events. Shared awareness can also be achieved through, or with support of, shared tools such as a centralized whiteboard, printed schedule or shared displays of patient data. Both Saleem and colleagues (2009) and Flanagan and colleagues (2013) found workarounds not only addressed cognitive work of an individual clinician, but also cognitive work and coordination processes of care teams (Flanagan, Saleem, Millitello, Russ, & Doebbeling, 2013; Saleem et al., 2009). They identified “awareness” (i.e., individual and shared awareness) as one of the most consistent reasons for workarounds. Keenan and colleagues (2013) argued that oral and written communication is difficult to address because absence of a centralized (i.e. easily accessible to the entire care team) care overview in the patient’s EHR (Keenan, Yakel, Dunn Lopez, Tschannen, & Ford, 2013). Health IT can improve care delivery and patient safety by supporting team coordination, in particular, facilitating communication and construction of shared awareness for patients under their care.

Opportunities to Improve Health IT-Mediated Clinical Workflow

Health IT has the potential to facilitate more efficient and safe patient care by assisting clinicians in information management and care coordination processes. Health IT can improve the problems surfaced in this literature review by supporting clinicians’ physical and cognitive effort (i.e., better usability), use of paper in workflow processes, and supporting team coordination. To address these, a better understanding of clinicians’ workflows is needed, in particular, a better understanding of the dimensions of clinicians’ cognitive work as it relates to system usability, information management needs, and communication and coordination needs (listed as Opportunities in Figure 5). To this end, I look to cognitive theories and constructs in human factors and human-computer interaction fields of study, which address many of the concerns that make the integration of computing and clinical practice difficult (listed as Needed Innovations is Figure 5). Cognitive theories and constructs are introduced in the next chapter.

Challenges	Opportunities	Needed Innovations
Interface design and system usability Information management processes Communication and coordination	Understand how clinicians' cognitive work relates to these challenges →	**Approach grounded in cognitive theories address integration of computing and clinical work at a micro-analytic level**

Figure 5. Summary of challenges clinicians have in efficient health IT-mediated workflow processes, and related opportunities and needed innovations.

In summary, health IT has the potential to facilitate more efficient and safe patient care by assisting clinicians in information management and care coordination processes. The review of literature identified the need for a comprehensive mixed-method approach to examine clinical workflow (Figure 2), and an approach grounded in cognitive theories that address the integration of computing and clinical work at a micro-analytic level (Figure 5). The theoretical and methodological framework for this research draws on interdisciplinary perspectives. The theoretical framework will be introduced and discussed in the next chapter.

Chapter III

THEORETICAL FRAMEWORKS & METHODOLOGICAL REVIEW

Introduction & Objective

Research into clinical workflow, in particular health IT-mediated workflow, is in need of a comprehensive methodological framework that can examine clinical workflow at varying levels of granularity and can inform design and use of health IT that better supports clinicians' cognitive work. This requires capture and analysis of work across clinicians, the information tools they use and their conversations, across settings and time. Cognitive science theories and frameworks enable an in-depth and context-specific examination and evaluation of clinical workflow. This research draws on distributed cognition theory (DCog), cognitive engineering and computational ethnography frameworks. DCog, in particular, is inherently well-suited to characterize health IT-mediated activity. This chapter reviews methods and constructs from these frameworks that have been used to study cognitive work. It guides the selection of data capture and analysis methods for this dissertation research. The objective of this chapter is to situate this work in a theoretical framework and make the case for the theoretically-grounded methodology that will be presented in Chapter V.

Distributed Cognition Theory (DCog)

Like any cognitive theory, DCog seeks to understand the organization of cognitive systems. It is a useful theoretical framework for studying complex, collaborative work. It has been employed to examine cognition and behavior in varied work settings. In his seminal study, Edwin Hutchins studied cognition of a naval team navigating a ship into harbor (E. Hutchins, 1995). In this study, he surfaced the sequence of navy crewmen's events to take bearings and manipulate the information that was needed to determine the ship's location and progress. Information-processing activities were characterized in terms of the coordinated action of the crew. Other studies include cognitive systems of work practices in cockpits (E. Hutchins & Klausen, 1996), air traffic control (Halverson, 1995), software teams (Flor & Hutchins, 1991) and engineering (Rogers & Ellis, 1994). Researchers have called for use of DCog to examine collaborative work in clinical environments (Hazlehurst, Gorman, & McMullen, 2008; Xiao, 2005).

Health care delivery is a good candidate for the use of DCog theory and methods because it is a system of complex, collaborative and dynamic work activities, where outcomes of the work depend on how well the system functions as a whole. It has been used to study complex clinical environments, such as critical care (Hazlehurst et al., 2003; Malhotra, Jordan, Shortliffe, & Patel, 2007; Rajkomar & Blandford, 2012), the surgical operating room (Hazlehurst, McMullen, & Gorman, 2007), psychiatric emergency department (Cohen, Blatter, Almeida, Shortliffe, & Patel, 2006) and telemedicine (Kaufman et al., 2009). In particular, it has been used to reveal details of work in complex collaborative settings, to focus on mediating roles of cognitive artifacts in supporting clinical care (Nemeth, O'Connor, Klock, & Cook, 2006), identify features of the distributed cognitive system that may be conducive to error (Cohen et al., 2006; Horsky et al., 2005; Malhotra et al., 2007), to study home telemedicine workflow (Kaufman et al., 2009), and to study the design and use of medical devices (D. Furniss, Masci, Curzon, Mayer, & Blandford, 2015; Rajkomar & Blandford, 2012).

The following section introduces key DCog principles and constructs.

DCog Principles & Constructs

The classical cognitive theory approach is bound to a single user, the artifacts that the user interacts with, and the individual's internal cognitive processes. In this traditional theory, the unit of analysis is an individual human, and cognition can be characterized as a sequence of operations or computations on mental (internal) representations for an individual (Patel & Kaufman, 2006). Internal representations are knowledge and structure in individuals' minds (Patel, Zhang, Yoskowitz, Green, & Sayan, 2008; J. Zhang & Norman, 1994) that correspond in some way with the external world (Patel & Kaufman, 2006). I reuse a clinical example from Patel and colleagues, who explain an internal representation "may reflect a clinician's hypothesis about a patient's condition after noticing an abnormal gait as he entered the clinic" (Patel & Kaufman, 2006). This classical cognitive approach has been widely employed in human-computer interaction research, but is limited by its focus on a single user.

DCog extends the focus of cognition by conceptualizing cognition as distributed across people and the environment. Cognitive processes exist wherever components of the process interact, irrespective of physical location. This broader unit of analysis for cognition is one of two theoretical principles that distinguishes DCog from other cognitive approaches (Hollan, Hutchins, & Kirsh, 2000). The second principle, regards the mechanisms that may take part in cognitive processes. It states that DCog recognizes more types of cognitive events beyond the manipulation of symbols inside the mind of an individual actor. The larger class of cognitive events that should be looked for include “manipulation of external objects and the flow of information representations among actors.” (Rajkomar & Blandford, 2012). In other words, distributed cognition is dependent upon the coordination of both internal and external representations (Rogers, 2012).

The image in Figure 6 captures a typical moment in a nurse practitioner's work. The overlays on the various information sources help to convey the DCog’s theoretical focus on how cognition is stretched across various people and artifacts—such as members of the care team, clinical information systems, email, phone, pager, cell phone, paper documents, notes, etc.

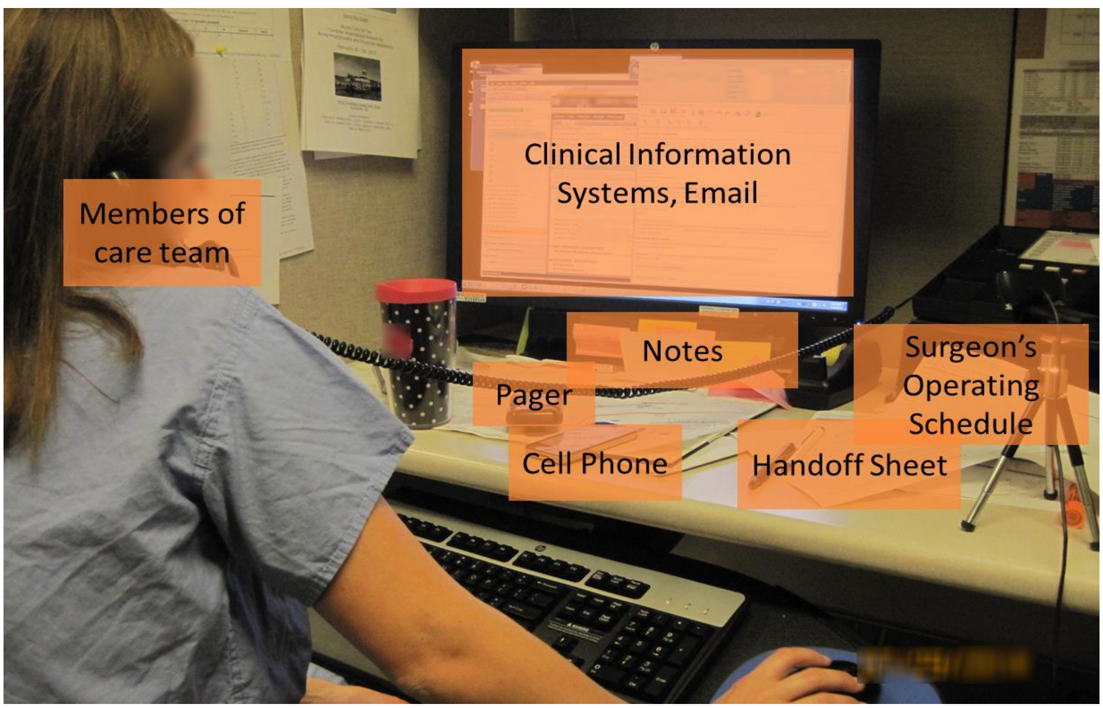


Figure 6. Distributed cognition theory (DCog) focuses on how cognition is stretched across people and artifacts.

Key constructs that are important to DCog studies include activity system, internal and external representations, representational states, artifacts and propagation of representational states.

DCog does not privilege the individual, acknowledging both humans and artifacts (i.e., tools and technologies) can bring representational media into coordination. As Halverson put it, DCog "presents artifacts, human actors, and organizational and social structures on an equal theoretical footing" (p. 254) (Halverson, 2002). Thus, DCog treats the ***activity system***, rather than the individual, as the unit of analysis (Hazlehurst et al., 2003; E. Hutchins, 1995). An activity system is composed of actors, their tools and environment (Hazlehurst et al., 2003; Hazlehurst et al., 2007).

A ***representation*** is generally defined as "a particular configuration of an information-bearing structure, such as a monitor display, a verbal utterance, or a printed label, that plays some functional role in a process within the system" (p. 540) (Hazlehurst et al., 2007). As previously defined, internal representations are knowledge and structure in individuals' minds (Patel et al., 2008; J. Zhang & Norman, 1994). External representations are "the knowledge and structure in the environment" (p. 180) (J. Zhang, 1997). They can be reflected in instances of an environment (e.g., the layout of people and equipment in the operating room (Hazlehurst et al., 2007), an artifact (e.g., paper notes, visual displays), and verbal utterance. A ***representational state***, then, is a "configuration of the elements in a medium that can be interpreted as a representation" (p. 117) (E. Hutchins, 1995). In other words, a representational state is an instance of a representation. In clinical work, representational states may include any number of "information bearing structures" including an EHR document, threads in a conversation, or text on a printed artifact. A representational state of an information artifact—such as a handoff document, nurse's notes, a daily progress note—is the information as well as the configuration of the information at any moment in time.

Artifacts are physical media, such as paper- and computer-based technologies and tools. Hutchins calls artifacts used to support work, mediating artifacts. Mediating artifacts include any artifacts that are brought into coordination in the performance of the task (E. Hutchins, 1995). Artifacts are important in DCog studies because their external representations can augment, enhance and improve cognition (Norman, 1990), as well as transform the ways individuals and groups work and think (E. Hutchins, 1995). They achieve this by facilitating cognitive processes, such as memory, attention and perception. Therefore, people often interact with and create external representations because it is easier and more efficient for people to process by interacting with an external representation than by working in the head alone (Kirsh, 2010). For example, a checklist of tasks to be completed supports a person's memory because the person can direct all cognitive resources to completing one task and then can return to the list to be reminded of the other tasks that still need to be completed. In this way, an artifact (e.g., checklist) can support a person's memory when his or her cognitive resources need to attend to emergent interruptions or if the task is composed of non-continuous activities. For these reasons, artifacts are typically used to support challenging activities such as work that is information-intensive, has information or task components separated by time and space, or that requires involvement of many information sources.

The role and function an artifact has in individual and collaborative work depends on affordances from characteristics such as the artifact's form, mobility, life span and interactivity. In an example of individual work, a clinician who needs to document a patient's vital signs on a non-mobile computer that is more than an arm's reach from the patient, may prefer to capture all of the patient's vital signs and write them on a paper note and then step away from the patient to document them in the computer. In this scenario, the clinician reduces the cognitive burden of the task by using the paper to note the patient vital signs instead of relying on his or her memory. In an example of collaborative work, a team of clinicians in a hospital unit may list all of the patients in the unit on a shared whiteboard. A whiteboard placed in a shared workstation where it can be easily viewed by the entire team can support the team's awareness of the patients. In clinical settings, a wide range of information artifacts are used to coordinate the delivery of patient care. Examples include large whiteboards, work schedules, desktop computers, mobile computers (e.g., laptop, tablet, cell phone), electronic patient records, and disposable paper note sheets.

In complex activity systems, human performance research should describe and understand the how artifacts are used to coordinate the delivery of patient care (Hazlehurst et al., 2007). According to DCog, the cognitive behavior of an activity system is revealed by the ***propagation of representational states*** across media, settings and time, and the processes involved in propagation. Behavior in an activity system—interactions between the actors, tools and environment—are directed by goals of an activity or task, and guided by organizational knowledge (e.g., rules, social roles, cultural values) (Hazlehurst et al., 2007; E. Hutchins, 1995). Therefore, system behavior and cognition can be visualized and examined through representational states and maps of how representational states are propagated across diverse media. The sequence and mechanisms by which the representational states transfer and transform enables analysis of how the system functions to achieve its goal. For example, on a given day of post-operative care in a hospital unit, two clinicians, who are both responsible for managing and monitoring the same five patients, independently review the medical history and recent status for each patient in the electronic chart and write pertinent information on paper notes. Then, together they visit each patient to validate information and gather new/additional information. Subsequently, through discussion, they make treatment decisions. Through these steps, the clinicians refer to the paper for information and continue to use the paper to document pertinent patient information and status of tasks, such as an order entry to-be-completed. Though a simplified example of how clinicians' paper notes support both individual and collaborative work. It also serves to exemplify how clinicians' cognitive work is revealed by examining how information and knowledge transfers and transforms across individuals and the tools they use. Through analysis of propagation of representational states, DCog theory enables the study of complex cooperative work where people and artifacts together maintain and manipulate representational states to carry out processes that perform work, such as problem-solving and task execution.

System behavior can also be called coordination work, information flow or workflow depending on the scope or perspective of study. Therefore, propagation and transformation of representational states surfaces ***information flow*** and information-processing activity. As previously mentioned, information representations can exist in an array of forms. Information movement in the system—may also be referred to as transfer or exchange—can be achieved in a number of ways, to include passing physical artifacts, sending a text page or electronic mail, entered in to a patient chart, verbally shared in-person or via phone, graphical representation, and facial expressions (E. Hutchins, 1995). An **information transformation** occurs when the representation of information changes, which can occur through artifacts and communications between people. For example, a table of numbers could be represented as a chart or graph (D. Furniss & Blandford, 2006). Similarly, the level of a patient's pain could be recorded on a numerical scale from 0 to 10. The mechanisms of information flow, to include information movement and transformations, are informative because not only is the behavior of the activity system described by the patterns of information flow, but DCog theory also contends that the sequential pattern of information movement can drastically change the behavior of the activity system (E. Hutchins, 1995). In fact, DCog is differentiated from other disciplines, such as conversation analysis and activity theory, that employ the term. What distinguishes DCog from these as well as sociotechnical theories is its explicitly cognitive stance on symbolic manipulation.

The goal of DCog analysis "is to describe how distributed units are *coordinated* by analyzing the interaction between individuals, the representational media used, and the environment within which the activity takes place" (Perry, 2003). When work is segmented into representational states and processes by which representations transfer and transform, the trained analyst can examine how changes in the activity system affect the workflow in the given context. By extension, the trained analyst "can speculate about how changes in technologies might affect future operations" in the given context (p. 254) (Halverson, 2002). A change in the activity system may be a change in the workers (e.g., number, roles or responsibilities), technologies or tools (e.g., EHR implementation, introduction of a paper handoff tool), or the environment (e.g., new office space). In the next section, I review how the *propagation of representational states* approach has been used in clinical informatics research.

Review of DCog Literature Related to Propagation of Representational States

DCog theory, in particular the *propagation of representational states* approach, has been used to study clinical work and to characterize important aspects and interactions that enable the activity system to function and work to be completed. In particular, the *propagation of representational states* provides a basis for detailed characterization and modeling of information flow and information-processing activity in cooperative work settings. As mentioned above, the goal of DCog analysis is to describe how distributed components of the activity system are coordinated. This requires analysis of the interactions among people, artifacts they employ, and the environment they are situated in. Here I present a review of key DCog literature and discuss how *the propagation of representational states* approach has been used to study clinical work. This review informed the data collection and analysis methods for this dissertation research.

Patient care delivery results from the coordination of multiple processes that propagate representational states across various media (Hazlehurst et al., 2007). There are multiple processes or configurations of system components that achieve work. Hutchins described three: (1) the processes of an individual, (2) an individual in coordination with a set of tools, or (3) a group of individuals in interaction with each other and a set of tools (E. Hutchins, 1995). These three configurations of system components can occur at different steps in a routine process, dependent on the task and setting at any point in time.

For example, these configurations exist across the different steps involved in a care team noticing a patient problem and completing a medication order to treat the problem. In such a scenario, a patient problem surfaces during a conversation between members of the patient's care team in patient rounds. The resident physician is asked to place a medication order for the patient, which is processed by the pharmacist, and sent to the nurse. Prior to administering the medication, the nurse reviews the order to determine whether it is consistent with the nurse's understanding of the patient state. Each of these actors will use a range of domain knowledge, artifacts and tacit understandings to process information, act on the order in view to achieve the goal. In this system, both actors and tools (i.e., human and non-human components of the system) can be cognitive agents.

Wright, Fields and Harrison developed the Distributed Resources Model (DRM) to apply DCog to human-computer interaction (HCI) modeling (Wright et al., 2000). It employs the DCog framework—the *propagation of representational states* approach—to examine and evaluate an activity system consisting of an individual actor (user) and his or her interactions with a computer-based information system (artifact). DRM has two components: (1) *information structures*, which are abstract resource types that control action, and (2) *interaction strategies*, which are process-oriented descriptions of how these information structures can be used for action (Horsky, Kaufman, Oppenheim, & Patel, 2003). The coordination and integration of these components describes a connection between devices, internal and external representations, and actions (Wright et al., 2000). DRM seeks to answer the question of what information is required to carry out a task and where it should be located: as an external object or as a piece of knowledge (internal) that the user brings to the task. DRM characterizes cognitive demands of computer-based systems by describing how resources (e.g., *information structures*) control action and how they can be coordinated to control or influence interaction. As a result, the model enables researchers to examine components of user interfaces that introduce unnecessary cognitive complexity on its users. Consistent with the assumption of DCog theory, a central tenet of DRM is that human performance is affected by the configuration of resources for action (e.g., *information structures*).

Table 1. Information structures defined by the body of literature on the Distributed Resources Model.

Abstract information type	**Description**	**How they can exist**
Plans	"resources for action that include a sequence of actions and anticipated states" (Wright et al., 2000)	Internal & External
Goals	"states the user wants to achieve, generated internally or emerging from system interaction" (Wright et al., 2000)	Internal & External
Possibilities or Affordances	"links, buttons, or menus that suggest possible next actions at a given state of the system" (Wright et al., 2000)	Internal & External
History	"the part of a plan already accomplished (e.g., a list of previously visited sites in a web browser)" (Wright et al., 2000)	Internal & External
Action-effect relations	"indicate the causal relationship between an action and the effected change in state" (Wright et al., 2000)	Internal & External
State	"the current configuration of resources, as embodied in the display screen at a given point" (Wright et al., 2000)	Internal & External
Biomedical Knowledge		Internal
Conceptual model of the system	The user's understanding of how the system works.	Internal

Source: Data from Wright et al., 2000; Horsky et al., 2003.

Wright and colleagues defined six abstract *information structures* that can exist as internal or external representations, and can be used to analyze interaction (Table 1). Depending on the coordination of these structures, the activity can be more or less supported. The following example, drawn from Figure 4 in (Wright et al., 2000), exemplifies this. The task is to follow a sequence of steps for a procedure. The process to determine what action to perform next, requires the user to compare or coordinate the complete procedure (i.e., *plan*) to the previous actions that have been performed (i.e., *history*) in order to identify the next item on the *plan*. The three illustrations in Figure 7 show different configurations of the *plan* and *history* representations. In Figure 7a, the *plan* resource is represented as a printed list of actions to perform. The *history* of actions is in the mind of the user. The user can mark the next item to perform with his or her finger, thereby differentiating it from the history. By marking the next item with his or her finger, the user is externalizing the next action to perform and the *history* of actions onto the same external space as the *plan*. In Figure 7b and 6c, the *plan* is represented by a computer system. In both cases, the *plan*, *history*, and marker for the next action are maintained by the computer system and represented in the same display (i.e., externalized in the same space). This example demonstrates that coordination was better supported when the resources that needed to be coordinated were represented in the same external space. More generally, this example demonstrates that the different configurations of resources of action (i.e., *plan* and *history*) determine the kind of coordination work required by the user to follow the plan.

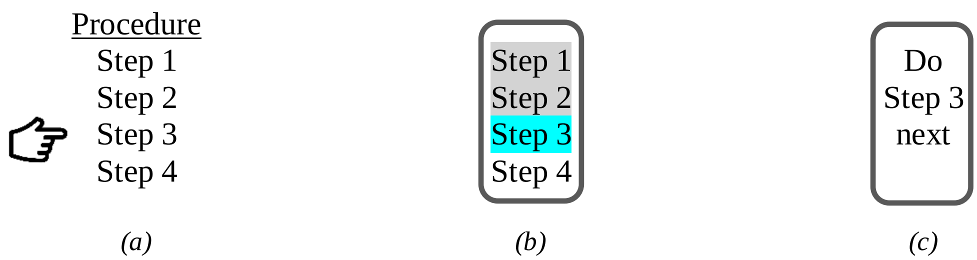


Figure 7. Three different representations of *plan* and *history* for a procedure display adapted from Wright et al., 2000.

Horskey and colleagues extended the DRM method for study of clinical information systems. In particular, they employed DRM to analyze the cognitive complexity of a computer-assisted provider order entry (CPOE) system. Consistent with DRM's unit of analysis, they evaluated the distribution of external and internal representations for a single user interacting with a single computer-based system (Horsky et al., 2003). As with many health IT systems, CPOE is a complex system that has the potential to reduce medical errors. They hypothesized that many of the difficulties in using the system are due to the cognitive demands imposed by the user interface. To test their hypothesis, they conducted a walkthrough analysis, which simulated an expert user completing an order entry task. This enabled them to characterize expert-like performance and highlight potential sources of difficulty using the interface to complete the task. In addition, they conducted an experiment with seven internal medicine physicians, who had used the system daily for three years, to analyze the patterns of errors made by experienced clinicians and their interactive strategies in using the system.

They found the configuration of resources in the CPOE system placed heavy and unnecessary cognitive burden on the user (Horsky et al., 2003). Efficient use of the system to complete tasks required the user to have a solid conceptual model of the system and be able to recall specific action-effect relations (defined in Table 1), which in turn relied on memory and experience with the system. For example, in one step of the task (State Four in (Horsky et al., 2003)), the goal is to select a specific order set. The screen is described as providing "an extensive alphabetized list of order-set labels. Some of the labels are, however, category headers that open an additional list of subsumed items, whereas others are single orders" (p. 14) (Horsky et al., 2003). The hierarchical structure of orders and order sets is not transparent; therefore, efficient task completion requires the user "to remember that labels containing the word ''sets'' are expandable categories, while the singular ''set'' designates an order set, and names starting with a dot (e.g., Admit) are single orders that are all represented as text in the same alphabetical list of items" (p. 14) (Horsky et al., 2003). If the user does not remember these, the user may engage in a lengthy trial and error exercise to find the appropriate order set. Besides time delays, other possible complications are failure to find an appropriate order set and the selection of the wrong order set (Horsky et al., 2003). In this scenario, the interface provides an external resource to aid task completion (i.e., the alphabetized list of order-set labels), but the "visual representation is suboptimal necessitating a reliance on internal resources" (p. 15) (Horsky et al., 2003). In other examples, Horsky and colleagues show how participants' errors could have potentially serious medical consequences, and how inefficient strategies required more work and resulted in redundancies.

In fact, in their experiment, no participant produced an error-free set of orders when compared to the expert walkthrough. Based on the in-depth characterization of user interaction possible using the DRM method, the research team could explain variation in user performance and characterize the relationship between resource distribution and ordering errors. While DRM was not intended to support quantitative predictions, for some cases, Horsky and colleagues reported quantitative variables to compare efficiency and cognitive effort of different interaction strategies. Quantitative variables included task duration, screen transitions and number of goals or steps required to complete a task. They can use such findings to direct user training to specific users who would most benefit from an improved conceptual model of the system.

Their findings also have implications for interface design. In particular, for improved configuration of resources on the interface to facilitate task completion. For example, they suggest "semantic matching rather than alphanumeric ordering or strict hierarchies may expedite searches for orders, sets, and text-based values in pick lists that frequently contain dozens of items" (p. 20) (Horsky et al., 2003). Their findings do not lead to generalizations about optimal interface configurations that can be applied across systems and settings. However, they found that less optimal configurations of resources on a user interface share two characteristics: "(1) introduce complexity into the performance of a task or (2) fail to provide the necessary resources for users to attain their goals" (p. 20) (Horsky et al., 2003).

The Distributed Resources Model (DRM) makes DCog more accessible to the human-computer interaction (HCI) community because of its single user and single system unit of analysis. On the other hand, this unit of analysis is also a limitation; DRM cannot be readily used to examine and evaluate work that involves many people, paper- and computer-based information sources, and various environments. The model can be used to classify how abstract resource structures (e.g., *plan*, *direction*) can be coordinated in interaction strategies to produce behavior. In DRM, representational states are referred to as *information structures*. In a broader unit of analysis, *information structure* is an insufficient replacement for *representational state* because it cannot easily be used to refer to social DCog and the descriptions are largely of static rather than dynamic representations or complex processes and trajectories. The following paragraphs, introduce other ways the *propagation of representational states* approach has been used to examine broader units of analysis, to include work that involves representational states across diverse media.

Similar to the DRM's *information structures, representational states* in other DCog analyses provide the system with information and control action. For example, Brian Hazlehurst and colleagues applied a *propagation of representational states* approach to describe part of a medication ordering process in an Intensive Care Unit (ICU) activity system (Hazlehurst et al., 2003). Through this approach they modelled the flow of information across diverse media to explain system behavior. The observed medication ordering process contrasts with the simple medication order process description that is often given; it involves non-linear steps and multiple actors, tools, types of information and environmental structures used by a care team. In particular, components of the process not only serve to accomplish the medication ordering task, but also to simultaneously support other important aspects of the unit's work. This is exemplified through a case study; the authors show that clinicians in the unit organized themselves with respect to the Medication Administration Record (MAR), each other and to their task work in a way that facilitates them in detecting and preventing errors, collaborative problem-solving and decision-making, and developing shared awareness (Hazlehurst et al., 2003). The MAR is one of the information tools used for medication ordering in the study site—it “is created by hand when a patient arrives in the ICU and then subsequently printed by the pharmacy computer system at midnight to form the next day’s medications record” (p. 285) (Hazlehurst et al., 2003). The researchers argue, that implementation of a centralizing technology, such as a CPOE system aimed to improve the medication ordering process, would change the distribution of information representations within the activity system. Such a change could have unintended consequences to other processes that also relied on those replaced representations and may hinder steps in the activity system that were either designed or have evolved to catch and correct mistakes, modify clinical practice, maintain communication channels, etc.

Not only does this study show that the *propagation of representational states* approach can be used to describe a multi-actor clinical setting and the complex processes and relationships between system components (Hazlehurst et al., 2003), but it also helps convey the importance of obtaining an in-depth understanding of information flow in a complex activity system. In particular, Hazlehurst and colleagues suggest a potential usefulness in explaining and possibly predicting consequences of implementation of centralizing technologies that change the distribution of information within the activity system (Hazlehurst et al., 2003).

In another study, Hazlehurst and colleagues applied a *propagation of representational states* approach to examine cognitive activity (i.e., cognition) of a team in the operating room (Hazlehurst et al., 2007). They characterized patterns of communication between a surgeon and a perfusionist that served to coordinate activities during cardiac surgery. Consistent with a DCog approach, they hypothesized, “mechanisms promoting or providing coordination serve to control the system by providing means for modulating and making predictable the system's transitions through task state space" (p. 549) (Hazlehurst et al., 2007). They found that a verbal communication pattern (i.e., a verbal utterance or verbal exchange) acts as a functional "tool" and can serve a function of transitioning the state to a successor state. Thus, these verbal communication processes act as a mechanism in the system's distributed cognition by enabling effective sequencing of action to accomplish tasks and achieve goals (Hazlehurst et al., 2007). The authors refer to these communication processes as *coordination devices.* Table 2 lists the six types of verbal exchanges they identified, along with a description of the role each plays in controlling behavior of the activity system. For example, "direction" is a pattern that seeks to transition the activity system to a new state (e.g., administering medications that affect blood coagulation) (Hazlehurst et al., 2007).

Table 2. Coordination devices defined by Hazlehurst and colleagues.

Type of verbal exchange	**Description**
Direction	Command an action that seeks to transition the activity system to a new state
Goal-sharing	Create expectation of a desired future state
Status	Create shared understandings about the current state
Alert	Convey abnormal or surprising information about the current state
Explanation	Create a rationale for the current state
Problem-solving	Reason toward a more complete understanding of the current state

Source: Data from Hazlehurst et al., 2007.

Hazlehurst and colleagues went one step further and identified how the verbal exchanges control and enable system behavior in the observed environment. They found that verbal exchanges (1) made the current situation clear and mutually understood, (2) made goals and envisioned future situations clear and thereby anticipated, and (3) expanded upon the activity system's knowledge base through discovery and sharing of experience. Based on these findings, the authors claim that situation awareness is a consequence of interactions of the system; situation awareness "arises out of the processes that manage information flow and action" (p. 594) (Hazlehurst et al., 2007). These two studies by Hazlehurst and colleagues demonstrate two ways that the *propagation of representational states* approach can be applied to clinical settings with multiple actors. While the settings and work differed, the studies demonstrated that a focus on the propagation of representational states by and between people, their tools, and their environment enables insight into information-processing, how the team performs decision-making and problem-solving, and how cognitive resources are configured and utilized to achieve their goal.

Christopher Nemeth's research into the distributed cognition in clinical settings takes a different approach than Hazlehurst's. As discussed above, Hazlehurst—who trained with cognitive scientist and DCog research Edwin Hutchins—most literally follows the DCog *propagation of representational states* approach developed by Hutchins, which privileges the actions within the activity system to understand the information-processing by and between actors, their tools, and their environment. On the other hand, Nemeth—who trained with physician, researcher and patient safety expert Richard I. Cook and industrial engineering researcher David D. Woods—privileged the material artifacts of a workplace to examine the distributed cognition. Nemeth and colleagues analyzed cognitive artifacts to understand their role in distributing cognition within clinical environments (Nemeth et al., 2006). While Nemeth's studies do not explicitly state they are following a *propagation of representational states* approach to study the distributed cognition in the system, they do draw on assumptions of DCog and the *propagation of representational states* approach to guide their methodology. In particular, they draw on the idea that when various kinds of structure (e.g., cognitive artifacts) are brought into coordination with functional skills it results in cognitive behavior in the activity system (E. Hutchins, 1999).

In one study, Nemeth and colleagues studied the development of the operating room Master Schedule, and how anesthesia coordinators (i.e., the frontline managers) use the Master Schedule to plan and manage anesthesia assignments for surgical procedures (Nemeth et al., 2006). The cognitive artifact-centered and clinical role-centered perspectives are explained by the two themes guiding their research into clinician cognition: "one theme showed how the artifact is created while the other theme used the artifact to reveal the basis for its creation" (i.e., how the artifact is created or changed by actors) (p. 1017) (Nemeth et al., 2006). Consistent with a *propagation of representational states* approach, Nemeth and colleagues described how representational states control and enable system behavior. They described and modelled how specific structures are brought into coordination in the creation of the Master Schedule. Unlike the previous studies presented in this chapter, Nemeth and colleagues did not further analyze these to define abstract mechanisms. Regarding anesthesia coordinators' use of the Master Schedule, the authors found it is used to anticipate, plan, and reconcile constrained resources.

This study gave insight into the nature of the artifact itself and its context of use in the clinical environment. The authors claimed that they revealed how the Master Schedule and related artifacts served as a means to coordinate activities, anticipate future events, reconcile conflicts and track progress. Nemeth and colleagues gave a few anecdotes to convey how the artifact was used in decision-making processes but, in general, the approach gave little insight into the interactions between users and artifacts in decision-making processes for planning and managing resource allocation. However, the study provided insight into information needs, identified critical features of the work domain and surfaced limitations of the technologies for supporting clinicians' cognitive work. Further, demonstrated a method that could be followed to yield further insight into clinicians' decision-making processes. This study demonstrates that an in-depth examination into clinicians' cognitive work can reveal meaningful insight into clinicians' information needs and mechanisms for managing information, and can meaningfully inform health IT solutions that support clinicians' work processes.

Hazlehurst's and Nemeth's approaches draw on DCog principles to examine distributed cognition in multi-actor and multi-artifact work settings. However, they do not define a formal model or method to facilitate others in replicating their approach. Ann Blandford and Dominic Furniss sought to fill that gap by proposing a method for applying DCog to a multi-agent system in a way that supports reasoning of strengths and weaknesses of the system (Blandford & Furniss, 2006; D. Furniss & Blandford, 2006). In response, they developed the Distributed Cognition for Teamwork (DiCoT) method. DiCoT is a codified method for applying DCog theory to the analysis of socio-technical systems. It focuses on the transformation and propagation of information in socio-technical systems, and guides the analyst in building models to capture the information flows, physical layouts and artifacts of multi-agent systems.

Blandford and D. Furniss present DiCoT through a study of an Emergency Medical Dispatch (EMD) work system in an exploratory, iterative approach of reviewing literature, data collection and analysis (Blandford & Furniss, 2006; D. Furniss & Blandford, 2006). They employed contextual inquiry to combine observation and interview with the context of study. Findings are presented as three separate model types—physical model, information flow model, and artifact model. The granularity of each model can adapt to what is relevant to the study. For example, the authors describe the physical organization of work in the EMD at two levels of granularity, a room-level model, which shows the layout of multiple desks, and a sector desk-level model, which shows more detail for one desk. The diagrams rely on visual representations as well as rich textual descriptions of the physical and communication structures and processes that support the work system to achieve its goals.

In the case of the information flow model, the researchers developed three perspectives to capture different aspects of the way information transferred around the EMD system. The first is a high-level view that focuses on the overall input, transformation, and output of the system (D. Furniss & Blandford, 2006). The second is an agent-based view that "focuses on the principle agents within the system and the flows between them. The properties of each of the main communication channels are identified" (p. 1184) (D. Furniss & Blandford, 2006). They describe the third view of the information flow model as an adaptation of the second. It focuses "on how information is buffered, filtered, and transformed with the system (referring specifically to the principles for information flow presented above)" (p. 1184) (D. Furniss & Blandford, 2006). The models give unique perspectives of the activity system that complement each other. For example, the information flow models focus on information without showing the interactions between humans and their computer systems and without paying much attention to the design of the computer systems or other media used to communicate the information. These are shown in the artifact model (D. Furniss & Blandford, 2006). The intent of the DiCoT approach is to use the models as a basis for discussion.

DiCoT has also been applied to analyze safety critical systems such as Emergency Medical Dispatch (EMD) (D. Furniss & Blandford, 2006), use of medical devices (i.e., infusion pumps) in an intensive care unit (Rajkomar & Blandford, 2012), mobile healthcare work (McKnight & Doherty, 2008), and underground line control (Webb, 2008). In 2014, Dominic Furniss and colleagues introduced an extension to DiCoT, the DiCoT Concentric Layers framework (DiCoT-CL). It focuses on how technology is coupled to different layers of sociotechnical context. DiCoT-CL is intended to guide implementation, evaluation, and use of medical devices and how they are embedded with their work system (D. Furniss et al., 2015). To do so, it can provide insight at both the micro-level (e.g., specific issues with the interface) and macro-level (e.g., problems with the way the device was configured when it was purchased months or years previously). "The ultimate purpose of DiCoT-CL is to identify issues and make recommendations for improving the technology and the sociotechnical system it is embedded within." It has been used to examine how an impatient blood glucose meter is coupled with its context (D. Furniss et al., 2015).

Other approaches to studying information flow surfaced in the literature review. For example, Tang and colleagues developed the InfoFlow Framework to guide data collection and analysis to describe information flow process, and to evaluate impact of new health care technologies on information flow (Tang et al., 2010). The framework was developed based on findings from a review of literature and their own studies of nurses' collaborative work, but is not theoretically grounded.

Theoretical grounding assists in development of evaluative questions, assessing and analyzing across instances and settings, and extrapolating findings across similar situations. Questions guiding a DCog propagation of representational states analysis are (also see Questions 1-6 in Table 3): What are the components of the activity system used to complete work (i.e., tools, actors, settings, representational states, etc.)? What is the sequence of interactions and representations that occur in workflow? How do clinicians manage information and coordinate care? What are barriers to information flow that may cause delays or errors in care delivery? How are the technologies limited in supporting clinicians' information management and coordination processes? Where and how can the activity system better support clinicians' information management and care coordination processes?

Summary of Propagation of Representational States

To optimize system behavior and human performance in patient care delivery in a given activity system, information flow and information processing events must first be understood. A *propagation of representational states* analytic approach enables this. It can be used to characterize the sequence of interactions and representations that occur in workflow and how clinicians manage information and coordinate care. These findings can be evaluated for barriers to information flow that may cause delays or errors in care delivery and how technologies are limited in supporting clinicians' information management and coordination processes. In addition, implications can be drawn for where and how the activity system can better support clinicians' in these processes.

The literature examines how the DCog conceptual framework can inform research into workflow analysis in clinical environments. However, DCog researchers have faced challenges in having a method that takes them from analysis to design (Wright et al., 2000). DRM can be used to classify how abstract resource structures can be coordinated to produce behavior, but is limited in application to a single-user, single-system. DiCoT method was developed to guide DCog analysis of collaborative work. While the DiCoT method better supports DCog's role as a descriptive framework by guiding descriptive models that can be used to facilitate design discussions, it, like other DCog analyses, yields only descriptive results. Something else is needed; therefore, this research also draws on cognitive engineering approach for approaches and assumptions for examination and analysis of human performance and system behavior.

Cognitive Engineering (CE)

Cognitive engineering (CE), also known as cognitive ergonomics and cognitive systems engineering, focuses on the understanding of human cognitive abilities and limitations in the context of work in order to improve overall performance of human-artifact work systems by supporting actors' cognitive work (Hoc, 2001; Patel & Kaufman, 2006). The goal is to enable the human to more effectively perform work by providing a better fit between the human user and the system. It seeks to support the cognitive functions associated with users' behavior through the design of IT systems that support cognitive work, such as the design of system components (e.g., user interfaces, automation, decision aids, and training). It can also lead to supporting human's cognitive performance through development of training programs and work redesign to manage cognitive workload and increase human reliability. Such efforts to support and improve human's cognitive performance can be particularly important for systems where the human user has to obtain information from various sources for reasoning and decision-making.

Cognitive engineering is a multidisciplinary approach concerned with the analysis, design, and evaluation of complex systems of people and technology to support human performance (Roth, Patterson, & Mumaw, 2002; Vicente, 1999). It draws on knowledge and experience from cognitive science, human factors, human-computer interaction design, and systems engineering (Gersh, McKneely, & Remington, 2005). It can be distinguished from these applied research disciplines in "its specific focus on the cognitive demands imposed by workplace environments" (Gersh et al., 2005). Figure 8 again shows the image of a typical moment in a nurse practitioner's work. In this case, the overlays convey the focus of CE analysis, which is on the interactions between the user and the computer.

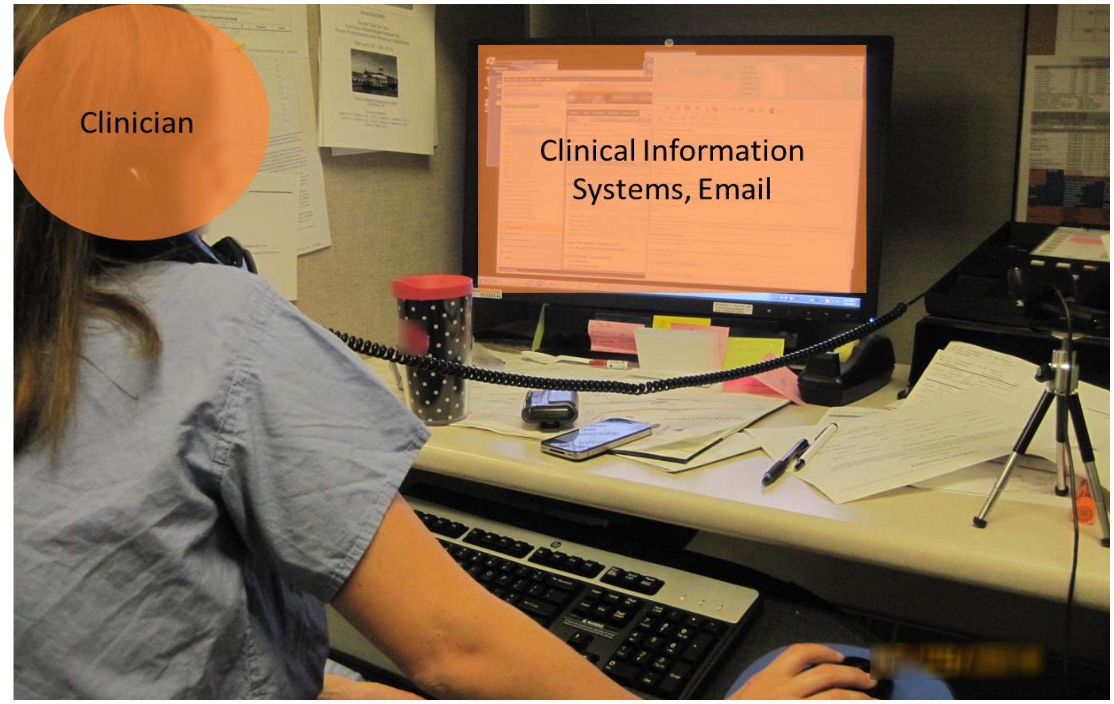


Figure 8. Cognitive engineering (CE) focuses on human-computer interactions.

In analyzing performance, the focus is on cognitive functions, such as attention, perception, memory, comprehension, problem-solving and decision-making (Kushniruk, Kaufman, Patel, Levesque, & Lottin, 1996; Norman, 1986). Cognitive engineering approaches are useful to iterative design and development of user-centered technologies. To guide design of computerized systems to support human performance, cognitive engineering approach has a focus on both the usability of the system or interface in question and in the analysis of users' skills and knowledge. It assesses usability and system complexity as reflected in cognitive load from both a quantitative and a qualitative perspective. Further, it can be used to identify clinicians' information processing needs. A user's interactive effort is determined by the physical interactions and mental (cognitive) processing performed to complete a task or goal. For example, the organization and representation of information and controls (i.e., buttons, scroll bar) on a user interface dictates the interactions required between the user and computer and, consequently, the usability of the system. A poor design is one that increases cognitive and/or physical effort required by the user. Highly complex EHR tasks coupled with poor integration of technologies into clinical workflow may serve to increase cognitive load and diminish resources available for clinical reasoning. Effective or optimal design that frees cognitive resources is important to support clinicians in delivering high quality, safe and timely care.

Cognitive engineering methods emphasize observation and **cognitive task analysis** in real work environments. A cognitive task analysis represents people performing tasks using concepts and tools of their work environment. It is useful for measuring and modeling users' cognitive activities that drive observable behaviors. Saitwal and colleagues (2010), for example, employed a cognitive task analysis approach to examine the complexity of an EHR interface (Saitwal, Feng, Walji, Patel, & Zhang, 2010). They provided quantitative evidence of the cognitive load on the user when completing key clinical workflow tasks related to information management and coordination (e.g., documentation and order entry). Specifically, Saitwal and colleagues found users faced three main challenges when navigating the EHR interface to complete 14 EHR-based tasks: (1) large number of average total steps to complete a task, (2) high average execution time, (3) large percentage of mental operators (Saitwal et al., 2010). Mental operators are mental procedures or actions performed by the user, such as retrieving information from memory, making a choice. As a result, they could suggest that the user interface could be improved by reducing (1) total number of steps and (2) the percentage of mental effort required to complete the tasks (Saitwal et al., 2010). This study by Saitwal and colleagues demonstrates how a cognitive engineering approach, in particular a cognitive task analysis, enabled researchers to quantify interactive behavior to drive interface design improvements.

The increasing use of technology in clinical settings to support patient care delivery along with advances in computational analysis tools have made way for the emergence of new data sources and new techniques for analyzing user behavior. Computer technologies provide system-generated data, which enables a larger data set then is reasonable for observation/ethnography-only studies. In fact, Hollan and colleagues foresaw this advancement toward use of automated data. They stated, “In human-computer interaction settings we expect automated recording of histories of interaction (Hill & Hollan, 1994) to become an increasingly important source of data” (Hollan et al., 2000). I draw on computational ethnography techniques to examine system-generated data of user behavior and to examine other descriptors/measures of efficient and effective user interaction.

Computational Ethnography Techniques

Computational ethnography is an emerging set of methods for conducting human-computer interaction (HCI) studies in healthcare and other domains (Zheng, Hanauer, Weibel, & Agha, 2015). Zheng and colleagues (Zheng et al., 2015) define computational ethnography as:

> *“a family of computational methods that leverages computer or sensor-based technologies to unobtrusively or nearly unobtrusively record end users’ routine, in situ activities in health or healthcare related domains for studies of interest to human–computer interaction.”*

Computational ethnography leverages automated methods to capture users' actual behaviors using a system or a device in real-world settings. It combines the richness of ethnographical methods with the advantages of automated computational approaches. Computational ethnographic methods include sequential pattern analysis and temporal process mining.

Sequential pattern analysis examines a large number of sequential events for recurring patterns or other meaning (Sanderson & Fisher, 1994). For example, Kannampallil and colleagues employed sequential pattern analysis to compare information-seeking strategies of different clinicians in critical care settings (Kannampallil et al., 2013). Specifically, they characterized how distributed information was searched, retrieved and used during clinical workflow. They concluded that there are costs (e.g. effort, time, and cognitive load) associated with particular strategies. Similarly, Zheng and colleagues investigated users' interaction with an EHR by uncovering hidden navigational patterns in EHR-generated logfile data (Zheng, Padman, Johnson, & Diamond, 2009). They identified the patterns of display features that users' accessed to complete a documentation task. Some patterns varied from the pathways that the designers and individuals in clinical management considered optimal.

Summary of Cognitive Engineering Analytic Approach

Improved health IT can facilitate clinicians in effective and efficient work by addressing the impact of interface design and system usability on clinicians' cognition. Therefore, a workflow methodology for examining clinical work needs to incorporate CE approaches to understand and assess the human-computer interactions related to information management and care coordination processes, and to inform improved design and system usability. Influence from computational ethnography techniques enables exploration and development of other measures of interactivity (e.g., sequence of users' interactions, variation across tasks, users or patient types). Questions guiding CE analyses (also see Questions 7-13 in Table 3): What interactive effort is involved in clinical work? How does interactive effort vary among clinicians, by task and/or patient case? What explains variation in users' measures of interactive behavior? What variation indicates a user is having difficulty? What are sources of complexity? Where would training resources be best allocated to reduce unnecessary variation? What interface design would reduce unnecessary user variation?

Integrating findings from computational ethnographic analysis with a CE approach would suggest different interface designs the facilitate users in following optimal patterns of interaction. Further, the analysis can be used in combination with other forms of data, such as ethnography or video-capture of end-users performing clinical tasks.

Table 3. Summary of theoretical assumptions, constructs, methods and questions relevant to the Methodological Framework.

	Distributed Cognition (DCog)	Cognitive Engineering (CE)
Goal	To describe how distributed components of the activity system are coordinated.	To improve human performance by improving the "fit" between the human user and technologies.
Assumptions	• There is much shared knowledge between individuals in an activity system, which impacts processes and communication practices. While some knowledge possessed by individuals is redundant, some is highly variable. • "Sharing access and knowledge enables the coordination of expectations to emerge which in turn form the basis of coordinated action" (Rogers, 1997). • Propagation of representational states reveals cognitive behavior of the activity system through focus on interactions (E. Hutchins, 1999). • Change to the flow of information can change behavior of the system. Likewise, change to a component of the activity system can change information flow. • When work is segmented into representational states, trained analyst can examine how past changes in the activity system affected workflow (retrospective) and project how future changes will affect workflow (prospective).	• Design of health IT affects users' cognitive work. Can improve human performance through design of health IT systems (interfaces, automation, decision aids, training). • Focus is on cognitive functions such as attention, perception, memory, comprehension, and decision making (Kushniruk et al., 1996; Norman, 1986). • Dual focus on the usability of the system or interface in question and in the analysis of users' skills and knowledge. 　○ Highlights the discrepancy between user's psychologically expressed goals and the physical controls embodied in a system (Roth et al., 2002). • Measures of interactive behavior examine fit between the human user and the system.
Constructs	Activity System, Cognitive Artifacts, Representational States, Information Flow	Cognitive Task Analysis, Usability, Quantitative Descriptors, Sequential Patterns

Methods *Data Collection*	• Cognitive ethnography including audio and video ethnography and artifact collection to capture distributed work • Interviews	• Video-analytic capture methods to focus on single-user single-system work (e.g., Morae video capture) • Think aloud protocols • System-generated data (e.g., system event log files)
Data Analysis	• Propagation of representational states (Problem-centered) • Information-centered and goal-centered models of information work • Qualitative analysis • Components of the activity system described	• Cognitive Task Analysis (Clinician-centered, EHR-based tasks) • Quantitative analysis of interactive behavior • Process mining techniques to include sequential pattern analysis (Cognitive Ethnography) • Qualitative analysis of think aloud protocols
Questions *To Characterize*	(1) What are the components of the activity system used to complete work (i.e., actors, artifacts, settings, etc.)? (2) What is the sequence of interactions and representations that occur in workflow? (3) How do clinicians manage information and coordinate care?	(7) What interactive effort is involved in clinical work? (e,g., mouse clicks, task duration, sequence patterns, etc.)? (8) How does interactive effort vary among clinicians, by task and/or patient case?
To Evaluate	(4) What are barriers to information flow that may cause delays or errors in care delivery? (5) How are the technologies limited in supporting clinicians' information management and coordination processes?	(9) What explains variation in users' measures of interactive behavior? (10) What variation indicates a user is having difficulty (either because of system or interface design or the user's skill and knowledge)? (11) What are sources of complexity?
To Improve	(6) Where and how can the activity system better support clinicians' information management and care coordination processes?	(12) Where would training resources be best allocated to reduce unnecessary variation? (13) What interface design would reduce unnecessary user variation?

Summary & Discussion

There is a need to scrutinize the way clinicians communicate, coordinate their work, and jointly perform problem-solving tasks (Perry, 2003). Particularly, there is a need for an integrated, in-depth approach that captures work processes across tools, people, and conversations, and at varying levels of granularity can inform improved design and use of health IT. Data analyses need to be guided by theoretical and methodological frameworks. This chapter introduced these two theoretical and methodological frameworks that inform this dissertation research—distributed cognition (DCog) and cognitive engineering (CE). Together, they provide a useful set of approaches to examine individual and team decision-making and problem-solving, and can be employed to guide design of information systems that improve human performance. Table 3 summarizes these theories and frameworks with constructs, methods for data collection and analysis, and guiding questions relevant to this dissertation work.

Each framework has specific foci and/or methods for studying workflow, but each addresses only a subset of the important layers of workflow analysis. Each of these are important to examining workflow to inform improvements. The propagation of representational states approach is employed to characterize information flow and to trace the trajectories of high-value concepts that are instrumental to clinical care. Cognitive task analysis is employed to quantify the patterns of interaction. Computational ethnography is employed to inform temporal/sequential data mining used to evaluate patterns of interaction.

Drawing on these approaches, this research develops a micro-analytic strategy in which workflow is broken down into constituent people, tools, information needs, and the interactions between them. The method can be used to analyze performance for both short tasks and longitudinal care processes (e.g., monitoring and managing a patient's pain level). It can identify critical features of the work domain and features of distributed team cognition. It can surface implicit knowledge, decision-making processes and work contexts. It can quantify the people, artifacts and operations involved in information management and care coordination processes, as well as model the information flow across artifacts in these processes. The method can identify interactions and dependencies between people, artifacts, and operations, allowing researchers to inform how improved health IT and information tools are designed and implemented.

Chapter IV

THE CLINICAL SETTING: COMPONENTS OF THE ACTIVITY SYSTEM

Introduction

This chapter provides a contextual description of the study site and corresponding activity system. This content would typically be presented in the methods chapter, but I chose to present it separately from the remaining methods to emphasize that the methodological framework can be applied to workflow in any clinical environment.

I drew on the Workflow Elements Model (WEM) developed by Unertl and colleagues (2010) to describe components of the activity system—the actors, artifacts, actions and their characteristics. The focus is on the components relevant to the analyses presented in the next chapter.

Setting

Research was conducted at the Colon & Rectal Surgery (CRS) Department at Mayo Clinic Hospital in Rochester, MN (CRS Rochester), an inpatient hospital setting at an academic tertiary healthcare center. Data collection occurred for two weeks, over two separate time periods.

This work represents an extension of a surgery practice redesign project that was seeking to understand clinical processes and information needs to inform design of new technologies that can improve patient safety and the quality and efficiency of health care delivery. It was reviewed by the Mayo Clinic Institutional Review Board (IRB) and judged to be exempt as human subjects' research.

Actors (Participants)

In CRS Rochester, patients are cared for by surgeons, fellows, resident physicians, nurse practitioners (NPs), physician assistants (PAs), nurses, and pharmacists. Other departments (e.g., social work, intensive care unit, urology, cardiology, etc.) may also be consulted. Hospitalist, in this context, refers to NPs and PAs who have responsibilities similar to a resident physician (e.g. order entry, progress note and dismissal summary documentation, patient education) but are employed by the department. Surgery residents work for an attending surgeon's service for 6-weeks before cycling to their next service.

I observed six clinicians perform various clinical tasks in their natural work setting and in context of their daily clinical workflow. Users' were four hospitalists, a PA (H1) and three NPs (H2, H3 and H4), and two residents, a 2nd year (R1) and 4th year (R2). H1, H2, H3 and H4 were experienced users of the system and routinely performed the tasks I observed. At the time of observation, they had worked in the unit between two and three years. R1 and R2 were doing a rotation in the unit and were less experienced users of the system in this setting. This study was centered on the hospitalist or resident physician, who shared responsibilities for coordinating across members of the patients care team, delivering direct patient care, order entry and documentation.

Artifacts

Clinicians at CRS Rochester rely on a number of computer and paper-based information sources (i.e., artifacts) to manage information and coordinate care. It is important to note that the computer artifacts are a set of disparate health IT systems. Consequently, the screen format and style of interaction for each differ substantially.

Select artifacts that are relevant to the task analyses are summarized in Table 4. Descriptions are derived from observed functionality and information available on the Mayo Clinic intranet, including a systems inventory.

Table 4. Computer and paper-based artifacts used in CRS Rochester.

Artifacts	Description
Computer-based	
Synthesis[a]	Clinical data aggregation and visualization tool. See Figure 9.
MICS LastWord	Mayo Integrated Clinical Systems (MICS) are an integrated group of electronic applications that support patient care at Mayo Clinic's Rochester campuses. MICS LastWord is the navigation structure that enables users to move across MICS applications. It consists of home screens, chart tabs, drop down menus, buttons and a patient banner similar to the one in Synthesis.
MICS Orders	The inpatient order entry application used primarily by hospitalists and residents. It is also used by clinicians to review all orders that have been placed for a patient.
MICS Clinical Notes[a]	Used for most documentation, to include daily progress notes, discharge summary and hospital summary documents. It facilitates data transfer for the completion of the progress note document.
QREADS	To view electronic images, such as CT scans, and radiologist's reports.
Flowchart (Chart+)	Part of an application used by nurses for documenting patient data.
Electronic Service List (ESL)	Web-based application that provides a high level summary of each patient, organized by each surgical service. It is a working document to facilitate clinicians' shift transitions. It is populated with patient data pulled from other systems (e.g., patient information, vital signs), admission note (e.g., problem and diagnoses), order entry application (e.g., medications), from the post-operative note (e.g., surgeries and procedures), and lab system (e.g., labs). Clinicians also document patient data directly into the ESLs (i.e., 'What Has Happened', 'What am I Worried About', 'Pending Tasks/Plan'). Hospitalists and residents typically update and review the ESL content for each patient under their care at the end of shift.
Shorthand	An Enterprise-wide application. It enables keystrokes for entry of information into applications. It has been leveraged to make EHR data entry more efficient and consistent.
Paper-based	
Paper ESL[a]	Print out of the web-based ESL. Clinicians' often annotate the paper artifact with patient information, tasks, and reminders. See Figure 12.
Follow patient list	List of patients who require consultations by the surgical service, but are primarily under the care of another department.

[a] These artifacts are further detailed in this section.

Synthesis is a customized interface developed by Mayo Clinic in Rochester, MN, for electronic health record (EHR) data aggregation and visualization. It offers users a single, integrated view of information from many sources—to include LastWord, Chart+, Remote View, QReads and other EMR systems. The Synthesis application window includes a list of patient records in a panel on the left side of the screen (the Navigation Panel). Synthesis includes a number of screens, separated into tabs, for viewing patient data. There are a total of 13 tabs, to include Summary, Labs, Medications, Vital Signs, Intake/Output, Documents/Images and Viewers/Reports. The Documents/Images screen is shown in Figure 9. Several tabs have subtabs which allow access to other screens.

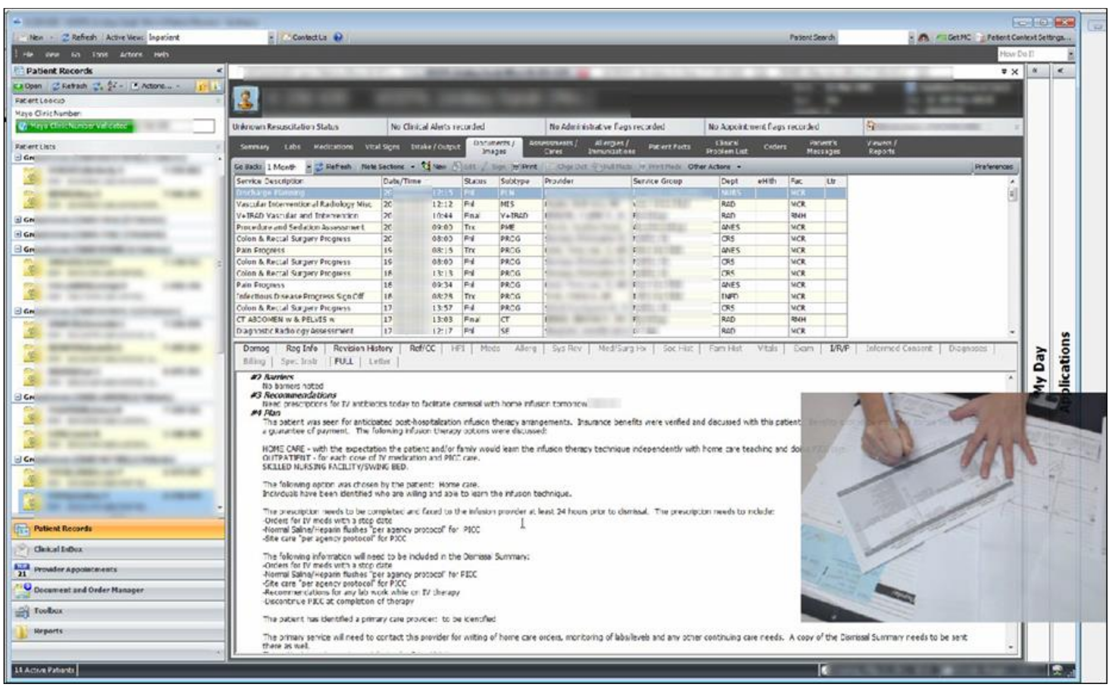


Figure 9. Screen capture of Synthesis EHR, when the Documents/Images tab is selected.

For all participants, the Summary screen is divided into six equally sized sections, each with a predefined subset of patient data for Allergies, Intake/Output, Medications, Documents, Vital Signs, and Labs. For example, only the patient's vital signs and lab data from the last 24 hours is shown in the Summary screen.

I collected Synthesis (EHR) event log files for 6-8 weeks for each of the 6 clinicians. The dates overlap with my on-site observations. For each resident, the 6-week period overlaps with their full 6-week rotation in the CRS department.

MICS Clinical Notes application is used by the hospitalists and resident physicians in CRS Rochester for all their documentation tasks, to include daily progress notes, discharge summary and hospital summary documents. The progress note document is made up of ten sections. Figure 10 shows a screen capture of a progress note while the participant is completing the service details (information along the top blue band of the display).

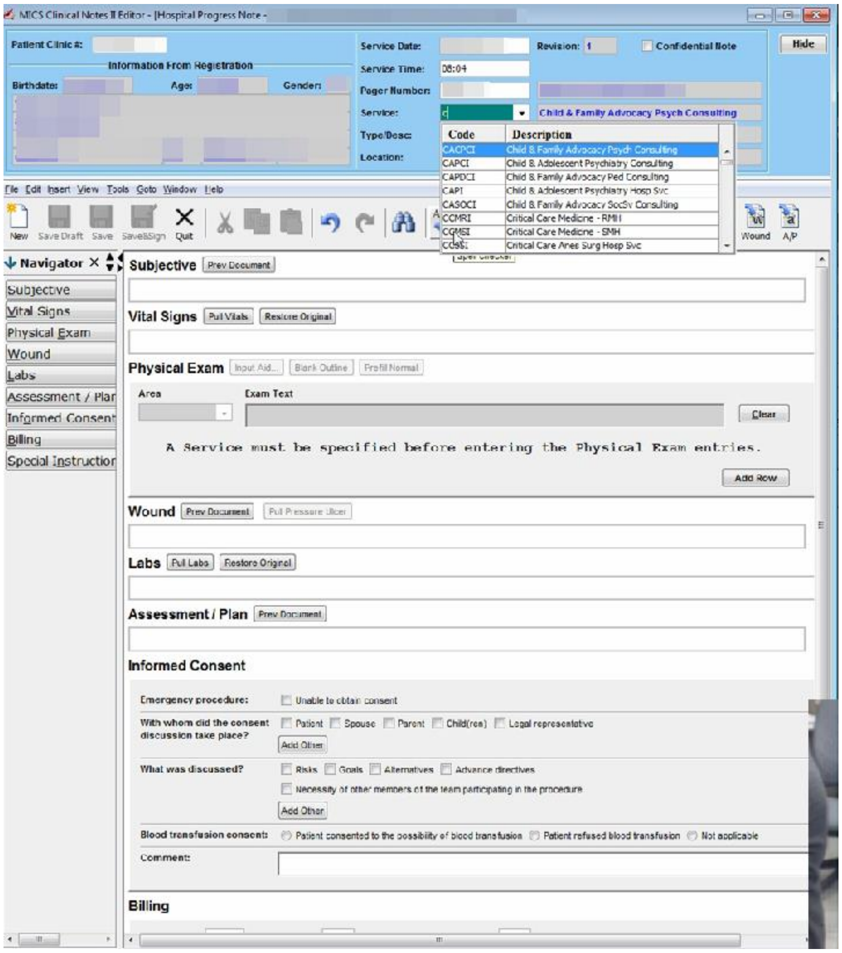


Figure 10. Screen capture of a progress note document template in MICS Clinical Notes application.

It facilitates data transfer for the completion of the progress note document. When selected, some buttons on the document screen pull in the patient’s most recent laboratory data, another button to pull in the patient’s most recent vital signs, and another that facilitates reuse of assessment and plan text from previous documents. While the first two mentioned pull in and populate recent data, if there is any, the third (i.e., the Assessment and Plan “Pull from Previous Document” feature) facilitates data review and reuse from past documents in the patient’s chart (Figure 11).

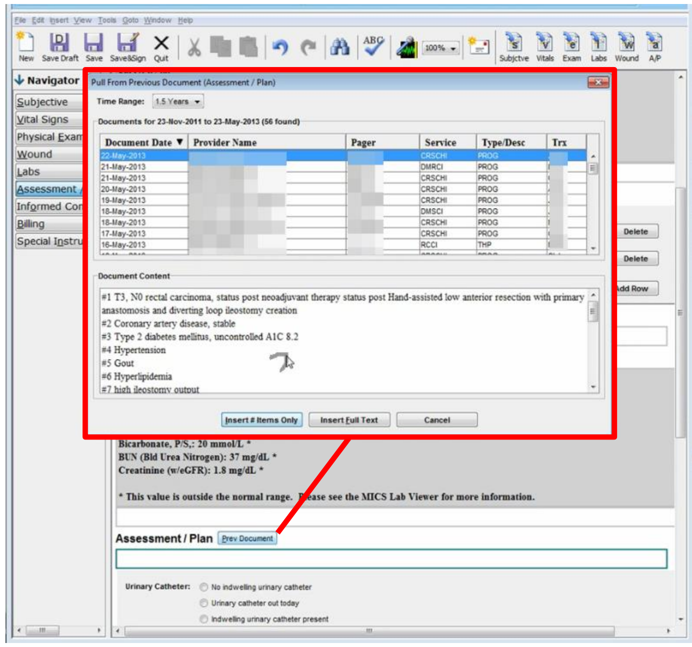


Figure 11. Screen capture of the "Pull from Previous Document" dialog box (shown outlined in a red box), which assists clinicians in reusing text from previous documents in the patient’s chart. The dialog box is in front of a progress note document window. The red line points to the “Prev Document” button located on the progress note document.

The **Paper ESL** was the primary paper-based resource used by each observed clinicians for all patients under their care (Figure 12). Paper ESLs have the same tabular format and categories as the computer-based ESL. Prior to InfoGather, at the beginning of their shift, hospitalists, residents and fellows print the paper ESLs for the surgeons’ services they are covering that day. A **surgeon service** refers to the patients assigned to a particular surgeon. It includes the patients that the surgeon operated on, and patients that the surgeon has been asked to consult on. During InfoGather, clinicians annotate the paper ESLs with patient information acquired from Synthesis (e.g. oral intake volume, urine output volume, stool count). They also note patient care tasks (e.g. order labs, order INR, order Sinogram), and reminders (e.g. follow up with Social Work, discharge today).

Figure 12 shows a paper ESL with a hospitalist's annotations after reviewing data for three patients. Clinicians continue to use—reference information and notes, and modify with annotations—the paper ESL throughout their shift. For example, immediately following InfoGather, hospitalists and residents round together in Resident Rounds, and round with the surgeon in Consultant Rounds soon after. During rounds, clinicians refer to information on the paper ESL as they review and discuss each patient's plan of care in view of recent patient data and make decisions to continue or revise the patient's care plan.

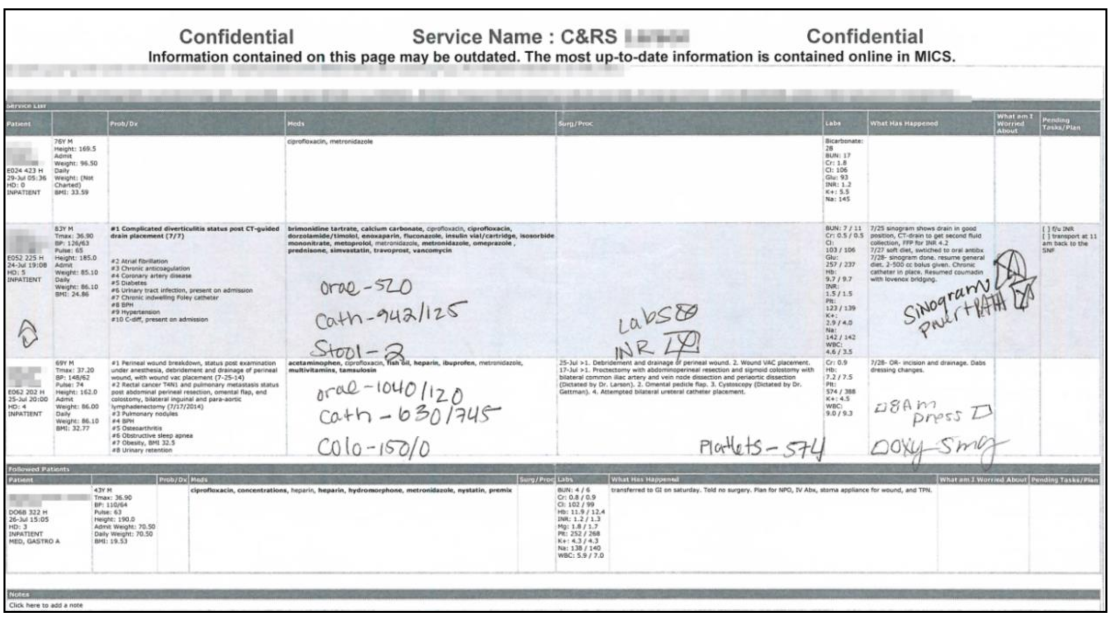


Figure 12. Image of a paper print out of the Electronic Service List (Paper ESL) with a hospitalist's annotations.

The printed ESL is usually discarded at the end of shift, though hospitalists may save printed ESLs for a few days in case they need to refer back to it. Use of the paper ESL to support workflow may affect patient care delivery workflow because the items (e.g., tasks. reminders) written on the paper ESL are not actionable, data on the paper ESL are not accessible to other members of the team, and updates of patient information in the EHR are not known to the clinician until she reviews the EHR again.

Tasks

Routine health IT-mediated clinical tasks in CRS Rochester include pre-rounds information gathering (InfoGather), daily hospital progress note documentation (ProgressNote), hospital summary documentation, discharge note documentation, order entry and handoff. I applied the methodological framework to study two tasks, InfoGather and ProgressNote. The tasks were similar for all clinicians. The following task descriptions are based on observations and interview data.

Pre-Rounds Information Gathering Task (InfoGather): Both hospitalists and residents individually perform InfoGather near the beginning of each shift and prior to rounds, for each patient under their care. Hospitalists and residents round together immediately afterwards. The goals of InfoGather are to gain awareness of current patients under their care, project future patient needs, and project their workload for the day's shift, to include patients to be discharged from the hospital and new patients to arrive that day(Burton, 2013). It is clinicians' first task and serves to anchor their understanding of their patients and their workload. To complete the task, each clinician reviews the most recent information on the patient medical status and care plan in computer- and paper-based information artifacts, and annotates a paper document that is subsequently referenced and modified throughout their shift. InfoGather occurs about the same time every day, is rarely interrupted and is well-bounded by time.

Progress Note Documentation (ProgressNote): Each day, one progress note is documented for each patient. It may be completed by the hospitalist or resident. It serves as a written medical legal document in the patient's medical record. The goal of the task is to document and communicate the patient's current medical status, updated care plan and pertinent issues. To complete the task, the clinician records events that occur during the hospitalization in terms of subjective and objective findings, include patient's new and active clinical problems, as well as the appropriate plan for each problem. ProgressNote may be started later in the morning—after Rounds—and notes are worked on and completed throughout the day as the clinician has time, which depends on workload, interruptions, and competing tasks.

Chapter V

METHODOLOGICAL FRAMEWORK: A MICRO-ANALYTIC APPROACH TO EXAMINE CLINICAL WORKFLOW

The contents of this chapter contain the proposed methodological framework in full. It was developed iteratively from review of literature, data collection and analysis. Development of some of the analysis techniques were published in two conference papers, which are presented in Appendix B and C.

Data Collection

The following methods were employed to capture the breadth of clinical work in the context of clinicians' routine workflow: (a) semi-structured and opportunistic interviews, (b) observation and shadowing of a clinician, (c) video ethnography of clinicians coordinating patient care, (d) Morae™ video capture and think-aloud protocol of users engaging in a series of health IT-based tasks across their work shift, (e) artifact collection including paper documents that serve to structure or enhance cognition, (f) collection of health IT-generated log files and (g) patient chart review. These methods are described in detail in this section.

Data were collected for a total of ten days across two periods of time about a year apart. During observation, I collected data on clinicians performing various clinical tasks to include InfoGather and ProgressNote. For InfoGather, video ethnography, Morae™ software and think aloud were used to capture five of the six clinicians for a total of 66 patients (H1=9, H2=21, H3=16, R1=14, R2=8). For ProgressNote, video ethnography, Morae™ software and think aloud were used to capture four of the six clinicians for a total of 21 patients (H1=9, H2=8, H3=2, R1=2).

I retrieved EHR-generated event log files for six participants for the six-week period that coincided with the residents' (R1 and R2) rotation in CRS Rochester. For the four hospitalists, I also retrieved EHR event log files for an additional two-week period that coincided with other observations in the department.

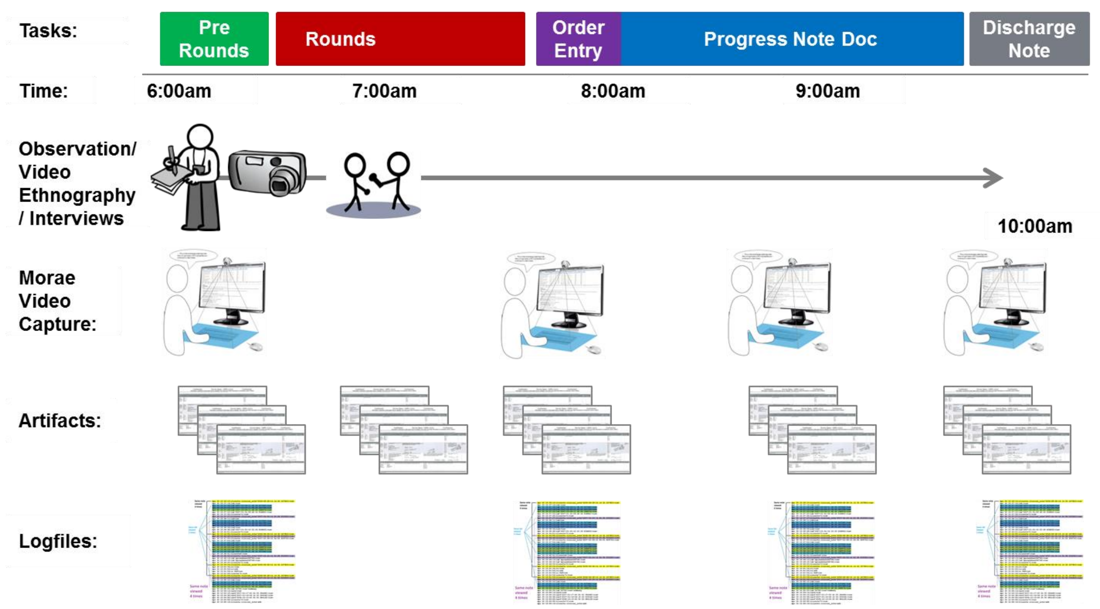


Figure 13. Illustration of a hospitalist's clinical tasks from 6-10:00am and data collection methods associated with each task.

Semi-Structured Interviews: For this research, I drew on semi-structured interviews with clinicians from varying roles (e.g., hospitalist, a senior resident, and nurse) conducted by Dr. Matthew Burton and Robert Sunday of the EASE project team. They used the Clinical Activity Interview Script, a tool in the Clinical Workflow Capture and Analysis Framework developed by Burton and colleagues (Burton, 2013). The questions aim to reveal details of clinicians' key work activities, to include purpose or goal, tasks associated with each activity, resources used, task sequence, and information and personnel dependencies. I reviewed video recordings of these interviews to inform my understanding of work practices and other components of the activity system.

Observation & Opportunistic Interviews: I conducted ethnographic observations in the context of the real work environment in CRS Rochester. Observations occurred over seven separate days between May 2013 and August 2014. Observation centered on the clinician role in the department that is responsible for coordinating across many members of the patient's care team, delivering direct patient care, order entry and documentation. In CRS Rochester, both hospitalists and residents shared these responsibilities. Participant selection depended on the clinician and care team's agreement to participate. Researchers asked participants questions during observation as participants' time and work permitted (opportunistic interviews).

Video Capture of Computer Displays: I employed Morae™ video capture software and think-aloud protocol of participants engaging in health IT-mediated tasks to allow for retrospective task analysis. Morae™ software was used for usability studies and it records users' activity with no interruption to the user's work (Patel & Kannampallil, 2015). The software provides a screen capture and a set of analytics (e.g., mouse clicks, keystrokes, and web-page changes). Through the use of a webcam, audio of participants verbalizing their thoughts (think-aloud) is captured as well as video recording of the participant's face or hands.

Think-Aloud Protocol: Clinicians were asked to think-aloud as they performed health IT-based tasks to reveal activity, goals, and cognitive processing. Verbalizations were transcribed verbatim for analysis. They help identify clinicians' information needs and to reveal cognitive activity that is not explicit in observed activity.

Video Ethnography: A researcher followed a clinician using a hand-held camera to capture video and audio of clinicians' work activities. The recording was continuous unless circumstances indicated a need to stop recording. The video recording of clinicians' work allowed for retrospective analysis, and captured the broader context of clinicians' work, such as tools used, locations where work is conducted, other actors involved, and facial expressions. This is particularly important to examine information flow and interactions beyond an individual clinician interacting with a computer.

Artifact Collection: Paper artifacts used by participants were collected or documented as a scan or photo. If an artifact was modified by the participant, pictures of the artifact were captured to document when and how the artifact was changed.

Log File Collection: System-generated event log files were collected for the observed participants and the primary EHR application (Synthesis) used by participants. Each event in the log file is recorded in a separate row or tuple, with associated metadata. At minimum, each event has a User ID (i.e., clinician ID), an Event Description (e.g., "Activated tab: Labs") and a Time Stamp (with date and time). Events that are associated with a patient chart also have the patient's clinic number.

Medical Chart Review: Selected patient medical charts were reviewed by the first author and a clinical collaborator (Robert Sunday) to determine the clinical context and complexity of patient cases based on criteria such as patient's primary diagnosis, surgical procedure, acuity, co-morbidities, number of specialists involved and length of hospital stay for the given visit, and number of medications the patient was on at admission. This data can be found in the data and documentation in patients' charts (e.g., admission note, pre-operative consultation note, daily progress notes, etc.).

Data Analysis

I employ a number of data analysis methods to characterize and evaluate information flow in DCog analysis and interactive behavior in the CE analysis. Further, I triangulated methods in search of converging evidence. Figure 14 illustrates the relationships between the data collection and analysis methods. Additionally, it clarifies how the DCog and CE analyses differ and where they overlap. Several DCog methods were used, including the analysis of representational states and informational flows around the media carrying these representations (e.g., EHR displays, paper artifacts). Several CE methods were used, including quantification of interactive behavior from coding and analytics, and process mining analysis. The methods focus both on aggregate behavior (across all patients and clinicians) and in-depth case studies (e.g., problems of unusual complexity) focusing on a single clinician or patient. In this section, I'll describe the analysis methods. In the subsequent section, Analyses Demonstrated, I'll present the analysis methods in greater detail by demonstrating them with the data set from CRS Rochester.

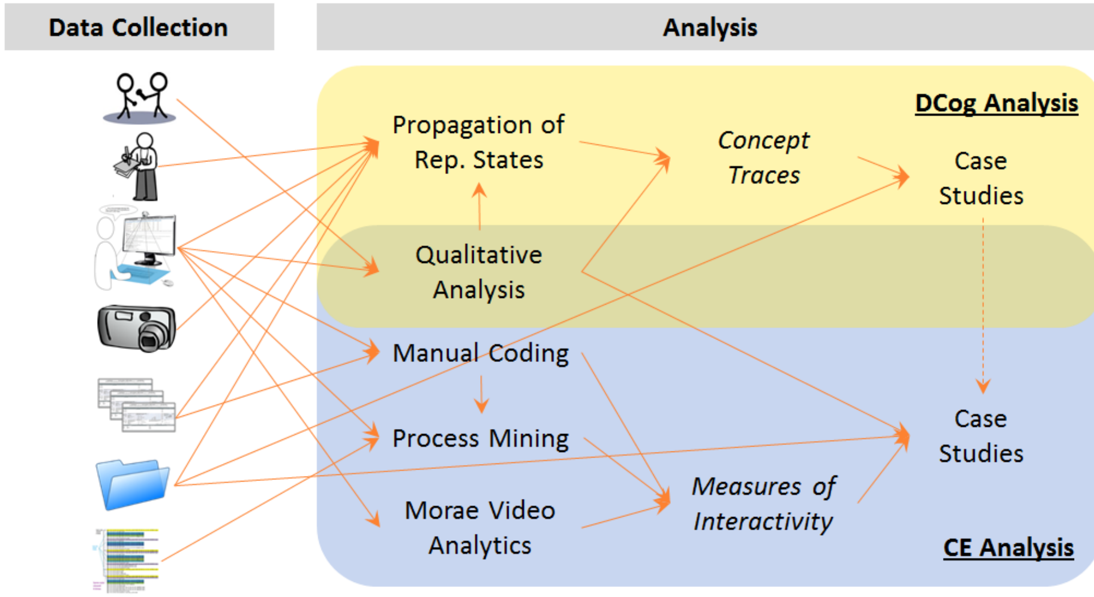


Figure 14. The Methodological Framework, showing the relationships between data collection and analysis methods.

Qualitative Analysis: Participants' think-aloud verbalizations, conversations and responses to opportunistic and semi-structured interviews were transcribed verbatim. The goal of qualitative analysis was to surface information the clinician was actively thinking about as well as how this information is used and transformed in clinicians' decision-making and problem-solving processes. It reveals cognitive activity that could not be observed in clinicians' interactive behavior or annotations. Conversations between clinicians were used to assess how patient information was shared, processed, and transformed between members of the care team to support patient care delivery. Think-aloud protocols recorded in concert with observable behavioral data, such as a participant's actions, enabled me to further characterize cognitive processes. This analysis was illustrated in the context of select case studies to answer both DCog and CE questions in Table 3.

A Micro-Level Analysis of the Propagation of Representational States: This approach characterized information flow in the activity system to examine information management and coordination processes. The analytic focus was on interactions between components of the activity system. A six-step process guides analysis of information flow and interactions in relation to clinician's work for an individual patient over a stretch of time. The approach integrates several types of captured data to characterize information flow across media, representations, conversations, actors and time (see also (S. K. Furniss, Burton, Larson, & Kaufman, 2016). Here, the focus was on patient issues related to high-value care goals that are applicable to patient care management in all post-surgical environments. The six-step process is summarized below.

First, *videos, transcripts, and artifacts were analyzed and sequential events were manually-coded* with regards to tasks and patients in focus. It was important to precisely document the tasks and times when the clinician worked on each patient in order to easily surface information flows and interactions for each patient.

Second, with focus on a single patient, analysts *traced representational states across media with sequences of video and screen image captures, images and evidence from artifacts, and transcripts of think-aloud dialogue and conversations*. For example, a hospitalist first worked on patient P014 during InfoGather task. For this step, analysts sequenced several data sources: (a) still images from the video capture to identify context of work (e.g., actors, artifacts, locations), (b) screen captures from the Morae™ video recording of the EHR screens viewed by the clinician (e.g., views of the patient's medical chart), (c) notes describing when and how the hospitalist read from or modified paper artifacts, (d) images of these paper artifacts, and (e) transcriptions of the hospitalist's think-aloud verbalizations describing the information viewed and how the information is being processed or reasoned about. This process is then repeated for the remaining events in the hospitalist's work when the patient, P014, was the focus (Figure 15).

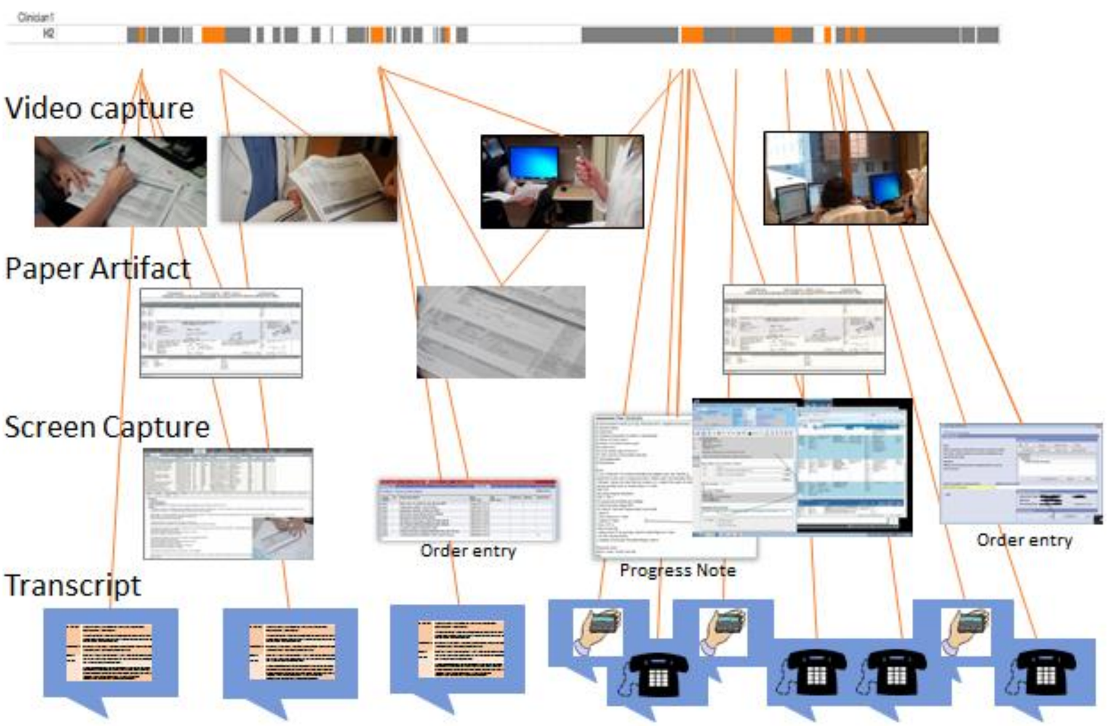


Figure 15. Diagram illustrating part of the propagation of representational states approach where the various data sources that reveal information flow for a single patient are sequenced. The top bar represents the observed time (6:00-10:00am) of the hospitalist performing a range of tasks. The orange segments represent the time and work allocated to a single patient. Data sources include images of video capture, of paper artifacts and health IT screen capture, and transcripts from think-aloud verbalizations, text pages, and conversations.

Third, to trace clinical concepts, analysts *closely examined the sequence of patient-centered work from step two and identified the patient's clinical issues addressed* by the clinician. For example, six clinical problems for post-operative patient P014 were identified, including: tachycardia (i.e., high heart rate), low serum potassium, positive bacteria culture, and patient-reported back pain.

Fourth, *clinical issues across work activities and representations were traced to identify associated clinical concepts*. For example, the hospitalist ordered an intravenous (IV) saline bolus to treat patient P014's tachycardia; therefore, *IV saline bolus* is associated with *tachycardia*.

Fifth, models of *the propagation of representational states* were made to characterize and visualize how information flowed, how the information artifacts were used, as well as the relationships and interactions between actors, artifacts and clinical concepts involved in the work.

Finally, a table was used to summarize the contextual elements and sequence of interactions and representations involved in the information flow. Contextual elements include the clinical issue in focus, actors involved, artifacts used by each actor, and locations where the interaction occurs. The time of each interaction is noted to help situate the events across the clinician's work. For each interaction, the interaction (or representational state or information flow) is described in brief, and each data transfer is characterized by change in media (e.g., paper to conversation).

Interactions involved in the information flow are also characterized in terms of cognitive effort using descriptions of state transformation and concept transformation. A *state transformation* characterizes a representation of data that is moved or transferred to a different media or artifact, but the meaning does not change. For example, a patient's heart rate value of 107 (the data) is transformed when the clinician writes "107" on her paper note sheet after viewing the patient's highest measured heart rate of 107 on the

Vital Signs screen in the EHR. A *concept transformation* is when some knowledge or decision-making has been applied to a representation of a clinical concept resulting in different but related representation. The data in the transformed state is different, but it exists because of the previous state. For example, the patient's heart rate value of 107 (the data, represented on the Vital Signs screen in the EHR) is transformed when the clinician views the patient's highest measured heart rate of 107 in the EHR and verbalizes that the patient is "tachycardia" or writes down "tachycardia". Such a verbalization or annotation is evidence that the clinician determined the patient's heart rate value of 107 to be elevated (abnormal). Without knowledge of the domain or context of the interaction, the two representations would be assumed to be unrelated. Knowledge of the domain or context of the interaction provides evidence that the second data representation exists because and is related to the first representation.

Case Studies: Case studies were selectively used in both DCog and CE analyses to present detailed analyses of clinical work and answer questions. They provide a rich illustration of observed behavior with qualitative data interwoven with quantitative descriptors or sequential pattern analysis to better understand users' behavior. For example, for the CE analysis for each task, I compared a case where the clinician followed a more complex interactive pattern to one that followed a less complex interactive pattern to explain what is causing the user to perform more actions to complete the task.

Process Mining: Process mining names a set of quantitative methods to characterize processes based on event logs. I employed process mining techniques to answer some of the CE questions in Table 3. The techniques are useful for assessing patterns, relationships and dependencies in a given data set. I employed sequential data analysis methods to characterize clinicians' patterns of interactive behavior performed in routine health IT-mediated tasks. In particular, a pattern discovery algorithm was used to mine, identify and quantify the frequency that screen transition patterns occurred in clinicians use of a system. In pattern diagrams, identical sequences are represented by one pattern. I defined criteria to distinguish sequences as follows: a sequence of screen transitions *S1-S2-S3… Sn* is similar to a sequence of transitions *T1-T2-T3… Tn* if and only if for all $0<i<n+1$. The analysis does not consider time or duration. So $S1=T1$ even though the duration between the events (i.e., screen activity) may differ.

The analyses were conducted using a business process mining tool, ProM 5.2, an open-source process-mining workbench used for business process management (Process mining workbench (PROM 5.2).2010), and Disco™ version 1.9.3. The input to ProM and Disco™ is a set of event logs, which can be processed, analyzed, and visualized. For the present purposes, the applications are essentially the same. PROM provides a wider range of analytic tools, whereas Disco™ is easier to use. Process mining has been used for a wide range of purposes in relation to business (van der Aalst, Wil MP et al., 2007) and for adherence to guidelines in healthcare (Grando, Schonenberg, & van der Aalst, Wil MP, 2011).

Event logs were preprocessed using Python. Code was written to de-identify event logs by replacing clinician IDs and patient clinic numbers with a study ID. Events not associated with a patient clinic number were removed. Each event in the analyzed data set contained four data elements—User ID (i.e., clinician ID), an Event Description (e.g., "Activated tab: Labs"), a Time Stamp (with date and time), and a patient's clinic number.

In preprocessing, the event logs were limited to the Event Descriptions that were associated with users' interactions and useful in answering the research questions. Video recordings of observed cases were reviewed with associated event logs to understand how the Event Descriptions aligned with users' EHR interactions.

Quantitative Descriptors: Quantitative descriptors were derived from the goal-action coding scheme and with the aid of analytic functions built into Morae™ software. These descriptive variables—task duration, mouse clicks, screen transitions, and keystrokes—are used to quantify and compare participants' interactive effort to complete a task. Thus, they are used to help answer CE questions in Table 3. The quantities provide relative measures of work and reveal insights into individual clinician's interactive strategies.

Analyses Demonstrated

Per the methodological framework, I employed the multiple methods described above to understand users' interactions with health IT and other clinical information artifacts. First, I draw on the propagation of representational states approach, a distributed cognition (DCog) analysis, to guide the characterization and evaluation of how information moves in the activity system. Two case studies are presented, and they convey the interactions between components of the activity system from the perspective of a single clinician's workflow in context of real work. Second, I draw on cognitive engineering (CE) questions and methods listed in Table 3 to guide characterization and evaluation of users' interactive effort required to complete health IT-based tasks. These analyses integrate qualitative and quantitative approaches to conduct cognitive task analyses for two routine health IT-based clinical tasks, InfoGather and ProgressNote.

Propagation of Representational States Characterization

A DCog approach guides description of how information flows in the activity system to support decision-making and problem-solving. In this section, a propagation of representational states approach is employed to examine cognitive behavior of the activity system. It was used to characterize and evaluate information management and coordination processes that are instrumental to care delivery. This analysis was guided by DCog questions and methods in Table 3. Two cases are presented here to trace the transfers and transformations of high-value clinical concepts across a clinician’s workflow. The cases are also used to give insight into the two tasks of interest, InfoGather and ProgressNote, and to contextualize the activity system. These are the same two case studies presented in(S. K. Furniss, Burton, Larson et al., 2016) but, in this section, they include additional analyses and are presented in greater detail.

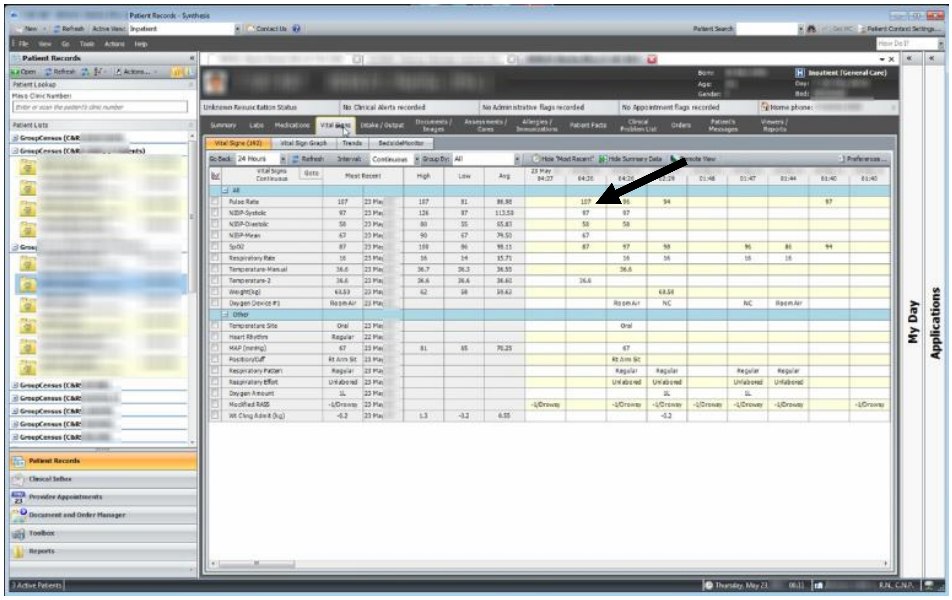
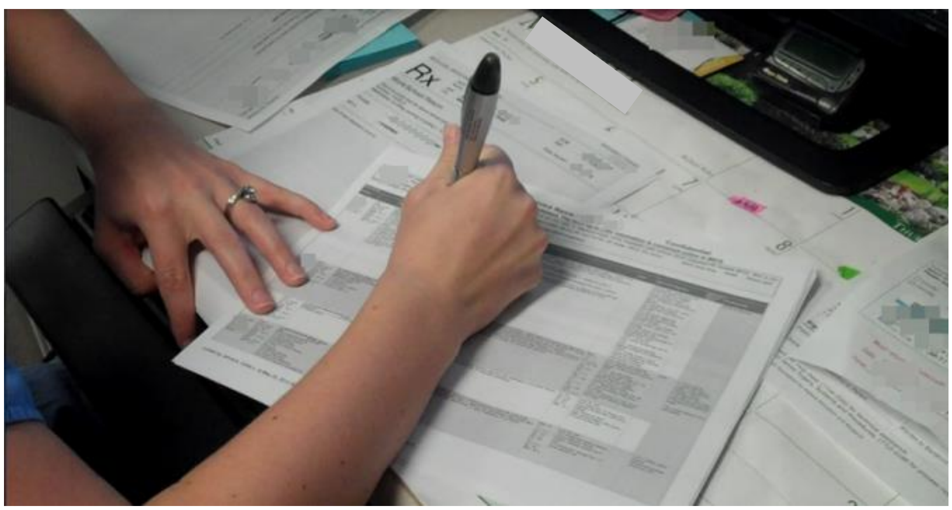
Case 1: Tachycardia in a Patient with Colon Cancer

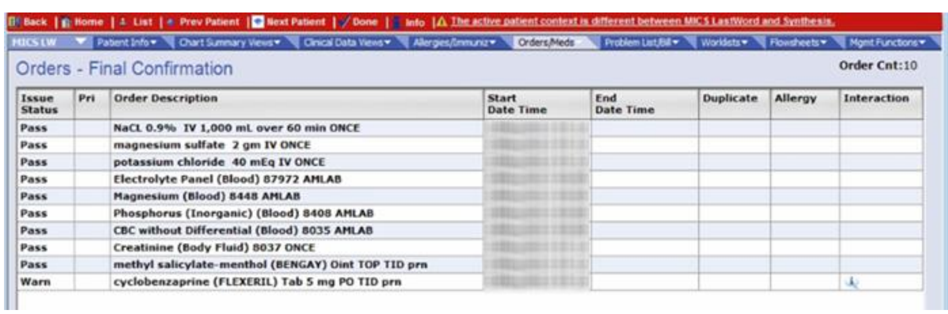
Actors involved in the case study are a patient (P014) and the patient’s hospitalist (H2), fellow (F1) and nurse (N1) on the observed day. P014 was one of 14 patients under H2’s care that day. This case study follows information related to a P014’s tachycardia (high heart rate) through the beginning of a H2’s day shift, between 6am and 10am. Tachycardia is particularly of clinical concern in a post-operative patient. The artifacts used by the actors were an EHR (Synthesis), MICS, an order entry system (Orders), a paper print-out of the web-based handoff tool (Paper ESL) and a nurse's paper note. Events take place in the hospitalists' work room, central resident and pharmacist work station, patient's hospital room and hallway outside the patient's room. In Table 5, the movement of information across media, time and tasks that relate to P014's tachycardia problem are conveyed through narrative, transcript excerpts and images. H2's work for P014's tachycardia is contextualized in tasks done for other patients under the clinician's care. The trace begins at the start of H2's day shift with InfoGather task.

Patient case. P014 was a 67-year-old female with history of colon cancer. On the day of observation, P014 was seven days post-surgery to correct an enterocutaneous fistula—an abnormal connection between the part of the gastrointestinal tract (e.g., small or large bowel) and the skin—as well as placement of a colostomy (end of large intestine is sutured to an opening in the abdominal wall) and cystotomy (surgical incision of bladder) with placement of stent to divert urine to an external stent.

Table 5. DCog Case 1 sequence of interactions and representational states described with transcript excerpts from think-aloud dialogue and conversations, and still images from video recordings, paper artifacts and screen captures. Additional narrative is provided in grey font to place the hospitalist's work on patient P014 in context of the hospitalist's work on the other 13 patients under her care that day.

Time	**State**	**Description**
Day1:		H2 arrived in Hospitalist Workroom at beginning of her shift. H2 created a Paper ESL for the two surgical services H2 was covering that day, by printing a copy of the computer-based ESL.
6:10-6:11a		H2 conducted InfoGather for one patient.

6:11- 6:12a	a	H2 conducted InfoGather for P014, During this time, H2 identified P014’s tachycardia when she saw the patient’s most recent documented pulse rate in the Vital Signs screen in the EHR was a high of 107. 
	b	H2 transferred the finding from the EHR to the Paper ESL with annotation that reads “Tachy 107”. 
6:12- 6:24a		H2 completed InfoGather for the other 11 patients.

6:27-6:29a	c	H2 and F1 rounded on P014. In the hallway, they discussed P014's care plan in context of the latest patient findings. H2 transferred the tachycardia finding from paper to conversation. Through conversation, the tachycardia finding is transformed to a treatment order for an intravenous (IV) saline bolus. *Fellow: "Okay so [P014] put out way too much out of her NG so she's dry so she needs a liter of bolus. […] Replace her lights, k-mag, give her liter intervals of NS, make sure she's on NS no LRs, […]"*
	d	H2 wrote "bolus" on the paper to serve as a reminder of the order that they decided on for the patient, and that H2 will need to act on and document. 
	e	H2 and F1 entered the patient's room to examine and update P014. During this time, H2 informed P014 of the tachycardia finding and the treatment plan.
6:33-7:09a		H2 and F1 completed Rounds for five other patients on that surgical service. H2 then returned to the hospitalists' workroom and entered an order for one of these patients into the computer order entry system.
7:10-7:14a	f	H2 read the "bolus" annotation which she wrote on the paper during rounds, and entered the order and other orders for P014 into the computer order entry system. 

Back | Home | List | Prev Patient | Next Patient | Done | Info | The active patient context is different between MICS LastWord and Synthesis.

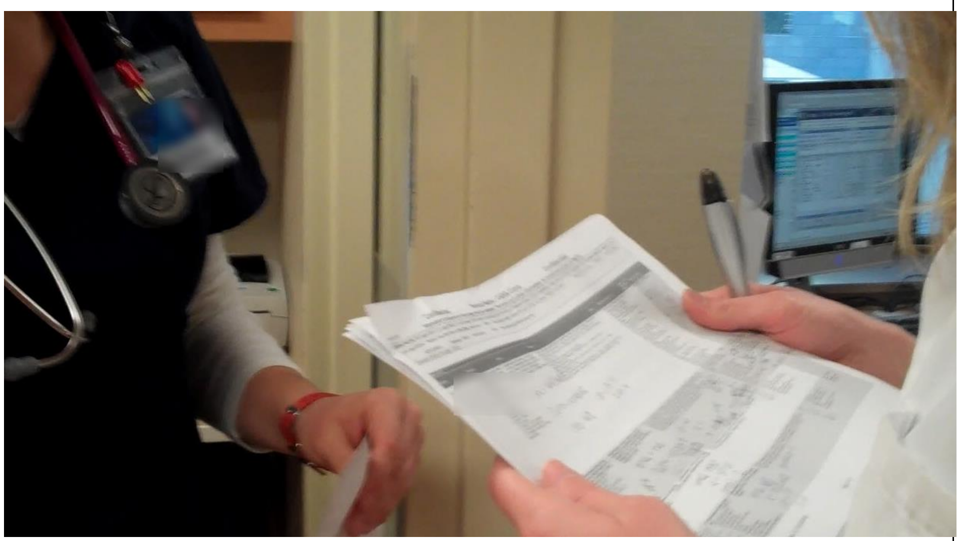
MICS LW | Patient Info | Chart Summary Views | Clinical Data Views | Allergies/Immuniz | Orders/Meds | Problem List/Bill | Worklists | Flowsheets | Mgmt Functions

Orders - Final Confirmation

Order Cnt:10

Issue Status	Pri	Order Description	Start Date Time	End Date Time	Duplicate	Allergy	Interaction
Pass		NaCL 0.9% IV 1,000 mL over 60 min ONCE					
Pass		magnesium sulfate 2 gm IV ONCE					
Pass		potassium chloride 40 mEq IV ONCE					
Pass		Electrolyte Panel (Blood) 87972 AMLAB					
Pass		Magnesium (Blood) 8448 AMLAB					
Pass		Phosphorus (Inorganic) (Blood) 8408 AMLAB					
Pass		CBC without Differential (Blood) 8035 AMLAB					
Pass		Creatinine (Body Fluid) 8037 ONCE					
Pass		methyl salicylate-menthol (BENGAY) Oint TOP TID prn					
Warn		cyclobenzaprine (FLEXERIL) Tab 5 mg PO TID prn					

		Via phone, H2 spoke with the resident for the other CRS service under H2's care that day. They discussed four patients. After the call, H2 received text pages regarding two patients. H2 then went to the Pharmacists' workroom to speak with a pharmacist about discharge planning for two patients on the other CRS surgical service under H2's care that day.

7:29a	g	The patient’s nurse (N1) approached H2 to discuss the IV saline bolus order H2 placed earlier. H2 shared the reasoning behind the treatment decision, that the saline is addressing the patient’s tachycardia. N1 projected that administering the saline would not result in increased urine output, as would typically be expected, due to a bladder leak that was causing urine to be suctioned from the bladder by the vacuum-assisted wound care device. They created an alternative communication plan given anticipated events because it was an expectation that a patient’s nurse report a lack of urine output to the patient’s hospitalist. *N: I saw you added that extra bolus and since that drain is pulling her urine now-* *H2: We're treating her tachycardia* *N: I'm not going to call you when her catheter output is zero, because that's expected right?* *H2: Boy, she must have a really big leak. […] You’re right, don’t call me with low urine output. […] I’ll just keep a lookout, and don’t give me a call unless you’re worried about something or something changes.* 
7:32- 7:35a		H2 and R3 conducted Resident Rounds on three patients via phone.
		H2 was on break.
8:04- 8:28a		H2 wrote daily progress notes for four patients.

8:29- 8:38a	h	H2 wrote the daily progress note for P014 in the electronic documentation system (ProgressNote task). The “bolus” annotation previously made on the paper served as a reminder of a part of P014’s care plan, which H2 documented in the note. The progress note is attached to the patient’s medical record in the EHR and available for other care team members to review. In the prior excerpt, there was a need to establish common ground with nurse N1 regarding the reasoning for the saline bolus order, yet in the progress note this reasoning is not shared. **Assessment / Plan** Prev Document #1 Enterocutaneous fistula s/p ex-lap, fistula take down, completion proctectomy, and end colostomy. #2 Hypothyroidism #3 Depression #4 Peripheral neuropathy secondary to chemotherapy #5 History of Colon cancer #6 History of recurrent breast cancer #9 Leukocytosis #10 acute anemia, Hgb 6.8 from 8.4 #12 fluid collection with probable urine leak #7 Hypomagnesemia #8 Hypokalemia PLAN: - CALL UROLOGY TO ASSESS POSSIBLE BLADDER LEAK. DR. [illegible] sx -keep Foley in place due to surgical procedure, bladder repair with indwelling stents. To be removed by urology as an outpatient. - Ditropan 5 mg po four times daily per urology rec's. Irrigate Foley gently as needed to keep patent. -leg bag teaching, Foley to remain in place x 3 weeks -NGT LIS -Encourage frequent ambulation -CPT 1/ CPT 2 -encourage deep breathing and coughing -continue dressing changes BID -f/u with Dr. Cima and Urogynecology in one month - replace K - suture removal in 2 weeks - continue IV fluids - bolus 1500 cc. -replace K and Mg - cultures from CT are growing, started on Cipro/Flagyl for 14 days - AM CBC and Electrolytes - complains of back pain: Flexeril and Bengay ordered Disposition: home barriers: stoma, wound, urine leak.
-9:27a		H2 wrote progress notes for four other patients.
9:28- 9:30a	i	In a phone conversation with Surgeon, H2 gives updates on P014 and other patients under shared care.
-9:50a		H2 completed hospital summary documentation, and outpatient order entry for three patients.

Case Summary. Hospitalist H2 saw the patient problem when viewing data in the EHR, and then used another health IT application an hour later to take action (place a treatment order) to resolve the problem. In two instances, H2 utilized the paper artifact to support care tasks for the patient that had to occur at different times and locations. H2’s annotations on the paper served as reminders and the paper artifact enabled cognition at the later needed times. There is an act of coordination between the nurse N1 and hospitalist H2 because N1 did not understand why the IV saline bolus order was placed given the patient's state. This conversation is the only instance where the relationship between the patient's tachycardia and the IV saline bolus order is explicit. Even the daily progress note document, which is the primary means by which the clinical assessment and care plan is shared with the patient's care team, does not make an explicit connection between the tachycardia and IV saline bolus treatment order.

The flow of representational states are diagrammed in Figure 16 and detailed in Table 6, beginning when the problem surfaced. These illustrations of the case are more narrowly focused on H2's work specific to P014's tachycardia issue.

The information related to P014's tachycardia transformed across nine representational states between 6-10am (Table 6). States *a* and *b* involve H2 transferring a piece of patient information from the computer (EHR) to paper (Paper ESL), then paper to conversation space with F1. A concept transformation occurred one time, in state c, during Resident Rounds, when H2 and F1 made the decision to treat the patient's tachycardia with an IV saline bolus. After the concept was transformed from problem to treatment plan in the conversation space, the treatment plan is transferred across the computer, paper or conversation space in six other interactions. In the first of these, H2 transfers the treatment decision to the Paper ESL with annotation "Bolus". This annotation is then used five times to facilitate information transfer in subsequent interactions (best conveyed in Figure 16). The information is transferred to paper during InfoGather and Resident Rounds, to health IT during Order Entry and ProgressNote, and to the conversation space during Resident Rounds and several unplanned team coordination activities.

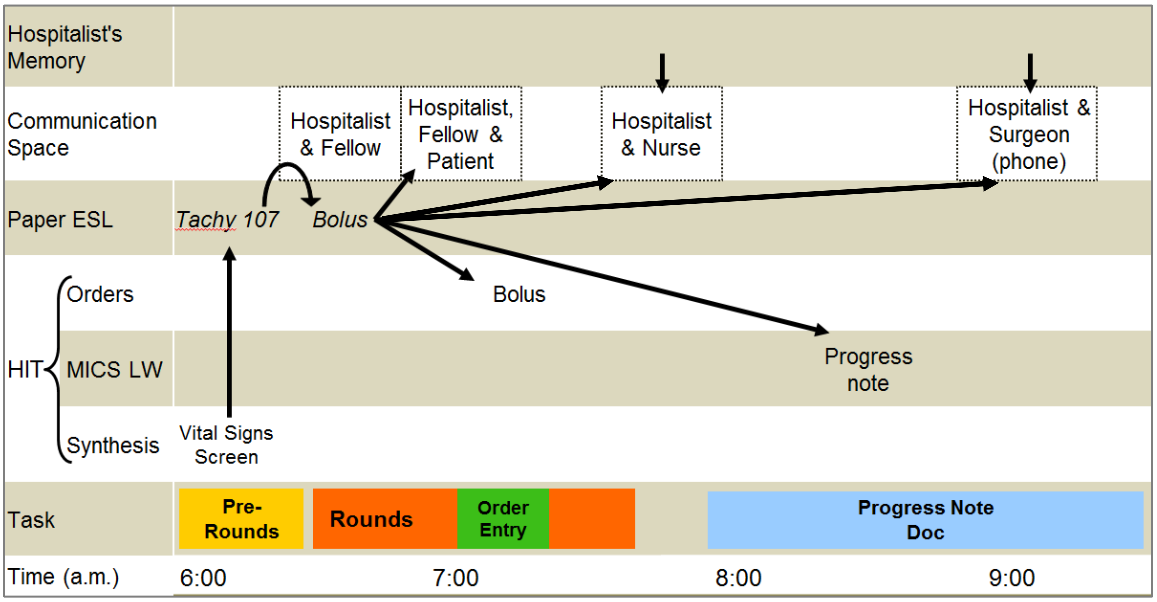


Figure 16. Model of DCog Case 1 illustrating how the sequence of representational states transfer across media, task, and time, and transform to associated clinical concepts to support the hospitalist's decision-making and patient care delivery. The information flow is described in Table 5 and Table 6.

Table 6. DCog Case 1 sequence of interactions and representational states summarized with contextual elements for each state.

Time	Location	Task	Actor (Artifact)	Interactions	
				Information Flow & Representational State described	**Media or Artifact Transfer described**
6:11-6:13a	Hospitalist workroom	Info-Gather	H2 (EHR)	(a) H2 views "107" in EHR Vital Signs screen	
			H2 (EHR; Paper ESL)	(b) H2 writes "Tachy 107" on Paper ESL that *identifies the heart rate value as problematic	Computer to paper
6:27-6:29a	Hallway	Resident Rounds	H2 (Paper ESL) F1 (Paper ESL)	(c) H2 mentions patient's tachycardia	Paper to conversation
			H2 (Paper ESL)	(d) H2 annotates Paper ESL with "bolus"	Conversation to paper
	Patient Room		H2 (Paper ESL) F1 (Paper ESL) P014 (None)	(e) H2 informs patient of problem and treatment plan	Paper to conversation
7:10a	Hospitalist workroom	Order Entry	H2 (Paper ESL; Orders/EHR)	(f) H2 enters bolus treatment in Orders	Paper to computer
7:29a	Central workstation		H2 (Paper ESL) N1 (Paper notes)	(g) H2 and N1 discuss treatment plan that *makes connection between high heart rate and bolus treatment	Memory to conversation & Paper to conversation
8:29-8:38a	Hospitalist workroom	Progress-Note	H2 (Paper ESL; MICS Clinical Notes; EHR)	(h) H2 writes bolus treatment in daily progress note	Paper to computer
9:30a	Hospitalist Workroom		H2 (Paper ESL; Phone; EHR) Surgeon (Unknown)	(i) H2 shares problem and treatment plan with Surgeon	Memory to conversation & Computer to conversation

Case 2: Wound Care for a Patient with Rectal Cancer

This case traces the sequence of representational states associated with a patient's wound care plan over two consecutive days. The actors involved in this case study on the first day are a patient (P059), hospitalist (H2), fellow (F2) and attending surgeon (S1). On the second day, a different hospitalist (H3) was caring for patient P059. Events occur in the hospitalists' work room, patient's hospital room and in the hallway outside the patient's room. The artifacts used include Paper ESLs, the patient, the clinical documentation system (MICS Clinical Notes), an order entry system (Orders), an EHR (Synthesis) and electronic mail. In this section, the patient case is described, followed by a narrative summary (Table 7) and table summary (Table 8) of the case study following information related to P059's wound care.

Patient case. P059 was a 69-year-old male with rectal cancer and a large wound following a surgical procedure two weeks prior. There were three primary wound care issues addressed by the team: 1) type of wound therapy the patient is to have when discharged from the hospital (i.e., vacuum-assisted wound closure (VAC therapy) versus standard therapy), 2) location of wound care (i.e., in the operating room versus in the patient's hospital room), and 3) the wound dressing changes needed while the patient is still in the hospital. For VAC therapy, a foam dressing is put inside the wound and a small vacuum pump is connected. The vacuum pump (commonly referred to as a "wound vac") creates negative pressure that pulls fluid from the wound. Standard therapy involves packing the wound with gauze dressings. A patient may prefer VAC therapy over standard therapy because VAC therapy dressings require less frequent changing compared to gauze dressings—VAC therapy dressings can often be changed every two to three days, whereas standard therapy gauze dressings for the same wound would be changed three times each day.

During the observation, P059's wound was managed with standard therapy. The care team's decisions involved consideration for patient preference, safety (e.g., prevent infection), who will assist the patient in wound care at home (i.e., family member or in-home nurse), and hospital resources (e.g., operating room availability). Pain management activities are included in the trace because post-operative pain can cause poor wound healing among other issues, such as tachycardia, hypertension, myocardial infarction, and insomnia.

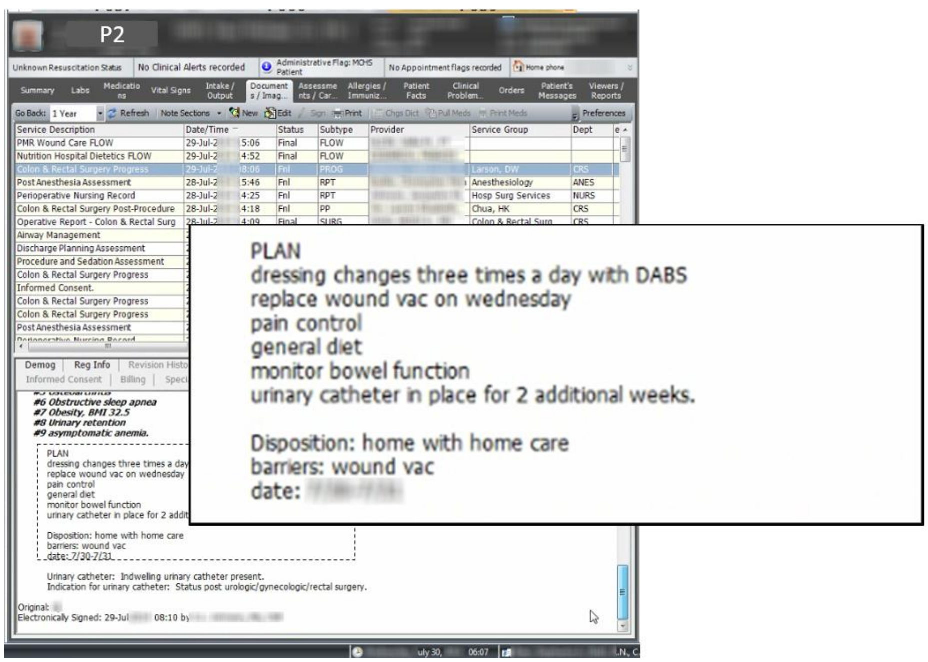
Case Summary. Observations of the care team from two consecutive days were presented. On the first day, hospitalist H2 reviews and discusses the P059's wound care plan with fellow F2. Their plan is modified later in the day when H2 reviews and discusses the wound care plan with the attending surgeon. At the end of the first day, variations of the patient's wound care plan are documented across three different media and not all documented plans are available to the patient's entire care team—1) daily progress note in the EHR is available to all care team members, 2) electronic handoff document available to a smaller care team (web-based ESL), and 3) email message available only to F2 and hospitalist H3. On the second day, during InfoGather, H3 reviews the three documentations. H3 is not able to reconcile the variation across documents; therefore, is not able to understand the wound care plan for the patient and seeks clarification.

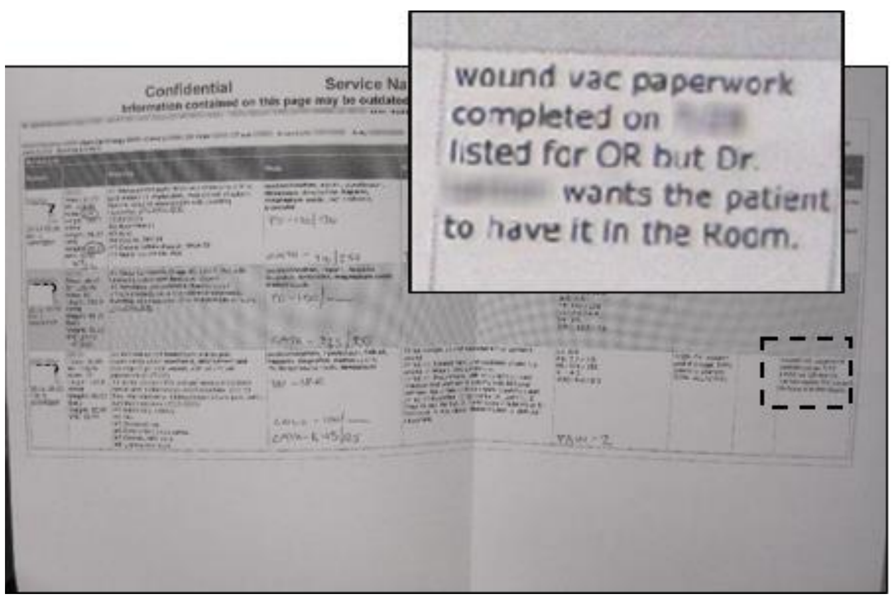
Table 7. DCog Case 2 sequence of interactions and representational states described with transcript excerpts from think-aloud dialogue and conversations, and still images from video recordings, paper artifacts and screen captures.

Time	State	Description
Day 1: 6:21a		H2 arrived in hospitalists' workroom at beginning of her shift. H2 created the Paper ESL for the 2 surgical services H2 is covering that day, by printing copy of the computer-based ESL.
6:33a		H2 conducted InfoGather for P059. (H2 did not appear to review information directly related to P059's wound care.)
7:10a	a, c	In the hallway outside the patient's hospital room, H2 and F2 discussed the wound care plan for P059 during patient Rounds. Through conversation, they decided to change the gauze dressing that day and order a wound vacuum pump to be placed in the operating room the next day. Transcript excerpt: *F: I don't know what time to change his dressing.* *H: Did they do it last night?* *F: No. We said no.* *H: So we'll do that today?* *F: Yeah, but they said it was really soupy.* *H: It needs to be changed 3 times a day.* *F: 3 times a day? I don't think it does.* *H: _____ it said 3 times a day.* *F: I think it was dabs.* *H: Alright, whatever. ____.* *F: When are you free today?* *H: I'm free anytime today. What time are you available?* *F: Probably around 8:00.* *H: Okay. Do it at 8:00 then.* *F: Yeah, I just want to look at the wound. And then still put the paperwork in for the wound vac.* 

<table>
<tr><td></td><td>b</td><td>H2 wrote “_8AM” task on paper ESL</td></tr>
<tr><td></td><td>d,e,f</td><td>While H2 and F2 are in the patient’s room, they informed P059 that they would return at 8am to look at the patient’s wound.

Transcript excerpt:
[…]
H: We’re going to task a peek at your bottom around 8 am okay? We’re going to take that dressing off the. So let’s actually put your leg on right now. Have you had a pain pill in a while?
[…Patient response omitted…]
F: Okay. We’ll put in a little extra pain medication so we can remove that dressing and put the next one in. […]</td></tr>
<tr><td></td><td>g</td><td>H2 wrote “_oxy 5mg” task on the Paper ESL.</td></tr>
<tr><td>8:05a</td><td>h</td><td>From her desktop computer in the Hospitalist’s workroom, H2 entered oxycodone order for P059 in Orders.</td></tr>
<tr><td>8:07a</td><td>i</td><td>H2 documented the plan from step a in the daily progress note for P059 (ProgressNote task). The plan included, “Dressing change three times a day with DABS” and “Replace wound vac on Wednesday.” The progress note was then in the EHR and available for other care team members to view. The note also informed the care team that placement of a wound vac for VAC therapy is a “barrier” to discharge, and that they planned to discharge P059 the next day.


</td></tr>
<tr><td>2:24p</td><td></td><td>From H2’s computer in the hospitalists’ workroom, H2 sent a text page to P059’s surgeon (S1) that read “[P059] ready for your visit. [H2]” so that S1 would come see the patient. The text paging system was a web browser accessed through the hospital’s intranet.</td></tr>
</table>

<table>
<tr><td>2:44p</td><td>j,k</td><td>H2 and the attending surgeon discussed P059’s state and wound care plan, in the hallwayThe attending surgeon permited VAC therapy, but requested that the wound vacuum pump be placed in the patient’s hospital room rather than in the operating room.
</td></tr>
<tr><td></td><td>l</td><td>H2 and S1 visited P059 at the patient’s hospital room. They informed the patient of the plan.</td></tr>
<tr><td>3:00p</td><td>m</td><td>Nearing the end her work shift, H2 updated the electronic handoff document, the ESL, with a note in section titled “__”. The note reads: “wound vac paperwork completed [yesterday] listed for [operating room] but [attending surgeon] wants the patient to have it in the room”.

</td></tr>
</table>

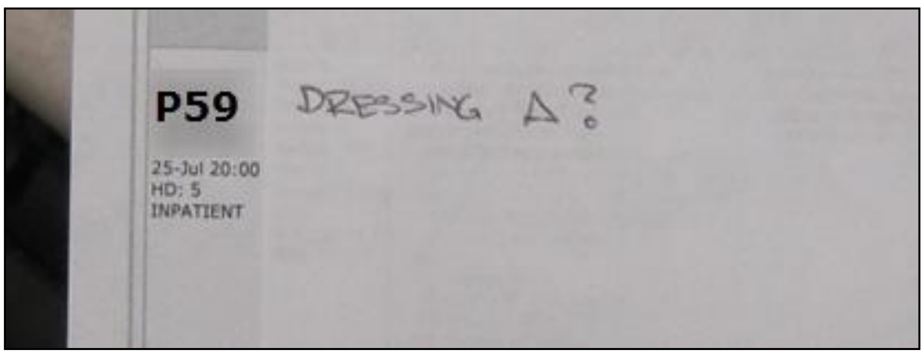
3:42p	n	Just before leaving for the day, H2 sent an email sign-out to fellow F2 and the hospitalist who will care for the patient the next day (H3). The email read: *"[S1] did not want a wound vac for [P059] but states it is okay if the wife cannot do dressing changes. He says no need for this to be in the OR tomorrow. Need to be at the bedside without sedation if possible. Please cancel surgical listing." The email continued with other information not specific to P059, "[H3] will be covering me tomorrow. ERP placed for the new two [patients]."*
Day2: 6:06a		H3 arrived in hospitalists' workroom at beginning of shift. H3 created a Paper ESL by printing a copy of the computer-based ESL.
	o	H3 reviewed the Paper ESL. Confused, H3 stated, *"But I don't know what 'it' is!"*
	o	H3 read the progress note created by H2 on the previous day, as well as the handoff email written and sent the previous day by H2. H3 has reviewed the three different representations of the patient's plan documented by H2 the previous day (i.e., progress note, handoff document, e-mail), and stated, *"I don't understand this. It says something different in all the places I'm looking."*
6:08a	p	H3 annotated the paper notes with *"dressing Δ?"* (shorthand for "dressing change?"). The annotation served as a reminder to H3 to ask F2 for clarity about P059's care plan. 

Table 8. DCog Case 2 sequence of interactions and representational states summarized with contextual elements for each state.

Time	Location	Task	Actor (Artifact)	Interactions: Information Flow & Representational State described	Interactions: Media or Artifact Transfers described
7:10a	Hallway	Resident Rounds	H2 (Paper ESL) F2 (Paper ESL)	(a) F2 inquires about next planned wound dressing change; they decide to change dressing at 8:00am	Paper to conversation (F2)
				(b) H2 writes "_8AM" on Paper ESL	Conversation to paper (H2)
				(c) F2 asks H2 to schedule wound vac placement in operating room; H2 states it was already completed	Memory to conversation (F2 & H2)
	Patient Room		H2 (Paper ESL) F2 (Paper ESL) P059 (Self)	(d) H2 inform patient of planned wound dressing change at 8am, and asks about last pain medication	Memory to conversation (H2)
				(e) P059 responds	Memory to conversation (P059)
				(f) F2 states plan to manage pain that *makes connection between dressing change to pain management	Memory to conversation (F2)
				(g) H2 writes "_oxy 5mg" on Paper ESL (shorthand for oxycodone, a pain medication)	Memory to paper (H2)
8:05a	Hospitalist Workroom	Order Entry	H2 (Paper ESL, Orders)	(h) H2 enters order for 5mg oxycodone in Orders	Paper to computer (H2)
8:07a		Progress-Note	H2 (Paper ESL, MICS Clinical Notes, EHR)	(i) H2 enters plans in progress note: "Dressing change three times a day with DABS" , Replace wound vac on [next day]." Also, wound vac placement is a "barrier" to the patient's discharge, and discharge planned for next day	Paper to computer (H2)
2:44p	Hallway		H2 (Paper ESL) Surgeon (EHR on mobile)	(j) H2 shares wound care plan with Surgeon	Memory + Paper to conversation (H2)

				(k) Surgeon states wound vac placement to be done in patient’s hospital room rather than in an operating room	Memory to conversation (Surgeon)
			H2 (Paper ESL) Surgeon (none) P059 (none)	(l) Surgeon inform patient of wound care plan	Memory to conversation (Surgeon)
3:00p	Hospitalist Workroom	Handoff	H2 (Paper ESL, web-based ESL, Outlook Email)	(m) H2 writes in web-based ESL: “wound vac paperwork completed [yesterday] listed for [operating room] but [Surgeon] wants the patient to have it in the room”	Memory to computer (H2)
3:42p	Hospitalist Workroom	Handoff		(n) H2 sends email to F2 and H3 that reads: “[Surgeon] did not want a wound vac for [P059] but states it is okay if the wife cannot do dressing changes. He says no need for this to be in the OR tomorrow. Need to be at the bedside without sedation if possible. Please cancel surgical listing.”	Memory to computer (H2)
Day2 6:06a	Hospitalist Workroom	Info-Gather	H3 (Paper ESL, Outlook Email, EHR)	(o) H3 reviews comments H2 wrote in ESL, progress note and email regarding the patient’s wound vac placement plan and expresses confusion about the plan	
6:08a				(p) H3 annotates Paper ESL with “*“dressing Δ?”* (shorthand for “dressing change?”)	Paper + Computer to paper (H3)

Results & Discussion of DCog Case Studies

In each DCog case study, a propagation of representational states approach was employed to convey the components of the activity system used to complete work (Question 1) and the movement of information as a sequence of interactions and representations (Question 2). The illustration and table summaries help to communicate these findings and show how clinicians manage information and coordinate care (Question 3). In this section, I draw on findings in the case studies to evaluate the barriers to information flow that may cause delays or errors in care delivery (Question 4) and how technologies are limited in supporting clinicians' cognitive work for information management and coordination activities (Question 5). Additional case studies were performed to help me draw conclusions, and are not presented here for the sake of brevity.

Clinicians transferred information across representational media (i.e., across computer applications, paper-based artifacts, verbal exchange) to complete care delivery tasks. In general, transfers to paper (computer-to-paper and conversation-to-paper) occurred to support clinician's memory. Clinicians carried the paper artifact with them throughout the day to make patient data readily accessible as clinicians' attention to each patient case was discontinuous throughout the day. For example, transfers from computer-to-paper artifacts enabled information transfers and transformations to occur away from a computer, in planned and unplanned coordination activities that occurred in a variety of hospital locations**.** For example, in InfoGather, clinicians annotated the Paper ESL with information transferred from the EHR, which made pertinent patient information available to them when they were away from a computer. In particular, members of a patient's care team were able to share and evaluate data and make patient care decisions in the hospital hallways. Similarly, information was transferred from conversation to paper to make that information available to the clinician at another time, task and/or location. For example, for ProgressNote, clinicians referred to annotations on the Paper ESL made during prior tasks to complete the progress notes for more complex patients.

Information transfers also occurred to document data or decisions to meet administrative needs and legal purposes, as well as to make updates, such as those regarding team's decision-making and patient's care plan, available to all care team members. Documentation included the daily progress note, hospital summary or discharge note. For example, to complete ProgressNote, clinicians transferred data from the Paper ESL, the EHR and other health IT applications. Data was transferred from notes previously documented in the patient's chart, from the web-based ESL, and recent labs and vital signs data from the EHR or other systems. MICS Clinical Notes, the health IT system used by clinicians to document patients' daily progress notes, facilitates data transfer for the completion of the progress note document. Specifically, there are buttons on the document screen that, when selected, pull in the patient's most recent laboratory data, another button to pull in the patient's most recent vital signs, and another that facilitates reuse of assessment and plan text from previous documents. While the first two mentioned pull in and populate recent data, if there is any, the third (i.e., the Assessment and Plan "Pull from Previous Document" feature) facilitates data review and reuse from past documents in the patient's chart.

The above examples describe instances of a *state transformation*, which is the movement or transfer of information from one media or state to another. I differentiate these from a *concept transformation*, which is when knowledge is applied to the data to make decisions.

Concept transformations resulted from problem-solving and decision-making processes that occurred in the mind of an individual clinician (i.e., implicit) or in conversation between clinicians (i.e., explicit). In the DCog approach, implicit processing is surfaced by the state transformations, such as those seen in order entry, documentation (e.g., daily progress note, discharge summary) and clinicians' annotations on supporting paper artifacts. For example, in Case 1 (Table 6) given state *a* (i.e., reading the patient's pulse rate value of 107 in the EHR Vital Signs screen), state *b* (i.e., annotating paper with "Tachy 107") surfaces the clinician's implicit processing of the 107 pulse rate value as an abnormal finding. An analyst with basic clinical knowledge may have drawn the relationship between tachycardia and a pulse rate of 107 without evidence from the full dataset (i.e., the adjacencies of the interactions, the clinician's verbalizations, the fact that the annotation includes 107 next to "Tachy"), However, one can extrapolate how the full dataset would be more helpful in identifying concept transformations that are more complex or less obvious. For example, in Case 1, the relationship between the patient's tachycardia and the saline bolus treatment was not obvious when the fellow asked the hospitalist to place an order for an IV saline bolus treatment. Rather, I observed the relationship between the order for an IV saline bolus as treatment for the patient's tachycardia in an impromptu conversation between the patient's nurse and hospitalist (state *g* in Table 6). There is no evidence of this association in the order entry, on the hospitalist's paper, or in the daily progress note authored by the hospitalist that day.

The DCog approach has defined transformational activities as when a representation of information changes, which can occur through altering artifacts and communications between people. For example, D. Furniss and Blandford describe, a table of numbers could be represented as a chart or graph (D. Furniss & Blandford, 2006). Similarly, the level of a patient's pain could be recorded on a numerical scale from 0 to 10. In the proposed framework, I specify this as a *state transformation* in order to differentiate it from a *concept transformation*, which I define as an inferential process resulting in a change in meaning. For example, an objective finding of pulse rate of 107 identified as abnormal and problematic to the patient achieving his or her clinical goals.

The representational states enabled interactions that involved information sharing in planned (or routine) activities and unplanned (or emergent) activities. In Case 1, for example, the representation produced on the Paper ESL during InfoGather allowed the clinician to share, evaluate and make decisions with another member of the patient's care team away from the EHR (e.g., in the hospital hallway). The representation of the treatment decision on the Paper ESL produced during Rounds enabled the clinician to share, act on, and document the treatment at a later time and in various locations. In particular, it was the affordances and constraints of the information artifacts that determined how representational states could control and enable system behavior. For example, the clinician relied on the mobility and informality of the Paper ESL to hold these representations and enable sharing, evaluation, decision making, order entry and documentation to occur across time and locations.

To identify how clinicians' manage information and coordinate care (Question 3), I looked at how representational states were brought into coordination. To manage information flow, clinicians relied on a number of tools, communications with the members of the patient's care team (i.e., patient, patient's family, other clinicians), and allotting and organizing tasks to allow for needed information activity (i.e., time to review patient information in the health IT systems prior to Rounds). The clinical team has a number of ways of communicating across distributed team members and time. Clinicians may inform others by sharing information verbally and/or documenting it in the patient's medical chart. EHR documents attached to patient medical record, web-based handoff document, and e-mail were the three used in Case studies 1 and 2. Phone and pager were also modes of communication employed. For the next question, I examine challenges that result from availability of multiple modes of information sharing and coordination.

Information management was integral for decision-making and coordination activities. I found that clinicians manage information flow in particular ways to facilitate decision-making and coordination processes. The array of mechanisms for information management is necessary because decision-making occurs at various locations, and is sometimes done by an individual and sometimes by a team. Information management is important to accuracy and efficiency of coordination work because a decision may be made by one clinician but acted on (e.g., placing an order) by a different clinician, and, similarly, a decision may be made and/or acted on by one clinician but is documented by a different clinician. For example, in Case 1, the treatment decision was not collaborative (i.e., it was made by the fellow); however, the action and documentation of the decision required collaboration (i.e., treatment order was placed and documented by the hospitalist).

To identify barriers and problems to information flow that may cause delays or errors in care delivery (Question 4), I examined DCog case studies for where health IT does not align with work processes and where there were risks to information loss or errors.

Barriers and problems include frequent information transfers, persistent use of paper artifacts, clinical reasoning absent in documents, conflicting data because multiple ways to communicate patient care plans (or no easy way of documenting change in care plan during the day), redundant data across documents and applications, and gaps in coordination. Together these burden the clinician as information and knowledge manager. I elaborate of each of these below and discuss the insights they provide into health IT's limitations in supporting clinicians' information management and coordination processes (Question 5), as well as, give suggestions for where and how the activity system can better support clinicians' in these processes (Question 5). The constraints and affordances of information sources impact the efficiency of work (Hazlehurst et al., 2007). Therefore, analysts seeking to improve the activity system need to closely assess actor's information needs, and use these to define requirements for future supporting health IT.

Frequent information transfers are problematic because each time information is transferred by a human, there is a potential for error (e.g., associating information to the wrong patient, losing information, incorrectly recording information (changing the information)). In fact, communication errors among clinicians are a key factor in medical errors. Arguably, the occurrence of so many information transfers is due to the constraints and affordances of the artifacts available to the clinicians. In particular, the EHR is limited in supporting clinicians' cognitive work because it is not easily accessible to a clinician when all needs arise for data access or data capture.

Clinicians' persistently used the Paper ESL because the paper artifact was mobile and allowed patient information to be available on-hand for team interactions that occurred away from a computer. The EHR is not readily accessible in all settings; therefore, the affordances of the EHR do not match those of the Paper ESL. In addition, clinicians' were able to annotate paper artifacts with data, tasks and reminders as the need arose. Therefore, making the EHR available on a mobile tool, such as a tablet computer, is not a sufficient replacement to the Paper ESL. It also needs to be flexible enough to support clinicians' annotations. It has similarly been found in other studies that paper-based workarounds are often created by clinicians to facilitate information management needs, such as the availability and organization of patient information(Embi et al., 2013; Gurses et al., 2009; Saleem et al., 2009). However, clinicians' use of paper-based artifacts (e.g., the Paper ESL) to support work creates risks to problems and errors in information flow. While a paper artifact is useful as a cognitive artifact (e.g., to record data and reminders to support patient care processes), it has limitations to managing information and coordination in such an activity system. For example, as new lab results are available in the EHR, they are not updated on the clinician's paper notes.

Elements of clinical reasoning were absent from documents, which can cause barriers to other members of a patient's care team having shared understanding about patient state and decision-making that led to the patient's care plan. The EHR is limited in that it encourages documenting extensive patient information without requiring clinicians to document rationale for decisions made. Clinicians may not always document decision-making and clinical reasoning because it would make the task more effortful to complete. Health IT could aid clinicians in documenting clinical reasoning by making it easy for clinicians to connect patient data to order entry and care plans. For example, to connect facts of patient state, such as "pain is controlled" with treatment plan so patient state and care plans can more easily be assessed dynamically and in context-specific views that serve different stakeholders—clinical, administrative, or patient/family. A non-technical solution of addressing documentation policy should also be considered.

Case study 2 showed that conflicting and redundant data about a patient's care plan could be documented by one clinician, and that it subsequently caused confusion to another clinician caring for that patient and made it more effortful for the second clinician to understand the patient's care plan, and may have delayed care. On day 1 of the case study, the hospitalist documented information on the patient's wound care plan in three different systems—in email, the ESL, and the daily progress note—over the course of the day in efforts to communicate changed and unchanged details to the patient's wound care plan. On day 2 of the case study, when a different hospitalist was caring for the patient, the new hospitalist had difficulty in completing InfoGather for the patient because the information conflicted and it was not clear which care plan was documented last (or was the most correct). This event was a result of health IT that permitted variation and inconsistencies in documentation. A standardized process of how clinicians use the artifacts to manage information, communicate and coordinate may reduce the chance for conflicting data. Based on the given example, such an improvement is likely to reduce potential for errors and delays in care, while also increasing the efficiency with which a clinician completes the InfoGather task.

Another instance of conflicting and redundant data was observed during ProgressNote. Despite the problematic aspects of data reuse, the observed health IT application (MICS Clinical Notes) facilitates clinicians in retrieving information from previous notes that they want to reuse in the current note. This affordance may have been developed to make the inevitable copy-and-paste from previous notes more efficient.

While the “Pull from Previous Document” dialogue box likely saves time in completing the Assessment and Plan section of the progress note, it still may produce redundant data entry. Again, a standardized process of how clinicians use the artifacts to manage information, communicate and coordinate may allow clinicians to benefit from the increased efficiency provided by such system affordances while reducing the chance for conflicting and redundant data.

The discontinuity in information work related to any one patient is a result of many factors in the work setting, to include the tools available and clinicians’ need to manage many patients in a shift. The clinicians relied on their memory and external artifacts to manage patient information. In particular, a paper printout of the electronic-based handoff tool, the Paper ESL, is important information artifact to clinicians because of its mobility, and other ways it supports of notetaking. Ultimately, it puts the burden on the clinician to be the information manager. This burden necessitates significant cognitive resources to manage information and coordination needs, and creates potential for unchecked information loss or mix up. Technology can be used to capture pertinent clinical findings at the point of collection/observation thereby allowing the clinician to use his or her cognitive resources on higher-level thinking.

The propagation of representational states approach characterized information flow across media, representations, conversations, actors and time, and surfaced information flows in the system of actors and artifacts to support clinicians’ information processing. The focus on information related to high-value care goals guided a trace of related clinical concepts. The approach surfaced issues across tasks, to include information that would otherwise have been missed (S. K. Furniss, Burton, Larson et al., 2016). The method can be used to analyze performance on both short tasks and longitudinal care processes (e.g., monitoring and managing a patient's pain level). It can surface implicit knowledge, decision-making processes, and critical features of the work domain. Given that health IT is increasingly being used in health care to facilitate information management and communication, this study supports the need to employ a distributed cognition (DCog) approach to identify key ways that future health IT can better facilitate clinicians' information management and care coordination processes.

Cognitive Task Analysis Approach

In this section, CE methods and questions listed in Table 3 are employed to characterize and evaluate users' interactions with health IT for two routine health IT-based tasks—InfoGather and ProgressNote. Clinicians' efforts are characterized by measures of interactivity—to include quantitative descriptors (e.g., task duration, mouse clicks, screen transitions, and keystrokes), and patterns of clinicians' actions and events involved to complete a task. The measures of interactivity provide relative measures of work and cognitive load to characterize and compare participants' interactive behavior required for the task. It should be noted that there are no normative benchmarks of quantities or patterns of interactive behavior for determining task complexity or EHR usability. In lieu of this, I contrast across sample populations, such as across clinicians, patient cases and tasks. The objective was to explain variation in task performance, as seen in measures of interactive behavior, to better understand cognitive work and sources of complexity. I also sought to demonstrate the methodological framework and seed hypotheses for future work.

Analytics from Morae™ recordings and retrospective review of videos were used to measure quantitative descriptors. Process mining analysis of system-generated and manually-coded event logs was used to describe users' interactive patterns. I integrated the various data sources and methods (e.g., video, Morae, think-aloud verbalizations, artifacts, chart review, etc.) to examine and explain variation in behavior, as well as to draw inferences about EHR usability issues.

Task 1: Pre-Rounds Information Gathering (InfoGather)

I analyzed InfoGather task during the development of the methodological framework, and reported findings in two studies, (S. K. Furniss, Burton, Grando, Larson, & Kaufman, 2016) and (Kaufman, Furniss, Grando, Larson, & Burton, 2015). In this section, select results from these two studies are integrated with additional analysis to best answer the CE questions in Table 3.

The EHR-generated event log sample consists of 1569 patient cases across 6 clinician participants. Quantitative and sequential analyses of InfoGather from EHR-generated event log data, were originally presented in (S. K. Furniss, Burton, Grando et al., 2016). Of the 1569 case sample, 66 patient cases across five of the participants were observed and recorded. For each observed case, data from Morae™ video capture and clinicians' think aloud verbalizations were used to manually code users' interactions with the EHR. Preliminary analysis of this data was reported in (Kaufman et al., 2015).

Action and Event Types. According to the EHR-generated event logs, participants accessed and viewed 26 different EHR screens. presents the seven most frequently viewed EHR screens. Among them are 12 of the 13 main EHR display tabs and the

Navigation panel (N), which is a collapsible vertical panel on the left of the EHR interface that contains the patient list and the search field for a user to access a patient chart. I defined it as a screen because it is relevant to users' EHR-interaction for accessing patient charts. Summary (S), Labs (L), and Vital Signs (V) were viewed for more than half of all cases, and Documents/Images (D) and Intake/Output (I) screens were viewed for more than two-thirds of all cases suggesting the importance of these displays as information sources(S. K. Furniss, Burton, Grando et al., 2016). No one screen was viewed for every patient case. Across the seven most frequently viewed screens, each was viewed more than once for some cases and up to 7 times (S and L) (Table 9). Repeat viewing is analyzed in greater detail below.

Table 9. Statistics for the seven most frequently accessed screens during InfoGather, based on EHR-generated event logs.

Screen	Screen Symbol	Case Frequency (% total cases)	Absolute Frequency	Max Repetitions
Navigation panel	*N*	1565 (99.7)	1649	3
Documents / Images	*D*	1055 (67.2)	1426	6
Intake / Output	*I*	1212 (77.2)	1425	5
Summary	*S*	870 (55.4)	1171	7
Labs	*L*	828 (52.8)	976	7
Vital Signs	*V*	836 (53.3)	966	5
Viewers/Reports	*VwR*	179 (11.4)	182	2
Medications	*M*	140 (8.9)	162	3

Source: This table was first presented in (S. K. Furniss, Burton, Grando et al., 2016).
Note: Case Frequency is the number of cases in which the screen was viewed at least once. Absolute Frequency is the number of times the screen was viewed. Max Repetitions is the highest number of time the screen was viewed per one case.

From observed and manually-coded cases, I learn that participants not only rely on a number of screens within the EHR, they also rely on other electronic and non-electronic information artifacts. Participants accessed five computer-based applications and three paper-based resources. Computer-based applications were the EHR (Synthesis), MICS LastWord to check if orders have been placed, QREADS to view radiology images and reports, Flowchart to view nurses' notes, and Microsoft Outlook to view emails from, or send emails to, other clinical team members. The EHR (Synthesis) was used for all patients. For 55 of the patients, the EHR was the only computer-based application used; at least one other application was used for 11 of 66 patients. At most, three different computer-based applications were used for a patient case. A paper-based source was used for all patients. Typically, it was the Paper ESL, a paper printout of the web-based handoff tool.

Interactive Patterns. The 1569 case sample was described by 519 variant screen transition patterns. The 15 most frequent patterns account for just over half of all cases (52.6%). Across the 10 most frequent patterns, each was followed between 132 and 38 times (Table 10). There were 418 patterns (26% of total cases) that were followed for only a single patient case. These 418 patterns explain 21% of H1's cases, 22% of H2's cases, 18% of H3's cases, 27% of H4's cases, 38% of R1's cases, and 30% of R2's cases (Table 10). I use this number as the measure of variation. Therefore, H3's task performance had the least variation (18% of H3's cases had a pattern that appeared once), whereas R1's task performance had the most variation (38% of R1's cases had a pattern that appeared one time).

Table 10. Screen sequence patterns and frequency measures for the 10 most frequent patterns performed in the InfoGather task.

Pattern	**Screen Sequence**	**Frequency (cases/pattern)**	**Normalized Pattern Occurrence**					
			H1	**H2**	**H3**	**H4**	**R1**	**R2**
1	N – D – I	132	0	0.23	0.27	0	<0.01	0
2	N – VwR – I – V – L	67	0	0	0	0.41	0	0
3	N – S – V – I – D	65	0.13	0	0	0	0.01	0.12
4	N – S	95	<0.01	0	0	0	0.22	0.03
5	N – S – V – I	66	0.16	0	0	0	0.02	0.06
6	N – S – L – V – I – D	68	0.24	0	0	0	0	0
7	N – D – I – V – L	46	0	0.19	0	0	0	0
8	N – D	52	<0.01	0.04	0.12	0	0.02	0
9	N – S – D	45	0	0	0	0	0.05	0.13
10	N – D – I – L	38	0	0.02	0.12	0	0	0
11-101	91 patterns	2-40 each	-	-	-	-	-	-
102-519	418 patterns	1 each[a]	0.21	0.22	0.18	0.27	0.38	0.30
	Total (case count)	***1569***	***288***	***248***	***274***	***162***	***393***	***204***

Source: This table was originally presented in(S. K. Furniss, Burton, Grando et al., 2016).
Note: Frequency gives the number of patient cases per pattern. Normalized Pattern Occurrence expresses the frequency the clinician uses a screen sequence pattern as a percent of their total cases. EHR screen codes: N (Navigation Panel), D (Documents/Images), S (Summary), L (Labs), V (Vital Signs), I (Intake/Output), VwR (Viewer Reports).
[a] The percent of cases in which clinicians had a unique pattern served as a preliminary measure of variation.

The 66 manually-coded patient cases were described by 27 screen-transition patterns, each employed 2 to 7 times(Kaufman et al., 2015). This small data set revealed some pattern variation that was also revealed by the EHR-generated log files; therefore, the evaluation of pattern variation focuses on the patterns from the 1569 cases, and relies on retrospective analysis of the observed cases to explain reasons for the pattern variation.

Given the relatively few EHR screens, variation in screen sequence patterns resulted in part from repeated screen viewing for many cases—when a screen is viewed two or more times in a patient case. Of the 66 observed patient cases, three clinicians performed repeated screen viewing for a third or more of their patient cases (1/9 for H1, 7 /21 for H2, 11/16 for H3, 10/12 for R1, and 2/8 for R2). From review of the full data set, Iwe learned that Documents/Images screen (D) was viewed twice for many of H3's cases as part of a preferred pattern. H3 first viewed D when a patient's chart was first opened because D was set as the default screen for this user. H3 explained, "Whenever I launch a patient, I'm looking at the notes to make sure there was no weird note put in overnight." H3 would view D towards the end of the task as well, which would allow H3 to review the notes in context of what H3 learned about the patient during the task. H2 also had D set as the default screen, but, unlike H3, the default did not appear to be useful to H2 for several cases. Instead, H2 seemed to use a two-phase approach. First, for most cases, H2 exhibited a consistent screen sequence (i.e., N-D-I-V-L) at the start of the task. Then, for some patients, H2 also visited additional screens, perhaps to see if there were things missed. R1 had the highest percentage of cases with repeated screen viewing. This is not surprising because R1, a second-year resident physician, was relatively inexperienced with the EHR and the CRS practice. R1 could not easily synthesize and consolidate information from the EHR. R1 selectively uses screens with representations that can provide better cognitive support. For example, R1 views both Summary (S) and Labs (L) screens consecutively and multiple times per task. R1 stated "the way they do electrolytes [in the tabular form in the Labs screen], I can't even sort through that in my mind very quickly so I go back to the skeleton here [on the Summary screen]." In this case, the most recent lab values are represented succinctly in fishbone format on the Summary screen and were the preferred representation.

Quantitative Descriptors. Quantitative descriptors of users' interactive behavior were determined only for the 66 observed patient cases. Quantitative descriptors include task duration, screen transitions and mouse clicks. Keystrokes were not quantified for this task because InfoGather is an information access task and does not involve much typing. There was significant variation in quantitative descriptors within and across participants (see Table 11). Across the 66 patients, the task took, on average, 5.6 screen transitions, 11.8 mouse clicks and 140 seconds. Across clinicians, average task duration was 65.5 to 306.7 seconds with a range of 22 to 688 seconds. Clinicians averaged 3.5 to 8.0 screen transitions with a range of 2 to 16 screen transitions, and the average mouse clicks varied from 8.3 to 14.4 with a range from 3 to 39. A screen transition resulted in 2 to 2.5 mouse clicks. Clinicians H1, H3 and R2 performed a similar number of mouse clicks, approximately 14, but they differ in average duration up to 40 seconds and average screen transitions up to 2.5 transitions.

Table 11. Quantitative descriptors describe the interactive behavior required for InfoGather, per-patient mean (standard deviation) and *range* for each of the five clinicians.

Clinician **Patients (n)**	H1 **9**	H2 **21**	H3 **16**	R1 **12**	R2 **8**
Duration (seconds)	127.9 (133.5) *52 – 476*	65.5 (35.0) *22 – 125*	112.7 (45.5) *34 – 192*	306.7 (191.1) *88 – 688*	152.9 (84.5) *33 – 205*
Screen Transitions	5.8 (2.5) *4 – 12*	3.5 (1.4) *2 – 7*	5.3 (2.3) *2 – 10*	8.0 (5.2) *2 – 16*	7.8 (4.2) *2 – 15*
L. Mouse Clicks	14.4 (10) *7 – 39*	8.3 (5.1) *3 – 21*	14.0 (6.4) *4 – 28*	--	13.9 (7.8) *3 – 27*
Mouse Scrolls	25.6 (34.8) *0 – 104*	14.4 (37.1) *0 – 143*	--	--	--

In examination of the variation across H1's nine observed patient cases, I find that the highest measures for H1 across all descriptors are associated with one patient, who H1 described as "a challenging patient". The work described by the quantitative descriptors (476 seconds, 12 screen transitions, 39 mouse clicks, and 104 mouse scrolls) are more than twice H1's average interactivity across all nine patients (see Table 12). Without this patient case, H1's performance is described by a lower average and less deviation—5.0 screen transitions (sd 0.9, range 4-7), 11.4 left mouse clicks (sd 4.2, range 7-19), and duration of 84.4 seconds (sd 30.2, range 81-151).

Table 12. Quantitative descriptors of InfoGather for H1—total activity across nine patient cases, the per-patient mean and standard deviation across nine cases, and total for one complex patient case.

Descriptors	Total across nine patients	Mean (sd) across nine patients	Total for one complex case
Duration (seconds)	1150.8 (19.2 min)	127.9 (133.5)	476
Screen Transitions	52	5.8 (2.5)	12
L. Mouse Clicks	130	14.4 (10)	39
Mouse scrolls	230	25.6 (34.8)	104

R1 has the highest average task duration. Patient case complexity (based on patient chart review) does not explain high task duration for many of R1's cases. However, R1 had the least experience with the EHR and is the least-experienced clinician. Therefore, I can assert that a users' EHR and clinical expertise will influence their efficiency in using health IT artifacts, efficiency measured by task duration.

On average, H2's average quantitative descriptors are less than the other clinicians' averages (Table 11); H2's averages are 21-66% of the other users' averages. On one of the two days observing H2, H2 was notably rushing through InfoGather for many of the 12 patients in order to start rounding with a waiting fellow. This supports that the amount of time the user has available will influence how they interact with the health IT artifact. Among the hospitalists, there was no apparent associatation between different clinical training and amount of variation. In fact, across the hospitalists, the variable averages describe a nurse practitioner and physician assistant (H3 and H1, respectively) more similarly than they describe the two nurse practitioners (H3 and H2) (Table 11). However, when grouped by clinical role, hospitalists' average duration clearly differs from the residents' average duration—94.2 seconds and 245.2 seconds, respecitively (Table 13). Further, hospitalists averaged 4.6 screen transitions, almost half of residents' 7.9 screen transition average (Table 13). Each hospitalist has nearly equivalent EHR expertise when compared to each other, and more EHR expertise compared to each resident. Therefore, this provides additional evidence supporting that EHR expertise will influence users' efficiency in using health IT artifacts.

Table 13. Average quantitative descriptors for InfoGather by clinician role type—hospitalist (H) and resident physician (R). For each, the per-patient mean (standard deviation) is given.

Clinician **Patients (n)**	H average **46**	R average **21**
Duration (seconds)	94.2 (71.6)	245.2 (172.5)
Screen Transitions	4.6 (2.2)	7.9 (4.7)
L. Mouse Clicks	11.5 (7.2)	--

I examined combinations of interactive measures to explain variation. In one case, I related repeated patterns to quantitative interactive descriptors in order to characterize the difference in complexity for each pattern (Kaufman et al., 2015). There was much variation in the quantitative descriptors and sequential patterns of the manually-coded sample but, for the given sample, there was no apparent association between pattern frequency and lower quantitative descriptors (Kaufman et al., 2015). Therefore, the more frequent or preferred patterns did not necessarily require the fewest interactions.

In a second case, I found evidence that may suggest that a combination of factors explain variation in work. Observations and retrospective review of video recordings revealed that participants formed new information needs during the task. For example, one participant stated “For ICU patients, in medications, I’ll go to infusions to make sure they’re not on any pressures or drips of any kind.” For each ICU patient, the clinician had an additional information need—to check that ICU patients are not on infusion pressures or drips. To get this information, the clinician had to transition to a new screen. In a second example, a participant stated, “It looks like [the patient] was a little hypotensive so I go all the way back to the beginning […]. I’m trying to go back to see her admit blood pressure so that if I get called about her blood pressure today, at least I’ll be familiar if she came with low blood pressure.” Because the patient was hypotensive (i.e., has low blood pressure), the participant wanted to know how it compared to the patient’s blood pressure when admitted to the hospital because admit blood pressure is used as a baseline measure in post-operative hospital care. To obtain this data, the particpant had to update (or modify) the display view to display a larger range of past data. In a third example, the participant stated, “So I’m looking at her Sinogram (an x-ray procedure). It says [drain 1] should be flushed daily with 10 cc of saline. So then I have to go into MICS, click on [Surgeon’s] patient, [click on] [the patient’s] name, [and] inpatient order entry to see if it was done. [It reads] drain flush twice daily. Okay." In this example, the participant read in the patient's care plan, documented in the previous day's progress note, that the patient's wound drain needed to be flushed twice daily. This led the participant to change applications to MICS to ensure that there was an active order for twice daily drain flush for the patient. Other examples were documented but not presented here.

Additional information needs arose from viewing notes listed in the "Pending Tasks" section of the paper ESL, viewing an abnormal value in the EHR or on the paper ESL, and from a memory of an incomplete task or patient need. Additional information needs required varying levels of additional work to access the data, from modifying the time interval of displayed data, navigating to a different screen within the application or navigating to a different application. Users' interactive behavior to satisfy these information needs would increase quantitative descriptors of effort and/or increase variation in patterns, depending on the interaction performed.

Task 2: Progress Note Documentation (ProgressNote)

In this section, I apply CE methods to best answer the CE questions in Table 3 for a second routine task, progress note documentation (ProgressNote). These results have not been presented in a previous study.

The EHR-generated event log sample consisted of 622 patient cases across 6 clinician participants. Of the 622 patient cases, 21 patient cases across 4 of the participants were observed and video recorded. For each observed case, data from Morae™ video capture and clinicians' think-aloud verbalizations were used to manually code users' interactions with health IT systems.

Action and event types. According to the EHR-generated event logs, participants accessed and viewed 29 different EHR screens and 122 clinical document types during the task. The document types not only differentiate note types (e.g., progress note, consult note, post-procedure note, evaluation, etc.), they also differentiate what clinical service authored the document (e.g., gastroenterology consult, cardiovascular consult, pain consult, etc.). For this analysis, the clinical documents were grouped into 11 document categories, which were defined with a clinical collaborator as clinically-relevant categories for post-operative hospital care—CRS Progress Note, Specialty Hospital Progress Note, General Hospital Progress Note, Surgical Procedure-associated Note, Diagnostic Procedure Note, Diagnostic Procedure Assessment Note, Consult Note, Hospital Admission Note, Hospital Summary, Nurse Documentation, and Follow-up Visit Note. There were two event types regarding digital dictation—Digital Dictation View and Digital Dictation Listen. These were unchanged as there was no way to know what the dictated note was in regards to. The CRS Progress Note category is for progress notes authored by a clinician in the Colon and Rectal Surgery (CRS) Division, the study setting. It is distinguished from progress notes authored by other services because it is the focus of this task analysis. Table 14 presents the 15 most frequently viewed EHR screens and document categories. Among the list are 6 document categories, which include CRS Progress Note (CrsPN), Surgical Procedure-associated Note (SurgN), the patient's Hospital Summary (HSum), and Specialty Hospital Progress Notes (SpecPN). The list also contains 8 of the 13 main EHR display tabs, as well as the left Navigation Panel (N), which is a collapsible vertical panel on the left of the EHR interface. It was defined as a screen in this study because it is relevant to users' EHR-interactions for accessing patient charts. Each of the 15 most-viewed screens was viewed more than once for some cases and up to 25 times (SpecPN) (see max repetitions in Table 14).

Table 14. Screen and document statistics for the ProgressNote task.

Screen and Document Category	Screen/Doc Symbol	Absolute Frequency	Max Repetitions
CRS Progress Note[d]	*CrsPN*	1392	18
Documents/Images	*D*	777	9
Navigation Panel	*N*	419	4
Summary	*S*	301	6
Surgical Procedure-associated Note[d]	*SurgN*	217	13
Medications: Active Medication Profile	*M*	178	11
Hospital Summary[d]	*HSum*	158	7
Labs	*L*	156	11
Intake / Output	*I*	147	5
Specialty Hospital Progress Note[d]	*SpecPN*	118	25
Medications: MAR	*Mar*	98	7
Patient Demographics	*Dem*	83	2
Vital Signs	*V*	77	8
Diagnostic Procedure Note[d]	*DxN*	62	5
Consult Note[d]	*ConN*	57	8

[d] Denotes the document categories.

Both CrsPN (CRS Progress Note) and D (the EHR's Documents/Images screen) were viewed for all patients. This is because the clinician navigates to the Documents/Images screen in the patient's EHR chart to initiate a new CrsPN. In this data set, CrsPN most often refers to the progress note document being worked on by the clinician in focus. However, it occasionally refers to a note associated with a previous day and/or authored by a different member of the patient's CRS care team.

Observations revealed that participants not only rely on a number of screens within the EHR, they also rely on other electronic and non-electronic information artifacts. Participants accessed four computer-based applications—the EHR (Synthesis), MICS Clinical Notes, Shorthand, and ESL—and one paper artifact—the Paper ESL. The EHR (Synthesis) and MICS Clinical Notes were used for all patient cases because the CRS Progress Note document is initiated from the EHR and is edited in MICS Clinical Notes. Shorthand was used to assist with data entry, and the web-based ESL to review and copy patient-specific data to aid in completing the task. Each user had access to their Paper ESL sheets during the task. These paper artifacts contained clinicians' annotations for each patient (i.e., patient information, tasks and reminders). Clinicians' use of paper to complete ProgressNote will be discussed further below.

Interactive patterns. Sequential analysis of the EHR event logs revealed that the 622 patient cases are described by 390 variant screen transition patterns. The 9 most frequent patterns account for 29% of the cases. Across the 9 most frequent patterns, each was followed between 54 and 6 times (Table 15). Table 15 also indicates the percent of clinicians' patient cases for which the clinician followed each pattern (normalized by clinician's total to reduce bias of varying sample sizes). The most frequent pattern occurred for 54 cases: Documents/Images to CRS Progress Note (Pattern 1: D-CrsPN). It was followed by H1 for 3% of H3's cases, H2 for 29% of H2's cases, H3 for 6% of H3's cases, H4 for 11% of H4's cases, and R2 for 5% of R2's cases. Both the second and third most frequent patterns were followed 28 times each. Navigation to Summary to Patient Demographics to Documents/Images to CRS Progress Note (Pattern 2: N-S-Dem-D-CrsPN) was followed by one clinician—36% of R2's cases. Navigation to Summary to

Documents/Images to CRS Progress Note (Pattern 3: N-S-D-CrsPN) was followed by two clinicians—24% of H1's cases and 3% of R1's cases.

Table 15. Screen sequence patterns and frequency measures for the 13 most frequent patterns performed in the ProgressNote Task.

Pattern	Screen Sequence	Frequency (cases/ pattern)	Normalized Pattern Occurrence					
			H1	H2	H3	H4	R1	R2
1	D - CrsPN	54	0.03	0.29	0.06	0.11	0	0.05
2	N - S - Dem - D - CrsPN	28	0	0	0	0	0	0.36
3	N - S - D - CrsPN	28	0.24	0	0	0	0.03	0
4	N - D - CrsPN	22	0	0.04	0.14	0	0	0
5	CrsPN	19	0.04	0.05	0.05	0.03	0	0.01
6	N - VwR - D - CrsPN	8	0	0	0	0.08	0	0
7	D - CrsPN - CrsPN - CrsPN	7	0	0.01	0.01	0.01	0.03	0.01
8	CrsPN - CrsPN	6	0	0.01	0.03	0.01	0	0
9	N - D - CrsPN - CrsPN - CrsPN	6	0	0.03	0.02	0	0	0
10	D - HSum - SurgN - CrsPN	5	0	0	0	0.05	0	0
11	N - S - D - CrsPN - CrsPN	5	0.04	0	0	0	0.01	0
12	N - S - D - HSum - CrsPN	5	0.05	0	0	0	0	0
13	N - D - SurgN - CrsPN	5	0	0	0.04	0	0	0
14-43	20 patterns	2-4 each	0.13	0.13	0.14	0.11	0.13	0.09
44-390	347 patterns	1 each[a]	0.47	0.45	0.51	0.60	0.81	0.47
	Total (case count)	***622***	***104***	***101***	***129***	***95***	***116***	***77***

Note: Frequency gives the number of patient cases per pattern. Normalized Pattern Occurrence expresses the frequency the clinician uses a screen sequence pattern as a percent of their total cases. EHR screen codes: N (Navigation Panel), D (Documents/Images), S (Summary), L (Labs), V (Vital Signs), I (Intake/Output), VwR (Viewer Reports), Dem (Patient Demographics). Document type codes: PN (CRS Progress Note), HSum (Hospital Summary), SurgN (Surgical Procedure-associated Note).
[a] The percent of cases in which clinicians had a unique pattern served as a preliminary measure of variation.

Over half of all cases (347 patterns; 55.8% of total cases) exhibited a pattern that appeared only once (Patterns 44-390). These 347 patterns explain 47% of H1's cases, 45% of H2's cases, 51% of H3's cases, 60% of H4's cases, 81% of R1's cases and 47% of R2's cases (Table 15). I use the number of sequence patterns with only one case associated as a measure of variation. Thus, H2's task performance had the least variation (45% of H2's cases had a pattern that appeared once), whereas R1's task performance had the most variation (81% of R1's cases had a pattern that appeared one time).

The patterns in Table 15 show that users started ProgressNote by navigating to D (Documents/Images screen), N (Navigation Panel) or directly to CrsPN (CRS Progress Note). The user could re-open a patient chart via the Navigation Panel (N), or by clicking on the chart tab in the patient demographics banner along the top of the EHR interface. The latter did not have a unique event description that could be easily identified in the event log analysis. The user could directly navigate to a previously started CrsPN (or other clinical document) through the Documents Manager, which was accessible in the EHR's left panel. This does not show up in patterns shown in Table 15 because it was used less often. It also appeared to be favored by certain users.

In most cases, D (Documents/Images screen) precedes CrsPN (CRS Progress Note) and other document categories. This is because the documents were accessed and viewed from the EHR's Documents/Images screen, which centralizes the patient's clinical documents from multiple health IT applications, to include MICS Clinical Notes, radiology images and reports from QReads, anesthesia documentation and other documents from Clinical Document Management Reports (CDM) and documents scanned or attached to the patient's chart via ICE.

Some patterns in Table 15 show that participants navigated to other screens and documents to complete the task. For example, Patterns 2, 3, 11 and 12 involve navigation through S (Summary screen), Pattern 3 through Dem (Patient Demographics screen). Pattern 6 through VwR (Viewers/Reports screen), Patterns 10 and 12 through HSum (Hospital Summary document), and Patterns 10 and 13 through a SurgN, a note that is associated with the patient's surgical procedure—such as an operative report, post-procedure note, and post-anesthesia assessment note. On the other hand, there are short patterns—such as D-CrsPN (Pattern 1), N-D-CrsPN (Pattern 4) and CrsPN (Pattern 5)—which suggests the participant can start and finish the task without accessing other screens or documents in the EHR, at least for some patients. Two of these (Patterns 1 and 5) were followed by most of the participants, providing additional evidence that this minimalist approach is sufficient for completing the progress note for certain patients.

A source of variation in ProgressNote patterns resulted from repeated viewing of CrsPN. For example, Patterns 7, 8, 9 and 11 show that a CrsPN was accessed more than once in the day. In some cases, a CrsPN event in the pattern is the clinician looking at a CRS progress note written on a previous day. More often, though, repeated viewing of the CrsPN is associated to the clinician returning to the CrsPN later in the day, near the end of the clinician's shift, to review the note for accuracy and completeness given that other patient care events may have happened since the note was started that morning. I observed this behavior and it was discussed in clinicians' think-aloud. Further supporting this assertion, a temporal view of the sequence patterns shows that for many patient cases, hours passed between the first and second occurrence of the CrsPN event.

Sequential pattern analysis was also employed to examine the manually-coded event log data set. The findings are integrated with the quantitative descriptors for this data set in the following paragraphs.

Quantitative descriptors. Quantitative descriptors of users' interactive behavior were determined for the 21 observed patient cases across 4 clinician participants—I have no observations for H4 and R2 for the task. Quantitative descriptors include task duration, screen transitions, mouse clicks and keystrokes. There is variation in quantitative descriptors within and across participants (see Table 16). Across clinicians, average task duration was 229.8 to 323.4 seconds with a range of 154 to 573 seconds. Clinicians averaged 9.4 to 14.5 screen transitions with a range of 6 to 19 screen transitions, and the average mouse clicks varied from 32.9 to 89.5 with a range from 24 to 109. A screen transition resulted in 3 to 6 mouse clicks. On average, per patient case, ProgressNote took less time to complete and fewer mouse clicks for H1 than for H2 and H3. However, H1 performed about the same number of screen transitions and keystrokes on average. This may suggest that some users are more efficient at completing the task and can complete the same work in less time.

Table 16. Quantitative descriptors characterize the interactive behavior for ProgressNote task: Per-patient mean (standard deviation) and r*ange* for each of four observed clinicians.

Clinician **Patients (n)**	H1 **8**	H2 **9**	H3 **2**	R1 **2**
Duration (seconds)	229.8 (65.8) *154 – 323*	323.4 (148.5) *154 – 573*	314.5 (84.2) *255 – 374*	*589-988*
Screen Transitions	10.1 (3.9) *6 – 19*	9.4 (3.4) *6 – 14*	14.5 (2.1) *13 – 16*	*57-73*
L. Mouse Clicks	32.9 (9.4) *24 – 53*	56.2 (19.8) *35 – 87*	89.5 (27.6) *70 – 109*	*189-344*
Mouse Scrolls	18.9 (18.0) *2 – 57*	129.4 (69.1) *19 – 230*	28.0 (8.5) *22 – 34*	--
Keystrokes	695.5 (207.8) *343 – 937*	576.8 (243.3) *261 – 930*	667.5 (299.1) *456 – 879*	--

I examined the variation across H2's cases because it is the largest sample from a single participant. Based on nine patient cases, H2, on average, took 323.4 seconds (5 minutes 23.4 seconds) and performed 9.4 screen transitions and 56.2 mouse clicks per case (Table 17). Across the nine patient cases, H2's task duration ranged between 154 to 573 seconds (2.5 to 9.5 minutes) to complete (see Table 17). Referring to patient cases 1-4, which averaged 212 seconds each (sd 46.5 seconds), H2 verbalized that they were easy cases because the patients were "all fine and are going home [today]". This supports that patient case complexity influences task duration.

Table 17. Quantitative descriptors of ProgressNote task for the nine observed patient cases completed by one clinician, H2.

Patient Case	Screen Transitions	Mouse Clicks	Duration (seconds)	# of items documented in Plan
1	7	35	196.0	6
2	6	36	154.0	4
3[a]	12	55	244.0	6
4	6	59	255.0	9
5[b]	11	86	573.0	18
6	6	36	195.0	4
7	9	53	369.0	7
8	13	87	440.0	7
9	14	59	485.0	8
Mean (SD)	9.3 (3.2)	56.2 (19.8)	323.4 (148.5)	7.7
Total	84	506	2911	

[a] Describes a case completed with an efficient interactive pattern.
[b] Describes a complicated case completed with a less efficient interactive pattern.

I further examined variation for sources of complexity by looking at H2's longest case—Case 5 (in Table 17), which required 9.5 minutes, 11 screen transitions, 86 mouse clicks and 58 actions to complete. While it took the most time to complete and these values lie on the high end of the range of observed values, they are not the highest (see Table 17). An important purpose of the ProgressNote task is to record the care plan for the patient; therefore, I examined the number of items (orders) written in the Plan. With 18 items, Case 5's Plan had the most number of items (Table 17). The other progress notes averaged 6.4 plan items (sd 1.8, range 4-9). Therefore, this further supports that patient case complexity influences task duration.

Sequential process mining techniques were applied to H2's manually-coded interactions to surface H2's patterns of interaction with the CrsPN sub-sections. Figure 17 compares an efficient (Path 1) and less efficient (Path 2) sequence of H2's interactions with CrsPN sub-sections. Of note, this representation does not scale to reflect the difference in task duration between the two patient cases. Also, Figure 17 does not reflect the clinician's interactions with other applications or with the Paper ESL. Path 1 represents Case 3 in Table 17, and Path 2 represents Case 5 in Table 17.

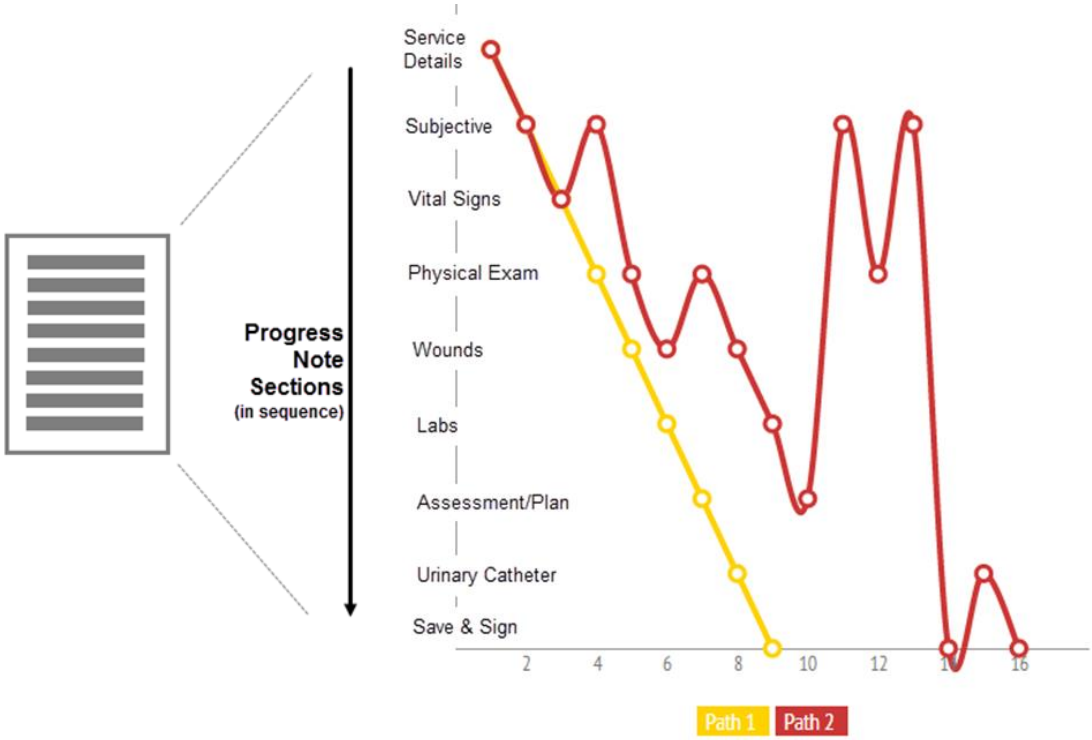


Figure 17. The sequence a hospitalist works on the sections of the progress note for an efficient task performance (Path 1) and a less efficient task performance (Path 2).

In Figure 17, Path 1 (Case 3) shows the clinician completing the note sections in sequence; therefore, efficiently. This is contrasted with Path 2 (Case 5), in which the clinician works on the CrsPN sub-sections in a non-sequential flow that involves repeated viewing of some sub-sections. Through review of video recordings, I observed that the clinician appeared to complete much of the CrsPN for Case 5 (Path 2) from memory. After progressing through the note in a near sequential pattern (steps 1-10 in Path 2), the clinician returns to the Subjective and Physical Exam sub-sections (steps 11-13 in Path 2) to add additional text regarding non-normal findings and atypical exam details specific to the patient. This backtracking or a straying from a sequential path that led to repeated viewing of sub-sections, is associated with H2's use of the Paper ESL. Therefore, in this case, the Paper ESL served as a reminder of the need to document abnormal findings for the patient case. Further supporting that the clinician uses the Paper ESL as a reminder of abnormal findings, the clinician did not appear to look at the Paper ESL at any point to complete CrsPNs for two other patient cases (Case 1 and Case 2 in Table 17), in which H2 followed the efficient path (Path 1), and no abnormal findings were documented in the Subjective and Physical Exam sub-sections of these notes.

It was also observed that H2 experienced several interruptions while completing ProgressNote for the less efficient Case 5 (Path 2), but experienced no interruptions when completing the task for more efficient Case 3 (Path 1). Therefore, interruptions may have influenced the less efficient interactive pattern and repeated viewing of CrsPN sub-sections. Interruptions are known to be disruptive and ubiquitous, and their effects need to be considered in design (e.g., by using natural pauses or "you were here" kind of markers). For example, Microsoft Office products now "you were here" reminders when a user re-opens a document.

For all nine progress notes, H2 copied text from a previous note or the ESL and pasted it into the progress note. Text was retrieved most often to complete the Assessment/Plan section, though text was occasionally retrieved to complete the Subjective section as well. In fact, all of the observed clinicians performed multiple screen transitions when completing the Assessment/Plan sub-section of each CrsPN. Often these multiple screen transitions were performed to review or copy data from other screens into the progress note. The system design facilitates reuse of Assessment/Plan narrative; the "Pull from Previous Document" dialog box facilitates the clinician in reviewing and "pulling", or reusing, Assessment/Plan text from previous clinical notes (Figure 11 in Chapter IV). Although a 'stand-alone' clinical encounter document may facilitate time-savings and administrative benefits, transferring information from one clinical document to another may propagate unidentified errors that could have adverse effects on patient management (e.g., copying outdated information on medications). For example, while the observed clinician appeared to review all data reused (copy and pasted, or pulled) from other sources, she showed how a previous patient note created by another member of the patient's care team had incorrect documentation, a result of pulling Assessment/Plan text from previous chart notes without updating. Upon seeing the incorrect documentation in the previous clinician's patient note that says the patient has a catheter, H2 verbalized the "patient has already had her catheter out." A screen capture of the "Pull from Previous Document" button and dialog box is given in Figure 11, in Chapter IV.

Occasionally, the clinician wanted to reuse text from other applications or notes that were not available through the dialog box. Where pulling did not facilitate access to the needed information, the clinician juxtaposed the application windows to provide a view of two windows at one time so that she could retype information read in one window into the progress note window (see Figure 18).

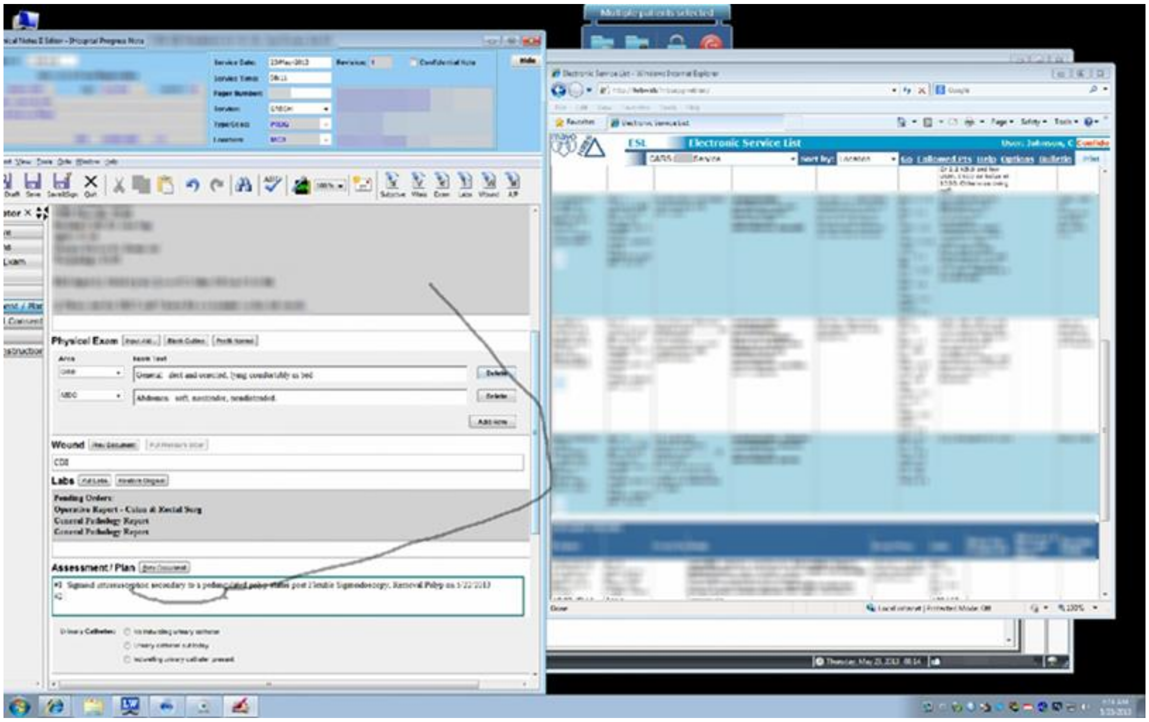


Figure 18. Screen capture showing a clinician's computer monitor with two screens in view to create access to needed information.

Results & Discussion of CE Task Analyses

In each CE task analysis, CE methods were employed to derive measures of users' interactive behavior in order to characterize the effort involved to complete a routine task (Question 7). These measures characterized how interactive effort varies among clinicians, by task and patient cases (Question 8). They were then examined with the full data set to explain this variation (Question 9). CE assumptions suggest that some workflow patterns are better than others to complete work processes. In this section, I draw on findings from InfoGather and ProgressNote to evaluate what variation indicates the user is having difficulty, be a result of the system or interface design or the user's skill and knowledge (Question 10). This can be used to identify sources of complexity

(Question 11). From these, I draw implications to where user training resources would be best allocated to reduce unnecessary variation (Question 12). In instances where complexity results from aspects of system or interface design, I draw implications to what interface design would reduce unnecessary user variation (Question 13).

Variation in measures of interactivity could be seen in both the quantitative descriptors and screen transition patterns within and across users. More specifically, in both InfoGather and ProgressNote analyses, variation in patterns was best evidenced by patterns that occurred for only one patient case each and by patterns that contained repeated screen viewing. I found evidence that variation in quantitative descriptors and measures of pattern variation were associated with the users' system settings, the interface, users' preferred interaction patterns, patient case complexity, users' experience (EHR and clinical), and the lack of cognitive support provided by the system to help the user synthesize and consolidate patient findings. By integrating the full data set it was possible to explain behavioral variation between users; however, due to this study's small sample size, it is not possible to generalize clinicians' behaviors. Future studies should further examine the correlations discussed here.

The early interactions in patterns performed for InfoGather and ProgressNote were explained by functionality of the EHR. For example, all InfoGather patterns started with N because it was the first task of the day and navigation through N required for users' first-time access to patient charts each day(S. K. Furniss, Burton, Grando et al., 2016; Kaufman et al., 2015). ProgressNote task is not the first EHR-based task the users perform each day; therefore, patient charts were often already open in the users' EHR profiles and there were multiple ways of re-opening a patient chart or progress note. The early interactions in patterns were also explained by EHR default settings. In InfoGather, it limited what screens the patterns started on to the three default setting (N to S, N to D and N to VwR). The variation in patterns explained by system default settings was evident in the small sample and became more apparent when I examined the EHR-generated event logs because the default settings limited the pattern possibilities. It was assumed that default settings improved workflow so that clinicians would not have to visit the screen twice. It could be that the default setting serves them better on another task. However, for the given tasks, these system default settings were not useful for all participants. In fact, the screen transitions caused by default settings require more effort by the participant to complete the task. Useful system defaults can decrease participants' task effort and improve efficiency; therefore, users' system default settings should be reviewed.

I found evidence that variation across users for a task was also associated with users' preferred patterns of interaction (or interaction strategy). Similar to above, such variation may be evident in one user largely following A-B-C-D-E, another A-E-D-C-B, and another A-X-Y-C-D-E to complete the same task. These are useful to the user because they lower the cognitive effort required by the user to complete the task. That is, it is less cognitive effort to follow the same pattern for most patients, even if it includes more interactions than are needed for some patient cases (i.e., unnecessary interactions). At least, it ensures that the user did not miss information. Therefore, such preferred patterns are a workaround because they were created in response to a system/interface that does not help direct the user's attention to new or relevant patient information. Preferred patterns were found in comparing variation across clinicians for the same task. These could be useful for further analysis to assess system usability and users' difficulty with the system. Perhaps, also to identify information needs.

Variation due to patient case complexity and particular patient states are inevitable. However, some of this variation may be predictable and can be integrated into system design to support users' cognitive work. For example, clinicians had information needs develop during the task that were in response to particular patient circumstances. For example, a patient transferred to and being cared for in the ICU, the hospitalist had to confirm that the patient IV orders were active and being followed. For a patient with an abnormal vital sign value, the clinician wanted to compare it to the patient's baseline value (from when the patient was admitted). And, third, when the clinician read that the patient's care plan should have active order for twice-daily wound drain cleaning, the clinician navigated to the orders application to confirm that there was such an active order for the patient. It is useful to understand that some interactions that increased variation were in response to specific patient states or case type. An improved system design may anticipate the users' information needs based on patient case types or a combination of patient case data. Future work could do a more thorough investigation into information needs for specific patient case types.

Patterns containing repeated screens or events (e.g., repeated screen viewing) was evidence of usability issues. Resources for usability analysis should be directed to understand reasons for repeated screen viewing. For example, in InfoGather, R1 had difficulty with the organization and visualization of lab results in a patient chart but found the visualization of lab results on the Summary screen to be easier to interpret. This lead to R1 navigating back and forth between the Labs (L) and Summary (S) screens. An example from ProgressNote is best seen in repeated navigation to and viewing of the CRS Progress Note (CrsPN) throughout the user's day. This revealed that the user has a need to review and update data in the document over the course of the user's shift, but design does not support this. A progress note that is not reviewed and updated later in the day, likely reflects the patient's care plan at the time it was authored (usually, in the morning hours); therefore, it may be inaccurate or incomplete later in the day by the end of the clinician's shift. If the clinician does not update the care plan in the daily progress note, than updates to the care plan are likely documented elsewhere, if at all. This has a consequence for other members of the patient's care team who have to review and reconcile data across various information sources. This was well exemplified in Case Study 2 from the DCog analysis; Case 2 showed that H2 documented variations to a patient care plan across three different information tools, and the difficulty it caused the hospitalist caring for the patient on the subsequent day. While H2 verbalized a preference not to review and update the daily progress note throughout the day, H2 verbalized a preference for doing so. Perhaps team members of H3 are less likely to face challenges in understanding patient state and care plan.

Variation can be used to identify users' with less EHR experience. They had high percent of variation across their sample of patterns followed for a given task, as well as repeated screen viewing. This can be useful in directing training resources. Variation in interactive behavior associated with clinicians' EHR and clinical experience was best evidenced by R1, who is the least experienced clinician and user of the EHR. R1 performed a high number of quantitative descriptors, or "interactive costs", across patient cases in both InfoGather and ProgressNote. An association between variation and users'

EHR and clinical experience was further evidenced by R1 having a high percent of unique user patterns compared to users who were more experienced with the EHR and clinically, and frequent repeated screen viewing. For InfoGather, R1 followed a unique screen pattern for 38% of R1's patient cases. For ProgressNote, R1 followed a unique screen transition pattern for 80% of R1's patient cases. This was the highest across the six clinicians in both tasks. This measure of pattern variation was significantly lower for the four hospitalists—it ranged from 18-27% for InfoGather and 45-60% for ProgressNote. This is not surprising because studies have shown that clinical training influences information gathering strategies and patient mental models. In particular, research has shown that more experienced users develop robust mental models(Kieras & Bovair, 1984).More variation is indicative of an incomplete mental model (e.g., understanding of where needed patient information is located or knowledge of potential shortcuts to access data); therefore, user training should facilitate the development of robust mental models .

It is easy to imagine that this may be for a trainee entering a new environment with an established EHR, or an experienced clinician adapting to a newly implemented EHR. Given that initial training to a new EHR is often done out of context of a real work environment (e.g., in a training lab) and often days or weeks pass between initial training and the EHR implementation, it could be useful to monitor clinicians' use patterns to prioritize and direct training resources. A user with a high percent of unique patterns for a task may be indicative of a user with less EHR experience and who could use training on more optimal and task-specific patterns of interaction.

A high percent of unique user patterns and repeated screen viewing may suggest users' inefficient task performance, an indicator of system usability (need to manage large number of items in memory) or of task complexity. For example, conflicting data gathered from another screen or from the paper handoff document may cause the clinician to return to a previously viewed screen. For example, for an efficient ProgressNote task, a clinician completes note sections in the sequence that the sections are presented within the interface. In less efficient cases, clinicians return to previously worked on note sections to add additional data (i.e., repeated note section editing). This behavior was associated with more complex patient cases, when clinicians' needed to view their annotations on the Paper ESL for reminders of the abnormal findings for that patient case. In this case, repeated viewing of a screen (or other event), was associated with patient case complexity. This also reveals the importance of the paper-based notes to support the clinician's memory of patients' abnormal findings.

For both tasks, there was no consistent association between variation in mouse clicks and indicators a user having difficulty. For example, in InfoGather, several clinicians performed a similar number of mouse clicks but differed in screen transitions and task duration. Although "click burden" is widely perceived to be a problem, mouse clicks alone may not be the best indicator of clinicians' work.

System design profoundly impacts efficiency measures because the work required to complete computer-based tasks depends on how health IT screen displays facilitate clinicians in perception, integration, and synthesis of relevant patient data. Therefore, I sought to identify aspects of the interface designs that increase variation and make it difficult for the user to follow the best or most efficient pattern, as well as to identify what interface design would reduce unnecessary variation (Question 13).

The measures of interactivity show enormous variation in EHR interactive behavior across and within clinicians for routine tasks. Some variation was associated with the user's experience level and their system default settings, which can be reduced with targeted training. Some variation was associated with emergent information needs that arose in response to particular patient case types or factors. A system that anticipates the users' information needs with context-sensitive design would reduce unnecessary variation. An improved system would accommodate some variation—such as differences in tasks, information needs—but reduce overall variation in view to promote more optimal pathways and perhaps greater confluence with clinical goals in task completion.

Context-sensitive design would reduce unnecessary variation not only by anticipating the users' information needs, but also by simplifying navigation. To reduce variation, improved system design could make a successor state more transparent to the user. I hypothesize that improved system design would reduce variation in screen transition patterns for routine tasks, reduce occurrence of repeated screen views, and reduce interactive effort as measured in quantitative descriptors, such as mouse clicks.

Interface design can also facilitate users to reduce variation by supporting users in keeping track of task progress for moments when the task is frequently interrupted and their attentional resources go toward something else before returning to the task. Design should consider that users' attentional resources are diverted for varying periods of time. For example, a clinician may need a short time frame to look at notes on a paper-based artifact, or a longer timeframe to address a phone call or an emergent event for another patient.

The increasing use of technology in clinical settings to support patient care delivery along with advances in computational analysis tools have made way for the emergence of new data sources and new techniques for analyzing user behavior. Computer technologies provide system-generated data, which enables a larger data set than is reasonable for observation/ethnography-only studies. In fact, Hollan and colleagues foresaw this advancement toward use of automated data. They stated, "In human-computer interaction settings we expect automated recording of histories of interaction (Hill & Hollan, 1994) to become an increasingly important source of data" (Hollan et al., 2000). I drew on computational ethnography techniques to examine system-generated data of users' behavior and to examine other measures of efficient and effective user interaction.

Process mining techniques have advantages of being able to assess manually-coded or computer-generated event log files, and the ability to manage large data sets. While manually-coded files can provide insightful detail, they are time consuming to produce. System-generated event logs are automated and record users' behaviors (e.g. accessing a health IT system, selecting a screen to view, selecting a document to view). Therefore, they potentially offer an alternative to time-consuming manual coding of users' interactions.

While system-generated files can be collected for a large sample of events and users, they are often limited in scope of users' interactive behavior and work. For example, the EHR-generated log files were limited in what data they could reveal about the ProgressNote task because the clinicians initiate the task (i.e., create a new progress note) through the EHR, but the task is primarily performed in a different application, MICS Clinical Notes. As a result, the EHR event logs cannot be used to examine sequences of the clinician working on sections of the note, which I examined in the manually-coded event logs. Still, the EHR event logs are able to reveal some information about the task, such as the EHR screen displays viewed (e.g., the Documents/Images and Intake/Output screens) and the documents accessed and viewed in the Documents/Images screen.

I draw on the other findings to make recommendations for what EHR event log files could capture that would be meaningful for studies of user interactive behavior and workflow analysis. Earlier, I defined high percent of unique user patterns, repeated screen viewing, and high quantities of interaction as indicators of users' challenges. Therefore, I recommend system-generated event logs capture this data to assist in workflow analysis studies.

Even with these improved system-generated event log data, there will be limitations in relying solely on system event logs to examine user behavior. For example, computer-based event log files do not reveal clinicians' use of paper artifacts. This is a limitation because understanding the use and importance of the paper ESL artifact was integral to understanding clinical workflow in CRS Rochester. More specifically, for example, information needs also could not be determined by looking at EHR interactions alone because some clinician participants relied on the paper artifact as an information source in place of an EHR display. In this case, the event log files would under-represent clinicians' information needs. To capture that some clinicians relied on the paper artifact as the sole information source for some information needs required detailed observation. Consequently, EHR interaction (or log file) data should not be relied on solely for telling a story of user's information needs.

Further, process mining analysis of event logs revealed the number of times a clinician visited a screen (Table 5); it did not necessarily correlate to the use of the screen or to information gathered because some users navigated through a screen but did not actually look at the data or intend to look at the data. For example, H1 viewed the Summary display for all patients because it was the default display when opening a new patient chart. H1 was not observed using the Summary display for InfoGather. H2 and H3 also did not use the Summary display. In contrast to H1, they never interacted with the Summary display because they did not navigate to it and because they had a different screen, the Documents/Images screen, set as default display when opening a patient's chart. H1, R1 and R2 have the Summary display set as default screen display when opening a patient's chart. Therefore, they all navigate through this screen, but observation of them conducting the task shows that only R1 uses the display for the data gathering task. As a result, it will be difficult to rely solely on system-generated event logs for studying health IT-based work. By integrating observation and ethnography with system-generated event log analysis, the methodology reveals these inefficient work patterns and helps to explain reasons they occur.

It became apparent that the manually-coded event logs differed from the EHR event logs in two important ways. First, while the EHR event logs describe participants' interactions with clinical documents and EHR screens, the manually-coded event logs describe these as well as participants' interactions with other health IT applications and with sub-sections of the progress note for each case (e.g., Subjective, Labs, Vital Signs, Physical Exam, Assessment and Plan). Therefore, the manually-coded event logs reveal a different level of granularity into the ProgressNote task than can be examined with just the EHR event logs. Second, most of the ProgressNote observations and video recordings captured the first time the participant worked on the CrsPN that day. For some of these patient cases, the participant accessed the CrsPN later in the day to review and/or revise the note. Therefore, for some patient cases, the measures of observed behavior may be underestimating effort required for the task. Participants' interactions with progress note document sub-sections are likely not described by EHR event logs because the progress note is documented in MICS Clinical Notes application. Despite having a small sample of manually-coded cases of participants' interactions with progress note sub-sections, I associated characteristics of patient cases, participants, etc. to measures of interactive behavior and seeded hypotheses for future work.

Such efforts to support and improve human's cognitive performance can be particularly important for systems where the human user has to obtain information from various sources for reasoning and decision-making.

Chapter VI

CONCLUSION

Post-operative hospital care exemplifies complex workflows characteristic of the most demanding clinical environments where work is multi-tasking, cognitive, and collaborative, and where patient care requires multiple clinicians to coordinate and utilize information artifacts. In particular, post-operative hospital care at CRS Rochester exemplifies how clinicians face challenges in performing health IT-mediated workflow due to issues with system usability, information management, communication, and coordination processes. It is my contention that many of the difficulties in health IT-mediated workflow are the result of health IT design and use that does not support the cognitive demands imposed by the activity system or the workflow it constitutes. Hospitals and institutions invest significant resources in implementation and ongoing use of health IT. There is ample evidence to suggest that a lack of workflow analysis is more likely to yield problems. I also believe that a relatively superficial workflow analysis cannot possibly mirror the complexity and variation that is observed even in a single setting. The primary contribution of this dissertation is a robust and unified methodological framework to examine clinical workflow. In particular, data collection and analysis methods from DCog and CE theoretical frameworks were integrated to characterize and evaluate clinicians' health IT-mediated work, and devise implications for improvement.

To demonstrate the methodological framework, it was applied to the study of post-operative hospital care at CRS Rochester. Analysis focused on two routine health IT-based tasks, InfoGather and ProgressNote, which are similar in all in-patient hospital care settings. The studies demonstrate the individual and collective contributions of the methods to characterizing and evaluating clinical workflow from varying perspectives, dimensions, and granularities.

For example, the DCog analysis (i.e., the propagation of representational states approach) traced information related to a particular clinical concept for a given patient as seen from a clinician's workflow. Alternatively, it could be used to trace information flow from a patient perspective. I also demonstrated how CE quantitative and sequential analyses can be used to focus on different dimensions of work. For example, I used quantities of interactive behavior to compare performance across clinicians, across clinical roles, clinicians' experience level (EHR and clinical experience), as well as across patient cases. Together, the methods allow researchers to examine work and effort at very fine levels of granularity.

In addition, the set of methods provides a toolset that allows the analyst to adapt to the given setting. The theoretically-grounded questions guide the analyst in this process, with a focus on characterizing the problem, performing an evaluation and drawing implications for improvement. In a given environment, I anticipate that the toolset will be sufficient to answer most of the aforementioned theoretically-grounded questions.

Contributions of the Methodological Framework

Collectively, the methodological framework contributes a toolset of mixed data collection methods that capture different dimensions of work. For example, without video capture, ethnography is often limited by observer bias and missing data because recorded data is subject to what the researcher has her attention on and the rate at which the she can document noteworthy observations. Video ethnography provides the context of the observed work and increases the methods that can be used to study clinicians' communications and work activities. Image captures of clinicians performing clinical activities at and away from the computer show how video footage allows the analyst to retrospectively reconstruct the participants' work with rich detail, to include the sequence of tasks, tools used, information discussed, location of events, and other participants involved.

The Morae™ video recordings of the observed cases enabled clinicians' interactive behavior to be manually-coded for this analysis. Retrospective review of Morae™ video recordings, along with other captured data enabled inferences to be drawn about users' interactive strategies and reasons for variation in task behavior. In addition, the Morae™ video recordings and manually-coded users' interactions, enabled comparison of observed behavior to patterns of interaction (e.g., screen transitions) recorded in the EHR-generated event logs. This allowed me to drill down deep and understand the factors influencing a user's interaction pattern. Collectively, the proposed data collection methods enable a complete and in-depth descriptive analysis of clinical work and information flow. To the best of my knowledge, this combination of methods is singularly unique in workflow research.

The methodological framework integrates several data analysis methods that can examine the breadth and depth of clinical workflow, as well as person-focused and system-focused perspectives of clinical work. In addition, the framework not only guides an analyst to characterize and evaluate clinicians' health IT-mediated work, but also to draw inferences as to how to improve health IT design and use that may ultimately contribute to increased system efficiency.

The unique applications of the DCog and CE analytic approaches are discussed in the next two sections.

The DCog Analytic Approach

The DCog propagation of representational states analytic approach is integral to describe how distributed components of the activity system are coordinated. It surfaces a rich description of actors' mechanisms of cognitive work for information sharing, exchange and processing in patient care delivery. In this dissertation, I elaborated on case studies presented in(S. K. Furniss, Burton, Larson et al., 2016) in order to better place the information traced in context of clinicians' work and to describe interactions that change representational states of the information and describe decision-making processes related to the patient's care plan. The micro-level propagation of representational states approach presented here contextualizes information flows in real work, enables assessment of information management and coordination processes, and identifies barriers to workflow.

The DCog analysis approach was used to characterize the sequence of interactions between the actors and information in order to reveal clinicians' information management and coordination processes. I defined a 6-step approach that can guide an analyst to characterize patient problem-centered information flow. This is a novel approach to study clinical work and to realizing the vision of health IT that provides patient-centered cognitive support. Important aspects of the approach include that it integrates data sources, focuses on a single patient, examines interactions and representations, traces clinical concepts, and visualizes/represents information flow. The focus on a single patient and tracing of clinical concepts, are unique contributions to (or applications of) the propagation of representational states approach.

Our approach documents sets of representational states at sequential interactions to convey patient-care processes. In doing so, I detailed concrete case studies of work and information flow in real-world settings, which can serve as a basis for discussions about how technologies and processes can better support clinicians' cognitive work and facilitate patient care coordination and teamwork. This fine-grained analysis of work and information flow surfaces aspects of workflow that are otherwise not visible in conventional analyses.

I also reported on empirical findings of note, specifically issues and problems in information management and coordination that collectively result in the clinician being burdened as information and knowledge manager. Empirical findings from the DCog analyses include five barriers to information flow—frequent information transfers, persistent use of paper, clinical reasoning absent in documents, conflicting and redundant data, and gaps in coordination. These barriers identified limitations in health IT—including the fact that health IT is not accessible where information work occurs and is not flexible to support clinicians' annotations, it encourages documenting extensive patient information without requiring clinicians to document a rationale for decisions made, it permits variation and inconsistencies in documentation, and it fails to support coordination and communication in some cases. I identified that improved integration between health IT systems and improved visualizations of patient data are an important step toward assisting clinicians in drawing associations between patient problems, treatment decisions (e.g., orders) and care goals. Health IT that has can do this while also having the mobility and flexibility afforded by paper artifacts, would greatly improve clinicians' information management and coordination work.

The case studies demonstrated how completeness or efficiency of information flow at one point in a clinician's workflow can impact completeness and/or efficiency of flow of related information during another task. That is, how functioning of the activity system as a whole can impact efficiency of work and information flow during a single task or interaction. The highly-granular perspective into information flow and clinicians' information management processes for specific high-value care goals enables researchers to answer a number of questions for characterization, evaluation and improvement of health IT systems.

The CE Analytic Approach

Whereas a DCog approach guides description of how information flows in the activity system to support decision-making and problem-solving, a CE approach guides quantitative evaluation of task effort and performance. CE seeks to support the cognitive functions associated with users' behavior through the design of IT systems that support cognitive work, including the design of system components (e.g., user interfaces, automation, and decision aids). It can also lead to supporting human's cognitive performance through development of training programs and work redesign to manage cognitive workload and increase human reliability. Guided by assumptions, methods and questions from CE and computational ethnography, I examined measures of clinicians' EHR interactive behavior (i.e., quantitative descriptors and screen sequence patterns) to characterize and evaluate the work involved to complete a task. When analyzing these data, I was able to look at sample populations—such as per user, role, pattern—for variation in performance across users and cases. The CE methods and questions also guided me to integrate findings from the full data set (e.g., observation, video, and clinicians' think aloud) to explain variation in clinicians' interactive behavior. Subsequently, I was able to draw inferences as to what aspects of design made it difficult for users to follow most efficient interactive path. It is not possible to definitively answer these questions with a small sample or even in a single study; however, the in-depth and convergent analyses can be used to provide a high definition snapshot which seeds hypotheses for future testing.

The CE analysis presented in the framework is a novel approach to integrating quantitative and qualitative analysis to quantify clinicians' EHR interactions, explain variation within and between users, identify sources of complexity, and draw implications for interface improvement and training.

Empirical findings from the CE analyses showed enormous variation in clinicians' measures of interactivity to complete the same task. Six sources of complexity that contributed to the variation were identified—system default settings, clinicians need to perform an exhaustive search for new information, user's EHR and clinical expertise, patient case complexity, interruptions, and emergent information needs. Implications for interface design that would improve efficiency include: simplifying navigation and anticipation users' information needs with context-sensitive design; directing user's attention to updated information; accommodating various skill levels (e.g., through visualizations); and supporting users in keeping track of task progress. In addition, I defined objectives for user training—to employ a training approach that facilitates development of a robust mental model of the application's functionality. Process mining techniques can be used to monitor clinicians' use patterns to direct and prioritize resources for observation and training.

These findings highlight the inadequacy of the one-size-fits-all EHR design, which best exemplifies most EHRs. Instead, there is a need to better understand productive or necessary sources of variation in clinical work so EHRs can support it.

Perhaps most importantly, it would not be possible to document the enormous variation in clinician's work practices and use of EHRs without a mixed-method micro-analytic approach. Too often workflow models endeavor to capture optimal pathways with little understanding of the factors that are likely to produce deviations from these "optimal" routes. It is no surprise then that EHRs don't accommodate variability particularly well. However, this research shows that there is enormous variability in EHR interactive behavior across and within clinicians for routine tasks. Such variation may not be surfaced in conventional workflow analysis and research methods. Instead, variation is only exposed when we drill down deep and use converging workflow methodologies. A better designed system could better support interaction, for example, by making a successor state more transparent to the user, which reduce variation in screen transition patterns for routine tasks and reduce effort as measured in quantitative descriptors, such as mouse clicks and repeated screen views. An improved system would accommodate some variation—such as differences in tasks, information needs, etc.—but reduce overall variation in view to promote more optimal pathways and perhaps greater confluence with clinical goals in task completion.

Contributions to an Applied Clinical Informatics Project at Mayo Clinic

This study contributed to the methodological approach for Mayo Clinic's ROOT (Registry Of Operations and Tasks) project. The ROOT Project is part of a quality initiative in advance of a large-scale EHR implementation that will replace many EHR platforms (e.g., GE Centricity, Cerner) and health IT applications that currently exist with a single EHR (Epic Systems). A single, enterprise-wide EHR will integrate operational processes currently employed across Mayo Clinic sites. This change will have a profound impact on the workflow of clinicians and staff in all settings.

In response, the ROOT Project is a systematic effort to capture and archive a data set of EHR, clinical workflow, and contextual information from five Mayo Clinic hospitals across the country. The data set will document the current pre-implementation workflows in the peri-operative (i.e., pre-op, intra-op, and post-op) units and emergency departments at each site. These data can later be compared to post-implementation workflows to reveal how workflows were changed by the conversion.

The methodological framework presented in this dissertation has been applied to the ROOT project to reveal and capture an in-depth understanding of work components (e.g., actors, artifacts, tasks, etc.), as well as the interactive behavior and dependencies between the components that influence health IT-mediated performance. To date, it has shown ability to capture, characterize, and evaluate distributed work in these environments, despite the differences in clinicians' processes, goals, health-IT applications, and other contextual factors.

Another objective of the ROOT project is to define a standard workflow analysis approach to be used when implementing, evaluating, or optimizing health IT at Mayo Clinic. The methodological framework presented in this dissertation and lessons learned from the development of the framework have contributed to ROOT's workflow analysis approach and will likely contribute to the future standard workflow analysis approach.

Limitations & Future Work

Given the formative nature of this study and small sample of clinician participants, the analyses presented in this paper encountered several limitations. However, it also served to seed hypotheses for future research. Limitations and future work are detailed in this section.

Much clinical decision making occurs in the mind of the clinician (it is implicit); therefore, it is difficult to observe that process objectively. I attempted to surface this thinking by asking clinicians to think-aloud, and capturing their think-aloud verbalizations. I also asked questions during observation to probe clinicians in hopes of surfacing this implicit thinking and reasoning. Despite employing a thorough approach, some decision-making was undoubtedly missed. An additional method that may better facilitate surfacing of clinicians' implicit thinking is retrospective interviews with the observed clinicians.

I was able to develop this methodology and complete these studies because I had almost unlimited access to settings, people and EHR event log files that many others may not have. Our research efforts closely aligned to CRS Rochester's quality improvement goals, which facilitated such access. With recognition of the important value in capturing an in-depth understanding of clinical workflows in-situ, I hope clinical organization and institutions will make it easier for researchers to have such access to their clinical environments in the near future.

I did not have access to system-generated event logs from all health IT applications used in CRS Rochester. Rather, I only had event logs from a single information system, the EHR (Synthesis). While it was the primary system used for patient documentation and coordination activities in this setting, hospitalists and residents relied on other health IT systems to support care delivery tasks. In particular, for InfoGather and ProgressNote, clinicians also rely on the web-based ESL, MICS Clinical Notes, MICS LastWord, Orders, Shorthand and Outlook, among others. As a result, the measures of interactive behavior underestimate interactions for some patient cases. Despite this limitation, the analysis revealed significant and informative variation in patterns of clinicians' EHR interactions. Future work can integrate event logs from multiple health IT systems.

This research demonstrated how system-generated event logs would be particularly useful for monitoring adherence of clinicians' workflow to guidelines and adherence of patient care delivery to clinical pathways. The system-generated event logs that I had access to did not contain the level of granularity and event types needed to monitor duration between events that have clear clinical relevance, such as time it takes to identify/detect a problem, time between problem identification to action on the problem, and time between problem identification and its resolution. However, lessons learned from this work will help to define useful event log types that health IT systems can generate to discover clinical workflows and to guide workflow improvements. For example, answering these questions would require event logs related to users' interactions with elements of the interface, such as viewing additional lab result data when hovering over the lab result value, clicking on the scroll bar to view additional data, etc.

Also in regards to event log analysis, a second-order analysis in which the sequence was not an exact match (e.g., different starting point, but otherwise follows the same pattern) may reveal additional similarities not detected by the first-order analysis. For example, the number of variant patterns is in part due to the variation in chart default settings. By looking at similarities in smaller units of screen sequences (e.g., three consecutive screens), it may be more informative about shared processes and information needs across clinicians.

The DCog analyses demonstrated how a focus on individual and team interactions in distributed work reveals information management and coordination processes, which could be used to identify barriers to information flow that complicate these processes. Future work can employ other computational ethnography techniques (e.g., temporal and network analyses) to examine care team coordination activities in patient-centered examination of clinical work. These studies will also yield valuable insights to defining useful event log types that health IT systems can generate.

The methodological framework's ability to examine clinical work at varying levels of granularity and perspectives is both a strength and a weakness. I recognize the need for a middle ground between this comprehensive methodology and leaner or quicker approaches. I believe the representation of assumptions, methods and questions in Table 3 can be utilized for future studies to identify their data collection and analysis needs, and study foci. In particular, selection of sample populations depends on the study purpose, data set and hypotheses. For example, to test the hypothesis that interactive behavior is associated to the primary diagnosis of the patient case requires that the sample populations be defined by the patients' primary diagnosis.

In future work, the methodological framework can be employed to explore the hypothesis that health IT that better supports information management and coordination work will need fewer workarounds. I anticipate that this will be particularly evident in the number or type of information transfers and transformations that are surfaced by the micro-level propagation of representational states analytic approach.

In revealing information flow and cognitive behavior involved in managing clinical information, the propagation of representational states approach can be used to assess clinician's information needs and where and when information is needed. This can be used to identify when computational offloading is productive. Additional questions that can inform improvements include: What information do clinicians need that they don't have access to? Where do they need it? Where and how can technology better support clinicians' information management, communication, and coordination needs?

In surfacing mechanisms of information management and coordination, I was able to identify constraints and resources of information artifacts. It will be interesting to do a DCog analysis before and after an information artifact is changed in a given activity system to examine how the change in an artifact impacts clinicians' mechanisms of information management and coordination. DCog questions that would guide such an analysis: In what ways does a new artifact change the flow of information? In what ways does a new artifact remove/replace representations used for multiple processes? Can we project the likelihood of differences in workflow patterns and efficiency given the introduction of a new system or interface? By integrating the CE methods, it will also be possible to quantify how change in an information artifact (e.g., implementing a new artifact, replacing or modifying an existing artifact, etc.) affects users' interactive effort. Such pre/post analyses would be useful in developing more specific hypotheses for how interactive descriptors from DCog and CE methods can be used to identify more optimal or efficient workflows.

In the past decade, we have witnessed impressive developments in health IT coupled with the profound challenges users encounter in using them productively. A deeper understanding of workflow in its many guises and manifestations can bring us closer to the realization of the great promises offered by the significant technological advancements.

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APPENDIX A

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APPENDIX B

PDF IMAGES OF THE ORIGINAL HFES PUBLICATION

The proceeding pages contain the PDF images of the original publication in the proceedings for the 2016 International Symposium on Human Factors and Ergonomics in Health Care, and presented at the Symposium on April 15, 2016 in San Diego, California. Citation for the original publication is: Furniss SK, Burton MM, Larson DW, Kaufman DR. Modeling Patient-Centered Cognitive Work for High-Value Care Goals. *Proceedings of the International Symposium on Human Factors and Ergonomics in Health Care*. 2016;5(1):112-119.

This paper presents steps for a propagation of representational states analysis approach to study how information flows across the activity system to support clinicians' problem-solving. Specifically, the approach examines the propagation of representational states across media, conversations, actors and time in relation to clinician's work for an individual patient. The approach is illustrated with two case studies. A mixed-method data collection approach was necessary to capture the clinician's continuous work activities and their context in sufficient depth. Due to constraints on submission length, the data collection methods are listed, but not explained. The selection and development of the data collection methods employed for the propagation of representational states analysis are incorporated into the full data collection methodology, which is presented in full in the methodology chapter, Chapter V

Modeling Patient-Centered Cognitive Work for High-Value Care Goals

Stephanie K. Furniss[1], Matthew M. Burton[1,2], David W. Larson[3], David R. Kaufman[1]
[1] Department of Biomedical Informatics, Arizona State University, Scottsdale, AZ, USA;
[2] Office of Information and Knowledge Management and
[3] Department of Colon and Rectal Surgery, Mayo Clinic, Rochester, MN, USA

Patient-centered cognitive support has been shown to be critically important to facilitate the effective use of health information technologies (HIT). There is a well-documented need to better understand HIT-mediated clinical workflow. Current technologies can burden clinicians' cognitive resources, which is associated with patient safety risks and medical errors. We sought to employ a distributed cognition approach to examine how information flows across the activity system to support clinicians' problem-solving. Specifically, we studied the propagation of representational states across media, conversations, actors and time in the coordination of patient-care processes. We examined multiple instances of work and information flow in a real-world setting, revealing problems in information flow: a) use of paper artifacts has limitations to facilitating coordination of care, b) clinicians challenged in developing shared awareness, c) responsibility of representing patient states is distributed across documents, d) clinical reasoning that informed care plans was absent from documents. Findings surface a challenge to automated monitoring of care goals; much of the information is present only in clinicians' minds and in informal documents.

INTRODUCTION

Patient-centered cognitive support has been identified as an over-arching grand challenge for the development of HIT (Stead & Lin, 2009). There has been significant investment in HIT, such as electronic healthcare records (EHRs), with the expectation that it will improve healthcare delivery through better management and availability of patient information. Thus far, the results regarding the success of HIT implementation and its productive use have been decidedly mixed. Problems include EHRs not integrating smoothly into clinical work processes and contributing to unintended consequences, such as decreased efficiency (J. Horsky, Kuperman, & Patel, 2005), mismatch between actual and assumed information flows (Ash et al., 2003), and inadequate support of team-based care (Ash, Berg, & Coiera, 2004), sometimes resulting in adverse events (Koppel et al., 2005). Effective use of HIT is at least partly dependent on the degree to which it provides cognitive support for the tasks of clinical workflow.

To improve HIT, we need to better understand HIT-mediated clinical workflow (Berg, 2001; Gorman, Lavelle, & Ash, 2003). Clinical workflow is a series of tasks performed by workers supported by processes and tools, for the benefit of the patient (Niazkhani, Pirnejad, Berg, & Aarts, 2009). Clinicians' current processes for completing routine clinical tasks, such as information gathering and progress note documentation, involve use of many information sources. Additionally, processes for other associated tasks, such as decision-making and order entry, are too often disconnected due to problems with design and component functionalities. Highly complex EHR tasks, coupled with poor integration of technologies into clinical workflow, may increase cognitive load and diminish resources available for clinical reasoning (D. R. Kaufman, Kannampallil, & Patel, 2015). An understanding of HIT-mediated clinical workflow requires an understanding of how information is distributed across tools and people. Given the complexities of clinical environments, there is a need for a methodologic approach to capture the various facets and variants of workflow.

The proposed methodology draws on the theory of distributed cognition (DCog) (Hutchins, 1995), which emphasizes how cognition is distributed across people and the environment (material, social, cultural), and depends upon the coordination of both internal and external representations. External representations can be reflected in instances of an environment (e.g., the layout of people and equipment in the operating room (Hazlehurst, McMullen, & Gorman, 2007)), an artifact (e.g., paper notes, visual displays), and verbal utterance. A representational state is defined by Hutchins as "a configuration of the elements in a medium that can be interpreted as a representation" (p117) (Hutchins, 1995). In DCog, workflow can be characterized as the sequence, or propagation, of internal and external representational states across media, settings and time (Hutchins, 1995).

In clinical work, representational states may include any number of "information bearing structures" including an EHR document, threads in a conversation or text on a printed artifact. Importantly, the activity system can be construed as the unit of analysis (Hazlehurst et al., 2007; Hutchins, 1995). Cognitive work and human performance is derived from an analysis of the propagation of representational states across and between people and artifacts in an activity system. For example, a patient problem surfaces during a conversation between members of the patient's care team in patient rounds. The resident physician is asked to place a medication order for the patient, which is processed by the pharmacist, and sent to the nurse. Prior to administering the medication, the nurse reviews the order to determine whether it is consistent with their understanding of the patient state. Each of these agents will use a range of domain knowledge, artifacts, technologies and tacit understandings to process information, act on the order in view to achieve the goal. Patient care results from the coordination of multiple processes that propagate representational states across various media (Hazlehurst et al., 2007).

DCog theory has been used to study clinical work and to characterize differences. Hazlehurst applied a propagation of representational states approach to characterize patterns of communication between surgeons and a perfusionist to coordinate activities during cardiac surgery. For example, "direction" is a pattern that seeks to transition the activity system to a new state (e.g., administering medications that affect blood coagulation. Further, Nemeth analyzed cognitive artifacts to understand their role in distributing cognition within clinical environments (Nemeth, O'Connor, Klock, & Cook, 2006). Specifically, they studied the development of the operating room master schedule, and its use for coordination of surgical procedure anesthesia assignments. The study demonstrated how the schedule and related artifacts served as a means to coordinate activities, anticipate future events, reconcile conflicts and track progress. The analysis of cognitive artifacts identifies critical features of work domains and surface gaps in the ways technologies support cognitive work (Nemeth et al., 2006).

The objective of this paper is to investigate how clinicians coordinate information flow to monitor and manage patients. Toward this end, we employ a methodology for capturing and modeling the trajectories of clinical data and information associated with clinical care goals across media, representations, conversations and time; the value of which is to surface details of how clinicians do complex, collaborative work. In this paper, we describe cognitive work through examination of representations of information, and how these representations act as intermediaries in the dynamic and coordinated work activities in post-surgical clinical setting. The methodology is illustrated through two case studies. This is part of a larger project, designed to characterize the various dimensions of clinicians' workflow in post-operative hospital care.

METHODS

Settings & Participants

Research was conducted at the Colon and Rectal Surgery Department (CRS) at Mayo Clinic Hospital in Rochester, MN, USA, which is an academic tertiary healthcare center. In CRS, patients are cared for by surgeons, fellows, resident physicians, nurse practitioners, physician assistants, nurses, and pharmacists. Nurse practitioners (NPs) and physician assistants (PAs) in CRS function as hospitalists. While "hospitalist" term is generally used to describe physicians who are employees of a hospital system, "hospitalist" in CRS refers to NPs and PAs who have responsibilities similar to a resident physician (e.g. order entry, progress note documentation, patient education) but are employed by health system.

Hospitalists utilize a number of computer systems in daily work, to include an EHR (Synthesis), a clinical documentation system (MICS LW), and an order entry system (Orders). Hospitalists and residents rely on a paper print out of the electronic handoff document (paper ESL) to support daily work.

Data were collected to support a surgery practice redesign initiative. The project was reviewed by Mayo IRB and deemed exempt.

Data Collection

We employed mixed methods to capture the breadth of clinical work in the context of clinicians' routine workflow: a) semi-structured and opportunistic interviews, b) observation and shadowing of a clinician, c) video ethnography of clinicians coordinating patient care, d) Morae™ video capture and think-aloud protocol of users engaging in a series of EHR tasks across their work shift and e) artifact collection including paper documents that serve to structure or enhance cognition. Data were collected for a total of ten days across two periods of time about a year apart.

Data Analysis

We sought to integrate and compare results from the different data sources to characterize propagation of representational states in relation to clinician's work for an individual patient over a stretch of time. The following five steps of analysis were employed:

1. We *analyzed videos, transcripts, and artifacts and manually coded sequential events* with regards to tasks and patients in focus. Identifying the documented tasks and times when the clinician worked on each patient, we could more easily surface work and information flows for each patient.

2. With focus on a single patient, we *traced representational states across media with sequences of video and screen image captures, images and evidence from artifacts and transcripts of conversations* (Figure 1). For example, a hospitalist first works on patient P1 during pre-rounds information gathering task. For this task, we sequenced still images from video capture to identify context (e.g., people, tools, location) of work, screen captures from the Morae™ video recording of the EHR screens of the patient's medical chart viewed by the clinician, notes describing when the hospitalist reads from or modifies paper artifacts, images of paper artifacts that are used or modified during the work for the patient, and transcriptions of the hospitalist's think-aloud verbalizations describing the information viewed and how the information is being processed or reasoned about. The remainder of the hospitalist's work activities for patient P1 are similarly described (Figure 1).

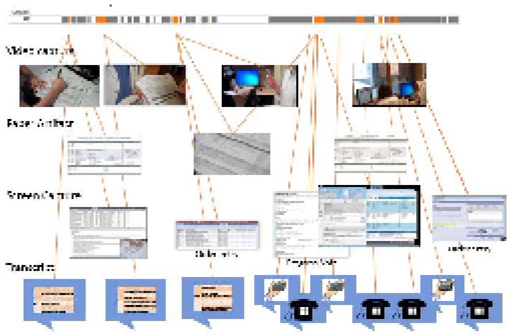

Figure 1. Diagram illustrating sequence of images of video capture, of paper artifacts and HIT screen capture, and transcripts from think-aloud verbalizations, text pages, and clinician-clinician and clinician-patient conversations. The top bar represents the observed time (6:00-10:00am) of the hospitalist performing a range of tasks. The orange segments represent the time and work allocated to a single patient.

3. To trace clinical concepts related to high-value care goals, we *analyzed the sequence of patient-centered work from step 2 and identify the clinical issues addressed* by the clinician. For example, we identified six clinical problems for post-operative patient P1, to include: high heart rate (i.e., tachycardia), low serum potassium, positive bacteria culture, and patient-reported back pain.

4. Then we *traced the clinical issues across work activities and representations to identify associated clinical concepts*. For example, the hospitalist ordered an intravenous saline bolus to treat patient P1's tachycardia; therefore, *saline bolus* is associated with *tachycardia*.

5. We *modeled the propagation of representational states* to describe and visualize how information flows, how the information tools are used, as well as the relationships and interactions between people, tools and concepts involved in the work. Figure 2 shows a diagram of the flow and transformations of information related to patient P1's tachycardia problem across media, time and tasks, beginning when the problem surfaced. The flow of representational states is examined in steps *a* - *g* in the Results section.

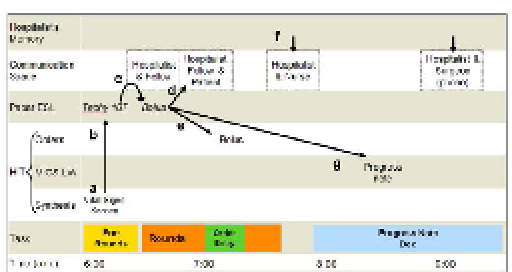

Figure 2. Model illustrates how the sequence of representational states transfer across media and transform to associated clinical concepts to support the hospitalist's problem-solving and patient care delivery.

RESULTS

We examine how clinicians use information tools to manage and monitor patients, and how information flows in the system of workers and artifacts to support clinicians' information processing. The focus is on patient issues related to high-value care goals that are applicable to patient care management in all post-surgical environments. The two case studies presented here characterize information flow across media, representations, conversations, actors and time.

Case 1: Tachycardia

This case focuses on steps *a* – *g* modeled in Figure 2, illustrating the sequence of representational states associated with a patient's tachycardia (high heart rate) between 6am and 10am on the observed day. Tachycardia is a clinically significant finding and is particularly of concern in a post-operative patient.

Actors involved in this case study are a patient (P1) and the patient's hospitalist (H1), fellow (F1) and nurse (N1) on the observed day. The tools used are the clinical information systems and paper document described in Methods. Events in the case study take place in the following locations in the hospital: hospitalists' work room, central resident and pharmacist work station, patient's hospital room and hallway outside the patient's room.

Patient P1 was a 67-year-old female with history of colon cancer. On the day of observation, P1 was seven days post-surgery to correct an enterocutaneous fistula—an abnormal connection between the part of the gastrointestinal tract (e.g., small or large bowel) and the skin—as well as placement of a colostomy (end of large intestine is sutured to an opening in the abdominal wall) and cystotomy (surgical incision of bladder) with placement of stent to divert urine to an external stent. The trace begins at the beginning of hospitalist H1's day shift with pre-rounds information gathering. Patient P1 is one of 14 patients under H1's care that day.

(a) At 6:11am, H1 identified the patient's tachycardia in the EHR during pre-rounds data gathering task (Figure 3).

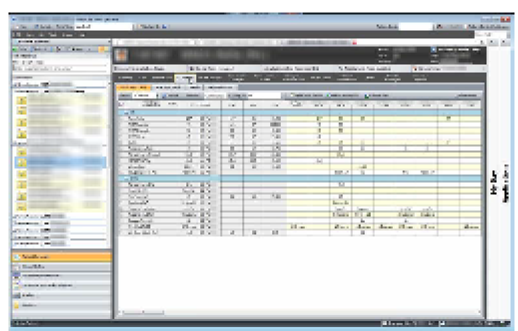

Figure 3. Screen capture of the Vital Signs display in the EHR.

(b) H1 transfers the finding from the EHR to the paper print-out of the handoff document (paper ESL) with annotation that reads "Tachy 107" (Figure 4).

Figure 4. Image of the hospitalist's hands and desk during pre-rounds information gathering task. During this task, the hospitalist annotates the paper ESL with data, tasks and reminders for each patient under her care that day.

(c) Hospitalist H1 and fellow F1 round on the patient from 6:27 to 6:29 am. They discuss the P1's care plan in context of patient data. Through conversation, the tachycardia finding is transformed to an order for an intravenous saline bolus. H1 writes "bolus" on the paper to serve as a reminder (Figure 5).

Figure 5. Image of the fellow (left) and hospitalist (right) discussing patient P1 in the hallway outside the patient's hospital room. Both clinicians are holding paper print-out of the handoff document. The hospitalist is writing "bolus" on the paper as a reminder of the order that needs to be made for the patient.

(d) H1 and F1 then enter the patient's room to examine and update patient P1. During this time, hospitalist H1 informs the patient of the tachycardia and treatment plan.

(e) At 7:10am, H1 reads the "bolus" annotation which she wrote on the paper during rounds, and enters the order into the computer order entry system (Figure 6).

Figure 6. Screen capture of the medication and lab orders the hospitalist enters to treat and evaluate the patient's tachycardia and other issues.

(f) At 7:29am, the patient's nurse (N1) approaches hospitalist H1 to discuss the saline bolus order H1 placed earlier (Figure 7). H1 shares the reasoning behind the treatment decision, that the bolus is addressing the patient's tachycardia. Nurse N1 projects that administering the saline will not result in increased urine output, as would typically be expected, due to a bladder leak that is causing urine to be suctioned from the bladder by the vacuum-assisted wound care device. N1 would typically report a lack of urine output to the hospitalist so they create an alternative communication plan given anticipated events. Table 1 gives an excerpt from the conversation transcript.

Figure 7. Image of the patient's nurse (left) and hospitalist (right) discussing the patient.

N1	*I saw you added that extra bolus and since that drain is pulling her urine now-*
H1	*We're treating her tachycardia*
N1	*I'm not going to call you when her catheter output is zero, because that's expected right?*
H1	*Boy, she must have a really big leak. [...] You're right, don't call me with low urine output. [...] I'll just keep a lookout, and don't give me a call unless you're worried about something or something changes.*

Table 1. Transcript excerpt from conversation between the patient's nurse (N1) and hospitalist (H1).

(g) Between 8:29-8:38am, H1 writes the daily progress note for patient P1 in the electronic documentation system. The "bolus" annotation previously made on the paper serves as reminder of a part of the plan, which H1 documents in the note (Figure 8). The progress note is attached to the patient's medical record in the EHR and available for other care team members to review. In the prior excerpt, there was a need to establish common ground with nurse N1 regarding the reasoning for the saline bolus order, yet in the progress note this reasoning is not shared.

Summary. Hospitalist H1 uses the EHR to perceive the patient problem and then an hour later to take action (place treatment order) to resolve the problem. In two instances, H1 utilized the paper artifact that was easy to annotate and transport to support patient care tasks for patient P1 that had to occur at different times and locations. H1's annotations on the paper served as reminders and the paper artifact enabled cognition at the later needed times.

There is an act of coordination between nurse N1 and hospitalist H1 because N1 doesn't understand why the saline bolus order was placed given patient P1's state. The conversation is the only instance where the relationship between P1's tachycardia and the saline bolus order is explicit. Even the daily progress note documentation, which is the primary means by which the clinical assessment and care plan is shared with members of the care team, does not make an explicit connection between the tachycardia and saline bolus order.

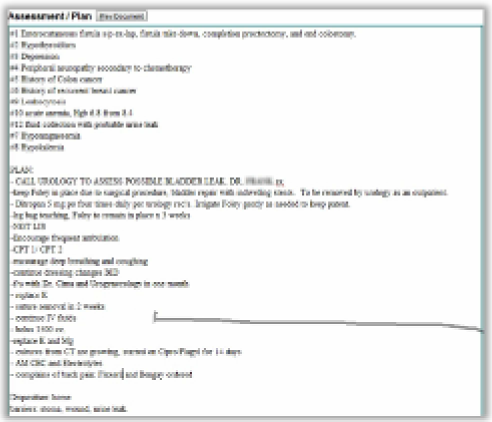

Figure 8. Screen capture of the clinical assessment and care plan documented by the hospitalist in the daily progress note.

Case 2: Wound Care

This case traces the sequence of representational states associated with a patient's wound care plan between 7am one day through 7am the next day (a 24-hour period).

Actors involved in this case study on the first day are a patient (P2) and the patient's hospitalist (H2), fellow (F2) and attending surgeon. On the second day, a different hospitalist (H3) is caring for patient P2. The clinical information systems and paper document used by the clinicians are described in Methods. Events occur in the hospitalists' work room, patient's hospital room and hallway outside the patient's room.

Patient P2 was a 69-year-old male with rectal cancer and a large wound following a surgical procedure two weeks prior. There were two primary wound care issues addressed by the team: 1) type of wound therapy (i.e., vacuum-assisted wound closure (VAC therapy) versus standard therapy) the patient is to have when discharged from the hospital, and 2) location of wound care (i.e., in the operating room versus in the patient's hospital room).

For VAC therapy, a foam dressing is put inside the wound and a small vacuum pump is connected. The vacuum pump (commonly referred to as a "wound vac") creates negative pressure that pulls fluid from the wound. Standard therapy involves packing the wound with gauze dressings. A patient may prefer VAC therapy over standard therapy because VAC therapy dressings require less frequent changing compared to gauze dressings—VAC therapy dressings can often be changed every two to three days, whereas standard therapy gauze dressings for the same wound would be changed three times each day.

During the observation, patient P2's wound is managed with standard therapy. The care team's decisions involved consideration for patient preference, safety (e.g., prevent infection), who will assist the patient in wound care at home (i.e., family member, in-home nurse), and hospital resources (e.g., operating room availability).

(a) At 7:10am, hospitalist H2 and fellow F2 discuss wound care plan for patient P2 during patient rounds (Figure 9). F2 states, *"[The gauze dressing] needs to be changed 3 times a day. […] Still, put the paperwork in for the wound vac."* They decide to change the gauze dressing that day and order a wound vacuum pump to be placed in the operating room the next day.

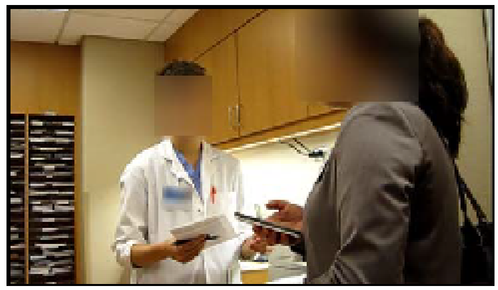

Figure 9. The hospitalist (left) and fellow (right) discuss the patient's wound care plan during patient rounds.

(b) At 8:07am, H2 documents the plan from step *a* in the daily progress note (Figure 10). The progress note is in the EHR and available for other care team members to view. The note also informs the care team that placement of a wound vac for VAC therapy is a "barrier" to discharge, and they plan to discharge patient P2 the next day (Figure 10).

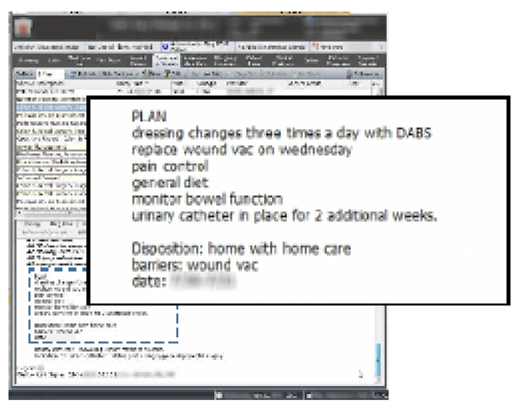

Figure 10. Screen capture of the patient's daily progress note documented by the hospitalist. The documented plan of care is enlarged (right).

(c) At 2:44pm, hospitalist H2 and the attending surgeon discuss the patient state and wound care plan (Figure 11), and visit patient P2 at the patient's hospital room. The attending surgeon permits VAC therapy, but wants the wound vacuum pump to be placed in the patient's hospital room rather than in the operating room.

Figure 11. The hospitalist (left) and attending surgeon (right) conversing in hallway outside the patient's hospital room.

(d) At 3:00pm, nearing the end her work shift, hospitalist H2 updates the electronic handoff document with a note that reads *"wound vac paperwork completed [yesterday] listed for [operating room] but [attending surgeon] wants the patient to have it in the room"* (Figure 12).

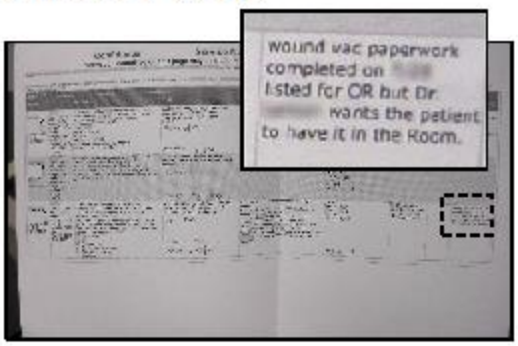

Figure 12. Image of a paper ESL showing the updated wound care plan entered by the hospitalist for the patient (enlarged on top right).

(e) At 3:40pm, just before leaving for the day, H2 sends an email sign-out to fellow F2 and the hospitalist who will care for the patient the next day (H3). The email reads, *"[attending surgeon] did not want a wound vac for [patient P2] but states it is okay if the wife can not do dressing changes. He says no need for this to be in the OR tomorrow. Need to be at the bedside without sedation if possible. Please cancel surgical listing.[…]"*

(f) On the following day, at 6:06am, hospitalist H3 prints and reviews the electronic handoff document (Figure 12). Confused, hospitalist H3 states, *"But I don't know what 'it' is!"*

(g) A few minutes later, at 6:08am, H3 has reviewed the three different representations of the patient's plan documented by H2 the previous day (i.e., progress note, handoff document, e-mail), and states, *"I don't understand this. It says something different in all the places I'm looking."*

(h) Hospitalist H3 annotates the paper notes with *"dressing Δ?"* (shorthand for "dressing change?"). The annotation serves as a reminder to H3 to ask fellow F2 for clarity about the patient's care plan (Figure 13).

Figure 13. Image of the hospitalist's print-out of the electronic handoff document (paper ESL) with the hospitalist's annotation intended to be a reminder to get clarity about the patient's wound care plan.

Summary. Observations of the care team from two consecutive days were presented. On the first day, hospitalist H2 reviews and discusses the patient P2's wound care plan with fellow F2. Their plan is modified later in the day when H2 reviews and discusses the wound care plan with the attending surgeon. At the end of the first day (after step *e*), variations of the patient's wound-care plan are documented across three different media and not all documented plans are available to the patient's entire care team—1) daily progress note in the EHR is available to all care team members, 2) electronic handoff document available to a smaller care team, and 3) email message available only to fellow F2 and hospitalist H3. On the second day, during pre-rounds information gathering, hospitalist H3 reviews the three documentations. H3 is not able to reconcile the variation across documents; therefore, is not able to understand the wound care plan for the patient and seeks clarification.

The clinical team has a number of ways of communicating across time (asynchronously) and distributed team members. EHR documents attached to patient medical record, web-based handoff document, and e-mail were the three used in this case study. Phone and pager also modes of communication, but more often relied on for synchronous communication. There does not appear to be standardized process of communicating a change to a patient's care plan across time. This causes confusion as varied patient care plans decided on throughout the day can each be documented. Through daily documentation, HIT captures the care plan at that instance. It does not appear to be easily updated to represent changes. It was not clear which care plans were active and which were inactive.

DISCUSSION

Clinicians rely on many information sources to manage and monitor patients under their care each day. Information sources include HIT, paper notes, the patient, and other clinicians. HIT has potential to facilitate information sharing and coordination, but to improve HIT requires an understanding of HIT-mediated workflow. Distributed cognition theory provides a framework to examine how information flows across people and artifacts within an activity system to achieve these shared goals.

In this study, we examined the propagation of representational states through the activity system to show the actions and effort required for care delivery. We traced information flows to examine the propagation of representational states across diverse media for a single patient from the perspective of a single clinician. In particular, we surfaced clinicians' information work involved in managing and monitoring patients under their care. We visualized and described how specific patient medical problems and care goals are represented and managed during a patient's post-operative hospital stay, examining the role of representations and media in facilitating cognition and clinical work. The two case studies revealed challenges to care coordination, as well as breakdowns and repairs in communication.

The study revealed problems in information flow some of which may compromise patient care. These include the use of paper artifacts as a workaround. Although useful as a cognitive artifact (e.g., clinicians' use of paper to record data and reminders to support patient care processes), it is limited as a coordination device (as it is not shared with other team members). Another problem pertains to challenges to clinicians in developing shared awareness of patient as evidenced in clinicians' interactions with clinical documents and data. Third, the information flow shows distributed responsibility of updating patient states across individuals and documents and the limitations of the artifacts in facilitating coordination. In addition, conversations surface elements of collaborative decisions-making and distributed clinical reasoning absent from documents.

This study represents a novel approach to the study of clinical work with a focus on HIT-mediated patient-centered cognitive support. This theoretically-grounded approach documents sequence of work activities as the propagation of representational states. This approach is enabled by in-depth data capture and analysis. In particular, video recordings allow repeated, retrospective analysis, and observation and coding of multitasking activities. Video of the clinician provided the context of the observed work, allowed us to reconstruct the participants' work with rich detail, to include the sequence of tasks, tools used, information discussed, location of events, and other participants involved. Detailed case studies of information flow in real-world settings can serve as a basis for discussions about how technologies can better support clinicians' cognitive work and facilitate patient care coordination.

A limitation of this work is that it was conducted in a single setting with a limited number of clinicians. Although we captured much of the cognitive work for a single clinician, we were not privy to the activities of the other team members when they were not interacting with the clinician in focus. Access to these members would have undoubtedly provided additional insight. In this brief paper, we present only two examples which necessarily limits the scope of inference.

Future work includes development of additional visualizations to characterize information flow through the propagation of representational states. We expect to create reusable representation of this knowledge that can be further refined, used for simulation models that examine alternative workflows, and are potentially transferable to other surgical settings. We are developing a taxonomy of problems and their related concepts with dependencies between these goal-related concepts (e.g. "tachycardia", "saline bolus") represented, and these concepts linked to standard terminologies (e.g. SNOMED, UMLS) so that our findings can be shared broadly.

Importantly, this study contributes to our larger research program, in which we apply various approaches to examine patterns of behavior and clinical workflow. We are integrating this work with our other analyses. Other approaches include temporal process mining analysis of screen transitions for patient care tasks, goal-action coding, and quantitative descriptors of interactive behavior (e.g., mouse clicks, screen transitions, task duration) (D. K. Kaufman, Furniss, Grando, Larson, & Burton, 2015). The ultimate objective of the research is to contribute to the development of tools that lead to better cognitive support in service of managing and monitoring patients.

CONCLUSION

In this study, we identified problems in information flow related to: a) limitations of paper artifacts in facilitating coordination of care, b) clinicians' challenges in developing shared awareness, c) distributed responsibility of representing patient states in documents, d) the clinical reasoning that informed care plans was largely absent from documents.

This work surfaces a challenge to the automated monitoring of care goals—much of the information is present only in clinicians' minds and in informal documents. The systematic analysis of clinical workflow can elucidate problems in coordination of clinical care and suggest potential solution strategies.

ACKNOWLEDGEMENTS

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APPENDIX C

PDF IMAGES OF THE ORIGINAL AMIA PUBLICATION

The proceeding pages contain the PDF images of the original publication in American Medical Informatics Association (AMIA) 2016 Symposium Proceedings and presented at the Symposium on November 15, 2016 in Chicago, IL. Full citation for the original publication is: Furniss SK, Burton MM, Grando MA, Larson DW, Kaufman DR. Integrating Process Mining and Cognitive Analysis to Study EHR Workflow. *AMIA Annu Symp Proc*. 2016;2016.

This paper presents an investigation of variation in EHR workflow of routine information gathering task by integrating qualitative and quantitative analysis. This study established feasibility of using mixed methods to understand clinicians' task-specific interaction with the EHR. We triangulated quantitative variables with patient chart review and qualitative data and found clinicians' EHR-interactive behavior was associated with their routine processes, patient case complexity, variant screen sequence patterns, and EHR default settings. The case study, as an outlier case, it surfaces some complexities of completing the task and negotiating the information sources.

Integrating Process Mining and Cognitive Analysis to Study EHR Workflow

Stephanie K. Furniss, MS[1], Matthew M. Burton, MD[1,2], Adela Grando, PhD[1],
David W. Larson, MD, MBA[3], David R. Kaufman, PhD[1]
[1]Department of Biomedical Informatics, Arizona State University, Scottsdale, AZ;
[2]Office of Information and Knowledge Management and
[3]Department of Colon and Rectal Surgery, Mayo Clinic, Rochester, MN

Abstract

There are numerous methods to study workflow. However, few produce the kinds of in-depth analyses needed to understand EHR-mediated workflow. Here we investigated variations in clinicians' EHR workflow. By integrating quantitative analysis of patterns of users' EHR-interactions with in-depth qualitative analysis of user performance. We characterized 6 clinicians' patterns of information-gathering using a sequential process-mining approach. The analysis revealed 519 different screen transition patterns performed across 1569 patient cases. No one pattern was followed for more than 10% of patient cases, the 15 most frequent patterns accounted for over half of patient cases (53%), and 27% of cases exhibited unique patterns. By triangulating quantitative and qualitative analyses, we found that participants' EHR-interactive behavior was associated with their routine processes, patient case complexity, and EHR default settings. The proposed approach has significant potential to inform resource allocation for observation and training. In-depth observations helped us to explain variation across users.

Introduction

Health information technologies (HIT), such as electronic healthcare records (EHRs), are expected to bring significant advancements to healthcare delivery through improved management and availability of patient information[1]. Thus far, there have been mixed results from HIT implementation and use. Problems include EHRs not integrating smoothly into clinical work processes and impacting workflow as seen in altered sequences in which tasks are performed[2], the duration required to complete tasks[2], the allocation of tasks among workers[2], development of workarounds[3], some resulting in adverse events[4] that compromise patient safety and quality of care delivered. The absence of a focus on system usability and on understanding patterns of workflow is a major impediment to adoption and widespread use.

Usability studies typically employ user-satisfaction surveys, focus groups, expert inspections and experiments involving usability testing[5]. Although these methods are informative, they involve a reliance on subjective judgment, may lack reliability and do not provide a sufficiently rich window into the clinical workflow process. Alternatively, there have been numerous studies of workflow that vary in method and scope[6]. There is a need to scrutinize EHR workflow in situ to surface patterns of interaction, characterize the distributions of those patterns and elucidate the factors that underlie them. In this study, we integrate a quantitative process mining analysis of sequential patterns of data access with a qualitative analysis of user performance to investigate and explain clinicians' work processes. Specifically, we focus on EHR workflow associated with a routine information gathering task (InfoGather).

Background

There is ample evidence to suggest that the implementation of HIT can negatively impact clinical workflows and thereby create staff dissatisfaction, inefficiency and HIT-mediated errors[4]. Current technologies place a burden on clinicians' working memory and increase cognitive load, which is associated with medical errors and risks to patient safety[7]. Cognitive load reflects the demands on user's working memory, and is a function of task complexity, user's skill level, and system usability[8]. The productive use of HIT is partly dependent on the degree to which it can provide cognitive support for tasks that comprise clinical workflow. It is also reasonable to assume that experienced practitioners can develop efficient and effective methods for executing routine tasks—such as information gathering, progress note documentation and order entry—that better leverage the affordances provided by the EHR. We can also hypothesize that clinicians employ suboptimal strategies that result in unnecessarily complex and inefficient trajectories that are more time consuming and error prone. These patterns are empirically discoverable through automated computational approaches that identify patterns of interaction. Further, we recognize that EHR workflow is not performed in vacuum, but rather is connected to a web of actions, interactions, relationships and dependencies between clinicians and work components (e.g., patient, clinician, information, tools, etc.). This necessitates convergent methods to surface the various factors that shape interaction. The regularities of cognitive work can only be discovered through detailed, time-intensive study of the specific setting[9].

We have developed a methodological framework that draws on three research traditions[8, 10]: cognitive engineering, distribution cognition and computational ethnography. Each framework provides a theoretical lens, identifying important foci and a set of methods that illuminate different facets of workflow. The cognitive engineering approach focuses on both the usability of the system or interface in question and in the analysis of users' skills and knowledge[11]. In analyzing performance, the focus is on cognitive functions such as attention, perception, memory, comprehension, problem solving, and decision making. The approach has a lengthy history in the study of human-computer interaction in general [11] and in its application to EHRs[12]. The cognitive engineering approach has also been used to explain why users employ suboptimal or inefficient procedures or strategies in interacting with systems[13]. The theory of distributed cognition (DCog)[9], conceptualizes cognition as distributed across people and artifacts, and dependent on knowledge in both internal (e.g., memory) and external (e.g., visual displays, paper notes) representations as well as their interactions[14]. One can employ DCog to characterize workflow as the sequence, or propagation of internal and external representational states across media, settings and time[9].

Computational Ethnography is an emerging set of methods for conducting human-computer interaction studies[5]. It combines the richness of ethnographical methods with the advantages of automated computational approaches. Zheng and colleagues define computational ethnography as "a family of computational methods that leverages computer or sensor-based technologies to unobtrusively or nearly unobtrusively record end users' routine, *in situ* activities in health or healthcare related domains for studies of interest to human–computer interaction." Sequential pattern analysis employs log files to search for recurring patterns within a large number of event sequences. The analysis can be used effectively in combination with other forms of data such as ethnography or video-capture of end-users performing clinical tasks. Zheng et al[15] investigated users' interaction with an EHR by uncovering hidden navigational patterns in EHR logfile data. Various patterns were seen to be at variance from optimal pathways as suggested by designers and individuals in clinical management. Similarly, Kannampallil et al[16] used workflow logfile data to compare the information-seeking strategies of clinicians in critical care settings. Specifically, they characterized how distributed information was searched, retrieved and used during clinical workflow.

In a previous feasibility study, we conducted a process mining analysis with manually-curated event log data from (Morae™) video recordings[13]. We found patient case complexity was associated with the complexity of the clinician-EHR interactive behavior for the computer-based pre-rounds information gathering task. Two analyses were conducted. The first characterized the most common patterns of screen transitions. The second analysis quantified the frequency of each screen transition pattern. We observed 27 total screen-transition patterns, each employed 2 to 7 times. We also correlated patterns with interaction measures including mouse clicks and task duration. The objective was to characterize the difference in complexity for each pattern. We observed that, on average, a screen transition resulted in 2 to 2.5 mouse clicks. The task durations per patient were highly variable and may be associated with other factors such as variation in clinical case complexity.

The objectives of this study are to explain variation in EHR workflow by integrating quantitative analysis of empirical patterns with an in-depth qualitative analysis of user performance. This study is part of a larger research project in which we seek to characterize, evaluate, diagnose and improve clinicians' workflow in post-operative hospital care[10].

Methods

Clinical Setting & Participants

Research was conducted in the Colon & Rectal Surgery Department (CRS) at Mayo Clinic, Rochester, MN, an academic tertiary healthcare center equipped with a comprehensive EHR since 2005. Patient data is accessed through a customized interface, Synthesis. In CRS Rochester, patients are cared for primarily by surgeons, fellows, resident physicians, hospitalists, nurses, and pharmacists. Hospitalist, in this context, refers to nurse practitioners (NPs) and physician assistants (PAs) who have responsibilities similar to a resident physician. This study was centered on the hospitalist or resident physician, who share responsibilities for coordinating across members of the patients care team, delivering direct patient care, order entry and documentation. Surgery residents work for an attending physician's service for 6-weeks before cycling to their next service. To date, we have observed four hospitalists, a PA (H1) and three NPs (H2, H3 and H4), and two residents, a 2nd year (R1) and 4th year (R2). H1, H2, H3 and H4 were experienced users of the system and routinely performed the tasks we observed. At observation, they had worked in the unit between 2 and 3 years. R1 and R2 were doing a rotation in the unit and were less experienced users of the system.

This work represents an extension of a surgery practice redesign project, which sought to understand clinical processes and information needs to inform design of new technologies that can improve patient safety and quality and efficiency of health care delivery. It was reviewed by the Mayo Clinic Institutional Review Board (IRB) and judged to be exempt as human subjects' research.

Pre-Rounds Information Gathering Task (InfoGather)

The data were collected as the clinicians were completing pre-rounds information gathering task (InfoGather). In context of workflow, InfoGather occurs close to the start of the day shift, approximately 6:00 am. Hospitalists and residents round together immediately afterwards. The goals of the task are to access the most recent information on patients' medical status, review care plans, as well as to anticipate patient needs for the current day[17]. It is clinicians' first task and serves to anchor their understanding of their patients and their workload. To conduct the task, each clinician reviews patient data in the computer and paper-based information resources, and annotates a paper document that is subsequently referenced and modified throughout their shift.

Data Collection: System event log files & Observation

We observed clinicians in context of their routine workflow and collected ethnographic data from an electronic source (i.e., system-generated log files for the observed participants and the primary EHR application (Synthesis) used by participants for the task).

Synthesis is a customized interface developed by the Mayo Clinic Hospital in Rochester, MN for EHR data aggregation and visualization. We retrieved system-generated event log files for six participants for the six-week period that coincided with the residents' (R1 and R2) rotation in the CRS department. We also retrieved EHR event log files for the four hospitalists for an additional two-week period that coincided with other observations in the department. At minimum, each event (row) in a log file has a User ID (i.e., clinician ID), an Event Description (e.g., "Activated tab: Labs") and a Time Stamp (with date and time). Events that are associated with a patient chart also have the patient's clinic number.

EHR event log files record users' interactions with the EHR interface, to include selection of a patient chart in the Navigation Panel as well as screen tabs and their associated subtabs in a patient's chart. The Synthesis application window includes a list of patient records in a panel on the left-side of the screen (Navigation Panel). Synthesis includes a number of screens, separated into tabs, for viewing patient data (top of Figure 1). There are a total of 13 tabs to include, Summary, Labs, Medications, Vital Signs, Intake/Output, Document/Images, Assessment/Cares, Allergies/Immunizations, Patient Facts, Clinical Problem List, Orders and Viewers/Reports. Several tabs have subtabs which allow access to other screens. For example, the Labs tab has 7 subtabs to include, Labs, Microbiology, Pathology and Pending Labs. For all participants, the Summary screen is divided into six equally sized sections, each with a predefined subset of patient data for Allergies, Intake/Output, Medications, Documents, Vital Signs, and Labs. For example, only a patient's lab data from the last 24 hours are shown in the Summary screen. The clinician would go to the Labs tab to see all past lab results.

We employed Morae™ video capture and think-aloud protocol of participants engaging in InfoGather to allow for retrospective task analysis. Morae™ software is used for usability studies and it records user activity with no interruption to the user's work[18]. The software provides a screen capture (see Figure 1), and allows use of a webcam to capture audio of participants verbalizing their thoughts (think-aloud) as well as video recording of the participant's face or hands (inset image in the lower right corner in Figure 1).

We have a broader understanding of the context of the work environment because it was the setting for a larger research project in which we also conducted semi-structured interviews of clinicians from varying roles (e.g., hospitalist, senior resident, and nurse), collected artifacts including paper documents, observed clinicians' work across tasks and reviewed patient charts. Interview questions aimed to reveal details of clinicians' key clinical work activities, to include purpose or goal, tasks associated with each activity and resources used. Retrospective patient chart review was performed to understand the complexity of a patient's clinical state.

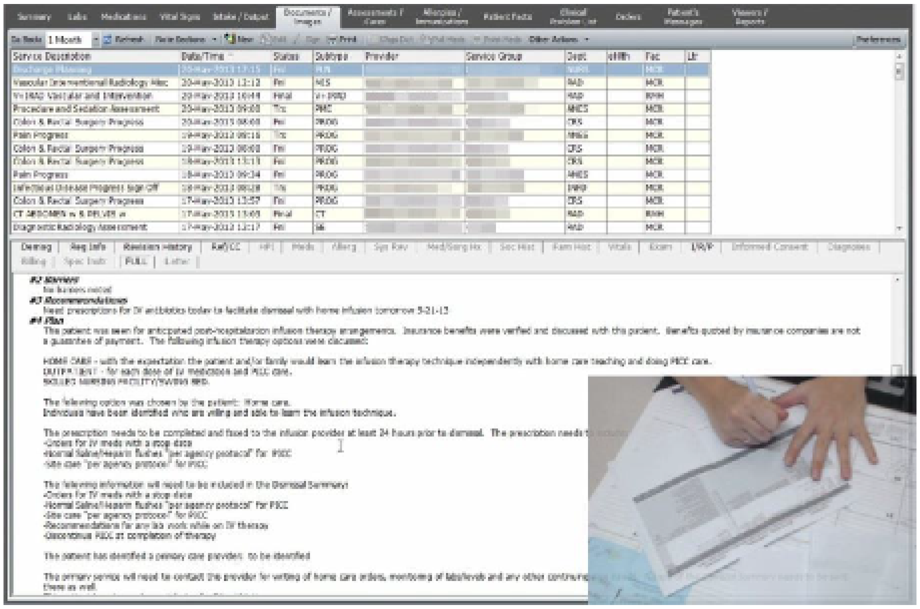

Figure 1. Screen capture from Morae™ video of an EHR display. The tabs across the top of the screen (and the menus below) constitute the EHR "screens" reflected in the process mining analysis. The inset picture in is an image from the webcam capturing the participant annotating a paper document, a printout of the handoff document.

Sequential Data Analysis

We employed temporal data mining (i.e., process mining) methods to identify clinicians' patterns of EHR interaction performed to complete InfoGather. The analyses were conducted using a business process mining tool, Disco™ version 1.9.3, a process-mining workbench used for business process management. Process mining has been used for a wide range of purposes in relation to business[19] and for adherence to guidelines in healthcare[20]. The input of Disco is a set of event logs (in our case, EHR logfiles associated with CRS clinicians), which can be processed, analyzed and visualized. Logfiles were preprocessed using Python. Code was written to de-identify log files by replacing clinician IDs and patient clinic numbers with a study ID. Video recordings of observed cases were reviewed with associated log files to understand how the Event Descriptions aligned with users' behavior.

Quantitative descriptors examined in this study include the number of cases per screen pattern, screen frequency and screen transitions, which were derived from the log files. These descriptors allow us to quantify and compare participants' interactive behavior required for the task. The quantities provide relative measures of work and reveal insights into the usability of EHR tools, patient case complexity and individual clinician's interactive strategies. We describe and examine the variation across patient cases and individual clinicians. Further, we integrate other methods (e.g., chart review, sequential analysis, qualitative analysis) to better explore the factors that contribute to the variation.

Qualitative Analysis & Case Study

We conducted qualitative analysis of clinicians' think-aloud verbalizations to explain patterns of EHR workflow. One of our objectives was to investigate the causes of repeat screen viewing. This was accomplished by reviewing video recordings of clinicians performing the task. In addition, a case study was selectively used to present detailed analysis of clinical work. It provides an illustration of observed behavior with qualitative data interwoven with quantitative descriptors to better understand users' behavior. For the selected case study, patient case complexity was evidenced by its quantitative descriptors; screen transitions, mouse clicks and task duration for the selected patient case were more than twice the clinician's, H1's, average across H1's observed cases. We previously published these quantitative descriptors and sequential analysis for a subset of cases, the 66 observed patient cases across five clinicians[13].

Results

Screen transition pattern analysis

To investigate clinicians' EHR interaction patterns for InfoGather, a routine computer-based task, we applied process mining to EHR-generated event log files. Our sample consisted of 1569 patient cases across 6 clinician participants. Participants accessed and viewed 26 different EHR screens. Among them are 12 of the 13 main display tabs (the seven most viewed are shown in Table 1). Also included is the Navigation panel (N), which is a collapsible vertical panel on the left of the EHR interface. We defined it as a screen in this study because it is relevant to users' EHR-interaction for accessing patient charts. Navigation was accessed for nearly all patients (99.7%, Table 1) because it includes the patient list and the search field for a user to access a patient chart. Once a patient chart has been opened during the user's session, the chart can be reopened by selecting the patient in the Navigation panel (N) or by selecting the chart's tab along the top of the Synthesis screen. Summary (S), Labs (L), and Vital Signs (V) were viewed for more than half of all cases, and Documents/Images (D) and Intake/Output (I) screens were viewed for more than two-thirds of all cases suggesting the importance of these displays as information sources. Seven screens (D, I, S, L, V, VwR and M) were viewed more than once for some cases and up to 7 times (S and L) (see max repetitions in Table 1). Repeat viewing is analyzed in greater detail below.

Table 1. Screen statistics. Case Frequency is the number of cases in which the screen was viewed at least once. Absolute Frequency is the number of times the screen was viewed. Max Repetitions is the highest number of time the screen was viewed per one case.

Screen	Screen Symbol	Case Frequency (% total cases)	Absolute Frequency	Max Repetitions
Navigation panel	*N*	1565 (99.7)	1649	3
Documents / Images	*D*	1055 (67.2)	1426	6
Intake / Output	*I*	1212 (77.2)	1425	5
Summary	*S*	870 (55.4)	1171	7
Labs	*L*	828 (52.8)	976	7
Vital Signs	*V*	836 (53.3)	966	5
Viewers/Reports	*VwR*	179 (11.4)	182	2
Medications	*M*	140 (8.9)	162	3

There were 519 variants of screen sequence patterns (Patterns in Table 2). The 15 most frequent patterns account for just over half of all cases (52.6%). All patterns start at the Navigation panel (N). Upon selecting a patient in Navigation (N), the user is immediately transferred to a screen in the newly opened patient's chart. As represented in the 15 patterns shown in Table 2, transitions lead from Navigation to Documents/Images (N-D), Navigation to Summary (N-S), and Navigation to Viewers/Reports (N-VwR). This is because the users had one of these three screens set as the default opening screen. Documents/Images (D) displayed when H2 and H3 opened a patient's chart, whereas Summary (S) was set as default for H1, R1 and R2 and Viewers/Reports (VwR) was the default for H4. Due to default settings, H1, R1, and R2 navigated through the Summary screen (S) for all of their patients, but observation of their behavior revealed that only R1 used Summary (S) to access patient data for the task. Because Summary (S) is not used by H1 and R2, navigating through this screen is an unnecessary "cost" for these clinicians.

Table 2 also indicates the percent of clinicians' patient cases for which the clinician followed each pattern (normalized by clinician's total to reduce the bias of varying sample sizes). The most frequent screen transition pattern occurred for 132 cases: Navigation to Documents/Images to Intake/Output (Pattern 1: N-D-I). It was followed by H2 for 23% of H2's cases, by H3 for 27% of H3's cases, and by R1 one time (0.3% of R1's cases). The second most frequent screen sequence occurred 67 times: Navigation to Viewers/Reports to Intake/Output to Vital Signs to Labs (Pattern 2: N-VwR-I-V-L). It was followed by one provider—H4 for 41% of H4's cases (Pattern 2). Among the top 15 patterns, three other patterns were each followed by one provider—24% of H1's cases (Pattern 6: N-S-L-V-I-D), 19% of H2's cases (Pattern 7: N-D-I-V-L), and 11% of H4's cases (Pattern 14: N-VwR-I-V-L-D). Due to the screen default settings, H2 and H3 sometimes followed the same patterns, while H1, R1 and R2 occasionally followed the same patterns, and they never followed H4's patterns. More than half of the remaining cases (418; 26.6% of total cases) exhibited a pattern that appeared only once (Patterns 102-519). We use the number of sequence patterns with only one case associated as the measure of variation. Thus, H3's task performance had the least variation (18% of H3's cases had a pattern that appeared once), whereas R1's task performance had the most variation (38% of R1's cases had a pattern that appeared one time) (Table 2).

Table 2. Screen sequence patterns and frequency measures for InfoGather. Screen sequences are shown for the 10 most frequent patterns. Frequency gives the number of patient cases per pattern. The third column expresses the frequency the clinician uses a screen sequence pattern as a percent of their total cases. EHR screen codes: N (Navigation Panel), D (Documents/Images), S (Summary), L (Labs), V (Vital Signs), I (Intake/Output), VwR (Viewer Reports). *The percent of cases in which clinicians had a unique pattern served as a preliminary measure of variation.

Pattern	Screen Sequence	Frequency (cases/pattern)	Percent of Clinician's Patterns						Total
			H1	H2	H3	H4	R1	R2	
1	N – D – I	132	0	0.23	0.27	0	<0.01	0	0.50
2	N – VwR – I – V – L	67	0	0	0	0.41	0	0	0.41
3	N – S – V – I – D	65	0.13	0	0	0	0.01	0.12	0.26
4	N – S	95	<0.01	0	0	0	0.22	0.03	0.26
5	N – S – V – I	66	0.16	0	0	0	0.02	0.06	0.24
6	N – S – L – V – I – D	68	0.24	0	0	0	0	0	0.24
7	N – D – I – V – L	46	0	0.19	0	0	0	0	0.19
8	N – D	52	<0.01	0.04	0.12	0	0.02	0	0.18
9	N – S – D	45	0	0	0	0	0.05	0.13	0.18
10	N – D – I – L	38	0	0.02	0.12	0	0	0	0.14
11-101	91 sequences	2-40 each	-	-	-	-	-	-	-
102-519	418 sequences	1 each*	0.21	0.22	0.18	0.27	0.38	0.30	1.56
	Total (case count)	*1569*	*288*	*248*	*274*	*162*	*393*	*204*	

Although some of the complexity can be accounted for by users' system settings, others may be accounted for by the interface or may reflect provider efficiency. For example, Pattern 6, employed by a single clinician for 24% of the clinician's cases, involved sequential transitions from left to right corresponding to the order of tabs along the top of the screen. Similarly, a different clinician employed sequential transitions that correspond to the order of tabs from right to left (Pattern 7). Still others may reflect variation in patient case complexity, which can be inferred from observations as discussed in the next section.

Analysis of Repeated Views: Of the 66 observed patient cases, 31 had at least one screen that was viewed two times (1/9 for H1, 7 /21 for H2, 11/16 for H3, 10/12 for R1, and 2/8 for R2). For example, in the screen sequence N-D-I-L-D, which H3 followed for three patients, Documents/Images (D) was viewed twice per patient. We inferred reasons for redundant screen viewing from clinicians' observed behavior. For most of H3's patients, Documents/Images (D) was viewed twice per patient because it appeared to be the clinician's routine process. H3 first viewed D when a patient's chart was first opened because D was set as the default screen for this user. H3 explained, "Whenever I launch a patient, I'm looking at the notes to make sure there was no weird note put in overnight." H3 would view D towards the end of the task as well, which would allow H3 to review the notes in context of what H3 learned about the patient during the task. H2 also had D set as the default screen, but, unlike H3, the default did not appear to be useful to H2 for several cases. Instead, H2 seemed to use a two-phase approach. First, for most cases, H2 exhibited a consistent screen sequence (i.e., N-D-I-V-L) at the start of the task. Then, for some patients, H2 also visited additional screens, perhaps to see if there were things missed. R1 had the highest percentage of cases with redundant screen viewing. This is not surprising because R1, a second-year resident physician, was relatively inexperienced with the EHR and the CRS practice. R1 could not easily synthesize and consolidate information from the EHR. R1 selectively uses screens with representations that can provide better cognitive support. For example, R1 views both Summary (S) and Labs (L) screens consecutively and multiple times per task. R1 stated "the way they do electrolytes [in the tabular form in the Labs screen], I can't even sort through that in my mind very quickly so I go back to the skeleton here [on the Summary screen]." In this case, the most recent lab values are represented succinctly in fishbone format on the Summary screen and were the preferred representation.

Case Study: Micro-Analysis of Qualitative and Quantitative data

To explain variation in clinicians' patterns, we drew on in-depth observation and qualitative analysis of clinicians' think-aloud. Here, we present a detailed task analysis for one patient case observed in H1's InfoGather workflow. H1's screen transition pattern was not repeated for any other case (Pattern 113: N-S-L-S-L-V-I-D). A review of the patient's chart conveyed the clinical complexity of the patient case in the reason for admission, length of stay, surgical procedures, number of medical services involved in care, and discharge requirements. The patient's hospitalization was a readmission for a leak and infection. A leak is an abnormal break in the wall of an organ, such as the colon, that allows for an abnormal transfer of contents from the organ to another organ or the body cavity. Observation was conducted on the thirteenth day of the patient's hospitalization, which was the discharge day. During the patient's stay, the patient underwent a re-operation and CRS consulted three other services to assist in patient care—critical care, pain service and infectious disease. These consultations are indicative of patient complexity and increased communication needs because information was distributed across additional members of the patient's care team.

To complete InfoGather, H1 reviewed patient information in the EHR and annotated a paper artifact (paper print out of the electronic handoff document) with patient data, tasks and reminders. Table 3 gives H1's think-aloud verbalizations, EHR screens viewed and running time for the one patient case. The verbalizations revealed patient information that H1 gathered from each screen (screen captured by the Morae™ video recording). For example, as shown in Table 3, blood pressure is read on the Vital Signs screen (time 01:15), and oral intake volume is read on Intake/Output screen (time 02:18). H1's verbalizations also reveal data gathered from the Pain Service and Infectious Disease Service notes on the Documents/Images screen (D) in the patient's chart (time 02:55 to 08:22).

Table 3. Case study narrative. H1's think-aloud, screens viewed and running time for one complex patient case.

Time (mm:ss)	Screen Viewed	H1 Narrative
00:00	Navigation (N)	
00:01	Summary (S)	
00:02	Labs (L)	*alright so she has... great.*
00:03	Summary (S)	
01:08	Labs (L)	*She's a mess.* *I'm thinking I'd like to hear everything going on [with this patient] because my electronic service list can only tell me so much.*
01:15	Vital Signs (V)	*It looks like she's a little hypotensive so I go all the way back to the beginning, which is only 24 hours.*
		I'm trying to go back to see her admit blood pressure so that if I get called about her blood pressure today, at least I'll be familiar if she came with low blood pressure. Alright, I feel better.
02:18	Intake/Output (I)	*And again, it's oral intake. I ignore the intermittent infusions. I ignore tubal ligations. number 1 drain nothing. number 2 drain..*
02:55	Documents/ Images (D)	*Okay, this is good; I need to know this. This is the discharge planning note cause she will go home with IV antibiotics. So I need to make sure ____ for her. So I write down kind of what I need.*
		IV meds, ____. ____ care... per agency protocol. Ordering IV antibiotics is very difficult, I mean outpatient, when I'm setting them up for outpatient. Because all of these things have to be there before they dismiss but we're not supposed to write things ahead of time so it gets kind of hard. *recommending lab work and dc PICC at end of therapy.* *Okay. So then what I do, since IV antibiotics I have to find infectious disease [note].* *So Zosyn 3.375 q six. PO gd through the 25th...continuous infusion... 13.5*
05:58		*...400 5d. Let's see what pain service is wanting.* *Because she is an involved patient, that's why I'm looking at this stuff.* *... ....Tylenol and Toprolxxx...*
		So I'm looking at her Sinogram. It says [drain #1] should be flushed daily with 10cc of saline. So then I have to go into MICS
08:22	MICS: Home Screen	*[I] click on [Surgeon] patient, [then] her name, [then] Inpatient Order entry to see if it was done.*
08:27	MICS: Order List	*[Order says to] Drain flush twice daily. Okay.*

Discussion

We characterized clinicians' EHR-interactions for the pre-rounds information gathering task (InfoGather) by applying process-mining methods to EHR-generated event log files. We hypothesized that there would be a few screen patterns that could explain a majority of the cases because it is a relatively simple task, there are not many screens that have primary patient data, and clinicians may have preferred patterns of screen transitions, which they follow for most of their patients. Screen viewing patterns may be motivated by an intent to seek out new information (e.g., new lab results). An alternative hypothesis is that there is a large amount of variation in EHR-interactive patterns, which may be explained by the differences in patient problems and patient states. Patients with similar problems and profiles (e.g., age and comorbidities) may require the same information-gathering strategy for the task.

There were 519 variant screen sequence patterns to describe the 1569 cases. No pattern described more than 10% of the sample. Fifteen patterns (3%) accounted for just over half of all cases. Because a majority of cases can be described by 3% of total screen patterns, it may suggest that EHR systems can be designed to better facilitate information gathering across screens. On the other hand, there were 418 patterns that only occurred for 1 patient case, which suggests there is much task variation across users or patient types. No pattern of three or more screens was followed by more than 3 of the 6 clinicians (Pattern 8, N-D, employing 2 screens was followed by 4 of 6 participants). Observations helped to explain some of the screen pattern variation. Across the 6 participants, there were 3 different settings that determined the first screen that was displayed when a patient chart was opened; H1, R1, and R2 had Summary (S) set as default, H2 and H3 had Documents/Images (D) set as default, and H4 had Viewers/Reports (VwR) set as default. The different screen default settings caused variation in screen patterns.

We hypothesized that the clinicians with less expertise would have more variation in screen transitions. The 6-clinician participant pool limits our ability to address this issue, but it can seed hypotheses for further testing. We expected R1, the least experienced user of the EHR among study participants as well as the less expert clinician, to have the most pattern variation. We observed that 38% of R1's cases exhibited a pattern that occurred only once compared to a 22% average variation across the four hospitalists. More variation is indicative of an incomplete mental model (e.g., understanding of where needed patient information is located or knowledge of potential shortcuts to access data). This is consistent with research showing that more experienced users develop robust mental models[21]. When a user follows the same pattern for many patients, it may be indicative of the user's spatial mental model of the system—where information is distributed across sources (applications and their screens). It may also reflect the user's information needs, and their preferred information sources. R2, in relation to R1, had more clinical expertise and was a more experienced user of the EHR. As expected, R2's pattern variation was lower than R1's (30% versus 38%). In relation to the hospitalists, we defined R2 as having equal or more clinical expertise but a less experienced user of the EHR in the CHS department. As expected, R2's pattern variation was also greater than the hospitalists' (30% versus 22% average).

Event log file analysis revealed that residents viewed more and different screens, whereas the hospitalists viewed fewer unique screens during the task. This may be additional evidence that residents are less experienced users of the system and, consequently, not as certain where to find patient data. Alternatively, it could be evidence that residents and hospitalists differ in terms of their information needs (e.g., residents are monitoring different or additional patient care goals so they need different or additional patient data). Further evidence that hospitalists and residents differ in terms of information needs and task goals came from R2's think-aloud, in which the resident appeared to do more decision-making on patients' care plans than the hospitalists did.

We hypothesized that most clinicians would conduct the task similarly because the routine nature of the task and, though there may be some variation in care goals across patients, there were care goals common to all patients in the unit. There are any number of reasons that may explain variation in these cases including each clinician's idiosyncratic strategies and patient-case differences. A second-order analysis in which the sequence was not an exact match (e.g., different starting point, but otherwise follows the same pattern) may reveal additional similarities not detected by the first-order analysis. For example, the number of variant patterns is in part due to the variation in chart default settings. By looking at similarities in smaller units of screen sequences, it may be more informative about shared processes and information needs across clinicians.

We triangulated quantitative variables with patient chart review and qualitative data and found clinicians' EHR-interactive behavior was associated with their routine processes, patient case complexity, variant screen sequence patterns, and EHR default settings. We presented a case study to help convey these findings. In particular, this case study exemplifies non-routine requirements of the InfoGather task. Our data suggests the selected patient case is complex because the quantitative descriptors (reported in [15]) are more than twice H1's average interactivity across all nine observed patients. Data presented in this study further supports this assertion: 1) H1 described the patient as "an involved patient". 2) To complete InfoGather, H1 followed a screen transition pattern variant that was unique in our sample. The pattern involved 7 transitions between main-tab EHR screens and 12 transitions including the EHR's subtabs and other clinical applications. 3) Among the 7 EHR screens, H1 visited two screens twice (S and L). This may suggest that redundant screen viewing for a patient case is also an indicator of patient case complexity. On the other hand, redundant screen viewing may suggest users' inefficient task performance, an indicator of system usability or of task complexity (e.g., conflicting data gathered from another screen or from the paper handoff document may cause the clinician to return to a previously viewed screen). As an outlier case, it surfaces some complexities of completing the task and negotiating the information sources.

Process mining enables researchers to variably focus data analysis on clinicians, patients, time, tasks and interactions, thereby providing insights into different dimensions of workflow. The level of analysis is limited only by the granularity of the event logs. A limitation of our data collection is that we only looked at event logs from one clinical information system and in one setting. Future work will combine event logs generated from additional clinical information systems. As we examine how automated event log files are useful to study EHR workflow, we can also inform what user behavior is captured in systems' event log files. That is, we can determine if there are particular user-computer activities that event logs could capture and that would be informative of users' cognitive work.

We conducted qualitative analysis on the subset of observed cases to investigate why some screens were viewed two or more times (redundant screen viewing) for one patient case. Three clinicians repeated screen viewing for a third or more of their patient cases. Reasons varied from clinician's lack of experience, lack of cognitive support provided by the system to synthesize and consolidate patient findings, system default settings and clinicians' deliberate routine work process. It was assumed that default setting improved workflow so that clinicians would not have to visit the screen twice. It could be that the default setting serves them better on another task. Future design could support task-based navigation through the system, which could reduce cognitive workload.

Future research will employ regression analysis to determine if there are associations between measures of patient complexity (e.g., procedure, primary diagnosis, number of medication at admission, days in hospital, number of services involved in care, etc.) and measures of task complexity (e.g., number of screen transitions, task duration, etc.). The case study supports further investigation of this. If there is an association between patient case complexity and task complexity, it could be used to quantify increased workload on clinicians from complex patients. Also, it could be evidence toward development of advanced clinical decision support systems that facilitate team awareness and collaboration of complex patients.

Cognitive studies grounded in DCog framework examine clinical work in the context of actual practice and can identify issues in human and system performance. A contribution of our approach to cognitive research is that we leverage large data sets of system-generated event log files to investigate users' behavior in conjunction with observational methods to explain variation in the empirical findings. In this study, we demonstrated the value of integrating quantitative data analysis with qualitative data to examine EHR workflow. This study indicates that process mining techniques can be used to evaluate variation of clinicians' task behavior across many clinicians, which can potentially be used to direct resource allocation for observation or training when patterns of interaction seem aberrant or inconsistent with clinical pathways. This study presents a part of a larger methodological framework that we are developing for the study of clinical and EHR workflow[10]. In the larger research project, we are studying workflow from multiple perspectives (e.g., tasks, clinicians, patients, tool). As we branch beyond analysis of a single task, we are exploring how to use system log files to examine care team coordination activities, particularly to study patient-centered clinical workflow. Variation in team processes surfaced through process mining can be used to focus observation efforts.

Conclusion

The presented study approach addresses the need for an integrated, in-depth approach that facilitates broad investigation of workflow across many settings, clinicians and patient cases, while also facilitating detailed analysis. We used system-generated event log files to characterize clinicians' EHR-interaction patterns for a routine computer-based task, along with observation to explain variation in the patterns. As demonstrated in this study, computational ethnography can be integrated with observation to balance the advantages and limitations of individual data collection methods and to enable collection of a broad and rich data set for studying clinical work.

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