Health Informatics

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Cognitive Informatics

Reengineering Clinical Workflow for Safer and More Efficient Care

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Foreword

Clinical care problems today include inefficiency, errors, and applying best evidence.

There is universal recognition that healthcare today is expensive and inefficient and is plagued by failure to deliver high quality. Nowhere is this truer than the United States, with its fragmented system of providers and payers and its singularly huge health expenditures per capita as a proportion of gross domestic product. It is hardly controversial to propose that part of the solution is to improve efficiency through communication and coordination among all the stakeholders.

Current communication and coordination are largely related to financial matters, especially payment to healthcare providers. Where "workflow" is addressed, it is largely administrative in nature (admission, discharge, transfer, referral for clinical procedures, and documentation for billing purposes). Yet the real workflow—moving the patient through the healthcare system to transform the sick patients to healthy ones and keep them that way, what the administrative processes were created for in the first place—often garners less study for process improvement. As a result, clinical workflows take a back seat to administrative ones. By way of illustration, I once worked at a hospital where transfer of a patient from a medical or surgical service to the rehabilitation service required formally discharging the patient, with attendant discharge summary and orders, and then readmitting them, with attendant intake and admission orders—even though the patient might not physically move from one bed to another. The opportunity for degraded continuity of care, such as order transcription errors, was only one of the problems that this process imposed.

In the United States, the Affordable Care Act has led to rapid adoption of electronic health record (EHR) systems, largely commercial products, many of which with serious flaws that had previously impeded their adoption. The unintended consequences of this experience can inform similar efforts in other countries. Nevertheless, EHR adoption has been held out as a way to improve healthcare effectiveness and efficiency through automation of, in part, the communication and coordination related to workflow processes.

It is fair to say that the clinical (previously "medical") informatics research community has been poised to help with information technology-based workflow for decades, at least since the inception of the Symposium on Computer Applications in Medical Care in 1977 (now renamed as the Annual Symposium of the American Medical Informatics Association). The work presented at that conference alone, over its 40-plus years, comprises many thousands of informatics projects, the majority of which failed to find long-term adoption.

While early evaluation of informatics solutions consisted of demonstrating that programs could run to completion without errors and could do so faster and more accurately than previous attempts, current evaluations examine issues such as usability and usefulness. Yet even systems that fair well in such assessments find that enthusiasm for their use is underwhelming.

To a large extent, the lack of success of most of these projects has been related to failure to integrate them into healthcare systems and, even where integrated, failure to support workflow processes in natural, intuitive ways. For example, nurses and physicians find work-arounds in using electronic clinician order entry systems to the detriment of patients, while alerts and reminders are overridden more often than not as being inappropriate and bothersome. In my own experience, I developed a tool called the Medline Button, the first version of a class of applications called infobuttons that attempt to anticipate and assist with clinician information needs, which executed medical literature searches based on a patient's ICD9 codes in the pre-PubMed era. It was a technical success, making the retrieval of relevant information possible with the touch of a button. However, it was a practical failure because it used data generated at the time of hospital discharge that were no longer relevant during a subsequent hospital admission.

What has largely been missing from efforts to health information technology-based efforts to improve clinical workflow, as evidenced by the Medline Button experience, are studies of cognitive processes of patient care providers and their impact on healthcare team communication and coordination. In subsequent infobutton research, for example, successful adoption did not occur until I partnered with Vimla Patel, one of this book's editors, and her team of cognitive scientists at McGill University to study clinicians' information needs through formal observational think-aloud studies in actual clinical settings.

This brings me to the purpose and place of this book. Its reviews, essays, and case studies will, collectively, raise the reader's awareness of the myriad issues that relate health information technology to clinical workflow, not from the perspective of administrative processes but based on cognitive processes that such systems are intended to support. Once enlightened with that perspective, the reader should consider the systems present (or needed) in his or her own institution and how they should be studied. Hopefully, some of these readers will be decision-makers at their institutions, who will be able to include cognitive researchers in the task of putting the findings of their research into practice. This book will then be at the right place at the right time to provide insight into the types of tools and evaluation expertise that will be needed to better match workflow systems to intended, rather than unintended, consequences.

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Part I
Clinical Workflow and Health Information Technologies

Chapter 1
Clinical Workflow in the Health IT Era

Kai Zheng, Johanna Westbrook, Thomas G. Kannampallil, and Vimla L. Patel

Health information technology (IT) in general, and electronic health records (EHR) in particular, hold great promise to cross the quality chasm of the healthcare system and to bend the curve of ever-rising costs (Institute of Medicine (U.S.) 2001; Girosi et al. 2005). However, health IT implementation projects globally have experienced a wide range of issues, from rollout delays to budget overruns (Kaplan and Harris-Salamone 2009). Successfully deployed systems often fail to generate anticipated results (Black et al. 2011; Kellermann and Jones 2013); some are even associated with unintended adverse consequences (Ash et al. 2007; Campbell et al. 2006; Koppel et al. 2005; Zheng et al. 2016).

In the U.S., for example, over $30 billion has been invested in accelerating EHR adoption and promoting its "meaningful use" through the appropriation from the Health Information Technology for Economic and Clinical Health (HITECH) Act 2009 (Blumenthal 2010; Blumenthal and Tavenner 2010). While the program has

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been largely successful in boosting EHR penetration rates across U.S. hospitals and clinics (The Office of the National Coordinator for Health Information Technology (ONC); Office of the Secretary, United States Department of Health and Human Services (HHS) 2018), research on the effectiveness of the systems implemented has showed mixed results (Jones et al. 2010; Romano and Stafford 2011). In their Health Affair article entitled "*What it will take to achieve the as-yet-unfulfilled promises of health information technology*," Kellermann and Jones concluded that despite the widespread adoption of health IT, the quality and efficiency of patient care in the U.S. were only marginally better; and the annual aggregate expenditures on healthcare continue to soar (Kellermann and Jones 2013).

Disruption to clinical workflow as a result of health IT implementation has been repeatedly shown as a major cause for the under-realized value of health IT. A key issue is that today's health IT systems are often designed to simply mimic existing paper-based forms, and thus provide little support for the cognitive tasks of clinicians or the workflow of the people who must actually use the system (National Research Council 2009). Similarly, in a systematic review of the health IT evaluation literature, Buntin and colleagues found that a considerable number of studies reported negative or mixed findings, and that "most negative findings within these articles relate to the work-flow implications of implementing health IT, such as order entry, staff interaction, and provider-to-patient communication" (Buntin et al. 2011: 467).

"More/New Work" and "Unfavorable Workflow Change" are two workflow disruptions that have been most often discussed in the literature; both are directly attributable to the radical changes to established clinical workflow associated with introduction of health IT (Ash et al. 2007; Campbell et al. 2006; National Research Council 2009; Niazkhani et al. 2009). While some changes are purposefully planned—to reengineer existing processes to take full advantage of new capabilities offered by health IT—some are manifestations of a wide range of problems such as poor software usability, misaligned end-user incentives, rushed implementation processes, and the lack of sociotechnical considerations to effectively integrate software systems into their complex behavioral, organizational, and societal contexts (Ash et al. 2007; Campbell et al. 2006; National Research Council 2009; Niazkhani et al. 2009).

It is therefore critical to develop a comprehensive understanding of the impact of health IT on clinical workflow, in addition to their root causes, mechanisms, and consequences. Unfortunately, studies of these phenomena are still relatively scarce, and available findings are often inconclusive or conflicting (Unertl et al. 2010; Zheng et al. 2010; Carayon and Karsh 2010). Further, a consensus on the research definition of "clinical workflow" remains elusive, especially in the context of assessing workflow changes introduced by health IT (Unertl et al. 2010).

While conceptual models are available, e.g., (Unertl et al. 2010) many challenges remain in the development and application of robust measures of changes to clinical workflow (Zheng et al. 2010). Methods used in existing workflow studies vary to a great extent (Unertl et al. 2010; Zheng et al. 2010; Carayon and Karsh 2010; Zheng et al. 2011; Lopetegui et al. 2014). Even among studies using the same method, a considerable degree of discrepancies exists in application of the method and interpretation of study results (Zheng et al. 2011; Lopetegui et al. 2014). For example, time and motion is considered to be the "gold standard" approach for obtaining quantitative assessments of clinical workflow; yet among the time and motion studies published to date, there has been a large degree of methodological inconsistencies in the design, execution, and results reporting of those studies, such as how inter-observer reliability is assessed and how multitasking is handled (Zheng et al. 2011; Lopetegui et al. 2014). This issue has significant implications for the rigor and generalizability of time and motion studies, diminishing our ability to accumulate knowledge as a field. As commented by Carayon and Karsh in a comprehensive literature survey report commissioned by the U.S. Agency for Healthcare Research and Quality (AHRQ), the empirical evidence of health IT's impact on clinical workflow has been "anecdotal, insufficiently supported, or otherwise deficient in terms of scientific rigor" (Carayon and Karsh 2010: 7).

This book intends to address several of these knowledge gaps by bringing together a team of experienced researchers and practitioners who have dedicated their career to studying and improving clinical workflow. Several chapters included in this book are results of a series of research or quality improvement efforts spanning multiple decades; some are syntheses of the research literature since early 1900s, bringing together what we know about clinical workflow, where gaps remain, and how these gaps can be addressed in future research.

This book is organized into four Parts and 19 Chapters. Part I, *Clinical Workflow and Health Information Technologies*, orientates readers to the problem domain, basic concepts (e.g., cognitive behavior and workflow modeling), and consequences of disrupted workflow due to health IT implementation.

Part II, *the State of the Art of Workflow Research*, summarizes workflow studies conducted in healthcare in the past few decades. We purposefully include in this section workflow research from a non-healthcare domain, aviation, to draw a comparison between how clinical workflow differs from workflows in other industries and how they are conceptualized and studied differently. Part II also includes a chapter specifically on multitasking and interruptions, which are two defining characteristics of clinical workflow that have significant efficiency, care quality, and patient safety implications; in addition to chapters that address nursing and patient perspectives, and workflow-related issues during patient handoff and when patients transition from one healthcare setting to another, i.e., workflow at the edges.

Part III, *Research Methods for Studying Clinical Workflow*, introduces research methodologies that have been commonly used in clinical workflow studies, including work sampling, time and motion, human factors engineering, and emerging methods that leverage sensor technology for automated data collection and real-time workflow assessment. Part III also includes a chapter that discusses the unique characteristics of quantitative workflow data and consequently unique challenges to statistically analyzing such data.

Part IV, *Applications and Case Studies*, first presents one large clinical workflow study supported by the U.S. Agency for Healthcare Research and Quality (AHRQ) that looked into how health IT systems, introduced as part of ambulatory care practice redesign, impact clinical workflow. Part IV then presents three case studies each focusing on a distinct perspective. These include effort in reengineering clinical workflow to enable a cross-continental collaboration on creating continuously monitored intensive care units, and efforts in enhancing clinical pathways, clinical rounding, and patient handoff communications.

By compiling a collection of high-quality scholarly works that seeks to provide clarity, consistency, and reproducibility in workflow research, we hope to create a repository of knowledge to inform future studies on health IT design, implementation, and evaluation. In addition to a research reader, this book offers pragmatic insights for practitioners in assessing workflow changes in the context of health IT adoption, and in implementing remedial interventions when such strategies are warranted. The book is also designed to present the state of the art on clinical workflow research, providing an excellent reader for graduate students in all clinical disciplines as well as in biomedical and health informatics.

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Chapter 2
Cognitive Behavior and Clinical Workflows

Jan Horsky

2.1 Cognitive Work in a Complex Domain

The intrinsic complexity of evidence-based, technologically advanced modern healthcare defines processes and affects work environments in ways that make them difficult to describe with consistency and create models with highly predictable outcomes. The healthcare industry comprises a wide array of organizational entities that range in scale from small private practices and independent clinics to hospitals and large healthcare delivery networks. They interact with a multitude of ancillary and support service businesses, insurance and payer companies, public administrative and regulatory bodies, private and public research centers and academic institutions that together form one of the most complex organizational structures in society (Begun et al. 2003; McDaniel et al. 2013). Individuals engaged directly or indirectly in patient care, its management and administration routinely collaborate across professional and institutional boundaries. The efficacy of their work and the safety of patients are vitally dependent on technology support that allows collection, storage, analysis and sharing of information and communication. Decision making and reasoning of clinicians in this highly interconnected environment is as often autonomous as it is interdependent and contingent on the expertise and decisions made in parallel by others. This intricate combination of individual and collective responsibilities, actions and decisions tends to generate many non-linear work processes that account for much of the dynamism and elasticity of both personal and collaborative workflows (Fig. 2.1).

Work characteristics that are specific and often unique to healthcare make predictive analyses of workflows in this domain problematic. The primary responsibility of clinicians is to ensure that patients receive timely, appropriate and

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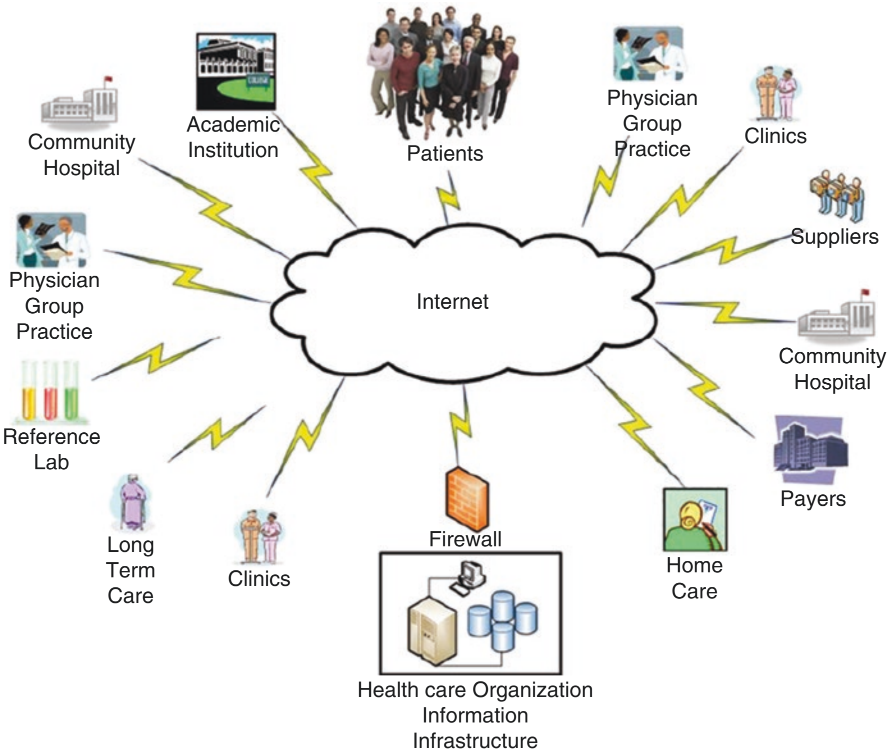

Fig. 2.1 Major organizational components of integrated healthcare industry. Reprinted from Vogel LH. Management of information in healthcare organizations. In: Shortliffe EH, Cimino JJ, editors. Biomedical informatics: computer applications in healthcare and biomedicine. London, Heidelberg, New York, Dordrecht: Springer; 2014. p. 443–74

effective care whenever and wherever needed. Goals and their sequence—the constituent parts of workflows—are in practice quickly reorganized and modified to accommodate new developments and may require interventions that conflict with prior or existing objectives or with normative pathways. Decisions and actions in many lines of clinical and ambulatory care are often deferred, substituted, traded off or finalized only to a sufficient degree so that tasks with higher priority may get fully completed when time or resources are limited. For example, planned procedures, evaluations or medication therapy may be changed when new laboratory test results become available or when newly discovered findings require immediate attention. Trauma patients are treated for injuries that are life-threatening while the care for other illnesses and conditions may be limited to stabilization or postponed until more favorable circumstances allow. Planned behavior and goal completion are routinely interrupted through personal contact, telephone conversations, pagers or computer-generated alerts. This dynamic is inherent to clinical work and generally considered to be necessary and often adaptive so that interventions can be directed toward the greatest need when situations evolve and change. Team members often provide help to one another when needed without waiting for explicit requests (Rivera-Rodriguez and Karsh 2010). Cognitive psychology research provides ample evidence about the disruptive effects of interruption on human cognition (Altmann and Trafton 2007) and reports from healthcare studies show that interruptions and distractions contribute to medical error (Ashcroft et al. 2005) and may increase the risk to patient safety during certain types of clinical tasks (Li et al. 2011). The fragmentation of work is many times unavoidable and clinicians incur extraneous cognitive burden and mental fatigue that often conflicts with their reasoning.

There are many public and private organizations with complicated internal structures that manage large workforce in which scientists, researchers, lawyers, professionals and administrative and support personnel with vastly different expertise and duties routinely collaborate. The National Aeronautics and Space Agency (NASA), for example, or many national airlines, technology corporations and power-generating companies conduct work and research projects in an environment that is science-based, safety-critical and contains considerable risks that need to be well understood and controlled. Healthcare shares many of these attributes and efforts to increase the safety, quality and effectiveness of care are often informed by initiatives successfully implemented in such industries—the long-term investment in information technology being a prime example. There are also considerable differences emanating from the inherent properties of an engineered system (the aircraft, engineering) and a biological, natural system (the patient, medical science). Healthcare has many characteristics that are not typically found in engineered systems (Durso and Drews 2010). Better insight into the specifics and idiosyncrasies of this information-intensive domain may accelerate the uneven pace of progress towards greater effectiveness and increased safety that is intended to be advanced by health information technology (HIT) and work organization.

Biomedicine is a scientific discipline that is in many respects quite unlike other applied and natural sciences. A defining but elusive feature of physiologic systems is their daunting complexity arising from the interaction of a myriad of structural units and regulatory feedback loops that operate over a wide range of temporal and spatial scales, enabling an organism to adapt to environmental stresses (Glass 2001). Medical care and research encompass the properties and behavior of human beings—organisms whose complexity have no counterpart in other scientific disciplines. Many aspects of these natural systems are opaque because interactions have to be deduced and may not be fully understood: individual elements of biological systems occurred without intentional design and are the result of reorganization and evolution in order to adapt to changing environment (Durso and Drews 2010). Medical investigations and discourse therefore includes the aspect of uncertainty that inevitably creates variability among individuals and makes clinical information systematically different from the information used in physics, engineering, or even clinical chemistry (Shortliffe and Barnett 2014).

Decision making involves reasoning with inherently probabilistic information. However, the level of uncertainty in diagnostic hypotheses or treatment options that clinicians seek to reduce by testing and by gathering data is further affected by the availability of information that is often incomplete or unreliable. Observations, laboratory results and narrative reports may not have been completed or cannot be immediately obtained; they may also be in apparent conflict or ambiguous, and their interpretation could be erroneous (Weber et al. 2017; Smithson 1999). For example, when the history of respiratory problems is not found in the patient record, its lack could be interpreted as an indication of the absence of prior problems by a clinician hypothesizing about the possibility of acute lung disease even if such assessment was simply not documented. The value of any patient information rises dramatically when the level of record completeness and comprehensiveness is high and typically needs to reach 85% or above to be truly useful to clinicians (Yasnoff 2014).

Somewhat ironically, paucity and excess of information may coincide even in the record of a single patient. Clinicians need to collect relevant assessments, case summaries, radiology reports laboratory values and other data and review them in context. The information may be stored in a single or in multiple electronic health record systems (EHR) or distributed over ancillary systems that may or may not be functionally interoperable. A patient treated by several hospitals and specialty services will have only a fraction of all recorded historical data in one system and a reviewing clinician may not be aware of critical events stored in remote, unconnected systems (Weber et al. 2017). Those that are gathered within a single EHR may be presented on screens in separate modules and sections that de facto silo them, further complicating their meaningful aggregation for a specific clinical purpose. Clinicians may need to repeatedly search and navigate through the record in order to retrieve relevant information (Stoller 2013). Narrative visit and progress notes may also contain repetitive, dated or inaccurate content that is created as the unintended consequence of too-facile recycling of old data through cut-and-paste behavior. This so-called “note bloat” inhibits the ongoing questioning and ascertainment process that helps monitor diagnostic accuracy as illnesses evolve over time (Graber et al. 2017).

The complex science, the pragmatics of making decisions with uncertain information, the intricacies of mixed collaborative and individual responsibilities and the dynamics of established and ill-defined goals are all characteristic of a field in which work demands can exceed the bounds of unaided human cognition (Masys 2002). The extent of knowledge that needs to be mastered also rapidly expands, often changing the understanding of existing medical concepts with new insights. It is estimated that while it took 50 years to double the volume of medical research publications in 1950, in 1980 it was merely 7 years, 3.5 years in 2010 and it is projected to be just 73 days in 2020 (Densen 2011). Health information technology that is unobtrusively embedded into workflows and effectively supports clinicians in their decision making, manages access to contextual knowledge and helps with data analysis and interpretation is as difficult to design and implement as it is necessary for safe and high-quality care.

2.2 Complexity of Medical Care Reflected in Workflows

Large healthcare institutions are paradigmatic examples of complex organizations where clinicians routinely engage in non-linear interactions with others and with information technology and where their work plans include many emergent goals (Martínez-García and Hernández-Lemus 2013). Complex work environments are distinctly different from those that are merely complicated: they are more difficult to analyze and future system states are not always predictable. Complicated problems and processes originate from singular causes or from the actions of identifiable agents and when they combine to create a problem state, the sources can be distinguished and addressed individually. Complex problems, on the other hand, evolve from networks of multiple interacting causes that may not be possible to differentiate and interventions to address them need to consider systems in their entirety. Feedback and circular processes in such systems also modify and intensify the causes so that effects are often disproportional to their origins (Poli 2013).

Health care can be characterized as a socio-natural system with many non-linear and non-additive functions that may be opaque and more difficult to understand and predict than engineered systems (e.g., aviation, manufacturing) where nonlinearity is often a sign of malfunction (Durso and Drews 2010). Standard, reusable processes that often engender safe practices and allow monitoring for anomalies that may eventually become problems have therefore more limited use in healthcare than in other safety-critical work environments. Clinicians may prioritize or trade off multiple immediate and longer-term goals to restore a patient to health or to reduce their discomfort. Objectives and goals that are initially vague and only gradually become more focused and defined as more insight is gained may be called emergent (Klein 2009). Emergent properties of systems and processes are difficult to model and predict because complex systems are non-reducible to their constituent parts. In the hypothetico-deductive approach to diagnostic reasoning, data and observations are added to the growing database of findings and are used to reformulate or refine the active hypotheses until one reaches a certain threshold of certainty and a management, disposition or therapeutic decisions can be made (Shortliffe and Blois 2014). Parts of a therapeutic plan that define a patient trajectory and workflows for multiple clinicians providing services and care may therefore be only tentative, even in situations when goals are clearly defined.

2.3 Workflow Modeling

Beginning in the late nineteen eighties, large American companies saw the benefit of studying cross-functional business processes rather than concentrating separately on functional and transactional operations such as procurement, manufacturing and sales. They defined the concept of a business process as a set of logically related tasks performed to achieve a specific business outcome—primarily, better service to clients (Davenport and Short 1990). Decisions that affect multiple processes are in this paradigm given more weight than ad-hoc, local decision making.

A somewhat parallel development in the healthcare industry in the nineteen nineties, spearheaded by academic institutions, professional societies and regulatory bodies, strived to improve the continuity of care across disciplines and to decrease unwarranted practice variation (Wennberg 1999). These entities started creating and disseminating collections of evidence-based recommendations for best practices, called clinical guidelines, that addressed specific clinical goals or conditions. They provide the basis for higher-level decision making and are often complemented by locally-developed clinical protocols to monitor compliance but usually do not define individual steps in a process. There are also clinical pathways, structured multidisciplinary plans of care, designed to support the implementations of clinical guidelines and protocols. However, there are today no formal industry standards for completing care processes and clinicians have largely their own ways of interacting with patients and executing tasks (Karsh 2009).

Workflow generally refers to the control dimension of a business process, that is the dependencies among tasks that must be respected during its execution (Delacoras and Klein 2000). The term is used more broadly in healthcare and its meaning can vary. It can describe goals and processes for an individual as well as for groups, the navigation paths through EHR screens, abstract representation of tasks, information needs, error conditions and alternate paths, or the steps that a clinician performs when delivering care according best practice suggestions and clinical guidelines.

Work environment analyses have historically investigated the business processes associated with care or the flow of patients and staff through large hospital buildings. The interest in analyzing clinical work processes and collaboration developed later, but rather than a planned strategy to improve the effectiveness and safety of care, the impetus was often a need to address inefficiencies and disruptions reactively when identified or introduced by new technology implementation. For example, there are no standard descriptions of workflow for care processes that would guide decisions about where and how to integrate computer-based decision-support interventions (Shiffman et al. 2004). Workflow studies, once scarce, are now being done more frequently although their findings are often inconclusive or conflicting (Zheng et al. 2015). Many lack scientific rigor because they describe workflows only indirectly or do not explain conflating or mediating factors such as training and organizational culture within the socio-technical context of HIT implementation and use (Carayon and Karsh 2010).

A theoretical perspective of work in healthcare organizations holds that complex social interactions, conflicting objectives, preferences and work demands determine the use and effect of information technology (Anderson and Aydin 2005). Predictive analyses require a robust understanding of organizational dynamics, characteristics of individuals, information systems and the knowledge of processes that occur during system planning, implementation and use; simply modeling the levels of independent variables hypothesized to predict change cannot be productive (Mohr 1982; Markus and Robey 1988). A useful paradigm for situating the description of work processes, pathways and interactions that healthcare workflow studies refer to may be found in the work of Holden and Karsh (Holden and Karsh 2009) who have formulated a theoretical model of multilevel work system to understand the behavior of clinicians working with the support of information technology. Derived in part empirically from HIT evaluation studies and implementation literature and also from theories used in communications sciences, psychology, sociology, management, organizational behavior and human factors research, it was applied to help explain the determinants of technology use behavior (Smith and Sainfort 1989; Carayon et al. 2003; Klein et al. 1994; House et al. 1995; Klein and Kozlowski 2000). The central proposition of this model is that the physical, cognitive and social-behavioral performance of a clinician is affected and constrained by nested structural elements of healthcare organization (Karsh 2009).

The four-level model describes the integration, or fit, of the clinician-HIT interaction, collaboration and workflow patterns on the base level within the constraints and workflow patterns active in the levels above. At the top of this hierarchy is the entire healthcare industry where standards, regulations, legislative oversight, social influence and labor force characteristics guide the work of organizations. Below are healthcare institutions of different size, from care delivery networks to private practices, that create administrative structures of their own, formulate policies, norms and best practices, set priorities and provide training, financial resources and expertise appropriate to its constituent work groups and units that are on the next level down. Each organizational setting has its own constraints determined by technological and administrative factors, by its core mission that affects the professional and specialization makeup of the workforce and by the characteristics of the target patient population that collectively contribute to the complexity of workflows and task structure. The work of individuals, at the base level, is therefore done in an environment that is responsive to the disruptive and conducive effects of elements and activities from each level on attention, decision making, problem solving and cognitive labor. Interfaces and conduits between and within levels create a rich and information-intensive work context for workflows at the clinic level, patient care workflows and clinician mental workflows (Holden and Karsh 2009).

A workflow model is a simplified representation of past, actual or future process that can be described by routing, allocation and execution components. It may have a narrow focus such as the support for decision making but usually there is a broader purpose (Reijers 2003). There are several frameworks and models that have been applied to the study of healthcare processes, from specific environments to more general settings. Bricon-Souf and colleagues describe a proprietary modeling approach for medical intensive care units that explicitly distinguishes urgency in determining the authorization of a resource to perform a task (Bricon-Souf et al. 1999). The Systems Engineering Initiative for Patient Safety (SEIPS) (Carayon et al. 2006) model is more broadly applicable and defines the work system as an interactive environment that structures workflows, affects the performance of clinicians and therefore, indirectly, patient outcomes. The authors also proposed the Workflow Elements Model (WEM) (Carayon et al. 2012), a related framework that conceptualizes the activity of individuals and groups working asynchronously as dynamic and temporal characteristics of workflows. System elements, in this view, create a context that constrains or enables workflows that encompass converging and diverging goals. The dynamism of these processes is considered the emergent property of work.

A compelling viewpoint on the analysis of healthcare work and complementary to the structural dynamism found in other models is the conceptual lens of the patient trajectory: the pathway of an individual patient through the process of care becomes the anchor point of analysis. The patient-oriented workflow model (Ozkaynak et al. 2013) references the cognitive, social and work behavior of agents in a complex sociotechnical system (Berg 1999a; Sittig and Singh 2010) where actions are not centered around individuals or groups but rather distributed among roles in the work setting that converge around the care of a specific patient. The process that partially determines the basic directions and outlines of the care process is a structured sequence of activities, events, and occurrences related to a patient's particular illness trajectory. The term concerns the way in which an illness typically unfolds in both sequential and temporal order and how management and treatment actions are planned (Reddy et al. 2006). Workflow analyses in this paradigm therefore focus on the embedding of illness trajectory within the care process. Clinicians planning care interventions and tests often need to understand where on the trajectory a patient currently is and where they should be relative to the characteristic unfolding of a disease progression. Their reasoning needs to concern not only individual data points at the time of decisions but also patterns and trends over time and their interpretation in the larger context of known outcomes over many patients (Hilligoss and Zheng 2013). Developing these models is methodologically and practically challenging, however, because of the large variability of data types that are meaningful and relevant in each setting and also due to the lack of a comprehensive and robust conceptual framework that limits their interpretation with consistency (Ozkaynak et al. 2013).

More recently, a multidimensional Triangle Evaluation Model (Ancker et al. 2012) was proposed to identify elements of healthcare structure and processes that should be assessed concurrently with quality and safety outcome variables. The structure-level predictors include HIT characteristics and how clinicians interact with it, organizational setting and patient population. These foci align well with the multi-level and dynamic perspective of healthcare work.

Dynamic workflows self-adapt to the present situation and evolve at execution time as a function of personal insight. Clinicians often encounter ill-defined and under-specified problems they need to solve and their cognitive task is to determine the form of the solution. Such systems are called "loosely coupled" and it is useful to see dynamic workflows as situated historical records where tightly-coupled elements provide a bound to loosely-coupled relationships and event sequences that are largely non-deterministic (Covvey et al. 2011). An example of work environment that can be characterized in such terms is emergency and critical care (Horsky et al. 2015).

2.4 Cognitive Behavior and Workflow Effects

A prominent attribute of clinical work is the concurrent presence of both tightly and loosely coupled organizational and work relationships. It is essential that smaller units organize their work autonomously from central control and that individuals have appropriate level of discretion to make independent decisions in order to manage the evolving needs of patient care. Typically, clinicians have loosely-coupled interactions with policy-setting authorities in administrative and medical oversight roles who monitor institutional guidelines and strategies and regulatory mandates from local and national bodies (the higher tiers in the multi-level model). They are highly trained professionals who collaborate with other experts but retain individual responsibility for decisions (Pinelle and Gutwin 2006). However, multi-disciplinary and specialized (e.g., surgical) teams often have an ordered structure with tightly-coupled and clearly defined roles and relationships. For example, attending physicians, residents, interns, medical students, nurses and support staff in hospitals have roles delineated in an explicit hierarchy and patient care and indirect services are directed and communicated through verbal and written orders.

A theoretical framework that is increasingly more used to study problem solving and collaborative work in healthcare is Distributed Cognition (DCog) that conceptualizes human cognition as extended beyond the boundaries of an individual and is manifest in artefacts (physical and electronic), social and work relationships (Hollan et al. 2000; Hutchins 1991, 1995, 2000). Its focus is on representational transformation of information that occurs in external media and are coordinated by human and technological actors (Wright et al. 2000; Furniss and Blandford 2006; Cowley and Vallée-Tourangeau 2017; Horsky et al. 2003). It is perhaps the most clearly articulated, critiqued, commonly used and well known form of exploring how distributed action can be examined as a cognitive process (Perry 2017). The problem structure that DCog can analyze with relatively little difficulty is often defined a-priori: goals are known and defined, changes follow pre-determined processes and many tasks are repetitive and could be trained. Studies that typically produce clearly identifiable examples of problem solving and cognition distributed over artefacts and collaborators usually involve well-defined activities, explicit boundaries of control and influence and an environment where work roles and protocols are pre-set and generally static and constrained, such as ship navigation or the work of aircraft pilots.

The tightly-coupled components of healthcare workflows are appropriate objects of such analyses. For example, the patient trajectory workflow model is closely related to that patient's illness trajectory as clinicians make decisions that follow a specific reasoning process, or an "illness script." It is conceptualized as an internal representation of the pathophysiology, epidemiology, time course, signs and symptoms of a particular illness or a disease and organized as a summary—or a mental and treatment (Custers 2015). Such models are initially acquired through medical training and further developed and internalized by professional experience. They represent knowledge in three broad categories: predisposing conditions (context), pathophysiological insult (causal chain) and clinical consequences (signs and symptoms) (Schmidt and Rikers 2007). Expert clinicians have over time expanded, refined and contextualized this knowledge to form durable mental models in which the presence or absence of significant script characteristics carry certain predictive value for a diagnosis. Their ability to differentiate between illnesses with similar presentations allows them to make more accurate diagnostic and care decisions more quickly.

Clinicians are less likely to associate illnesses with a particular script when they have atypical presentation or when they encounter them infrequently. Their diagnostic reasoning then becomes more laborious and vulnerable to errors, biases and misconceptions (Jones et al. 2014). Uncertainty is inherent in clinical work and its level is associated with diseases that vary greatly in the degree of symptom ambiguity (Leykum et al. 2014). For example, patients who have a more typical progression of an illness can be more reliably and predictably treated according to existing standards of care than others for whom population-derived guidelines are a poor fit and who require more personalized care. The downside is that outcomes dependent on individual characteristics or manifestations that may be unknowable are far less certain.

DCog analyses are less effective for the analysis of loosely-coupled structures that have dynamic workflows and emergent goals. Uncertainty takes many forms in healthcare (Plsek and Greenhalgh 2001) and can be attributed to three main sources: the complexity of the system itself, the poorly predictable trajectories of illnesses, and the limits of scientific knowledge (Han et al. 2011). It has been conceptualized as a multidimensional phenomenon with theoretically distinct domains and constructs that are potentially measurable and related to different outcomes, mechanisms of action and management strategies (Gerrity et al. 1990). For example, a measure developed to study clinical reasoning strategies during patient visits includes an assessment of uncertainty that refers to how well the limitations of available information are recognized and explained and how solutions are planned to adjust to the current situation (Weir et al. 2012). A study of clinical reasoning and communication in an emergency department examined the amount of detail conveyed in narrative accounts of care during handoffs as an approximation of the uncertainty level (Horsky et al. 2015). However, uncertainty of diagnostic and treatment decisions within complex systems is often irreducible and its measurement and management challenging. It is the product of non-linear dynamics and the information needed to reduce this type of uncertainty may not exist (Lanham et al. 2014). Application of the DCog approach in settings where shifting problem space and where specific, local solutions are central to the performance of both individual actors and the entire system therefore remains problematic.

There are several published reports on DCog analyses that have come close in their application to highly dynamic and loosely structured settings (Hazlehurst et al. 2007, 2008; Holder 1999) although the problems described have been carefully "bounded" to create a simplified problem space that does not account for the layers of setting context (Cowley and Vallée-Tourangeau 2017). Many other studies, however, have used DCog as a methodological and explanatory framework or were designed to extend its methodology (Horsky et al. 2003; Kaufman et al. 2003, 2009; Furniss et al. 2016a; Sedig et al. 2015; Grundgeiger et al. 2010; Cohen et al. 2006;

Xiao 2005; Nemeth et al. 2004; Berg 1999b; Zhang 2002; Zhang and Norman 1994; Horsky 2008). Importantly, the DCog framework allows researchers to identify and discuss the difference between tightly and loosely coupled activity systems in terms of their informational content and problem solving activities (Cowley and Vallée-Tourangeau 2017).

The distributed and highly specialized healthcare model, characteristic for advanced medicine, requires a high level of effective coordination among clinicians and experts. It means that all parties need to understand the position of their collaborators in the shared problem space and how their mental models and work progress align in order to reduce diagnostic or therapeutic uncertainty and resolve ill-structured problems. Situation Awareness (SA) and decision-making also becomes distributed and an emergent property of a collaborative system: it represents something that resides in the interaction between agents of the system rather than separately in the minds of individuals (Salmon 2009). Analyses then need to pay attention to how agents are made aware of ongoing but problem-unrelated situation monitoring in order to self-organize (Perry 2017).

There are natural limits to the span and effectiveness of attention, perception and recognition memory, learning, problem solving, reasoning and decision making that bound their application primarily to the core purpose of clinical work—pursuing medical goals. These resources are simultaneously needed for interaction with technology, organization and work coordination (Karsh 2009). Situation Awareness relates to the dynamic and transient state of a mental model which is produced by an ongoing process of information gathering and interpretation (Hendy 1995). It is a construct that can be thought of as an internal mental model of the current state of an individual's environment, or the perception of the elements in the environment within a volume of time and space, the comprehension of their meaning and the projection of their status in the near future (Mica 1988). SA is one component of dynamic, distributed decision making, along with task, system and individual factors. It changes as the environment changes in response to decisions and actions of individuals or due to automated technology interventions (Wright et al. 2004). Dynamic systems are therefore extremely demanding on human cognitive resources. Mental workload increases along with system complexity while situation awareness is more difficult to maintain.

Even in routine medical practice, cognitive workload is immense. Family physicians, for example, have to perceive, process, integrate and make decision on four to five problems in one visit (Beasley et al. 2004). They need to identify and diagnose each problem and plan testing and treatment. The complexity of decisions further rises with the number of comorbidities and concurrent problems that may interact or have causal relationships and when indicated treatment options may be in conflict. The burden on primary care clinicians in terms of coordination, information gathering, cognitive workload and decision-making is also compounded by often incomplete information; it is estimated that physicians have about eight unanswered questions for every ten ambulatory visits (Bates et al. 2003). Sophisticated and robust information technology and evidence-based decision support are essential tools and are indispensable for safe, high-performing and high quality care.

2.5 Effects of Technology

Implementation of new technology invariably changes the way clinical work is done, from documentation to decision making and care coordination. Personal and group workflows are always affected, often to a significant degree, and those who need to adapt ubiquitous routines and long-standing practice to a new model and to internalize unfamiliar procedures have a range of viewpoints on the beneficial and detrimental effects of a new approach on their own work and on the quality of care in general. The utility and safety of new systems and the effectiveness of reorganized work may be perceived differently by individuals but evidence from published research studies shows a net increase in patient safety that can be attributed to the use of advanced information technology, despite the still large number of preventable patient injuries that occur every year. Harm likely comes from relatively few initial causes, including hospital-acquired infections, adverse drug events, surgical injuries, deep venous thromboses and pulmonary emboli, falls and pressure ulcers that account for most of the adverse events in hospitals (Bates and Sheikh 2015). However, it is the quality of HIT design, advanced functions and rigorous implementation that seems to lead to gains in safety and efficiency—EHRs with only basic functions are less likely to have a significant positive effect. For example, a review of randomized clinical trials evaluating order entry and decision support interventions reported that only three out of ten studies showed measurable decrease of unsafe prescribing and only a half reduced medication errors (Lainer et al. 2013). At the same time, only about a half of US hospitals use EHRs with integrated advanced decision support and other functions known to reduce error, in what appears to be an emerging digital divide (Adler-Milstein et al. 2017).

Vendors and, to a lesser extent, academic and healthcare institutions, create products for the HIT market that is vast and diverse. The systems need to have many components that retain largely immutable design structures in order to keep the software reliable and to have the ability to maintain and develop it even as individual implementations are adapted to function according to local requirements. Dynamic work systems, however, produce unique work environments where single technology may have distinctly different effects (Zheng et al. 2015). The shared responsibility of all key stakeholders in the multilevel work system described earlier, (Holden and Karsh 2009) such as vendors, care providers, healthcare organizations, information technology departments and public and private agencies, is to monitor and manage the safety of HIT and to guide their efforts towards resolving their often conflicting priorities and requirements (Singh and Sittig 2016). For example, vendors and developers should provide health systems with guidance on decisions regarding configuration (e.g., changing default settings of medication administration times to better match local workflows), customization and optimizing usability while clinician must be responsible for learning how to use the EHR safely (Sittig et al. 2018). Technology that can effectively meet the work demands of complex socio-technical systems requires the active participation and expertise of all involved parties from inception to implementation.

What clinicians say they want in HIT may be limited by their own understanding of the complexity of their work or by their design vocabulary and the ability to convey to non-medical professionals their reasoning about care decisions. Understanding what would help people in their complex work is not as simple as asking them what they want, an all too common approach (Andre and Wickens 1995). Highly skilled professionals have often very limited insight into their own performance, and even more limited ability to articulate what might improve it. Substantial research on how clinical work is done, rooted in theories of cognition and collaborative work, is required to gain understanding of cognitive behavior of clinicians in the context of multi-layered and dynamically changing workflows.

Clinician-oriented approaches can capture the effect of technology on specific and diverse individual roles and their work. However, designers, implementers and workflow engineers should not fall into the "one size fits all" fallacy as validation of a design in practice requires thorough experimental testing based on well-defined performance criteria and rich, nuanced understanding of healthcare work (Karsh et al. 2010). Established methods such cognitive analysis (Bisantz et al. 2015; Hettinger et al. 2017; Roth and Bisantz 2013; Vicente 1999; Schraagen et al. 2000), workflow and task analysis and human-centered design evaluations have consistently generated useful guidance to HIT designers (Roth et al. 2002; Zhang 2014; Lowry 2014; Schumacher and Lowry 2010). The medical field is uniquely complex but not impenetrable to researchers from outside of the domain, even as it is a highly intricate and structured process of problem discovery and clarification in the context of unbounded complexity (Carroll 1997).

Researchers in the informatics, usability and workflow engineering fields in collaboration with clinical experts and biomedical scientists need to convey their findings to designers and developers in forms that best inform their work. A recent workshop about the usability of medication-alerting CDS and its evaluation outlined how this transfer of knowledge into practical design guidance may take place (Marcilly et al. 2016). Participants preferred design principles to be formulated as checklists and guidelines for design and procurement of software and hardware technology, and to help them interpret and understand critiques of prototypes that clinicians provided as a part of user-centered cyclical evaluation. An important component of specific advisories was their justification in terms of potential harm if they were to be ignored, evidence from prior studies and visual examples (e.g., prototypes, wireframes and screenshots) illustrating optimal and poor alternatives of design and function. Maintaining the research-to-practice continuum of discovery transfer effectively ensures that evidence-based design can make HIT better cognitive and interactive tools in clinical work.

2.6 Current and Emerging Trends

Precision medicine is gaining momentum as the care model most likely to benefit from the confluence of expansive new knowledge, especially in genetics, and advanced information technology. The term refers to the increasing specificity of patient characterization that is possible through genomic and phenomic analytic methodologies. Patients admitted to large medical centers are in the near future likely to receive genotyping analyses in addition to the usual data obtained by recording the many tests and procedures routinely performed along with the history taking and physical examination (Collen and Greenes 2015). The process will create vast arrays of newly organized data that will benefit decision support for complex medical diagnosis and treatment problems that will be more directly related to specific individuals. For example, known genetic variations would suggest with high levels of certainty the optimally safe and effective medication therapy.

Design initiative that is central to the goals of precision medicine is providing clinical decision support (CDS) interventions in forms that are appropriate to intended cognitive tasks and contextualized into workflows. A recent study that closely analyzed decision making during medication ordering and the effect of CDS alerts on the reasoning of clinicians showed that they conceptualized patient risk as a complex set of interdependent tradeoffs specific to individual patients and had a tendency not to follow automated advice they considered of low or dubious clinical value (Horsky et al. 2017). In the words of the participants, the value of an intervention (e.g., medication interaction and allergy alerts, in this study) was largely in its relevance to the patient they were treating. The specific clinical context in which they evaluated the specificity and appropriateness of given advice included comorbidities, prior drug tolerance and other illness-related factors, and, importantly, the proportion and significance of known, uncertain and absent information. The alert content and the logic of its triggering algorithm would have to meet a high threshold in its inclusiveness of patient-specific and knowledge-based information in order to be considered a reliable tool by many clinicians. In turn, high reliability cultivates over time higher confidence in CDS accuracy and the frequency of its use increases.

The convergence of two fast-developing areas of informatics may provide the necessary data sources that precision medicine requires for advanced, comprehensive interventions. Current, curated and evidence-based knowledge derived from analytical and machine-learning discovery processes on large repositories of clinical and research data (big data analytics) ensures that optimal care recommendations can be formulated on the basis of data from millions of patient lives and decades of clinical history. Knowledge learned from the aggregated data of large patient groups then can be applied with better precision to individuals as the expanding collection of laboratory, test and genetic information allows more accurate determination of what recommendations are most directly relevant. Clinicians would then be assisted in making informed decisions by the best available evidence specific to their patients. Observations and findings captured in patient records that can be correlated instantaneously with latest biomedical research are the objectives of many current investigation initiatives.

Delivering this complex set of information and insights effectively into care workflows is an ongoing challenge for HIT designers. Complex genomic profiling data that need to be stored and processed in conjunction with existing clinical data will increase exponentially demands on IT infrastructure and computing power (West et al. 2006). Escalating demands on cognitive and coordinated activities such as demands for knowledge, monitoring, attentional control, information, and communication among team members (including human machine communication) will also need to be supported by systems with excellent human-computer interaction characteristics and usability. Workload associated with using a computer interface or interacting with an autonomous or intelligent machine agent will need to be minimized as clinicians cannot divert attention to new tasks, new memory demands and distractions from their primary medical work (Woods and Patterson 2001). Cognitive engineering analyses, for example, can yield sets of crucial cognitive support requirements to guide design and to provide explicit links between identified needs and specific design features and concepts (Hettinger et al. 2017). Healthcare institutions may choose to redesign their work system, including workflows, at opportune moments such as when updates to a current EHR are made or when transitioning to a new system and work towards a more efficient model described and modelled by cognitive engineering analyses (Beuscart-Zéphir et al. 2010).

An important goal of cognitive engineering is to make socio-technical systems more reliable with the use of cognitive modeling. Interventions and designs that do not consider complex systems as a single unit of analysis are unlikely to have a systematic and lasting effect on safety and quality. Cognitive support will have only limited effect without the consideration of use context and organizational constraints and poor workflow fit will force potentially unsafe workarounds to circumvent limitations (Carayon et al. 2014). There is currently no clear way to distinguish theoretically between workarounds that have the potential for negative consequences and should be actively discouraged or eliminated, workarounds that would benefit from transitioning into formal documentation in policies and procedures and HIT, and workarounds that are necessary to allow only for exceptional circumstances as goals are traded off but should be discouraged during routine situations (Patterson 2018).

Processes and factors that affect latent safety problems in complex, dynamic socio-technical systems such as cognitive workload, situation awareness, coordination and other measured constructs often require labor-intensive assessment studies that institutions may not be able to carry out to a sufficient degree or repeat after reorganizations and new technology additions. Recently, several unobtrusive methods of data collection using sensor-based technology (SBT) allowed cost and time effective measurement of physical, physiological, cognitive, and behavioral processes at the individual (e.g., mental workload, stress), team (e.g., cohesion, communication, team composition) and system level (e.g., workflow) (Hughes et al. 2018). The methods often combine technology such as Radio Frequency Identification (RFID) tags and physiological monitoring systems into a complementary approach that can identify or infer workflows and high-level events. For example, a group of researchers combined RFID tag workflow monitoring with ethnographic observations, augmenting data collection with multidimensional activity information that allowed observers to focus on cognitive details rather than simply annotating movement activities (Vankipuram et al. 2011).

Objective assessment of technical and teamwork skills or tracking and monitoring of clinicians and patient engagement could be conducted and interpreted with relatively few resources. Real-time data from several sensors and other sources can also be triangulated and correlated to provide contextual information that could not have been obtained with other techniques (Alemdar and Ersoy 2010). In one study, researchers characterized the interactions of clinicians gathering information for rounds discussions and patient-case presentations in the EHR by applying process-mining methods to EHR-generated event log files. They triangulated quantitative findings with patient chart review and qualitative data to find that interactive behavior was associated with workflow routines, patient case complexity and variant screen sequence patterns (Furniss et al. 2016b).

Cognitive engineers and others whose work supports complex collaborative processes need to address the challenge of gathering empirical evidence and integrating the contributions of emergent constructs, mental models and distributed knowledge into analyses. Coordination is at the core of team cognition, and human-centered technologies should keep this in the forefront of design concepts and frameworks (Morrow and Fiore 2013).

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Chapter 3
Unintended Adverse Consequences of Health IT Implementation: Workflow Issues and Their Cascading Effects

Elizabeth V. Eikey, Yunan Chen, and Kai Zheng

3.1 Introduction

Health information technology (known as health IT or HIT) has great promise as a means to improve quality of care and patient safety. However, the introduction of health IT can impact healthcare practices in ways that are not planned, leading to unintended consequences. The term "unintended consequences" refers to unforeseen or unpredicted results to a specific action (Campbell et al. 2006). These consequences can be positive, negative, or neutral. In this chapter, we focus on unintended consequences that are found to have a detrimental effect. This is not to say that there are no unanticipated positive effects associated with health IT implementation; within this chapter we simply choose to focus on one aspect that has been more commonly studied.

To date, a considerable body of health IT evaluation research has been devoted to understanding the unintended consequences of health IT. While many papers have reviewed relevant literature in this space (Zadeh and Tremblay 2016; Harrington et al. 2011; Marcilly et al. 2015; Kim et al. 2017; Maslove et al. 2011; Menachemi and Collum 2011; Salahuddin et al. 2016; Niazkhani et al. 2009; Gephart et al. 2015; Bloomrosen et al. 2011; Pirnejad et al. 2010; Voshall et al. 2013; Vanderhook and Abraham 2017; Kuziemsky et al. 2016), the purpose of this chapter is to discuss the unintended consequences in the context of clinical *workflow*. Workflow is a core component of clinical practice because it encompasses all of the activities and processes through which patient care is

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delivered. According to the US Department of Health and Human Services (2017), workflow can broadly be defined as *"the sequence of physical and mental tasks performed by various people within and between work environments. It can occur at several levels (one person, between people, across organizations) and can occur sequentially or simultaneously."*

Understanding workflow in clinical settings is essential to designing and deploying usable health IT. *"A critically important component of an organization's preparation for an HIT implementation is a thorough review of its workflow processes, procedures, and role assignments; yet the complexity of the healthcare workflow makes it resistant to many conventional workflow modeling and automation approaches"* p. 88 (Bloomrosen et al. 2011). Without carefully engineered integration with clinical workflow, health IT systems will not be embraced by end users and they may cause unintended negative consequences that adversely impact quality and safety of patient care (Sheehan and Bakken 2012).

The term unintended consequences in the context of health IT became popularized in the early to mid 2000s by researchers studying the effects of patient care information systems (Paper et al. 2004) and computerized provider/prescriber order entry (CPOE) (Ash et al. 2006). However, the recognition that health IT implementation could bring with it unintended effects was not new, which had been reported in the literature even earlier (e.g., Goldstein et al. 2002). In recent years, unintended adverse consequences (UACs) has become one of the most commonly used terms in the literature to emphasize the detrimental impact of unintended consequences such as more/new work for clinicians and disrupted/altered communication patterns (Campbell et al. 2006; Zheng et al. 2010a; Cresswell et al. 2017).

While many researchers use the term unintended consequences to refer broadly to unanticipated effects related to workflow as a result of health IT implementation (Nanji et al. 2014; Horsky et al. 2006; Harrison et al. 2007; Gephart et al. 2016; Wu et al. 2013; Sergeeva et al. 2016), some researchers call these impacts (Zheng et al. 2010a; Wu et al. 2013; Vishwanath et al. 2010), effects (Vishwanath et al. 2010), residual consequences (Nanji et al. 2014), or simply problems (Horsky et al. 2006). For example, Vishwanath et al. (2010) did not explicitly discuss unintended consequences but talked in depth about the impact of electronic health record (EHR) use on outpatient workflows. Wu et al. (2013), on the other hand, used the term unintended consequences, but they also repeatedly referred to these issues simply as impacts. The varied terminology use suggests a broad interest among the health IT research community in studying unintended consequences. However, it also means that it is difficult to synthesize this body of research because of the lack of consensus on how such issues should be defined and described.

This chapter briefly summarizes the extant literature on how health IT implementation may unintentionally introduce adverse consequences to clinical workflow, with the following two goals. First, we attempt to characterize the chain of impact by distinguishing primary unintended consequences that lead to changes in workflow from secondary unintended consequences that originate from the workflow alterations. Second, we attempt to provide a discussion on the causes of and some proposed solutions for these workflow-related unintended adverse consequences.

3.2 Characterizing Unintended Consequences

Understanding health IT's impact on workflow can be challenging due in part to the fact that workflow encompasses all activities around clinical care. The introduction of health IT is often associated with direct changes in established workflow, such as new types of work and new task interdependencies, which has been widely noted in the literature (Campbell et al. 2006; Gephart et al. 2015; Kuziemsky et al. 2016). We refer to these as primary unintended consequences. In addition, there are other indirect impacts that occur as a result of these primary consequences. For example, some studies (although varying in their methodological approaches) have found that clinicians may adopt unsafe workarounds in response to disrupted and fragmented workflow, which can lead to an increase in errors resulting in patient safety threats (Ash et al. 2004; Yen et al. 2017; Coiera 2015). This cascading effect, from workflow consequences to other secondary impacts, is illustrated in Fig. 3.1.

3.2.1 Workflow Issues as Primary Unintended Consequences

In many cases, unintended consequences of health IT implementation directly affect the work practices of both clinicians (e.g., physicians, nurses, pharmacists) and nonclinical staff (e.g., medical billing and coders, receptionists, and IT staff), even though the former is far more frequently studied. Unintended consequences to clinicians' workflow, as documented in the literature to date, include new or increased

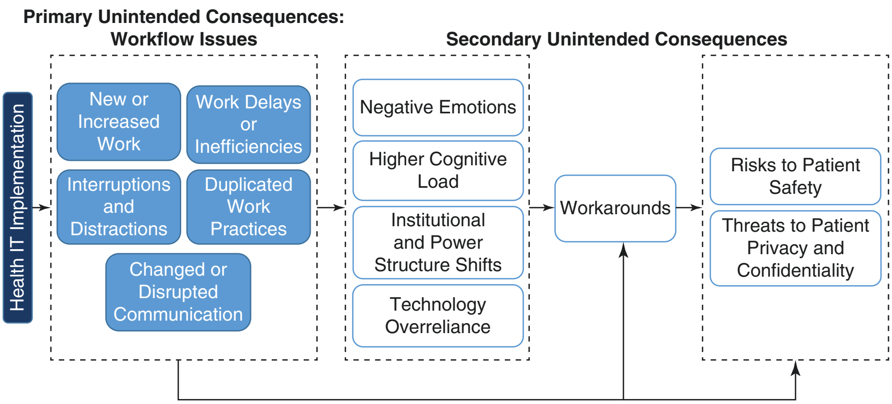

Fig. 3.1 Primary and secondary unintended adverse consequences of health IT

workload (Campbell et al. 2006; Gephart et al. 2016; Van den and Hafkamp 2017); delayed work or time inefficiencies (Zadeh and Tremblay 2016; Zheng et al. 2010a; Horsky et al. 2006; Ramaiah et al. 2012); interruptions or distractions (Zheng et al. 2010a; Nanji et al. 2014; Wu et al. 2013; Sergeeva et al. 2016); duplicated work practices (Campbell et al. 2006; Nanji et al. 2014; Horsky et al. 2006; Gephart et al. 2016; Cifuentes et al. 2015); and changed or disrupted communication (Campbell et al. 2006; Wu et al. 2013).

New or increased work: Health IT can create new types of work or alter the nature of existing work that may lead to increased workload. For instance, one study found that the use of a CPOE system required added steps in order to get to the "patient overview" as compared to the work practices before the CPOE implementation (Campbell et al. 2006). Further, healthcare providers' workload may increase when they are forced to enter new types of information into computerized systems that were not previously required (Campbell et al. 2006; Gephart et al. 2016) and respond to computer-generated alerts that may not contain relevant or helpful information (Campbell et al. 2006). The issue of workload increase appears to disproportionally affect nurses (Gephart et al. 2016; Van den and Hafkamp 2017), even though studies have also found that physicians' administrative workload may also increase due to health IT use (Van den and Hafkamp 2017).

Interruptions and distractions: As a result of added or more fragmented work, health IT may interrupt clinicians' work processes or distract them from performing their clinical tasks. These disruptions may originate from computerized clinical systems (e.g., EHR and CPOE) due to poorly designed alerts and more rigid structured data entry requirements. With the introduction of health IT, clinicians must use a computer to complete certain tasks, which may inherently disrupt their usual workflow. For instance, clinicians may need to spend more time and exert more energy to find a nearby computer workstation to enter patient information (Zheng et al. 2010a), which is an added step not part of the paper-based workflows. Sometimes, computer-based automation may also result in distractions. For example, in the case of pharmacy workflow, a study found that pharmacy staff were disrupted by the need to restock prescriptions that patients never picked up because of an auto-filling feature added to their health IT system (Nanji et al. 2014). More recently, interruptions are also found due to the rapid increase of use of mobile devices in clinical settings. While mobile devices improve access to information and response time (Wu et al. 2013; Sergeeva et al. 2016), they can also become a salient source of disruptions. For instance, the "in the moment" communication afforded by mobile platforms causes frequent interruptions (e.g., imagine a clinician's phone going off every few minutes) (Wu et al. 2013) and disrupts collaborative work practices (Sergeeva et al. 2016). Chapter 7 of this book, *Interruptions and Multitasking in Clinical Work: A Summary of the Evidence*, offers a more in-depth discussion on interruptions and distractions that may be directly related to the adoption of health IT.

Work delays or inefficiencies: Along these same lines, sometimes the introduction of new health IT creates delays in work and decreases time efficiency. For instance, Campbell et al. (2006) reported that CPOE systems could slow the process of clinical documentation and ordering. Similarly, in the context of pharmacy workflow, Zadeh and Tremblay (2016) conducted a literature review on studies of e-prescribing systems from 2008 to 2014 and found that 38% of the studies reported reduced pharmacy workflow efficiency as a result of unintended consequences. Further, inefficiencies are not only found internally within a clinical space, but also from breakdowns of IT-based external interactions with insurance companies, laboratories, pharmacies, etc., which may also cause work delays (Ramaiah et al. 2012). While there are discrepancies between some qualitative and quantitative studies with respect to how health IT impacts workflow efficiency, these may be due to how workflow is defined and measured. For example, Zheng et al. (2010a) reported that many time and motion studies had found the impact on workflow efficiency to be negligible; whereas qualitative studies had found consistent perceptions of decreased efficiency. They explained that this discrepancy may be due to the "design of the time and motion studies, which is focused on measuring clinicians' 'time expenditures' among different clinical activities rather than inspecting clinical 'workflow' from the true 'flow of the work' perspective". Therefore, they developed a set of new methods (e.g., workflow fragmentation assessments, pattern recognition, and data visualization) to assess workflow efficiency and found that the implementation of a CPOE system caused a higher frequency of task switching and more fragmented workflow. This work suggests that analyses merely focusing on time utilization may not be adequate to capture workflow inefficiencies.

Duplicated work practices: Another major unintended consequence related to clinical workflow is duplicated work practices. Sometimes health IT requires clinicians to enter redundant information (Gephart et al. 2016; Cifuentes et al. 2015) or copy data from paper forms into the system (Horsky et al. 2006). For instance, Cifuentes et al. (2015) reported that clinicians often needed to double-enter their work into multiple computerized systems that were not interconnected. In other cases, health IT causes duplicated results, such as with the case of medications. For example, in Campbell et al.'s (2006) early work, they found that emergency orders were often duplicated because they were entered into the CPOE system and then phoned in to ensure efficiency. Similarly, in more recent studies, Nanji et al. (2014) found that medication prescriptions were being dually transmitted—once through fax and once through the e-prescribing system—which often resulted in the same medications being filled more than once for each patient.

Changed or disrupted communication: Communication is critical to clinical work and workflow, which may be altered or disrupted as the result of health IT use. CPOE systems, for example, may inhibit interpersonal communication because ordering information is now conveyed through electronic means that eliminate face-to-face interactions, during which important miscommunication and omissions may be discovered (Campbell et al. 2006). Similarly, Wu et al. (2013) conducted a study on the use of electronic communication tools, particularly smartphones, in clinical settings, and found that they could cause a decrease in verbal communication and negatively impact the relationships among clinicians. Thus, instead of promoting effective communication among healthcare providers and staff, health IT systems often provide only an illusion of communication whereby it is assumed the intended recipient will view and act upon the information entered into the system. However, this may not always be the case in reality (Campbell et al. 2006).

3.2.2 Secondary Unintended Consequences Resulting from Workflow Issues

As a result of the workflow issues, clinicians often face secondary consequences, such as negative emotions, higher cognitive load, shifts in institutional and power structure, and overreliance on technology. When clinicians are overburdened or upset, they may resort to workarounds in an attempt to ease these secondary consequences. These workarounds, and the workarounds that directly result from the workflow issues, can negatively impact patient safety and privacy.

3.2.2.1 Adverse Effects on Clinicians

Workflow issues that result from health IT adoption can impact clinicians in many unintended and negative ways, including provoking negative emotions (Campbell et al. 2006; Sittig and Kaalaas-Sittg 2005), increasing task fragmentation (Zheng et al. 2010a; Yen et al. 2017), changing institutional and power structure (Campbell et al. 2006), and creating an overreliance on technology (Campbell et al. 2006). As healthcare providers try to learn an new computerized system and contest with changes to their work processes, they may experience guilt, annoyance, sadness, hostility, and disgust (Sittig and Kaalaas-Sittg 2005). These unexpected and negative emotions often occur due to disruptions to clinical workflow and negative feedback from the system (Sittig and Kaalaas-Sittg 2005). Not only are these negative feelings unpleasant for clinicians, but they may also make it difficult for clinicians to attend to complex clinical tasks (Campbell et al. 2006; Sittig and Kaalaas-Sittg 2005).

Changes and disruptions to established workflow can also result in task fragmentation reflected as higher frequencies of task switching and multitasking (Zheng et al. 2010a; Yen et al. 2017). This can be disruptive to clinicians' work and are often associated with increased cognitive load and unnecessary physical activities (Yen et al. 2017; Laxmisan et al. 2007; Zheng et al. 2010b). For example, frequent login and logout actions, interruptive alerts, irrelevant reminders, and abrupt phone calls can all lead to more fragmented workflows and higher chance for errors (Yen et al. 2017; Coiera 2015).

By requiring added work and altering the ownership of certain clinical activities and tasks, health IT can impact individuals' roles and responsibilities in an organization (Van den and Hafkamp 2017), leading to changes in institutional and power structure (Campbell et al. 2006). For instance, CPOE systems redistribute work through role-based authorization, which rigidly controls who can do what (Campbell et al. 2006). Further, role misfits could occur where individuals experience reduced autonomy (Van den and Hafkamp 2017). An example is that after the implementation of a new EHR system, nurses must wait for an official order from a physician placed through the system in order to remove a patient's IV, which could be independently performed by nurses in the past (Van den and Hafkamp 2017). This change shifts the power structure and could create resentment between different types of medical professionals (Campbell et al. 2006).

As clinicians become accustomed to health IT, they may also develop an over-reliance on technology (Campbell et al. 2006; Shepard 2017), where certain clinical tasks simply can no longer be accomplished without technology. This can be problematic when technology fails. It is inevitable that health IT will experience downtimes, both planned and unplanned (Shepard 2017; Kashiwagi et al. 2017). In the event of a system failure, clinicians may no longer have the relevant information or knowledge (e.g., standard dosages and medication contradictions) to perform a task, which they relied on health IT to provide (Campbell et al. 2006). This can result in delayed care and/or increased patient safety risks (Campbell et al. 2006; Kashiwagi et al. 2017; Larsen et al. 2018).

3.2.2.2 Workarounds

Workarounds are mitigating strategies commonly employed by clinicians to overcome barriers to their work introduced by a variety of factors, including primary unintended consequences and their secondary effects. Workarounds can be individual, managerial, or artifact-based, depending on who initiates the workaround and how it is enacted. Common examples of workarounds include using paper and other software systems as intermediaries (Cresswell et al. 2017; Menon et al. 2016) and staying logged into the system under a coworker's credential to save time (Ser et al. 2014). In the context of test result management, Menon et al. (2016) found that among the primary care clinicians studied who used workarounds, 70% reported using paper-based methods and 22% reported using a combination of paper and computer-based approaches.

Sometimes workarounds can become a routine practice to address workflow issues (Salahuddin et al. 2016). For instance, to combat inefficiencies and to facilitate care coordination, clinicians may write down patient information on a piece of paper (Menon et al. 2016) or take photos of the screen of a computer workstation (Eikey et al. 2015). Generally, workarounds are aimed at alleviating secondary consequences that emerge as a result of workflow issues, rather than addressing the underlying workflow issues directly. For example, changes to work processes due to IT use may increase the cognitive load of clinicians, requiring them to use paper-based methods as a memory aid (Menon et al. 2016).

Many researchers have studied workarounds as part of the attempt to better understand disruptions to clinical workflow (Voshall et al. 2013; Cresswell et al. 2017; Ramaiah et al. 2012; Menon et al. 2016). Workarounds are an important phenomenon in this context, as they often signal unaddressed workflow issues. Some workarounds, e.g., those circumventing IT-enforced documentation requirements or patient safety protocols, may also lead to additional adverse consequences (Cresswell et al. 2017; Menon et al. 2016). While workarounds are often informal practices to mitigate workflow issues, they can also become formal organizational mandates when a direct solution is not readily available (Cresswell et al. 2017).

3.2.2.3 Risks to Patient Safety

The most concerning adverse impact as a result of workflow issues and/or unsafe workarounds is added risks to patient safety (Cresswell et al. 2017; Gephart et al. 2016; Menon et al. 2016). Disruptions to workflow can increase the likelihood of errors, leading to serious adverse events (Campbell et al. 2006; Pirnejad et al. 2010; Voshall et al. 2013; Cresswell et al. 2017; Nanji et al. 2014; Horsky et al. 2006; Ash et al. 2004; Menon et al. 2016). Poor usability of health IT also contributes to the problem. For example, poorly designed software user interfaces may make it much easier for clinicians to select the wrong option or input an order for the wrong patient (Ash et al. 2004; Schiff et al. 2016). Schiff et al. (2016) provided an overview of common design problems of CPOE, including an illustration of how the overwhelming number of acetaminophen choices displayed on a computer screen could facilitate new types of errors. In addition, health IT requires complete and structured data, which can also cause cognitive overload that makes clinicians more susceptible to making mistakes (Ash et al. 2004; Yen et al. 2017; Coiera 2015; Chao 2016).

3.2.2.4 Threats to Patient Privacy and Confidentiality

Lastly, workflow issues and unsafe workarounds can adversely affect patient privacy and confidentiality. Particularly, the use of workarounds such as paper notes, screenshots, and photos to improve memory and efficiency can threaten patient privacy and confidentiality by recording and transferring sensitive patient information in an unsecure manner. Although there are often privacy policies and security measures in place in clinical environments, clinicians may work around them when they deem these policies and measures as inhibitors to their work practices (Eikey et al. 2015; Murphy and Reddy 2014; Chen and Xu 2013).

3.3 Causes and Solutions of Workflow Issues

We now shift the focus to the causes of workflow issues and briefly discuss some solutions that have been proposed in the literature. Most commonly, workflow issues occur when there is poor alignment between work practices and health IT design (Campbell et al. 2006; Horsky et al. 2006; Gephart et al. 2016). Health IT tends to rigidly model workflow according to organizational policies and regulatory requirements, which may not necessarily reflect the reality of day-to-day clinical practice (Campbell et al. 2006). Nuanced, non-linear, complex, and sometimes invisible processes are not easily incorporated in IT design. Health IT also tends to neglect the varied nature of workflow needs; that is, the work practices around the same task may be very different depending on an individual's role, the patient's conditions, etc. (Campbell et al. 2006). Health IT changes work practices, and work practices and social systems around health IT impact how they are used (Harrison et al. 2007).

Affordances of newly introduced technologies may also result in workflow issues. In some cases, barriers to workflow are introduced intentionally for valid reasons; for example, authentication requirements and automatic system timeouts (Eikey et al. 2015; Murphy and Reddy 2014; Chen and Xu 2013) are "limitations" designed purposefully to protect data security and patient privacy, even though they may cause undesirable delays and workflow disruptions. In addition, sometimes the affordances of technology adapted for clinical settings make them prone to disrupt workflow. For instance, smartphones could easily become a source of workflow interruption because of their ability to allow healthcare professionals to contact each other "in the moment" (Wu et al. 2013). Similarly, despite benefits, a study showed that use of iPods in the operating room can be distracting because they are by design fun and entertaining; they allow healthcare providers to do personal activities that may divert their attention from clinical work (Sergeeva et al. 2016).

Additionally, workflow issues may stem from a lack of standardization across different healthcare organizations, such as hospitals, specialty clinics, laboratories, pharmacies, and insurance companies (Ramaiah et al. 2012). While health IT at one site may be well-integrated with the local work practices, clinicians' and staff's work may be negatively impacted when there are barriers to effectively communicating with other entities through health IT. Unfortunately, while significant advancements of health information exchange have been made in recent years, the interoperability between different health IT systems remains poor, which could cause delays and disruptions (Ramaiah et al. 2012).

Throughout the literature, there are numerous proposed solutions to preventing and improving workflow issues and mitigating their unintended adverse effects. First, it has been repeatedly shown that developing a thorough understanding of workflow in clinical settings, both before and after health IT implementation, is critical (Campbell et al. 2006; Gephart et al. 2016). This requires health IT designers and implementers shift their focus from "anticipated" use to actual use (Harrison et al. 2007) and consider multiple perspectives when designing and evaluating systems (Wu et al. 2013). Some researchers have also argued for the importance of considering the sociotechnical integration of health IT with its use context. For instance, Harrison et al. (2007) developed the Interactive Sociotechnical Analysis (ISTA) framework as a means to better understand healthcare organizations as a sociotechnical system and "stop viewing HIT innovations as things, but instead treat them as elements within unfolding processes of sociotechnical interaction" p. 543.

Constantly gathering feedback from frontline clinicians and staff is also crucial to identify unintended workflow issues and making necessary health IT or organizational changes (Campbell et al. 2006). Such feedback should be taken seriously and incorporated in a timely manner into a redesign to customize health IT to better fit end users' workflow (Gephart et al. 2016). As part of this feedback, workarounds also need to be transparent. By tracking workarounds and making them more visible, we can determine if there is solid rationale justifying their use and if actions should be taken to formalize them as part of organizational processes (Cresswell et al. 2017) or to mitigate their risks (Cresswell et al. 2017). The design of IT systems is not stagnant and thus, we must iteratively make design revisions as we discover more about clinical workflow and how it is affected by the use of health IT (Campbell et al. 2006).

3.4 Future Work

Designing a health IT system that is perfectly aligned with clinical workflow is very challenging. This is particularly true for *unintended* workflow disruptions which, by definition, cannot be easily anticipated by software designers and implementers. That said, developing a thorough understanding of the clinical work and clinical workflow in the setting where the system will be deployed is possible and can help to mitigate undesirable effects (Harrison et al. 2007). Then, post-implementation, we need close collaboration between system designers, developers, implementers, clinician champions, and all other end users to monitor adoption and appropriation and make necessary changes to the system or use additional training to improve workflow and ease secondary consequences. Systems must also be flexible enough to be quickly adapted, capable of incorporating feedback and suggestions. That is, all health IT systems must be treated as a constant "work in progress" in order to maximize their benefits while minimizing potential harm to clinicians, staff, and patients.

Further, it should be acknowledged that radical workflow change as a result of health IT adoption is inevitable. New, IT-enabled processes necessitate new care models and new workflow patterns. However, as demonstrated in the literature, many workflow disruptions associated with health IT implementation could have been avoided, and some of the adverse effects are due to the lack of communication with clinicians and staff on change management and setting up the right expectations. Thus, we need to develop ways to ease end users' negative emotions, reduce their cognitive load, alleviate concerns about power and role changes, and ensure they do not become over-reliant on technology. Additionally, we need to pay particular attention to unsafe workarounds and their potential detrimental effects on patient safety, privacy, and confidentiality.

This chapter represents a first step toward understanding and unpacking the relationship between what we have termed as primary and secondary unintended consequences. However, in studying unintended consequences of health IT related to workflow, we have to take a holistic approach that addresses systems, users, managerial issues, and the context and considers the secondary or indirect effects resulting from primary workflow changes. We hope this chapter sparks more research on the different categories of unintended consequences, as well as the causal and perhaps even cyclical connections between them.

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Part II
The State of the Art of Workflow Research

Chapter 4
A Review of Clinical Workflow Studies and Methods

Philip Payne, Marcelo Lopetegui, and Sean Yu

4.1 Introduction

Workflow is an integral part of healthcare delivery. In this context, *workflow* can be formally defined as: *"the sequence of steps involved in moving from the beginning to the end of a working process*[1]*."* Building upon this definition, we can also define a working *process* as: *"a series of actions or operations conducing to an end.*[1]*"*.

The ability to observe, instrument, and understand workflow provides critical information for a variety of applications, including but not limited to:

- Enhancing the quality, safety, and outcomes of care delivery
- Identifying opportunities to overcome barriers to technology adoption and adaptation in complex healthcare settings
- Improving the efficiency and timeliness of clinical and translational research

The process of modelling and analyzing workflow is often executed through *Time Motion Studies* (TMS). TMS, alternatively referred to as "*time-motion studies*" or "*time and motion studies*", are defined in the National Library of Medicine Medical Subject Heading system (MeSH) as *"the observation and analysis of movements in a task with emphasis on the amount of time required to perform the*

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task." TMS methodologies originated as a business efficiency technique through the collective contributions of Frederick Taylor (Time Studies) (Taylor 1914) and Frank and Lillian Gilbreth (Motion Studies) (Baumgart and Neuhauser 2009).

The widespread use of TMS in the healthcare setting is a relatively recent development, and has proven to provide a valuable means for collecting quantitative workflow data in a broad spectrum of settings, ranging from evaluating the effectiveness of system implementations (Amusan et al. 2008) and assessment of costs (Schiller et al. 2008), to describing general workflow (Kloss et al. 2010) and utilization of time by clinicians (Kim et al. 2011). In clinical workflow studies, TMS gather quantitative workflow assessments specifically through continuous direct observation, which has been shown to be more accurate than work-sampling (Wirth et al. 1977) and self-reporting (Gordon et al. 2008; Ampt et al. 2007), and is increasingly being accepted as the "gold standard" for measuring and quantifying clinical workflow (Burke et al. 2000; Bratt et al. 1999). The general "design pattern" for the conduct of TMS is illustrated in Fig. 4.1 below:

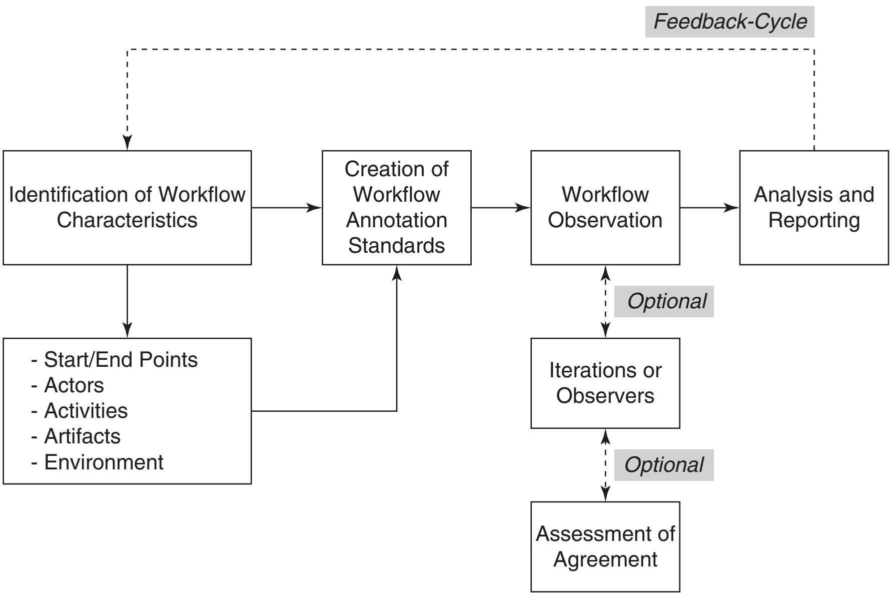

Fig. 4.1 Overview of prototypical workflow study design pattern. In this pattern, the process begins with the identification of key characteristics that serve to define a workflow of interest. Such characteristics are then used to create workflow annotation (or codification) standards that enable the collection of constituent data during various observation types. Subsequently, workflow observations are conducted, and the data generated therein are codified per the preceding annotation standards. Such observations usually include temporal data concerning instances and durations of workflow related activities. In some studies, observations are iterative, or involve multiple observers, necessitating the assessment of inter-observer or inter-observation agreement. Finally, the results of the preceding steps are analyzed and reported on, often employing descriptive statistics, and key findings are "fed back" to inform future workflow studies or optimization efforts

4.2 Key Concepts and Definitions Surrounding Time Motion Study Methodologies

As a tool for obtaining quantitative assessments of clinical workflow, TMS have been adapted and used in the healthcare setting since the early twentieth century. Without a unifying standard, however, the definition and scope of TMS have shifted significantly. Although we agree with the definition provided by the Agency for Healthcare Research and Quality, "*an observation method used to determine the timing and duration of tasks or procedures*", a recent review concluded that the term "TMS" had been used to describe *"a broad spectrum of dissimilar methods whose only common factor is the capture and/or analysis of the duration of one or more events"* (Lopetegui et al. 2014*)*. In the literature, there are many studies reported as TMS but they instead used methods such as self-reports and analysis of automatically generated timestamps. Moreover, among the studies that would be considered TMS, there is significant variability in the implementation and reporting of their findings, making aggregation of results difficult. Therefore, there is a need for researchers to properly categorize and rigorously define their methodologies. In a recent review (Lopetegui et al. 2014), we depicted four major classes of methods used in the literature currently classified as TMS, namely:

1. Methods that produce time-motion data by external observers (**external observation**)
2. Methods that produce time-motion data by the participants being studied (**self-observation**)
3. Methods that produce time-motion data automatically by computerized systems (**automated observation**)
4. Methods that lead to the creation of models and frameworks that can be used to support and/or enable the interpretation of data and findings generated during the course of TMS (**model formulation**)

Below, we provide a description of each of these methods and exemplary studies that have utilize them:

4.2.1 External Observation

In this type of studies, dedicated external observers perform the task of collecting time-motion data. Data collection can be done asynchronously by having the observer analyze video recordings of the study participant's behavior in the work environment, also called "time-action analysis" (Minekus et al. 2013; van Oldenrijk et al. 2008). More often, it is conducted by having the observer directly shadow and observe the participant in real time.

Studies involving external observers use mainly two data collection methods: continuous observation and work sampling. In continuous observation, the external observer maintains the attention on the study participant and continuously records the time taken to perform one or multiple tasks, implying that the action of recording is triggered by an action performed by the participant. It is a useful approach to collect data for non-centralized tasks, sensible for short tasks, and provides granular and detailed field data. However, this method is resource consuming, and there is opportunity for biases as participants may feel disturbed. Sometimes, participants may also demonstrate improved performance when being observed: a phenomenon known as the Hawthorne effect.[1]

Unlike continuous observation, which measures the elapsed time for a task, work sampling identifies the task being performed at a given instant (Hakes and Whittington 2011), repeating the measure at predefined fixed or random intervals during the observation. It is premised on the repetitive nature of work, and assumes the probabilistic generalization of the sampling findings to describe how workers spend their time overall. Compared to continuous observation, a major benefit of work sampling is that the observer can work with multiple study participants during a single observation period. Further, work sampling has been reported as an efficient approach for studies designed to classify work activities into fewer categories. With more categories describing less frequent tasks, the required number of observations may increase substantially (Burke et al. 2000), thus losing the advantage afforded by this method. Strictly speaking, work sampling estimates the proportion of time spent on an activity based on observations conducted at random time points (Barnett 2008).

The temporality of the sampling methodology has been debated in the literature, concluding that systematic work sampling often results in flawed and biased estimates; and random work sampling is a better approach (Oddone and Simel 1994) especially when assessing tasks that are performed periodically. However, one of the pioneering researchers of TMS argues that the reduction in biases provided by randomization is overweighed by the complexities in scheduling the observations, advocating in favor of fixed periodic intervals (Finkler et al. 1993). We observed this issue in our recent review: all work sampling studies involving external observers used a systematic fixed time interval: e.g.,. 1 min (Murden and Pintz 2003), 5 min (Deshpande et al. 2012), and so forth. A study used a much higher frequency of sampling at every 15 s, which the authors referred to as “Davis observation code” (Yawn et al. 2003). Under optimal circumstances, work sampling has been proposed as a useful and efficient methodology for analyzing the distribution of work activities in relation to the types of activities they perform (Pelletier and Duffield 2003). This method, however, falls short for questions related to task durations, occurrences, or workflow studies. A highly cited paper concludes that work sampling may not provide an acceptably precise approximation of the results that could be obtained by continuous observation time motion studies (Burke et al. 2000).

[1] This was first reported in Chicago during the 1920s, when after studying methods for increasing productivity it was found that regardless of the change introduced in the working environment, the result was always an increase in productivity. It is now explained as “an increase in worker productivity produced by the psychological stimulus of being singled out and made to feel important” (Franke and Kaul 1978).

4.2.2 *Self-Report*

In this group of studies, time-related data are generated by study participants themselves. Although self-report can be a low-cost means for measuring work activities, perceptual differences among the participants who self-report their data can lead to discrepancies in how activities are categorized (Keohane et al. 2008). Also, participants may either lie about what they are doing, or change normal routine in order to generate data that they believe to be more favorable (Burke et al. 2000). This shortcoming has been demonstrated outside TMS when comparing self-reported data and observational data in studies of dentists providing preventive services: self-reported frequencies consistently exceeded observed frequencies (Demko et al. 2008).

Self-reports are also considered unreliable because they tend to over-estimate clinicians' contact time with patients and under-estimate their non-productive time, compared to work sampling using an external observer (Bratt et al. 1999). Anecdotally, one study comparing the number of duty-hour violations among residents found no difference between self-reports and computer-recorded timestamps (Todd et al. 2011); however instead of reporting the agreement between the two sources of data, they compared if a threshold of work hours was exceeded, but not the specific durations. This reinforces the need to be aware of the inherent human biases in terms of the design and selection of outcomes when using self-reports as the main source of research data.

Data collection methods used by studies in this group can be first classified as synchronous or asynchronous. Commonly used approaches on the asynchronous side of the spectrum include interviews, focus groups, and surveys. These methods directly solicit information from study participants regarding the time it takes them to perform different tasks and/or different steps of a process. Asynchronous self-report methods are considered limited due to their reliance on participants' subjective account of their workflow and working conditions (Hauschild et al. 2011). It has been widely acknowledged that clinicians are poor estimators of measures commonly found in TMS, such as task durations. For example, when comparing physician recall of event durations in the operating room, self-reported survey responses over-estimated the durations by 30 min on average, from a few minutes up to 2 h, when compared to durations extracted from the surgery log (McCall et al. 2006).

Commonly used approaches on the synchronous side of the spectrum are active tracking and self-reported work sampling. In active tracking, study participants are asked to log time motion data based on their work activities, either immediately after completing a task, or at a later time (e.g., by the end of the work day). On the other hand, self-reported work sampling involves repeated recording of work activities at pre-determined or random time points by study participants. As previously discussed, random work sampling is more commonly used (Yee et al. 2012), which is often facilitated by some types of electronic devices that remind participants at random intervals to record data. In a study that compared self-reported work sampling and traditional/external work sampling for measuring nursing tasks (Ampt et al. 2007), the self-reported method was found to be an unreliable means for obtaining an accurate reflection of the work tasks conducted by ward-based nurses. Also, nurses preferred the presence of an external observer, as recording activities while conducting clinical duties can be burdensome (Keohane et al. 2008). Despite the limitation, self-reported work sampling is easier to conduct and is more scalable with relatively low cost. Indeed, one of the largest TMS to date used the self-report work sampling method to study nursing work across 36 hospitals (Hendrich et al. 2008).

4.2.3 Automated-Observation

In this group of studies, timestamps and durations of tasks are captured automatically by sensors or computerized systems. Usually the physical movement of study participants, or their interaction with clinical IT systems, trigger the recording of time-motion data, providing a rich "motion" dimension and precise "time" measurements. It is important to note that studies of this category do not refer to those that use computerized tools for external observers (e.g., a tablet PC with TMS research data collection software). Instead, in these studies, time-motion data are being recorded automatically without the presence of an external observer, and without any active involvement of study participants.

Automated time-motion data streams may come from a broad range of sources, including indoor or global positioning systems, accelerometers, electrodes, radio frequency identification (RFID), and clinical IT systems. From study participants' perspective, this method provides a passive and non-intrusive means for capturing time-motion data while they perform their usual clinical tasks. Examples include location-tracking devices (e.g., RFID tags) that record events when the participant approaches sensors, time-stamped logs of interaction events within an electronic health record (EHR) system, and sensor movements on a laparoscopic surgery training module.

With the availability of such continuous event logs, researchers have better tools to determine the structure underlying the sequence of events, or a flowchart-like process model. Markov Models or Hidden Markov Models have been commonly used to model workflows in the healthcare setting including trauma resuscitations (Mache et al. 2008) or patient trajectories (Mache et al. 2010a); and process mining techniques have also been employed to discover process models from event logs, check conformance/deviation of particular event logs, and suggest changes to the process to enhance workflow (Mache et al. 2009).

Although timestamps recorded by motion sensors have been demonstrated as a reliable source of data (Marjamaa et al. 2006), time-stamped logs from software usage need to be interpreted carefully. If the variable of interest is the duration of interactions with the software system (e.g., charting time), it may be constitutes an accurate measure. However, if the variable of interest would need to be deduced from the computer-recorded timestamp as a proxy (e.g., how long it takes for a patient to transfer to another unit), it might become problematic. For example, a TMS conducted in an emergency department compared continuous observation results to timestamps extracted from the EHR, concluding that on average the EHR-based events were recorded 2 min before they actually took place (median, interquartile range 31 min before to 3 min) (Gordon et al. 2008).

4.2.4 Model Formulation

In this final class of studies, the primary emphasis is not on conducting empirical investigation using TMS, but rather the creation of conceptual frameworks or equivalent constructs that can support and enable the interpretation of the results of TMS. These include efforts to create models that define the major characteristics that can be measured or understood through TMS, such as actors, activities, and environmental features pertinent to a given workflow (Sittig and Singh 2010). Such efforts can also include studies that focus on the creation of taxonomies and nomenclatures, as well as quantitative metrics, that serve to assist in the aggregation and interpretation of multiple, complimentary TMS (Yen et al. 2016; Lopetegui et al. 2013).

4.3 TMS Data Capture Tools

Since the early 2000s, several research teams have worked on building electronic data capture tools to facilitate the conduct of TMS. Among them, the most relevant contributions include:

- **Marc Overhage, Lisa Pizziferri, and Yi Zhang.** Considered the pioneer of TMS in studying clinical workflow, Overhage and his colleagues introduced the Palm Pocket Digital Assistant program in 2001 (Overhage et al. 2001). This tool incorporates multi-level classification of clinical activities with which observers could label visible physical activities (e.g., talking on phone) and then group them into conceptual categories (e.g., direct patient care). Pizziferri et al. further adapted Overhage et al.'s categorization schema by adding new tasks and categories, and created a Microsoft Access-based application that could be deployed on touchscreen tablet computers (Pizziferri et al. 2005). They also introduced the concept of "primary task" to accommodate multitasking. Later, Zhang et al. adapted Pizziferri et al.'s tool by including a nursing activities taxonomy, and requiring certain additional attributes to be captured such as location, whom the activity served, position while performing the task (standing/sitting/walking), admission or discharge, and the clinical purpose of the activity (Zhang et al. 2011). They also extended the tool by adding the capability for recording communication multitasking (when a clinician is performing a clinical task while simultaneously communicating with others). Finally, they manually mapped the task list to the Omaha System which is a comprehensive practice and documentation standardized taxonomy designed to describe client care in combined terms [problem + category + target + care description].

- **Philip Asaro.** Asaro developed a Palm-based application for conducting TMS in an emergency department in 2003. His tool also included a categorization schema for tasks, and allowed simultaneous recording of two activities with independent timing. He also published a novel synchronized data capture method in 2004 to study patient flow (Asaro 2004), wherein multiple data collectors observed different providers using a synchronized timestamp allowing reconstruction of tasks/events of ED care for individual patients. Then, in 2008, he used the tool to evaluate the impact of a computerized prescriber order entry (CPOE) system on nursing documentation workflow (Asaro and Boxerman 2008).
- **Johanna Westbrook.** In 2007, Westbrook and her colleagues developed a Pocket PC application which included ten broad work task categories, additional participants involved in the task, and tools/equipment used to perform the task. It also allows external observers to record concurrent tasks independently, and incorporates a novel interruption module to record broken/resumed tasks and the ability to fix input errors. Westbrook et al. also pioneered on assessing inter-observer reliability using the agreement of overall percentage time in tasks. Their method was named WOMBAT (Work observation Method by Activity Timing), and has since been used in several studies (Ballermann et al. 2011; Westbrook et al. 2007, 2008, 2010; Westbrook and Woods 2009).
- **Stephanie Mache.** In 2008, Mache et al. developed and evaluated a Pocket PC-based "computer-based medical work assessment program" (Mache et al. 2008). They generated a list of tasks that physicians commonly perform across different settings, and their application allows for the recording of primary and secondary tasks for multitasking events, as well as interruptions. In addition, they developed a new inter-observer reliability assessment method based on time and naming of the tasks. By creating and piloting new taxonomies for specific scenarios, this tool has been used repeatedly in German workflow studies regarding surgeons (Mache et al. 2010a), junior OB/GYN's (Kloss et al. 2010), junior gastroenterology physicians (Mache et al. 2009), pediatricians (Mache et al. 2010b), oncology residents (Mache et al. 2011), anesthesiologists (Hauschild et al. 2011), and emergency physicians (Mache et al. 2012).
- **Philip Payne.** In 2012, Payne et al. introduced the Time Capture Tool (TimeCaT) (Lopetegui et al. 2012): a comprehensive, flexible, and user-centered web application designed to support data capture for TMS. This tool aimed for widespread adoption by a collaborative network of TMS researchers who would be willing to contribute to further development and standardization of formulations regarding multitasking, inter-observer reliability assessment, and taxonomy selection. The end goal of the project was to create standardized TMS methods and thus the ability to produce comparable results that can be readily aggregated to facilitate knowledge discovery. Continued ongoing efforts of this project include the development and validation of an inter-observer reliability scoring algorithm, the creation of an online clinical task ontology, and a quantitative workflow comparison method.

Some of these tools are described in more depth in Chap. 12: Computer Tools for Recording Clinical Workflow Data.

4.4 Seminal Time Motion Studies in Healthcare

Building upon the concepts and definitions presented earlier in this chapter, in the following section, we summarize a set of seminal papers reporting significant TMS-based studies conducted in healthcare. As shown in Table 4.1, each of these papers is described in terms of the driving problem being investigated, the methods used, as well as intended outcomes or optimization objectives.

Table 4.1 Summary of seminal papers describing the use of time-motion studies in the health and life science domains, indicating the driving problem being investigated, the methods used, as well as intended outcomes or optimization objectives of those studies

Title	Driving problem	Methods used	Intended outcomes or optimization objectives
A new sociotechnical model for studying health information technology in complex adaptive healthcare systems	To identify the factors the influence or otherwise impact the design and deployment of healthcare information technology platforms in the clinical environment	**Model formulation**	Improving quality and safety of patient care activities
Reference: Sittig DF, Singh H. A new sociotechnical model for studying health information technology in complex adaptive healthcare systems. Qual Saf Health Care. 2010;19(Suppl 3):i68–74			
Workarounds to barcode medication administration systems: their occurrences, causes, and threats to patient safety	Understanding how physical work-arounds impact patient safety in the context of medication reconciliation	**External observation**	Improving quality and safety of patient care activities
Reference: Koppel R, Wetterneck T, Telles JL, Karsh BT. Workarounds to barcode medication administration systems: their occurrences, causes, and threats to patient safety. J Am Med Inform Assoc. 2008;15(4):408–23			
A 36-hospital time and motion study: how do medical-surgical nurses spend their time?	Identifying the common tasks and activities that surgical nurses engage in during the course of normal workflow, and any impediments to their effective/efficient execution	**Self-observation**	Managing patient throughput and resource utilization in healthcare delivery environments
Reference: Hendrich A, Chow MP, Skierczynski BA, Lu Z. A 36-hospital time and motion study: how do medical-surgical nurses spend their time? Permanente J. 2008;12(3):25			
How hospitalists spend their time: insights on efficiency and safety	Identifying the common tasks and activities that hospitalists engage in during the course of normal workflow, and any impediments to their effective/efficient execution	**External observation, Automated-observation**	Managing patient throughput and resource utilization in healthcare delivery environments
Reference: O'leary KJ, Liebovitz DM, Baker DW. How hospitalists spend their time: insights on efficiency and safety. J Hosp Med. 2006;1(2):88–93			

(continued)

Table 4.1 (continued)

Title	Driving problem	Methods used	Intended outcomes or optimization objectives
Electronic health records in specialty care: a time-motion study	Understanding how clinicians interact with EHRs in specialty care settings and the impact of human-factors associated with said workflow on clinical decision making	**External observation**	Understanding and optimizing clinical decision making
Reference: Lo HG, Newmark LP, Yoon C, Volk LA, Carlson VL, Kittler AF, Lippincott M, Wang T, Bates DW. Electronic health records in specialty care: a time-motion study. J Am Med Inform Assoc. 2007;14(5):609–15			
Primary care physician time utilization before and after implementation of an electronic health record: a time-motion study	Identifying barriers to EHR adoption in primary care setting, using paper-based records as a comparator	**External observation**	Understanding and optimizing clinical decision making
Reference: Pizziferri L, Kittler AF, Volk LA, Honour MM, Gupta S, Wang S, Wang T, Lippincott M, Li Q, Bates DW. Primary care physician time utilization before and after implementation of an electronic health record: a time-motion study. J Biomed Inform. 2005;38(3):176–88			

4.5 Limitations and Future Directions

Nearly a century after the introduction of TMS to the healthcare arena, there is a genuine interest in aggregating results from TMS studies to generate knowledge regarding healthcare workflow, efficiency, patient safety, and quality. There is also a growing interest in using aggregated TMS results to support decision making on the acquisition and implementation of health information technologies (IT). Regrettably, existing attempts to aggregate results conclude that study comparison is very difficult due to the considerable variation in design, conduct, and reporting of such studies (Zheng et al. 2011). Efforts to summarize findings across TMS are further challenged due to the heterogeneity in activity categorizations and a lack of methodological standardization (Tipping et al. 2011).

First steps towards standardizing TMS include the work of Zheng et al. who, after analyzing a subset of 24 "time and motion studies" specifically assessing health IT implementations, proposed a checklist aiming at standardizing the reporting of such studies' methods and results (Zheng et al. 2011). Also, methodological standardization has been proposed by Patel et al., by introducing a methodological framework for evaluating clinical cognitive activities in complex real-world environments that provides a guiding framework for characterizing the patterns of activities (Kannampallil et al. 2016). Although these efforts are important initial steps toward standardizing TMS, they do not address the persistent lack of common understanding concerning the definition of what is or is not a "time motion study". Ultimately, a crucial step toward standardization and validation of time motion studies in the healthcare domain involves establishing a common understanding of TMS, accompanied by a proper identification of the distinct techniques it encompasses and aspects of the field that remain open and active areas of investigation. This chapter represents an initial attempt.

Based on the current state-of-the-art practice of the design and execution of TMS, we believe that there are a number of future directions for the field that will serve to enhance or extend the scope and impact of the TMS methodologies. These directions include but are not limited to:

- Leveraging ***sensor data*** to expand the scope/nature of TMS, so that automated observation methods can incorporate higher volumes of "streaming" data collected from a variety of instrumented artifacts in a given environment. Such use of sensor data could include the tracking of activities performed by individual clinicians, utilization of technology-based tools, and the manipulation of physical environments. Leveraging such data will require the development of new TMS methodologies capable of dealing with data sources that exhibit variable volumes, velocities, and variability (i.e., "big data.")
- Creating ***continuous learning environments*** based on feedback from workflow studies, wherein we need to shorten the timeframe via which findings from TMS are provided back to the individuals being observed in order to support real-time or near-real-time decision making and workflow redesign. This could be made possible through using sensors to enable automated data collection, as well as improving the computational and data analytics capabilities that support/enable automated interpretation, summarization, and visualization of such TMS data (e.g., disintermediating analysis and reporting stage of TMS adhering to the prototypical design pattern shown in Fig. 4.1).
- Finally, if we are successful in leveraging sensor technologies and creating continuous learning environments, we will be able to deliver ***workflow-aware information at the point of care*** (e.g., contextual, just-in-time information). Such a paradigm shift would fulfill the primary promise of clinical informatics, which is to deliver right information to the right person in the right format. Given the importance of clinical workflow on human cognition and decision making, increasingly fine-grained understanding of such factors, afforded by TMS and novel data and analytics techniques, provides a basis for achieving this goal.

4.6 Conclusions

The original use of the term Time Motion Studies, which combines the work by Taylor's focusing on "time", and Gilbreths' on "motion" (Gilbreth 1914), refers to a method for improving efficiency and establishing employee productivity standards. In TMS, a task is broken into steps, and the sequence of movements or actions performed by study participants to accomplish those steps is observed to detect motion and to measure precise time taken for each movement or action. The extant literature of TMS includes a broad spectrum of distinct methodologies, including surveys, patient chart reviews, work sampling, and continuous observation. A commonality across these studies is the use of data generated via TMS to improve clinical workflow, with the ultimate objective of improving outcomes such as resource utilization, efficiency, safety, and patient health. As we look forward and envision the future of this stream of TMS-based research, our assessment of the current state of practice suggests the following improvement opportunities:

- Enhancing and extending the methods for evaluating processes and outcomes associated with workflow studies;
- Translating the results of workflow studies into data-driven interventions that could be delivered at the point of care and beyond; and
- Improving the adoption and optimal use of technology in complex healthcare environments based on a better understanding of workflow-related inhibiting or enabling factors;

However, to achieve these goals, it requires us to address several important gaps in knowledge and practice, such as:

- Ensuring the adoption and use of TMS methods become more widespread, and demonstrate the benefits in a variety of empirical settings and practitioner communities;
- Creating a sustainable body of scholarly and applied work surrounding both methodological innovations and applied science relevant to TMS; and
- Perhaps most importantly, ensuring that we use consistent language and nomenclature to describe all of these endeavors, such that a robust, applicable body of knowledge and best practices is being created and maintained.

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Chapter 5
A Workflow Perspective in Aviation

Guy André Boy

5.1 Introduction

Aviation is changing from air traffic control (ATC) to air traffic management (ATM), where both systems and people are immersed into massive amount of software. Workflow is changing because people and systems now interact in a different manner, using different cognitive and socio-cognitive processes and functions. Digitalization of the airspace logically leads to different kinds of function allocation.

Since the 1980s, we never stopped automating aviation systems. Consequently, flying has become more cognitive, moving pilots' cognitive functions from doing to thinking. Today, automation in aviation should be better called digitalization of air-ground socio-technical systems. Digitalization of the airspace is a matter of looking for the right mix of technology, organization and people's activities that should be concurrently designed and tested to discover emergent patterns, which themselves should be incrementally considered.

The massive use of information technology in aviation led to drastic innovations. Main reasons why automation and innovation have been and still are drivers of aviation evolution are: exponential increase of the number of aircraft that causes congested network; higher air traffic complexity; unpredictable delays; and other things that result in severe congestions at key airports, rising fuel costs and pollution.

Aircraft cockpits were greatly transformed during the 1980s involving the development of a large number of embedded systems. Digitalization of aircraft systems increased the need for cognitive engineering developments, especially in the digitalization of commercial aircraft cockpits. More specifically, flying tasks evolved from manual mechanical control to management of embedded systems.

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In the same way, air traffic recently started to evolve from control to management. Two major programs are considering this shift, SESAR in Europe (Single European Sky ATM Research) and NextGen (Next Generation Air Transportation System) in the USA. The main goal is for us to better understand new airspace management models that take into account traffic growth, safety constraints and capacity management. Such efforts should result in appropriate human-systems integration of new multi-agent systems of systems, and teams of teams.

Automation in aviation is not new. Autopilots were introduced in commercial aviation in the 1930s (e.g., the Boeing 247 commercial aircraft flew with an autopilot in 1933). However, we learned a lot from aircraft automation during the last three decades of the twentieth century, especially shifting from analog to digital automation. Anytime we automate, we rigidify tasks and therefore activities. Automated systems are very context-dependent (i.e., they work fine when they are operated in very well-known contexts, but may dysfunction outside of these contexts).

Digitalization of embedded systems made us evolve toward cyber-physical systems (CPSs) and the Internet-of-things (IoT). We then deal with much larger systems of systems that require new types of investigation. More specifically, such new systems, which include both people and machines, become more autonomous in broader contexts, which also need to be further understood and subsequently defined. This evolution from automation to autonomy requires that we emphasize flexibility issues. More specifically, if automation is associated with rigidity (i.e., procedure based), autonomy should be associated with flexibility (i.e., problem-solving based) where people should be considered at the center.

In this chapter, following up our human-centered design (HCD) approach, we will provide human-systems integration (HSI) solutions more than human factors problems. This will enable us to have a basis for comparing evolutions in aviation and health care. A discussion will be started. We will conclude and provide perspectives.

5.2 Using the AUTOS Pyramid to Support Workflow Analysis

Workflow evolved with respect to technology (more specifically, automation), organization (in commercial aircraft, we moved from 5 technical crewmembers during the fifties to 4, then 3, and 2 in the beginning of the 1980s), and jobs (different kinds of functions changed drastically because systems were able to execute tasks that were performed by people before).

A typical flight is divided into phases, sub-phases, and so on. For example, after passenger boarding, there is the taxi phase, then the runway rolling phase (before takeoff), takeoff, after takeoff, initial climb, climb, cruise, and so on. These phases are contextual pattern that determine appropriate set of tasks. In order to define workflow patterns, we use the AUTOS pyramid for each of these contextual patterns, which can be normal, abnormal or emergency.

The AUTOS pyramid was first introduced in HCD as the AUTO tetrahedron (Boy 1998) to help relate four entities: Artifact (i.e. system), User, Task and Organizational environment. We subsequently added contextual patterns, which we called "Situations" that represent the various possible events where the artifact could be used (Boy 2011). The AUTOS pyramid supports HSI making sure that all important entities (i.e., Artifacts, Users, Tasks, Organizations and Situations) are taken into account, as well as their properties and interconnections (provided on the edges of the pyramid).

5.2.1 Artifacts, Users and Tasks

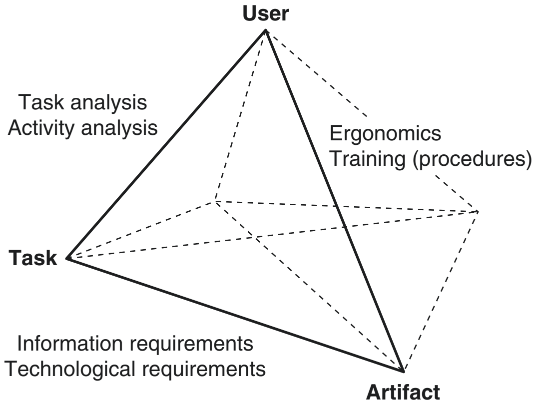
An artifact is anything that is built by people. In this chapter, artifacts will denote systems. A system is a set of interconnected components (i.e., physical parts) and procedures (i.e., software parts) forming a complex whole that is intended to be useful for doing something. Artifacts may be aircraft, avionics systems, devices and components of these systems for example. Artifacts are often integrated sets of existing technology. Sometime, they are made of brand new technology. Here is a short list of interactive artifacts: force feedback, loudspeakers, screens, signals, buttons, keyboard, joystick, mouse, trackball, microphone, 3D mouse, data suit (or interactive seat), metaphor for interaction, visual rendering, 3D sound rendering, 3D geometrical model and so on. These artifacts are usually integrated with mechanical artifacts such as pipes, containers, engines, pressurizers, turbines, flaps, slats, wheels, brakes and so on.

Users may be novices, experienced personnel or experts, coming from and evolving in various cultures (e.g., pilots, air traffic controllers, dispatchers). They may be tired, stressed, making errors, old or young, as well as in very good shape and mood. Users have been taken into account by human factors and ergonomics (HFE) during the last five decades in the context of engineering-centered engineering, generating the concepts of user interfaces and operational procedures.

Tasks vary from handling quality control, flight management, managing a passenger cabin, repairing, designing, supplying or managing a team or an organization. Each task involves one or several cognitive functions that related users must learn and use. The AUT triangle (Fig. 5.1) enables the explanation of three edges: task and activity analysis (U-T); information requirements and technological limitations (T-A); ergonomics and training (procedures) (A-U).

Today, almost any system includes software, which mediates user intentions and provides appropriate feedback. Automation introduces constraints and, as already said, more rigidity. End-users do not have the final action (automation does), they need to plan more than in the past. Work becomes more cognitive and (artificially) social, i.e., there are new social activities that need to be performed in order for the

Fig. 5.1 The AUT triangle



other relevant actors to do their jobs appropriately. This even becomes more obvious when cognition is distributed among many human and machine agents.

Cockpits were incrementally shaped to human anthropometrical requirements in order to ease manipulation of the various instruments. This of course is always strongly related to technology limitations also. Anthropometry developed its own language and methods. It is now actively used in design to define workspaces according to human factors such as accommodation, compatibility, operability, and maintainability by the user population. Workspaces are generally designed for 90–95% coverage of the user population. Anthropometric databases are constantly maintained to provide appropriate information to designers and engineers. Nevertheless, designers and engineers need to be guided to use these databases in order to make appropriate choices.

Fatigue is a major concern in aviation, and strongly depends on work organization. Therefore, it is important to know about circadian rhythms and the way people adapt to shift work and long work hours for example. Consequences are intimately associated with health and safety risks. Fatigue studies provide more knowledge and knowhow on how to proceed with work time schedules, appropriate training, systematic checks, and health indicators following. Of course, this needs to be integrated in regulatory procedures. Useful information can be found in the Handbook of Human-Machine Interaction (Gander et al. 2011).

In aviation, cognitive factors start with workload assessment. This statement may seem to be restrictive and old fashion, but the reader should think twice about workload before starting any work in human factors. On one side, workload is a concept that is very difficult to define. It is both an output of human performance and a necessary input to optimize performance, i.e., we produce workload to perform better, up to a point where we need to change our work strategy. But on the other side, we need to figure out a model that would quantify a degree of load produced by a human being while working. Of course, this model should be based on real measurements performed on the human being. Many models of workload have been proposed and used in aviation (Bainbridge 1978; Hart 1982; Boy and Tessier 1985). Workload also deals with the complexity of the task being performed. In particular, people can do several things at the same time, in parallel; this involves the use of several different peripheral resources simultaneously (Wickens 1992). Sperandio (1980) studied the way air traffic controllers handle several aircraft at the same time, and showed that the time spent on radio increased with the number of aircraft being controlled: 18% of their time spent in radio communication for one controlled aircraft whereas 87% for nine aircraft controlled in parallel. In other words, task complexity tends to increase human operator efficiency.

Human-systems interaction moves into human-systems cooperation when systems become more autonomous. In this case, it is more appropriate to talk about agent-agent cooperation. Hoc and Lemoine studied dynamic task allocation (DTA) of conflict resolution between aircraft in air-traffic control on a large-scale simulator. The more the assistance, the more anticipative the mode of operation in controllers and the easier the human-human cooperation (HHC). These positive effects of the computer support are interpreted in terms of decreased workload and increased shared information space (Hoc and Lemoine 1998).

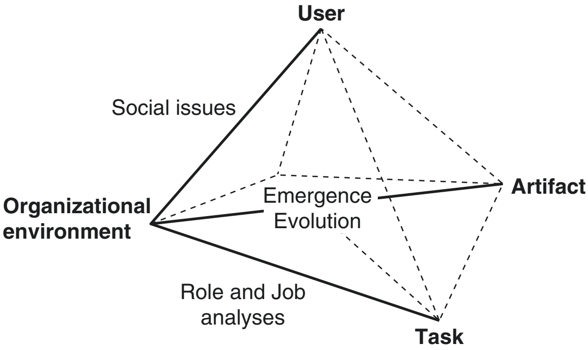
Situation awareness (SA) is another concept that is useful to introduce here, especially as a potential indicator for safety in highly automated human-machine systems. During the last decades, lots of efforts have been carried out to assess SA such as the Situation Awareness Global Assessment Technique (SAGAT) (Endsley 1988, 1996). Several efforts have been developed to assess SA in the aeronautics domain (Mogford 1997); the main problem is the characterization of the influence of action on situation awareness. Indeed, human operator's actions are always situated, especially in life-critical environments, and SA does not mean the same when actions are intentional as when they are reactive. In human-machine interaction, this is a very important issue since actions are always both intentional (deliberative) and reactive because they are mainly performed in a close loop (Boy 2015).

5.2.2 Considering Organizations in Design

The Orchestra model was proposed in aviation to better understand authority sharing (Boy and Grote 2009; Boy 2013). Technological design requires multidisciplinary design teams (i.e., a design team must include people who have related background, competence and experience on each of these relevant artifacts incrementally integrated). In addition, design team members need to understand each other (i.e., they need to be able to read the same music theory, even if they do have the same scores). They need to be appropriately coordinated both at the task level (i.e., scores need to be harmonized by a composer) and the activity level (i.e., design team members, as musicians, need to be coordinated by a conductor at performance time).

An organizational environment for design does not only include all design team players (i.e., human agents), but also technological means (i.e., system agents). At this point, human-systems integration is not only for the sake of the product, but also for the sake of the design team itself. For this reason, design cards constitute

Fig. 5.2 The AUTO tetrahedron



useful support (Boy 2013). Considering organizations in design introduces three additional edges (Fig. 5.2): social issues (U-O); role and job analyses (T-O); emergence and evolution (A-O).

There are two fields of research that grew independently for the last three decades: crew resource management (CRM) in aviation, and computer-supported cooperative (CSCW) work in HCI. The former was motivated by social micro-world of aircraft cockpits where pilots need to cooperate and coordinate to fly safely and efficiently. CRM started during a workshop on *resource management on the flight deck* sponsored by NASA in 1979 (Cooper et al. 1980). At that time, the motivation was the correlation between air crashes and human errors as failures of interpersonal communications, decision-making, and leadership (Helmreich et al. 1999). CRM training developed within airlines in order to change attitudes and behavior of flight crews. CRM deals with personalities of the various human agents involved in work situations, and is mainly focused on teaching, i.e., each agent learns to better understand his or her personality in order to improve the overall cooperation and coordination of the working group. The same kind of issues should be taken into account in design teams and solutions incrementally implemented and evaluated.

Interaction is also influenced by the organizational environment that is itself organized around human(s) and system(s). More explicitly, HSI could focus on someone facing his/her laptop writing a paper; it could also be someone driving a car with passengers; it could be focused on an air traffic management system that includes pilots, controllers and various kinds of aviation systems. People are now able to interact with computerized systems or with other people via computerized systems. We recently put to the front authority as a major HCD concept. When a system or other parties do the job, or part of the job, for someone, there is delegation. What is delegated? Is it the task? Is it the authority in the execution of this task? By authority, we mean accountability (responsibility) and control. Such questions should find answers within the design team both analytically and experimentally through human-in-the-loop simulations (HITLS).

Organization complexity is linked to social cognition, agent-network complexity, and more generally multi-agent management issues. There are four principles for multi-agent management: agent activity (i.e., what the other agent is doing now and for how long); agent activity history (i.e., what the other agent has done); agent activity rationale (i.e., why the other agent is doing what it does); and agent activity intention (i.e., what the other agent is going to do next and when). Multi-agent management needs to be understood through a role (and job) analysis. To summarize, O-factors mainly deal with the required level of *coupling* between the various purposeful agents to handle the new artifact.

5.2.3 Testing in a Large Variety of Situations

The AUTOS framework (Fig. 5.3) is an extension of the AUTO tetrahedron that introduces a new dimension, the "Situation", which was implicitly included in the "Organizational environment". The three new edges are: usability/usefulness (A-S); situation awareness (U-S); situated actions (T-S); cooperation/coordination (O-S).

Interaction depends on the situation where it takes place. Situations could be normal or abnormal. They could even be emergencies. This is why we will emphasize the scenario-based approach to design and engineering. Resulting methods are based on descriptions of people using technology in order to better understand how this technology is, or could be, used to redefine their activities. Scenarios can be created very early during the design process and incrementally modified to support product construction and refinement.

Scenarios are good to identify functions at design time and operations time. They tend to rationalize the way the various agents interact among each other. They enable the definition of organizational configurations and time-wise chronologies.

Situation complexity is often caused by interruptions and more generally disturbances. It involves safety and high workload situations. It is commonly analyzed by decomposing contexts into sub-contexts. Within each sub-context, the situation is characterized by uncertainty, unpredictability and various kinds of abnormalities. To summarize, situational factors deal with the *predictability* and *appropriate completeness* (scenario representativeness) of the various situations in which the new artifact will be used.

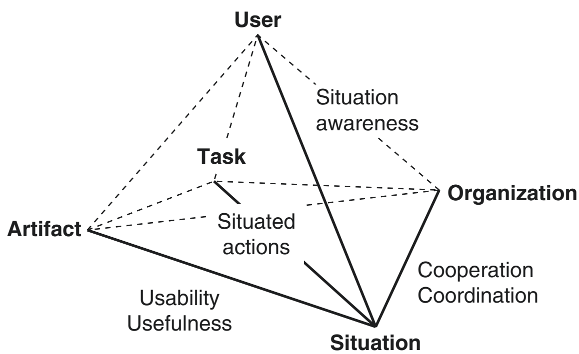


Fig. 5.3 The AUTOS pyramid

5.2.4 Using the AUTOS Pyramid in Practice

Software is very easy to modify. Consequently, design teams develop prototypes that they modify all the time! Interaction is not only a matter of end product; it is also a matter of agile development process. End-users are not the only ones to interact with a delivered product; designers and engineers also interact with the product in order to fix it up toward maturity… even after its delivery. This is why agile approaches based on design cards (Boy 2016) are extremely useful and effective (Schwaber 1997; Sutherland 2014). In addition, scenario-based design is an HCD approach that fosters understandability (situation awareness), complexity, reliability, maturity and induced organizational constraints (rigidity versus flexibility).

Software complexity can be split into internal complexity (or system complexity) and interface complexity. Internal complexity is related to the degree of explanation required to the user to understand what is going on when necessary. Concepts related to system complexity are: flexibility (both system flexibility and flexibility of use); system maturity (before getting mature, a system is an accumulation of functions—the "another function syndrome"—and it becomes mature through a series of articulations and integrations); automation (linked to the level of operational assistance, authority delegation and automation culture); and operational documentation. Technical documentation complexity is very interesting to be tested because it is directly linked to the explanation of artifact complexity. The harder a system is to use; the more related technical documentation or performance support are required in order to provide appropriate assistance at the right time in the right format.

What should we understand when we use a product? How does it work? How should it be used? At what level of depth should we go inside the product to use it appropriately? In the early ages of the car industry, most car drivers were also mechanics because when they had a problem they needed to fix it by themselves; the technology was too new to have specialized people. These drivers were highly skilled engineers both generalists and specialists on cars. Today, things have drastically changed; drivers are no longer knowledgeable and skilled to fix cars; there are specialists that do this job because software is far too complex to understand without appropriate help. Recent evolution transformed the job of mechanics into system engineers who know how to use specialized software that enables to diagnose failures and fix them. They do not have to fully understand what is going on inside the engine, a software program does it for them and explain problems to them; when the overall system is well-designed of course. This would be the ideal case; in practice, most problems come from organizational and situational factors induced by the use of such technology (e.g., appropriate people may not be available at the right time to fix problems when they arise).

Interface complexity is characterized by content management, information density and ergonomics rules. Content management is, in particular, linked to information relevance, alarm management, and display content management. Information density is linked to decluttering (Doyon-Poulin et al. 2014), information modality, diversity, and information-limited attractors, i.e., objects on the instrument or display that are poorly informative for the execution of the task but nevertheless attract user's attention. The "PC screen do-it all syndrome" is a good indicator of information density (elicited improvement-factors were screen size and zooming). Redundancy is always a good rule whether it repeats information for crosschecking, confirmation or comfort, or by explaining the "how", "where", and "when" an action can be performed. Ergonomics rules formalize user friendliness, i.e., consistency, customization, human reliability, affordances, feedback, visibility and appropriateness of involved cognitive functions.

Task complexity involves procedure adequacy, appropriate multi-agent cooperation (e.g., air-ground coupling in the aerospace domain) and rapid prototyping (i.e., task complexity cannot be properly understood if the resulting activity of agents involved in it is not observable). Task complexity is linked to the number of subtasks, task difficulty, induced risk, consistency (lexical, syntactic, semantic and pragmatic) and the temporal dimension (perception-action frequency and time pressure in particular). Task complexity is due to operations maturity, delegation and mode management. Mode management is related to role analysis. To summarize, T-factors mainly deal with *task difficulty* according to a spectrum from best practice to well-identified categories of tasks.

Do not forget that CFA requires HITLS to observe activity. Activity analysis could be defined as the identification and description of activities in an organization, and evaluation of their impact on its operations. Activity analysis determines: (1) what activities are executed; (2) how many people perform the activities; (3) how much time they spend on them; (4) how much and which resources are consumed; (5) what operational data best reflects the performance of activities; and (6) how much value these activities provide to the organization. This analysis is accomplished through direct observation, interviews, questionnaires, and review of the work records addressed to users of prototypes at different stages of design and development.

5.3 Cockpit Evolution: From Control to Management

Twentieth century engineering was dominated by mechanical engineering. Engineers built trains, cars, airplanes and power plants by assembling mechanical things. During the last decades, computer science and information technology massively penetrated mechanical machines to incrementally create systems, which included physical hardware and cognitive software. Everything started with the automation around the center of gravity using yoke or side stick and thrust levers (Fig. 5.4). The first embedded system was a single agent regulating parameters, such as speed and heading, one parameter at a time. Time constant of the feedback was around 500 ms. Pilots had to adapt to this embedded system by changing from control of flight parameters to supervision of embedded system behavior with respect to a set point.

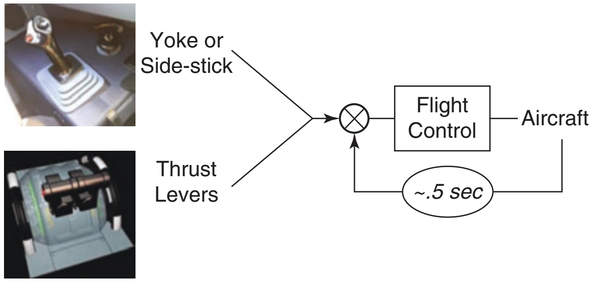


Fig. 5.4 Trajectory control embedded system: Flying around the center of gravity (The 4-loop approach to aeronautical automation evolution was inspired to me by Etienne Tarnovski during a keynote that he gave at HCI-Aero'06, Seattle, USA)

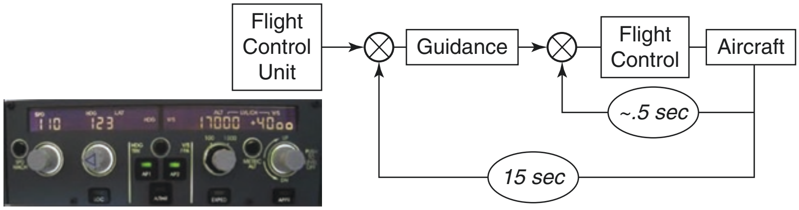


Fig. 5.5 Guidance embedded system: Guiding on basic trajectory

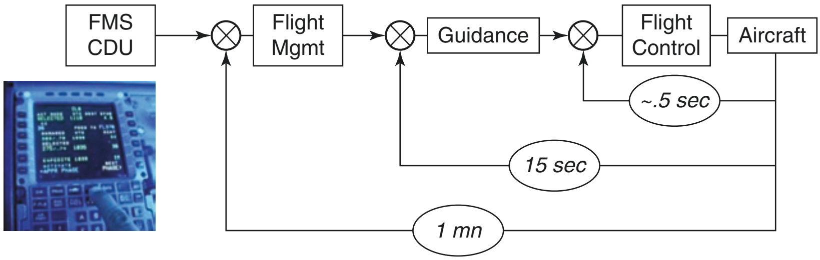


Fig. 5.6 Navigation automation loop: Guiding the flight plan

The guidance system was developed circa the early eighties (Fig. 5.5). This second feedback loop took into account several parameters. Its time constant was around 15 s. Note that this feedback loop was implemented on top of the trajectory control system. High-level modes of automation appeared and were managed on the flight control unit panel. At the same time, integrated and digital autopilot and auto-throttle were installed.

The third embedded system concerned navigation automation with a time constant of about one minute (Fig. 5.6). Guidance and flight management became integrated. This was the first real revolution in the evolution of aeronautical embedded systems. We were shifting from control of flight parameters to management of embedded systems. Software became dominant and the number of artificial agents on aircraft grew exponentially. For that matter, pilots have now to deal with a variety of embedded systems that are not only humans but also software-based agents. Problems may emerge when these software-based agents communicate among each other. This issue will be analyzed later in the chapter.

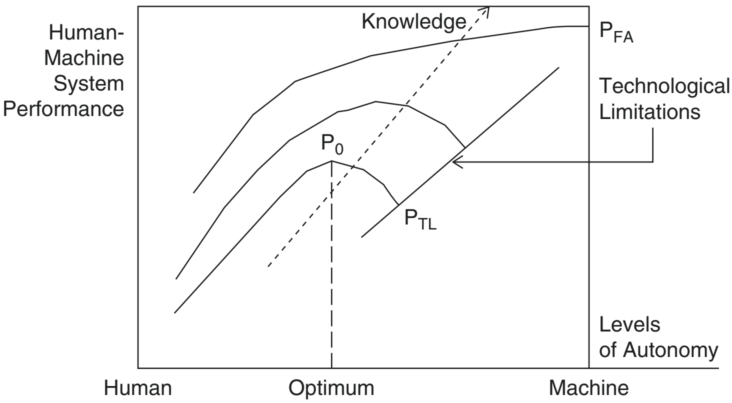


Fig. 5.7 Human-machine system performance versus levels of autonomy (adaptation of Boy's NASA technical document 1988)

Whenever people extend their capabilities with appropriate embedded systems that can be called "cognitive prostheses" (Hamilton 2001), they increase their performance. However, if these cognitive prostheses use automation to a point that is not clearly understood from an operational standpoint, performance may decrease and, in some cases, cause serious problems. This is what Earl Wiener called "clumsy automation" (Wiener 1989). When I was working on the Orbital Refueling System of the Space Shuttle in the mid-eighties (Boy 1987), I found out that there is an optimum P_0 in terms of autonomy level and performance of the overall human-machine system (Fig. 5.7).

Technology-centered engineering typically automates at the point P_{TL} (i.e., on the technological limitations limit). It takes experimental tests and efforts to go back to P_0. HCD takes into account the existence of P_0, and incrementally tries to find out this optimum through creative design and formative evaluation using HITLS. Interestingly, the more we know about autonomy of the various human and machine agents, the more the optimum P_0 move to the right and goes up on Fig. 5.7. Of course, if we knew everything about the environment and the various agents involved in the various interactions, the optimum P_{FA} would be on the full autonomy of the machine (e.g., in the case of an aircraft, P_{FA} would correspond to a drone).

This shift of optimum P_0 to the right is strongly related to maturity. In HCD, we distinguish between technology maturity and maturity of practice. The former deals with reliability, availability and robustness of the technology being designed and developed. The latter deals with people's adaptation to and resilience of the technology; often new practices emerge from technology use. We then need to observe usages as early as possible to anticipate surprises before it is too late. HCD proposes methods and tools that enable HCD teams to detect these emergent properties at design time (e.g., using HITLS). In any case, there is a maturity period required to assess if a product can be delivered or not.

5.4 Organizational Automation and Management

We have seen that pilot's job moved from control of flight parameters to management of embedded systems during the 1980s. This job revolution in the cockpit is now shifting to air traffic (i.e., air traffic control is moving toward air-traffic management). In other words, single agent's shift from control to management is currently evolving to a multi-agent shift. Why? What are underlying organizational issues?

The main cause is the number increase effect. According to Boeing's Current Market Outlook 2014–2033, average airline traffic yearly growth is estimated at a rate of 5%. Knowing that most big airports, such as Hartsfield–Jackson Atlanta International Airport, are already over-saturated, the air traffic capacity issue requires complexity science approaches, and more specifically a multi-agent approach, where agents are aircraft. Connectivity among these agents has to become explicit. If aircraft separation has to be reduced during approach and landing for example, current human-centered air traffic control techniques need to be re-visited and in many cases drastically changed. This is a matter of technology, organizations and people. On the technology side of the problem to be solved, each aircraft should know about the location and identity of the other aircraft around it. Aircraft should then be equipped with appropriate sensors and receptors, such as Automatic Dependence Surveillance—Broadcast (ADS-B) system. Satellite data have to be used to identify a clear dynamic model of the sky, in terms of both traffic and weather. We can also use weather radar data from all aircraft and fuse them with satellite data to increase 3D validity of weather models. Same kind of fusion can be done for air traffic using more conventional radar system data. Resulting data can be used to develop an embedded system providing each aircraft with a protection safety net (i.e., each aircraft knows the traffic around it and is able to decide tactical maneuvers to increase global safety). The protection safety net of each aircraft is an embedded system related to other aircraft equivalent and a coordination ground system that orchestrates the overall traffic.

This approach definitely defines a new kind of organizational automation, which is multi-agent. This multi-agent approach involves interaction among people and systems, among systems, and among people (often through information technology). Since there will be a layer of information technology gluing the various air and ground systems, new factors are emerging such as cyber-security. Air traffic management of the future will be almost entirely based on highly interconnected cyber-physical systems (CPSs). New kinds of risks will emerge from the activity of this giant airspace CPS-based infrastructure. In particular, malicious actors will be able to attack these systems from anywhere in the world. Consequently, we need to further develop methods and tools that enable studying security and resilience of such CPS-based infrastructure, and find appropriate solutions. Protection will have to be found from technology (safety and security nets), organizations (collaboration among agents), and people (increasing training and expertise).

Air-ground integration is an example of human-systems integration point of view that involves function allocation. Since Fitt's law that provided the HABA-MABA[1] recommendations for single-agent function allocation, very little has been done on multi-agent function allocation. Function allocation rationale is to determine which functions should be carried out by humans and which by machines (Fitts 1951). Cognitive function analysis (CFA) is an effective approach to this kind of problem in a multi-agent environment (Boy 1998, 2011). CFA includes physical functions also (remember that a cognitive function is defined by a set of resources that may be cognitive functions and/or physical functions). In addition, the Orchestra model (Boy 2013) provides a very useful framework to model and simulate resulting cognitive functions of the human-systems system being developed. Consequently, agent needs to be further modeled in terms of cognitive and physical functions, as well as the way they are inter-connected—this is typically doing a CFA. CFA results can be presented as a cognitive/physical function network (or interactive map), which is a good support for studying interaction complexity, distributed situation awareness and multi-agent decision-making.

5.5 Starting a Discussion

5.5.1 Tangibility

In the beginning of the twenty-first century, embedded systems are reframing the structure-function duality. Instead of functionalizing structure to create automated machines (the twentieth century approach), we are now structuralizing software functions. Therefore, automation problems, which were created during the last decades of the twentieth century, are no longer the main issue because software can be tested from the early days of the design process using advanced virtual engineering, making HCD possible (i.e., taking into account human factors at design time). Cognitive function analysis can be validated because, in addition to task analysis, activity can be observed in HITLS using virtual prototypes and real users. Consequently, technological and organizational requirements can be nurtured by early solid function analyses.

The main issue has then become structure, and therefore tangibility. Since almost everything can be modeled and simulated on computers, and we now have 3D printing, structure can be very easily obtained. Traditionally in aeronautics, this was taken into account by flight tests. This is needed for the validation of any life-critical system. The right balance between cognitive and physical functions should be tested, as well as between abstractions and physical structures. Tangibility needs to be tested in terms of physical tangibility and figurative tangibility. The former is based on criteria such as simple reachability, complex accessibility, fatigue, noise management, resource availability and so on. The latter is based criteria such as

[1] Fitt's HABA-MABA (humans-are-better-at/machines-are-better-at) approach provided generic strengths and weaknesses of humans and machines.

monitoring, situation awareness, decision-making, risk taking and so on. Of course, these criteria can be detailed with respect to the level of granularity required at the current stage of the design process. Digital HITLS at design time contributes to the development of more appropriate HSI requirements. It does not remove the need for actual flight tests once the real system is developed, but contributes to improve their effectivity and cost.

5.5.2 Maturity

Lots of efforts and money have been spent to increase system reliability that contributed to aviation safety. As already said, safety of the future ATM involves increased attention on interactions among its various agents. The qualification of these "new" agents is an issue that concerns this investigation on authority sharing. We would like to go beyond the safety-reliability discussion, and propose to focus on maturity.

Since the general trend is to manage short-term benefits instead of long-term sustainability, it is not surprising that we currently observe a discrepancy in provision and qualification of human operators. Since human reliability remains very critical, if human operators are even less available and qualified, the situation will become worse. We are beginning to understand that human factors issues are no longer so much the result of engineering decisions but of economically-induced decisions.

Therefore, if we want to keep or improve the current level of safety, with an increase of airspace capacity, some drastic changes will need to be made in the way we understand and manage technology and organizations. In particular, safety-critical systems should be mature for safe use when they are delivered. The concept of maturity could be misleading because we already have in industry the quality-based Capacity Maturity Model (Paulk et al. 1993) that supports maturity of manufacturing processes. We are interested in product and practice maturity. Product maturity requires a strong focus on human-centered high-level requirements, as well as participatory design and development all along the life cycle of the product (Boy 2005). Product maturity engineering involves a careful elicitation of the attributes that shape the related maturity of practice. We typically say that maturity of practice is reached when a reasonable number of surprises or emerging factors have been identified and related causes fixed. Obviously, product maturity engineering addresses the long term and is not appropriate for short-term goals and practice of current economy-driven organizations. It should be!

During the early stages of a development process such as the ATM of the future, the participation of the various representative actors is mandatory. This participatory approach requires that not only pilots and controllers, i.e., end-users and musicians, but also designers and regulators, i.e., the music instrument makers and composers, share a common frame of reference. In addition, the job definitions process cannot be improvised and must be planned since we know that initial definitions will have to be revised all along the life cycle of the overall ATM development process. Consequently, authority distribution for the design of the various instruments (this is where HCI specialists enter into play) is a matter of incremental development and testing. In PAUSA, we took a scenario-based approach (Carroll 1995) to carry out such an authority distribution supported by the development of human factors principles and criteria, socio-technical models and HITLS.

The growing number of interdependencies among ATM agents led us to propose a measure of socio-cognitive stability (SCS) derived from various contributions, including Latour's account on socio-technical stability (Callon 1991; Latour 1987), emerging cognitive functions (Boy 1998), distributed cognition (Hutchins 1995), and socio-cognitive research and engineering (Hemingway 1999; Sharples et al. 2002). We make a distinction between local and global SCS. Local SCS is related to agent's workload, situation awareness, ability to make appropriate decisions and, finally, correct action execution. It can be supported by appropriate redundancies and various kinds of cognitive support such as trends, relevant situational information and possible actions. Global SCS is concerned with the appropriateness of functions allocated to agents, pace of information flows and related coordination. It is very similar to the level of synchronization of rhythms in a symphony. Globally, socio-cognitive support could be found in a safety net that would take into account the evolution of interacting agents and propose a constraining safety envelope in real time.

Three kinds of metrics have been deduced during the PAUSA project:

- **Complexity** is expressed as the number of relevant aircraft to be managed per appropriate volumetric zone (AVZ) at each time. An AVZ is calculated with respect to the type of flow pattern, e.g., aircraft crossing, spacing and merging. The definition of such an appropriate volumetric zone requires the assistance of operational ATC controllers. From a socio-cognitive perspective in ATM, complexity should be considered together with capacity. This is what the COCA (COmplexity & CApacity) project investigated (Athènes et al. 2002; Cummings and Tsonis 2006; Hilburn 2004; Laudeman et al. 1998; Leveson et al. 2009).
- **Time pressure criticality** is the amount of workload that an agent (or a group of agents) requires to stabilize an ATM system after a disturbance. Such workload measure could be assessed as the ratio between the sum of required times for each action on the total available time (Boy 1983).
- **Flexibility** is defined as the ease of modification of an air-ground contract in real-time. Flexibility assessments should guide ATM human-centered automation and organizational setting. Overall, increasing capacity also increases complexity and uncertainty, which need to be managed by finding the right balance between reducing uncertainties through centralized planning and coping with uncertainties through decentralized action. Loose coupling is required for actors to use their autonomy in accordance with system goals (Grote 2004).

This chapter was written to provide salient workflow aspects, as well as evolutions of human-systems integration in aviation. How can we compare these aspects and evolutions with those in healthcare? Can increase of the number of aircraft be compared to increase of the number of patients? For sure, complexity analysis is required in both domains. Of course, we cannot substitute aircraft by patients! However, the need for dispatch is similar. In aviation, interconnectivity among various kinds of aircraft have to be always considered along with attributes such as long-haul flights, failures, aircraft size and performance. Same could said in healthcare, interconnectivity among various kinds of patients have to be always considered along with attributes such as seriousness of their health.

Time pressure criticality is also a factor shared by aviation and healthcare, as all in life-critical systems. We tend to plan trajectories in advance (i.e., 4D trajectories), and this led to trajectory-based operations (TBO). However, this works fine in normal situations, but may fail in abnormal and emergency situations where procedure-based planning rigidity becomes an obstacle to problem-solving flexibility requirements. This involves human skills and knowledge not only on basic flying capabilities but also on embedded systems and their capabilities. This is the reason why organizational automation, especially workflow automation, should be developed considering appropriate function allocation. Cognitive function analysis is strongly advised.

5.6 Conclusion and Perspectives

Workflow design and management is a matter of functions and structures that need to be articulated correctly. The first difficulty comes from system complexity (i.e., systems of systems, teams of teams, several critical attributes to be considered, emergent phenomena and properties to be incrementally elicited and re-injected into the overall system). It is then important to identify non-linear processes and bottlenecks (bifurcations in the complexity science sense). For that matter, the AUTOS pyramid and cognitive function analysis greatly supported analysis, design and evaluation of highly automated systems in aviation. We started to automate aircraft and we are now automating air traffic. The actual shift is from rigid (low-level) automation to flexible (high-level) autonomy, where authority sharing has to be considered seriously (i.e., who is in charge and accountable to whom).

The socio-technical evolution of aviation systems led to very successful results in terms of accident deaths, decreasing exponentially since the 1980s toward zero.[2] This evolution includes automation (now digitalization), regulations and a unique safety culture. However, digitalization has become the most important issue in aviation human-systems integration. Software is very easy to modify, but involves us into a virtual world where new phenomena emerge such as cybersecurity. If we can carry out HCD development very early during the life cycle of a system (i.e., activ-

[2] "Airlines recorded zero accident deaths in commercial passenger jets last year, according to a Dutch consulting firm and an aviation safety group that tracks crashes, making 2017 the safest year on record for commercial air travel" (https://www.reuters.com/article/us-aviation-safety/2017-safest-year-on-record-for-commercial-passenger-air-travel-groups-idUSKBN1EQ17L).

ity and function analyses can be performed very early using human-in-the-loop simulations), tangibility testing remains a highest priority (i.e., physical tangibility regarding structures and figurative tangibility regarding functions).

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Chapter 6
Characterizing Collaborative Workflow and Health Information Technology

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6.1 Introduction to Healthcare Teamwork

Healthcare system factors such as an increased prevalence of chronic illness, an aging population, increased patient complexity and a strong desire for quality, safety, and coordination of care have highlighted the need for team-based care delivery (Committee on Patient Safety and Health Information Technology; Institute of Medicine 2011; Mitchell et al. 2012; Roett and Coleman 2013). However, while this need has been well described, it remains a challenge to implement team-based care delivery in today's healthcare practice (Bates 2015).

Teams can be broadly defined "a distinguishable set of two or more people who interact dynamically, interdependently, and adaptively toward a common and valued goal/object/mission, who have each been assigned specific roles or functions to perform, and who have a limited life span of membership" (Salas et al. 1992). However, there are in fact many different ways by which teams can be characterized Some ways that teams have been classified are by their information behavior, organizational configuration, duration (e.g., long- versus short-term teams), and manner of interaction (e.g., synchronous and asynchronous) (Nancarrow et al. 2013;

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Xyrichis and Ream 2008). Despite these differences, a commonality is the need for different degrees of connectivity that varies according to the type of team and the context in which communication and coordination between team members occur. Given the distributed manner in which teams often work, health information technology (IT) can play a significant role in supporting communication and cooperation between members of a care team. Hence, understanding the nature of team connectivity is essential for the design and evaluation of health IT to support team-based care delivery (Kuziemsky et al. 2016a). However, existing research has shown that there is often a gap between the collaborative work practices of teams and the health IT that we design to support them (Leslie et al. 2017; Rudin et al. 2016).

6.2 Characterizing Healthcare Teams

Closing this gap requires us to first understand how teams work in order to derive system requirements for health IT to support teamwork. A common way to characterize healthcare teams is by the structure of the team. The basic form of structural classification is whether a team is composed of one type of providers (unidisciplinary team) or multiple provider types (multidisciplinary, interdisciplinary or transdisciplinary team). Teams consisting of multiple provider types can be further classified according to the manner in which team members interact when delivering care. In a *multidisciplinary* team, team members from different disciplines work on a common goal and share information accordingly, but each member stays within the boundaries of their own discipline as they work towards the shared goal (Choi and Pak 2006). Multidisciplinary teams are analogous to swim lanes in that each provider only engages in his/her own care delivery processes with little or no interaction across the lanes (Choi and Pak 2006). Surgical teams are a common example of multidisciplinary teams in which providers of each type are responsible for performing distinct and highly specialized tasks (Casimiro et al. 2015). In contrast, in an *interdisciplinary* team, team members work across disciplines (i.e., across the swim lanes) as interaction and communication between team members are necessary to accomplishing the team's shared goals. Interdisciplinary teams are common in complex care scenarios such as palliative care (Casimiro et al. 2015). Lastly, in a *transdisciplinary* team, team members are not bound to their disciplines, and may work across roles through shared goals and skillsets (Galvin et al. 2014; Hall et al. 2012). Transdisciplinary teams are common in remote areas where all provider types may not be available and thus a provider, such as a nurse practitioner, may need to play multiple roles (e.g., dietician, therapist, etc.) when caring for patients.

Teams can also be characterized according to their life cycles and longevity of workflow. Some teams interact only for short durations (e.g., certain teams in the emergency room [ED]) where team is disbanded once the task at hand completes; while other teams (e.g. cancer care or chronic disease management teams) engage in workflows that may extend over months even years (Andreatta 2010; Tang et al. 2015). Teams may be assembled with specific needs or ad-hoc workflows; and team personnel can also be characterized as being stable, or dynamic, and may work synchronously or asynchronously (Hollenbeck et al. 2012).

Teams can be also characterized by the degree of collaboration that their members engage in. While it is common to refer to healthcare teams as being 'collaborative,' collaboration is in fact a specific process that carries with it the implications for how a team should operate (Eikey et al. 2015). Although collaboration is often used interchangeably with other terms such as communication, coordination and cooperation, collaboration is a distinctive process (Abraham and Reddy 2013) which refers to "planned or spontaneous engagements that take place between individuals or teams of individuals, whether in-person or mediated by technology, where information is exchanged in some way (either explicitly, i.e. verbally or written, or implicitly, i.e. through shared understanding of gestures, emotions, etc.), and often occur across different roles (i.e. physician and nurse) to deliver patient care" (Eikey et al. 2015: 263). True collaboration involves multiple processes. The popular 3C Collaboration Model (i.e., Communication–Coordination–Cooperation) describes how collaboration involves processes such as communication to exchange information to generate tasks that are then organized via coordination to ensure the successful completion of the overall care task (Hugo et al. 2008; Paul and Reddy 2010; Reddy and Spence 2008).

Finally, the social or behavioral aspects of healthcare teams can also be significant. This is because teams often involve professionals from multiple disciplines and/or medical specialties who contribute with varying roles and responsibilities. For example, physicians are in charge of developing clinical diagnosis and treatment plan; nurses for carrying out the treatment plan; phlebotomists for drawing blood; lab technicians for analyzing patient samples; dieticians for making nutrition recommendations, etc. (Ellingson 2002) Hence, in order to achieve effective teamwork both within and across these various disciplines, all members of the team must demonstrate certain teamwork competencies (e.g. team knowledge, team skill and team attitude) (Baker et al. 2006; Nancarrow et al. 2013). Table 6.1 shows some of the key behavioral characteristics of a team for ensuring effective teamwork (Baker et al. 2006).

6.3 Formalizing Team-Based Workflows

Workflow has been described as the number one pain point between health IT and users (Singh et al. 2013), with the formation and functioning of healthcare teams being a particular challenge (Payne et al. 2016). Thus, a first step toward mindful health IT design is to formalize team-based workflows so that computerized systems can better support the characteristics of the underlying teamwork. While the above section describes numerous characteristics of healthcare teams, to date, there has been limited formalization of team-based workflows in clinical settings. Drawing upon our prior work, we formalize the above characteristics of team-based workflows according to their structural and behavioral aspects (Press et al. 2012). This formalization is shown in Fig. 6.1.

Table 6.1 Behavioral characteristics of effective teams (adapted from Baker et al. 2006)

Features of effective teams	Supporting function	Potential strategy
Team leadership (Baker et al. 2006; Nancarrow et al. 2013)	Offers clear direction and management with the ability to coordinate the activities of other team members	Seeking and evaluating information for task coordination among team members
Mutual performance monitoring (Baker et al. 2006; McIntyre and Salas 1995; Salas et al. 1994)	Ability to develop shared understanding of the team environment and apply appropriate task strategies to accurately monitor members' performance	• Identifying mistakes and lapses in other team members' actions • Providing feedback regarding other team members' actions to aid correction
Mutual support (McIntyre and Salas 1995; Porter et al. 2003; Salas et al. 1994)	Ability to support team member needs based on accurate knowledge of their responsibilities.	Shifting of tasks to underutilized team members
Adaptability (Cannon-Bowers and Salas 1997; Kozlowski et al. 1999)	Ability to adjust strategies based on information gained from work environment using compensatory behavior and reallocation of shared team resources	Identifying opportunities for growth and innovation for routine practices
Shared mental model (Klimoski and Mohammed 1994; Mathieu et al. 2000; Stout et al. 1996)	Organizes knowledge structure of the relationships between the task and team member interactions	Anticipating and predicting team members' needs
Awareness (Dourish and Bellotti 1992)	Provision of requisite knowledge to integrate individual and team tasks necessary to achieve a shared goal	Creating awareness of other team members' tasks
Common ground (Clark and Brennan 1991)	Shared knowledge, language and beliefs necessary for team communication and exchange to occur	Team training and use of common terminologies
Collective orientation (Driskell and Salas 1992; Shamir 1990; Wagner 1995)	Being accountable for one another during team interactions	Appraising teammates' input
Mutual trust (Bandow 2001; Weber et al. 2004)	Trusting the ability of the team members to perform their roles and protect the teams' mutual interests	Willingness to admit mistakes and accept feedback

In Fig. 6.1, we characterize the structure of a team by its degree of interaction and the temporal characteristics of tasks and personnel. The behavioral aspects define factors such as leadership, trust and collaborative competencies, as well as behaviors that influence how collaborative workflows are actually carried out (Xiao et al. 2013). Characterizing team workflows by structures and behaviors helps us better understand how to link team characteristics to outcomes, and the impact of health IT on team-based workflows. While all structural and behavioral aspects included in Fig. 6.1 are important, this chapter particularly focuses on collaborative team workflows, which are an integral part of team-based care delivery yet there is

Team Workflow Characterization

Structure

- **Team Composition**
  - Multidisciplinary
  - Interdisciplinary
  - Transdisciplinary
- **Task and Personnel**
  - Temporality
  - Workflow and personnel stability
  - Synchronous or asynchronous

Behavior

- **Leadership**
- **Trust**
- **Shared mental models**
- **Accountability**
- **Collaborative Competencies**
  - Common ground
  - Awareness
- **Collaborative Behaviors**
  - Information seeking
  - Communication
  - Decision making
  - Interactional behaviors

Fig. 6.1 Team-based workflow characterization based on structures and behaviors

still much needed to learn about their complexity (Kuziemsky 2016). Further, how health IT should be designed to support collaborative team workflows remains an area that has been understudied (Eikey et al. 2015).

6.4 Collaborative Workflows

As described in the previous section, collaboration is challenging for team-based workflows. Clinical processes are often collaborative in nature, and activities and tasks depend on effective management of team-based workflows (Kannampallil et al. 2011; Niazkhani et al. 2009). While individual workflows involve the interaction between an individual care provider and his/her work environment (Malhotra et al. 2007), team-based workflows involve multiple interactions within the healthcare setting including collaboration between multiple providers of a care team. Understanding the movement across the 'individual-collaborative' interchange, and how individual and team needs are reconciled, is a key part of understanding collaborative workflows (Kuziemsky et al. 2016b).

In the following subsections, we illustrate how team characteristics are manifested in collaborative team-based workflows. In particular, we highlight key research studies that have been conducted to examine collaborative behaviors related to information seeking, interactions, communication and decision making.

6.4.1 Collaborative Information Seeking (CIS) Behaviors

Collaborative information seeking (CIS), in simple terms, refers to the interactive and often mutually beneficial process of seeking information as defined explicitly by and among collaborative team members (Shah 2012). An example of CIS noted in the literature is to communicate evidence with regard to clinical practice using information sought through expert support provided by educators, librarians and other specialists (Hansen et al. 2015).

To understand the context of collaborative information activities of healthcare teams, several researchers have conducted field studies to observe and examine the underlying CIS-related features of team-based workflows. For example, Reddy and Jansen (2008) compared ethnographic field studies of patient care teams at a surgical intensive care unit (ICU) of an urban hospital and the ED of a rural hospital. They found three major characteristics of CIS behaviors: communication, complexity of information needs and information retrieval technologies. The authors also compared CIS behaviors to individual information behaviors at different levels (i.e., information behavior, information seeking, information searching), and found that CIS behaviors have more complex characteristics. These complex characteristics encompasses interaction between collaborative team members from different specialties and systems, as well as the need to communicate vital information within these interactions. Based on the conceptual understanding of CIS behaviors, the authors designed and developed a porotype collaborative information retrieval system called MUSE (Multi-User Search Engine) to aid communication between team members for more effective information seeking and retrieval.

In another study, Reddy and Spence (2008) conducted ethnographic observations to further understand collaborative information-seeking activities of multidisciplinary patient care teams in the ED. Findings from their investigation illustrate that ED team members have both organizational and clinical information needs, which are magnified during information flow breakdowns. They also identified seven categories of information needs as expressed by questions asked by ED care teams. These included patient specific, organizational, plan of care, miscellaneous, clarification (more details), teaching and medication related questions. They also identified three triggers for CIS activities including lack of expertise, lack of immediate accessible information, and complex information needs.

In a follow-up study, Paul and Reddy (2010) evaluated CIS and sense-making behaviors of healthcare providers, again in an ED setting. This study shows that "sensemaking" of information took place during three main occasions: when there was information ambiguity (requiring clarification from different team members); when there was role-based information distribution (unequal distribution of information shared among team members due to their different care roles); and when there was lack of expertise (health professionals lacking expertise on a particular situation, and needing collaborative sense making with other members in a multidisciplinary team). Based on their findings on the sense-making trajectories within CIS, the authors proposed two design principles for creating software systems to facilitate CIS: (1) implementing CIS tools that support the continuity of the process and products of sense making via visualizing the trajectories, using methods such as timelines that show chronological information by the various group members and sense made of the highlighted information; and (2) implementing CIS tools that provide action awareness via notifications, and activity awareness via visualizing timelines of the actions, related to a highlighted activity.

In another study of CIS, Shah and Gonazalez (2010) adapted Kuhlthau's information search processes (ISP) model and mapped collaborative information-seeking processes to the different stages of the ISP model. The ISP model incorporates a cognitive (thought) and affective (feeling) dimension that reflects user's perspectives on the flow of activities that they engage in when performing an information-seeking task. Based on the six stages of the ISP model (i.e., initiation, selection, exploration, formulation, collection and presentation), the authors analyzed affective feelings (positive or negative) as a result of actions and messages exchanged between team members during CIS. The authors found that positive messages were associated with pleasant feelings (e.g., clarity, satisfaction); and negative messages were associated with unpleasant feelings (e.g., confusions). Their analysis provided more insights into individual and group dynamics during CIS activities, and also showed a high correlation between initiation (related to uncertainty) and selection (related to optimism); and between exploration (related to confusion/frustration/doubt), formulation (related to clarity) and collection (related to sense of direction/confidence) of information, with participants often switching between these stages while interacting with collaborators. The authors also found a negative correlation between presentation (related to relief/satisfaction/or disappointment) and exploration, formulation and collection.

Drawing upon the core findings from prior information studies, Karunakaran et al. (2013) developed a conceptual collaborative information behavior (CIB) model to highlight three distinct phases of CIB in healthcare organizations. Phase 1 involves problem identification based on shared understanding; Phase 2 involves purposely seeking information by two or more individuals in a team in order to satisfy a shared goal; and Phase 3 involves incorporating information gathered into the team's existing knowledge base to achieve a common understanding between individuals in the team. Central activities in these three phases include information sharing and evaluation; collaborative grounding (shared understanding that assimilates and reflects upon available information); and collaborative sense making (individuals with different perspectives making sense of messy information).

6.4.2 Collaborative Interactional Behaviors

Defining collaborative interaction is a rather complicated endeavor. To do that, Lewis (2006) used five points of convergence and three points of divergence based on the definitions from the collaboration literature. The five points of convergence focused on collaboration being:

- More of an activity rather than an state/object (for example learning collaboratively);
- Team members regard for one another (collaborative interaction only exists when relationships between participants are formed);
- Equalization of team members irrespective of participants' high or low status;
- Process of collaborative interaction with a start, middle and end of the activity which changes at different point in time; and

- Participants are often willing to get involved in the collaborative process and are never coerced.

The three points of divergence were:

- Collaborative activities often occur at different time dimensions such as short or long-time spans with different goals;
- Collaborative interaction serves as a platform to highlight and acknowledge differences in a productive way while taking advantage of similarities among team members.
- Have a shared goal with or without considering individual payoffs.

Examples of collaborative interaction illustrated in the literature include:

- A physician collaborates with her patient to decide on the best treatment for the patient's condition; the physician provides her medical expertise and the patient offers knowledge about her body, history and goals (Lewis 2006).
- Healthcare team members encouraging situations that promote collaborative interactions such as: open dialogue, collaborative rounds, implementing pre- and post-operation team briefing, and creating interdisciplinary committees or task forces that discuss challenges (O'Daniel and Rosenstein 2008).

Numerous studies have been conducted to evaluate the importance of collaborative interactional behavior in team-based workflows, which includes collaborative interactions among members of a healthcare team, with patients, and with health IT. Apker et al. (2006) did an exploratory study to investigate nurses' communication of professionalism during interactions with other members of the care team. Findings from their study showed that the participating nurses used four communication skillsets, including collaboration, credibility, compassion and coordination (4Cs). The authors also identified specific communicative behaviors associated with each of the four skillsets: collaboration is associated with organizing, filtering and providing pertinent information to team members; credibility is associated with clear communication about the information shared; compassion is associated with display of consideration and caring for team member concerns; and coordination involves tasks delegation to other team members while encouraging participants input (Apker et al. 2006). Implications from their study highlighted the pros and cons of varied communication expectations of nursing staff. These varied expectations could serve as a catalyst to embolden nurses on developing new skills to increase their overall productivity. However, varied communication expectations could also lead to tension in the workplace between different clinical roles, which could precipitate stressors that cause nurses burnout, leaving their current positions or completely quitting their nursing profession. Therefore, implementing the 4Cs in nursing education and nursing practice provides an important strategy for improving nurses' communication skills.

In another exploratory study, Hau et al. (2017) investigated the effects of various interaction behaviors of service front liners (i.e., healthcare providers) and customers (i.e., patients), and how they can work together to co-create value. Their investigation depicted a research model with four components of front liner interactions: individuated, relational, ethical and empowered; and customers' interactions with front liners have three components: information seeking, information sharing and responsible behavior. The cumulative effects of these interactions enable value co-creation by both front liners and customers, which has an indirect influence on costumers' perceived value through the 'participation–activating' interaction behavior. Findings from their analyses also identified a significant positive effect of interaction behaviors on patient participation, through which more patient resources are contributed to creating healthcare service. They concluded that the interactions between front liners and customers can be broken down into participation-activating interactions versus value-enhancing interactions, both of which enhance perceived value by customers.

To investigate nurse-physician collaborative interaction behaviors, Lindeke and Sieckert (2005) analyzed workspace collaboration between nurses and physicians, and suggested different collaborative strategies, including self-development, team-development and communication-development, that can be used to improve nurse-physician communication. Self-development strategies are defined as various individual characteristics that influence the level of collaboration between professionals in healthcare settings. These include developing emotional maturity, understanding the perspective of others, and avoiding compassion fatigue/burnout. Team development strategies involve team building, respectful negotiation, conflict management, containment of negative behaviors and workplace design to facilitate collaboration. Finally, communication-development strategies include implementing effective communication tactics (e.g., prioritizing the context with current information and disregarding peripheral data) that are often vital in emergency situations; and using electronic communication means mindfully (e.g., to be courteous and friendly while evaluating and clarifying the messages received).

In a related study on collaborative interaction behaviors, Schadewaldt et al. (2016) examined the experiences and perceptions of nurse practitioners (NPs) and medical practitioners (MPs) working collaboratively in a primary care setting. The authors used mixed research methods such as thematic analyses of qualitative data obtained from observations, work documents describing collaborative practices, and interviews of NPs and MPs; as well as descriptive analyses of quantitative data obtained from questionnaires completed by MPs and NPs. Findings from their study demonstrated intensive collaboration activities between NPs and MPs, which were deemed by the study participants as being beneficial to patients. In addition, their qualitative analysis results highlighted three themes regarding the collaborative experience of NPs and MPs. These themes include: (1) the influence of system structures (i.e. policies and regulations, local infrastructure); for example, the study participants criticized that the current NP reimbursement rates and the available Medicare benefit schedule were inadequate and unfair; (2) influence and consequences of individual role enactment through the coexistence of overlapping, complementary, traditional roles and emerging roles; and (3) participants making adjustments to new routines, and individuals' willingness and personal commitment being crucial to collaborative work. Based on these findings, the authors suggested decision makers of healthcare reform implement strategic support for collaborative clinical work, such as enhancing nurses' sense of autonomy in the workplace to strengthen their positions, and ensuring continuous practice of collaboration.

Besides interpersonal collaborative interactions among members of healthcare teams, researchers have also investigated how collaboration is mediated using health IT systems. Examples include the use of mobile devices during patient rounding and handoff, which has been shown to improve team workflows (Motulsky et al. 2017; Srinivas et al. 2015); and the use of computerized clinical decision-support systems designed to facilitate the interaction between physicians and other healthcare professionals (El-Sappagh and El-Masri 2014).

Additionally, interactions mediated by health IT are necessary when team-oriented clinical processes do not afford team members the convenience of face-to-face interactions. These can be attributed to barriers such as physical distance in a distributed work environment, or team members working at different points in time (e.g., across different shifts) (Garingo et al. 2016; Marini et al. 2015; Rincon et al. 2012). For example, Marini et al. (2015) illustrated how robotic tele-rounding impacted multidisciplinary team members (e.g., surgical residents, nurses, surgical/medical intensivists) in a surgical ICU and their collaborative workflows. In this study, the authors found that patients and their families interacted with the intensivists through flat-screen monitors on the robots. Their evaluation results showed that use of tele-rounding had no negative effect on patient outcomes, intensivist satisfaction with patient care and residents' educational experience. However, the technology did not meet the nurses' expectations as they deemed that physical presence of an intensivist was an essential part of surgical ICU care.

6.4.3 Collaborative Communication Behaviors

Collaborative communication is a concept that embodies a combination of specific relationship-building communication qualities among team members working towards a common goal (Farrelly et al. 2003). This concept is often associated with favorable outcomes such as lower risk-adjusted patient mortality, increased nurse satisfaction with improved professional relationships, and enhanced physician learning, professional relationships and research utilization (Boyle and Kochinda 2004).

For example, one study illustrated the importance of collaborative communication during patient rounds using a Patient's Insight and Views of Teamwork (PIVOT) survey that solicits patient perception of teamwork (Beaird et al. 2017). This study was conducted in an inpatient acute care cardiology ward, and involved implementing an intervention—a structured interdisciplinary bedside rounding initiative called Rounding with Heart (RWH). Based on their observation of specific behaviors recognized in the RWH process, the authors reported multiple benefits associated with the intervention, namely: openness/inclusivity, patient centeredness, attending role/

shared leadership, non-confrontational learning, efficacy and team at bedside. The findings of the study also showed that patients had favorable perceptions of the RWH-based teamwork rounding process. The researchers also noted that RWH gave team members an opportunity to build mutual respect and collegiality through daily interactions, and could therefore be used as a means to address negative teamwork behaviors.

Although collaborative communication is an integral part of inpatient rounding, its effectiveness could be diminished due to a number of challenges. Hendricks et al. (2017) conducted a qualitative study to understand such barriers across four acute care units at a large urban hospital. They found that major factors affecting collaborative communication behaviors during interprofessional patient rounds are related to either team members or the healthcare environment, and are best described as opposite manifestations and highlighted in pairs (barriers versus facilitators). For team members, these facilitator–barrier pairs include high versus low turnover of team membership, structured versus unstructured rounding, valuing versus skepticism about interprofessional practice, and confidence versus hesitancy about skills. For the healthcare environment, the facilitator–barrier pairs are: rounding aligned versus mismatched with hospital's mission, time for rounding versus competing demands, geographically cohorted versus distributed teams, and readiness for change and innovation versus saturation.

Similar to collaborative communication during inpatient rounds, the effectiveness of patient handoffs also critically depends on seamless team communication to facilitate team-based workflows. To achieve a safe handing-off process of vulnerable patients such as neonates, Vanderbilt et al. (2017) suggested use of handoff training and communication practices among neonatal interprofessional teams including members specializing in obstetrics, gynecology and neonatology. They also recommended that the training should involve comprehensive, systematic, and standardized processes within handoff communication and through graduate and continuing medical education.

Another study investigating collaboration during patient handoffs led to the development of a continuity of care model that assesses clinicians' workflow before, during and after handoff in the critical care unit (Abraham et al. 2012). This model highlights important contextual factors that influence continuity of care provided by interdisciplinary teams. In the study, the authors used clinician-centered data and mixed inductive–deductive approaches to demonstrate the complex and interactive nature of patient handoffs as well as to capture and highlight sources of communication breakdowns. The descriptive framework developed through the study encompasses key features within the handoff communication process such as (1) multiple information flow paths and decision points, (2) non-linear and recursive nature of decision making and collaborative problem-solving activities, and (3) interactive nature of handoffs in a pragmatic critical care environment.

Additionally, it is important to ensure the consistency of the same patient information gathered by different members of the care team. Mamykina et al. (2016) evaluated handoff communication and coordination of patient care teams in a cardiothoracic ICU. Using categorical cluster analysis and a modified pyramid method, the authors assessed the degree of shared mental models between team members. The results revealed emerging patterns in the content and structure of interdisciplinary handoff communication, as well as content overlapping (e.g., patient name and an introductory history of the patient's presenting problem). With regard to the structure of interdisciplinary teams, the authors identified that different provider roles focused on different categories of content during their handoff communication. Based on these findings, they suggested the design of future handoff tools need to be conscious of the differences in clinician roles in order to properly coordinate these roles with existing practice.

In a related handoff study also conducted in the cardiothoracic ICU setting, Collins et al. (2012) analyzed handoff artifacts using sematic coding based on the interdisciplinary handoff information coding (IHIC) framework. The IHIC framework provides lists of handoff content specific to different disciplines and is a particularly useful tool to assist researchers in identifying handoff content important to nurses and physicians within certain clinical environments such as the ICU. Findings from their analysis showed a high degree of overlap in the content of nurses' and physicians' handoff artifacts. There was also a high degree of structure used for organizing and communicating handoff data when coordinating care across multiple disciplines within the critical care unit.

Similarly, Abraham et al. (2017) used mixed methods to develop and evaluate the degree of overlap in handoff communication across multiple care providers. Semantic similarity was used as the measure to estimate content overlap between nurse–nurse and resident–resident handoff communication for the same patients. Findings from their analysis showed a substantial amount of overlap for clinical content including active problems, assessments of active problems, patient identifying information, past medical history and medication/treatments; and less overlap for other content categories such as allergies, family-related information, code status and anticipatory guidance.

6.4.4 Collaborative Decision-Making Behaviors

Collaborative decision-making behaviors in healthcare can be defined as the process of engagement that seeks to devise an optimal plan of actions with a main focus on the highest-priority health-related problems that emerge from the confluence of medical and non-medical issues (O'Grady and Jadad 2010).

An example that depicts the collaborative decision-making process is involving patients in making decisions for cancer treatments after having them review treatment options along with their physicians, which has been shown to improve treatment effectiveness and patient satisfaction (Levit et al. 2013). Another study cited the benefits of collaborative decision making is the implementation of an integrated knowledge translation program involving researchers, managers, policy makers and clinicians in cancer screen and diagnosis (Gagliardi et al. 2014). The study reported an increased level of participation in cancer screening associated with the introduction of the program.

In a more recent study, Bomba (2017) highlighted the value of implementing a shared decision-making model during the course of patient care. They suggested that a shared decision-making process should be patient-centered, and made as a routine practice because of its potential to improve clinicians' ability for managing patients with complex chronic conditions. This shared decision-making process encourages clinicians offer their viewpoint that is aligned with the patient's goals for care. Essentially, all parties involved in the decision-making process, including patients, physicians and other decision makers (e.g. power of attorneys), should actively collaborate in making joint decisions related to care. This activity is particularly vital when a patient lacks the capacity and can no longer make decisions for themselves; or for care planning in advance when the patient would need to make decisions in preparation for an unforeseeable illness or injury.

To make shared decision-making processes less complex and easier to operationalize, Elwyn et al. (2012) introduced a three-step model based on existing conceptual description of collaborative decision making. The three steps are: choice talk, option talk and decision talk. Choice talk is a step to make sure patients understand available options of care; option talk provides detailed information related to the available options; and decision talk helps patients decide what is best for them based on their preferences. Notably, shared decision making requires building good relationships between patients and medical professionals during clinical encounters to encourage information sharing; as well as supporting patients in deliberating and expressing their preferences and views. This shared decision making will eventually help patients make informed decisions in their care process.

Similarly, Holmes-Rovner et al. used qualitative methods to evaluate a shared decision-making (SDP) program to determine its feasibility in fee-for-service healthcare organizations including physician offices and inpatient facilities (Holmes-Rovner et al. 2000). The program implemented in the study contained a set of interactive videodisks developed by the Foundation for Informed Medical Making (FIMDM), which were designed to improve efficiency in physician and patient treatment selection based on patient preferences. Their investigation showed that the shared decision-making program was perceived favorably by patients, with a right amount of information for patients to review before making an informed decision. Based on the findings from their study, the authors suggested that shared decision making should be incorporated into the informed consent process; and can be used as a quality indicator for provider- or payer-negotiated requirements during routine care procedures; (Holmes-Rovner et al. 2000).

6.5 Theoretical and Methodological Approaches for Studying Collaborative Workflows

Several theoretical and methodological frameworks have been proposed in the literature for studying collaborative workflows at both micro- and macro-levels. There are also frameworks specifically developed for studying collaboration in the context of health IT.

6.5.1 Micro-Level Approaches

There have been several micro-level frameworks available for studying the empirical aspects of collaboration, including patterns in which team members specify responsibilities and accountabilities for task completion (Grando et al. 2011; Papapanagiotou and Fleuriot 2014); different collaborative processes performed by teams including communication and decision making (Eikey et al. 2015; Kuziemsky et al. 2011; Nancarrow et al. 2013; Xyrichis and Ream 2008); and the means by which team leadership is established and tasks are assigned according to competencies and capabilities of team members (Wilk et al. 2016).

Micro-level conceptual models also exist, which can be used to guide studies on competencies needed in forming and maintaining collaboration, including common ground; shared knowledge and beliefs that enable collaboration to occur (Collins et al. 2012; Kuziemsky and Varpio 2010); and awareness—defined by Dourish and Bellotti as "the understanding of the activities of others which provides a context for your own activity (Dourish and Bellotti 1992)." These conceptual models are not directly relevant to team-based workflows; instead, they look at common knowledge and protocols that need to be developed, and shared among team members, as facilitators of a collaborative workflow. Finally, theoretical approaches for studying collaboration include the Actor Network Theory (McDougall et al. 2016) and the Activity Theory (Sadeghi et al. 2014).

6.5.2 Macro-Level Approaches

Macro-level frameworks are useful to develop a better understanding of collaborative workflows at the broader team-level by looking at the manner in which team members interact over time while completing their designated tasks. One such approach is social network analysis, which has been used to study the degree to which provider connectivity is associated with medication errors (Creswick and Westbrook 2015); and also to understand medication information exchange amongst team members (Chan et al. 2017). Other macro-level approaches for studying collaborative workflows include simulation, agent-based modeling and system dynamic modeling (Isern and Moreno 2015; Rosenman et al. 2018; Truijens et al. 2015).

6.5.3 Moving from Individual to Collaborative Workflow

Central to both micro- and macro-level approaches is the movement from individual to collaborative workflow. This movement can be challenging as it often requires changing the way in which individuals conduct their workflows (Kuziemsky 2015; Reddy and Spence 2008). Thus, an essential part of studies of collaborative workflows is understanding the relationship between individuals and teams (Lingard et al. 2017). Trade-offs often have to be made in moving between individual and collaborative workflows (Kuziemsky 2015), which emphasizes the need for developing common ground and shared mental models as a precursor to developing collaborative workflows. It is also worth noting that collaborative concepts and the rules that govern collaboration are dynamic and constantly evolving, and therefore collaborative workflows will need to be revised over time (Kuziemsky 2016).

6.6 Health Information Technology and Teams

Many health IT systems are developed with a focus on individual users, despite the fact that they are used equally often, or even more often, to support healthcare teams (Berg 1999; Berg et al. 1998). For instance, the core function of electronic health records (EHR) is generally viewed as a repository of patient information used by individual healthcare providers. While EHRs do serve as a patient information repository, they also help to support the collaboration between members of a care team by allowing them to be aware of what has been done for the patient by other team members (Reddy et al. 2003). Clearly, health IT systems such as EHRs or computerized physician order entry (CPOE) are used to support teamwork far more than what has been originally envisioned by their designers.

Although health IT-facilitated teamwork plays a crucial role in modern care processes, most health IT evaluation studies have focused on how well these systems support *individual* users; for instance, the suitability and effectiveness of their user interface for single-user interaction (Nelson et al. 1992). With a few exceptions (Berg 1999; Gorman et al. 2000; Reddy et al. 2001), evaluating the capability of health IT systems in supporting team collaboration is often neglected. This neglection could have severe consequences. For example, Han et al. demonstrated in their study the danger of implementing a CPOE system without paying adequate attention to collaborative workflows (Han et al. 2005). In their study conducted in a pediatric hospital, the authors found an increased mortality rate that was attributable in part to the implementation of the CPOE system. As they and others (Sittig et al. 2006) pointed out, a key reason for the adverse effect observed was that the system failed to support collaborative work activities, and in some cases prevented collaboration that would normally had taken place at the bedside and elsewhere in the hospital. The consequences of the “misfit” between health IT design and collaborative teamwork can thus be catastrophic.

One important way in which health IT systems support healthcare teams is by raising the awareness of patient conditions amongst team members. Individuals can coordinate their work more efficiently if they know about each another’s activities. For example, Bricon-Souf et al. (1999) argued that successful collaboration could not happen without effective information sharing among members of healthcare teams about their respective patient care activities. Obtaining shared awareness is therefore vital, and patients may suffer when such awareness breaks down (Reddy and Spence 2008). For instance, in a study conducted in a surgical ICU, Reddy et al. (2001) described a critical incident of patient requiring intubation due to the lack of nurse–physician communication regarding the patient's rising sodium levels. If the physician had been alerted quickly—i.e., if there were shared awareness between the nurse and the physician about this condition—the physician could have taken less drastic measures.

Teamwork activities are detailed, demanding, time-critical, and collaborative. At the center of this work is the patient whose health is dependent on the effective coordination between physicians, nurses, pharmacists, and a large number of other healthcare roles. In the highly collaborative and information-intensive clinical environments, health IT systems play a crucial role in supporting teamwork activities. They have become an indispensable tool for maintaining communication necessary for the effective and efficient functioning of collaborative healthcare teams.

6.7 Moving Forward for Health IT Design to Support Collaboration

Designing health IT to support collaboration is challenging due to the complexity of collaborative patient care delivery. To arrive at an effective design, we must first develop a thorough understanding of collaborative workflows of healthcare teams. This chapter addresses some of this quest, by describing collaborative workflows and related health IT design considerations. This chapter also contributes by presenting a synthesis of how to study collaborative healthcare processes. Collaborative workflows in hospitals and clinics are a social construction between patient data, healthcare providers and clinical processes, and we need to understand how these connections form prior to introducing technologies to automate them. Health IT design for collaborative workflows also goes beyond simply automating clinical tasks. There are a variety of technologies each playing a different role in supporting collaborative care delivery; for example, social media tools can be used to improve the connectivity for collaborating providers across disparate locations over the care continuum. However, establishing connectivity is not the same as supporting collaboration. Rather, collaboration requires the establishment of collaborative competencies such as common ground and shared awareness that may be specific for the task at hand.

While team training is a commonly used approach for supporting team-based care delivery, recent work has suggested that focusing on how to organize teamwork structures is equally important (Christofer et al. 2017). This chapter contributes to this line of thinking, in that we characterize team workflows according to their structures and associated behaviors. Structures represent different aspects of team configurations such as team composition or the degree of collaboration in a team. Behavioral aspects include the tacit or social workings of a team, and include trust, shared mental models, and collaborative competencies such as awareness and common ground.

A main takeaway from this chapter is that there is no *one-size-fits-all* strategy for designing health IT that effectively supports collaboration. Instead, the design must be customized to specific team structures and behaviors. Further, this chapter focuses on collaborative workflows, particularly collaborative information-seeking, communication, decision-making and interactional behaviors. All of these behaviors emphasize the need to nurture relationships between team members to develop rules of engagement to achieve and sustain effective team workflows. Rules of engagement are necessary to equalize team members and to reconcile differences in terminology or workflow that may impair collaboration. Drawing upon existing research on common ground and shared awareness can help us develop formalization of rules of engagement to ensure effective and efficient collaborative workflows.

Lastly, this chapter also contributes to the knowledge on how to evaluate collaborative workflows over time. In designing for collaboration, it is important to recognize that collaborative processes such as information-seeking or communicative behaviors are not static, but are dynamic and constantly evolving. To that end, health IT systems that we design to support collaborative workflows will need to be flexible so that they can adapt to accommodate changes in the collaborative processes.

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Chapter 7
Interruptions and Multitasking in Clinical Work: A Summary of the Evidence

Johanna I. Westbrook, Magdalena Z. Raban, and Scott R. Walter

7.1 Studying Interruptions and Multitasking

Any discussion of interruptions and multitasking needs to consider what is meant by these terms in relation to how they can be defined and measured. Many researchers (Walter et al. 2015; Grundgeiger et al. 2016; Rivera-Rodriguez and Karsch 2010) have noted the considerable heterogeneity and ambiguity of definitions used in the investigation of these phenomena, despite their common focus on the disruptive aspects of clinical work. Definitions of interruptions in healthcare have largely drawn from those applied to the study of interruptions in controlled experimental psychology (Trafton et al. 2003) settings. Much of this psychological experimentation has focused on investigating the cognitive costs to an individual when required to switch between tasks, either as a consequence of multitasking or being interrupted (Douglas et al. 2017). These ideas have been interpreted in a range of ways when introduced into the uncontrolled and more complex healthcare context. Several attempts have been made to review definitions and terms used in the healthcare domain and to either distil them into a universal definition (McFarlane 1997) or to define a set of common attributes (Brixey et al. 2007; Sasangohar et al. 2012). However, attempts to synthesise several definitions have often resulted in somewhat vague conceptualisations that have not moved this area of study towards definitional consensus. Walter et al. (2018) have instead argued for the need to move away from traditional interruption concepts towards the development of a more context-appropriate conceptualisation centred around the disruptive aspects of clinical work.

Compared to interruptions, multitasking in clinical work has been less well studied, yet it has been identified as another aspect of clinical work that may have work-

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flow and patient safety implications. Two distinct forms of multitasking have been characterised in the literature. Concurrent multitasking (or dual task performance) comprises two or more tasks being simultaneously conducted. This definition of multitasking is the most commonly applied in observational studies of clinical work (Douglas et al. 2017). In contrast, interleaved multitasking involves switching between several tasks that are progressing in parallel. For example, an emergency physician managing two patients at the same time and switching between tasks for these patients. Douglas et al. (2017) discuss both the concepts and definitions associated with the study of multitasking in healthcare, including the crossover between some multitasking and interruption definitions.

Despite the heterogeneity in definitions, there has been an underlying focus in observational studies of interruption and multitasking on aspects of clinical work that can contribute to individuals' cognitive load. When designing a new study, the central considerations in relation to the definitions to be applied are as follows. First, definitions should address the aims of the investigation and be able to be operationalised; second, both the definitions and the details of how they are operationalised need to be reported clearly. This is rarely done well in studies to date, but is essential to allow accurate interpretation of findings and comparison between studies.

7.2 Assessing the Frequency and Characteristics of Interruptions and Multitasking

Direct observational studies have been the main method by which interruptions and multitasking are studied in healthcare. Walter et al. (2015) provide a comprehensive discussion of some of the core challenges to performing quantitative observational studies of clinical work 'in the wild'. To determine the frequency and the relative burden of interruptions and multitasking in clinical work, there is a necessity to identify a denominator. Most commonly interruptions have been reported as a rate using time as the denominator, for example, the number of interruptions per hour. However, when interruptions are examined during specific clinical tasks, studies often report the proportion of these tasks that were interrupted. Studies examining concurrent multitasking have also used time as the denominator, but instead of counting the number of multitasking instances, they often measure the time spent in multitasking and report it as a proportion of the total time.

Table 7.1 provides a summary of the interruption rates and multitasking proportions reported across a range of studies using direct observation of clinical work in different countries. Comparisons of interruption rates across studies can be difficult due to the differences in definitions and observational methodology. The studies summarised in Table 7.1 use broadly similar definitions of interruption, analogous to the first definition presented in Table 7.2, and the same observational technique and data collection tool (Westbrook and Ampt 2009).

Table 7.1 Reported interruption rates per hour in studies that used similar interruption definitions and the Work Observation Method By Activity Timing (WOMBAT) technique and software for data collection

Population studied	Setting	Interruption rate (number of interruptions per hour)	Percentage of time spent in concurrent multitasking	Country	Reference
Physicians	General wards	2.9	20%	Australia	Westbrook et al. (2008)
Physicians	Surgical wards	13.1	33.5%	Italy	Bellandi et al. (2018)
Junior medical officers	General wards on weekends	6.6	20.9%	Australia	Richardson et al. (2016)
Resident physicians	General wards at night (10 pm to 8 am)	1.3	6.4%	Australia	Arabadzhiyska et al. (2013)
Nurses	General wards	2.0	5.8%	Australia	Westbrook et al. (2011b)
Nurses	Surgical wards	13.6	27.2%	Italy	Bellandi et al. (2018)
Nurses	Intensive care unit	3.3	–	Canada	Ballerman et al. (2011)
Pharmacists	General hospital wards[a]	3.1	2.4%	Australia	Lo et al. (2010)
Pharmacists	General hospital wards[b]	4.4	8.7%	Australia	Lo et al. (2010)
Pharmacists	Paediatric hospital	3.5	4.4%	Australia	Lehnbom et al. (2016)
Physicians	Emergency department	6.6	12.8%	Australia	Westbrook et al. (2010a)
Physicians	Emergency department	7.9	4.6%	Australia	Westbrook et al. (2018)
Attending and resident physicians	Intensive care unit	2.5	67%	USA	Hefter et al. (2016)
Registrars (Fellows)	Intensive care unit	4.2	24.4%	Australia	Li et al. (2015)
Physicians	Intensive care unit	3.8	–	Canada	Ballerman et al. (2011)
Respiratory therapists	Intensive care unit	3.5	–	Canada	Ballerman et al. (2011)
Unit/ward clerks	Intensive care unit	4.4	–	Canada	Ballerman et al. (2011)
Nuclear medicine technologists	General hospital	4.5	16.6%	Australia	Larcos et al. (2017)

[a]Pharmacists on wards without electronic medication system
[b]Pharmacists on wards with electronic medication system

Table 7.2 Examples of definitions of interruptions and multitasking applied in healthcare studies

Term	Definition	Reference
Interruption	External stimuli which results in an individual ceasing a task to attend to a new task. For example, ceasing a task to answer a question	Westbrook et al. (2008, 2011a)
Interruption	Process of coordinating abrupt change in people's activities	McFarlane (1997)
Interruption	A break in performance of a human activity initiated by a source internal or external to the recipients, with the occurrence situated within the context	Brixey et al. (2010)
Concurrent (or dual task) multitasking	The performance of two or more tasks conducting simultaneously. For example writing notes while also talking	Douglas et al. (2017)
Interleaved multitasking	The management of multiple tasks in which there is switching between tasks that are progressing in parallel	Douglas et al. (2017)
IT Interruptions	Perceived, IT-based external events with a range of content that captures cognitive attention and breaks the continuity of an individual's primary task activities	Addas and Pinsonneault (2015)

Observational studies of clinicians have shown that interruption rates tend to be higher in critical care settings (Westbrook et al. 2010a, 2018), among specialist consultants (specialists), and for particular types of clinical tasks (Westbrook et al. 2010a, b, 2011a; Walter et al. 2017). Most interruptions are generated by other co-workers, rather than patients, and are related to the provision of patient care (Walter et al. 2017; Weigl et al. 2012; Bellandi et al. 2018; Ratwani et al. 2017). Interruption rates also appear to vary between night and day shifts, (Arabadzhiyska et al. 2013) and between weekdays and weekends (Richardson et al. 2016). As may be expected, interruption rates appear to vary by country, with one study from Italy reporting rates two times higher for physicians and six times higher for nurses on surgical wards, than those reported in studies conducted in other countries (Bellandi et al. 2018).

Similar to interruption rates, the proportions of time spent multitasking vary between healthcare settings, health professionals, and countries (Walter et al. 2014). However, in contrast to interruption rates for the emergency department (ED), which are higher than on wards, ED physicians spend a lower proportion of their time multitasking. This may be indicative of the fact that individuals have greater autonomy over decisions to multitask than over interruptions, the latter of which are almost always in response to an external stimulus. In an environment in which external stimuli are frequent, such as the ED, physicians may choose to multitask to a lesser degree in order to reduce their cognitive load.

Some studies have focused on the frequency of interruptions and multitasking during particular clinical processes. These are often safety critical activities with direct implications for patient care, such as medication administration by nurses. Since interruption rates can vary between the types of clinical activities, understanding the frequency with which they occur during safety critical tasks has been regarded as important under the assumption that high rates are associated with increased safety risk.

Studies that have looked at interruptions during medication administration have used varying measures of interruption rates, making comparisons between studies fraught. Two studies in Australia estimated that between 35% and 53% of medication administrations are interrupted (Westbrook et al. 2010b, 2017). In the UK, nurses were interrupted an average of 2.6 times per medication round (i.e., during the administration of all medications for all the patients under a nurse's care) and in the US, 63% of medication passes (i.e., the administration of all medications to one patient) involved an interruption not relevant to the task at hand.

The reporting of multitasking during medication tasks has also used a variety of measures. One Australian study reported that multitasking occurred during 25% of medication tasks (Westbrook et al. 2011a), with concurrent professional communication occurring in 10.7% of medication tasks. Another Australian study estimated that nurses engaged in an average of 4.6 multitasks per 100 administrations (Westbrook et al. 2017). Other studies have compared multitasking rates in medication tasks to overall multitasking rates. In the ED, physicians were observed to multitask 4.6% of their overall time, but 20.1% of the time they spent prescribing (Westbrook et al. 2018).

7.3 The Role and Effects of Interruptions in Clinical Work

A considerable body of research on interruptions in healthcare has focussed on their potentially negative role in placing tasks at risk of error, incompletion or in reducing task efficiency. As the previous section illustrates, many descriptive studies have sought to capture the nature, source and occurrence of interruptions, largely in order to inform the design of effective interventions that are able to prevent or ameliorate their potentially negative effects. However, research evidence which directly links the occurrence of interruptions to negative task outcomes in clinical contexts remains relatively scant. An observational study in operating rooms showed that anaesthetists who immediately engaged with interruptions failed to check blood product details prior to transfusion (Liu et al. 2009). While a more recent study of caesarean section surgeries showed an association between procedure length and interruptions, but not with procedural complications (Willett et al. 2018). In an experimental study with radiologists who were interrupted while reviewing and dictating diagnostic reports, there was no significant impact of interruptions on diagnostic quality. A simulation study of physicians conducting central venous catheter insertion found that interruptions increased the time taken for the task as well as the number of attempts required (Jones et al. 2017). A few studies in the ED have identified a failure of physicians to return to interrupted tasks following interruption, but no specific consequences for care (Fong and Ratwani 2018; Westbrook et al. 2010a).

A direct observational study in two teaching hospitals, which examined the relationship between medication administration error and interruptions to nurses, found a significant positive relationship, whereby interruptions were associated with more errors and greater severity of errors (Westbrook et al. 2010b). Further, a study of emergency physicians demonstrated a significant positive relationship between interruptions and prescribing errors (Westbrook et al. 2018). That said, such studies reporting direct associations between interruptions and errors in clinical settings are still relatively rare. The methodological difficulties in identifying and reliably measuring task errors against which to assess the impact of interruptions are a significant and ongoing challenge (Lo et al. 2010). Unlike experimental studies, which focus on the association between a stimulus and individual response, studies of interruptions in the wild are very different. Clinical work is highly team-based, and the effects of disruptions on such collaborative work practices are not easily measurable (Kannampallil et al. 2016).

In concert with studies attempting to examine the negative effects of interruptions and multitasking on clinical work, there has been increased attention on understanding how in fact both activities may be important to clinical workflow. This work has focused more on understanding how interruptions and multitasking can be used effectively in managing the dynamic nature of clinical work. For example, studies by Walter et al. (2017) in the ED demonstrated the ways in which senior clinicians make themselves available to interruption as an integral element in supervising the work of more junior clinicians. Thus, in this context interruptions could be viewed as a key technique to achieve both efficient and effective workflows, which contribute to increased patient safety. Research in other fields on high reliability organisations may be of value in understanding how these work strategies may be beneficial.

One of the ways in which high reliability organisations are able to operate successfully in complex environments is to organise for collective mindfulness. Collective mindfulness has been described as *"a quality of organisational attention that increases the likelihood that people will notice unique details or situations and act upon them*" (p. 410) (Sutcliffe and Vogus 2014). Thus, some of the newer research findings illustrating the ways in which interruptions are used in healthcare point to their potential role in collective mindfulness, particularly in settings such as emergency departments. Further studies are required to explore the more nuanced ways in which interruptions may play an enabling role in safe and efficient care, besides being a potentially negative contributor to cognitive load and task errors.

Excessive rates of interruptions are assumed to negatively impact on clinicians' cognitive loads. Thus, distinguishing between necessary and unnecessary interruptions has been considered in some studies as a way to target interventions more effectively. For example, in a study of interruptions during medication administration, Westbrook et al. (2017) categorised whether observed interruptions were directly related to the medication administration tasks underway. They also excluded any emergency interruptions (e.g., a patient requiring resuscitation, or a patient who fell). Overall, they found that only a small proportion of interruptions were related to the medication tasks in progress. Other studies have asked clinicians the extent to which interruptions were of value (Weigl et al. 2017; McGillis Hall et al. 2010).

In contrast to the negative connotations directed at interruptions, multitasking is often viewed as a prized skill, even to the extent that the ability to multitask has been listed as a necessary skill for US emergency physicians (Perina et al. 2012). Considerably less research has been conducted towards measuring the likely effectiveness of multitasking in clinical settings (Werner et al. 2015). Existing evidence seems to suggest that multitasking may be associated with no improvement in task efficiency during handover (van Rensen et al. 2012) and multitasking among emergency physicians was shown to be associated with tasks failures during medication prescribing (Westbrook et al. 2018). Further, Weigl and colleagues (2017) found that ED physicians who received interruptions about patients that they were managing in parallel reported increased stress levels.

7.4 Interventions to Reduce Interruptions to Clinical Work

Drawing upon concepts used in aviation, such as the sterile cockpit, the most common approach to reducing unnecessary interruptions has been the use of barrier or isolation techniques. These have most frequently been trialled in studies designed to reduce interruption rates for nurses, especially during the medication administration process. These interventions have included the use of 'do not interrupt' tabards, sashes or flags, which signal that nurses are involved in a medication task and should not be interrupted; and locating specific medication administration processes in areas demarcated as 'interruption-free' zones. There is some evidence suggesting that such interventions can be effective (Raban and Westbrook 2014; Huckels-Baumgart et al. 2017; Dall'Oglio et al. 2017). A systematic review in 2014 (Raban and Westbrook 2014) reported 10 studies of interventions which had undertaken a quantitative assessment of their effectiveness on reducing interruptions and/or medication administration errors. Four reported a decrease in interruptions and one an increase. Three studies had multi-component interventions which incorporated a 'do not interrupt' element, and all reported a reduction in error rate. However, none of these studies used a controlled design so that attribution of the change in interruption rate to the respective intervention was not possible (Raban and Westbrook 2014). A subsequent randomised controlled trial (Westbrook et al. 2017) showed a significant decrease in interruption rate following the introduction of a 'do not interrupt' bundled intervention, but the authors of this study raised questions about the clinical significance of the magnitude of the reduction in interruptions on error rates (from 50 interruptions per 100 administrations to 34/100). Further issues have been raised about the acceptability and sustainability of this form of intervention in busy clinical environments (Westbrook et al. 2017). Thus, despite many studies seeking to demonstrate the value of barrier interventions to reduce interruptions there has been limited progress in establishing their effectiveness or long-term sustainability.

Improved understanding of interruptive behaviours in healthcare has prompted the reconceptualisation of potential interventions, in terms of a focus on how they can be used most effectively to support resilient work practices. Gao et al. (2017) suggest alternative approaches. First, the use of resilient engineering, which takes the view that if interruptions are a potential source of negative disruption to work then interventions should be targeted towards assisting clinicians to continue or quickly resume their primary task in the event of disruption. Such interventions might include the provision of cues which allow clinicians to easily resume tasks when interrupted. For example, Prakash et al. (2014) used visual timers to support nurses administering IV medications. Clinical information systems which identify fields remaining unfilled may be another type of cue to alert clinicians to incomplete steps in an interrupted procedure.

Identifying the cause of unnecessary interruptions and specifically addressing them through changes in resources or practices is another approach. For example, several studies of medication administration processes noted interruptions due to a nurse seeking access to the restricted drug keys. The cost to the nurse who is interrupting is low, but for the nurse being interrupted there is no clinical value and the cost may be high in terms of distraction from his/her primary task. Thus, identifying strategies such as considering the way in which drug rounds are organised and the likely demands placed on scarce resources (in this instance the drug keys) provides opportunities for reducing unnecessary interruptions of benefit to all staff.

Consideration of interruptions as an element of behaviours displayed in high reliability organisations is also likely to be a valuable approach. This does not suggest an unfettered use of interruptions, but an examination of the ways in which interruptions contribute to enacting collective mindfulness, and then identifying ways to optimise their use. Further, drawing attention to the role of interruptive behaviours through appropriate training should not be underestimated. In addition, specific training in handling interruptions in different clinical settings is also likely to be beneficial (Hayes et al. 2017; Cades et al. 2011).

7.5 Impact of Information Technology on Interruptions

Information technologies both create a source of new interruptions (e.g., in the form of electronic alerts (Baysari et al. 2011) and mobile devices allowing constant communication (Vaisman and Wu 2017)) as well as potentially reducing the need for some interruptions by providing greater concurrent access to information. Alert fatigue due to the excessive use of computerised alerts, which leads to a large proportion of alerts being ignored, continues to be a significant problem. However, once again the context in which these disruptions to clinical work occur has been shown to be important. For example, an Australian study (Baysari et al. 2011) showed that less than 20% of interruptive medication alerts generated by a computerised system were read by physicians on ward rounds, yet in the same hospital junior physicians at night considered over 80% of these alerts when prescribing medications (Jaensch et al. 2013). Thus, these interruptions to clinical workflow were deemed to provide variable clinical benefit.

Collins et al. (2006, 2007) investigated the impact of distractions and interruptions during clinicians' use of clinical information systems, and suggested that they may introduce new opportunities for errors related to data entry and data retrieval. However, there has been limited research specifically focusing on how interruptions impact clinicians use of clinical information systems. For example, the extent to which interruptions may be a contributor to new IT-related errors (Magrabi et al. 2012; Westbrook et al. 2013), which include incidents such as the incorrect selection of items from drop-down menus, or the opening of the incorrect patient record, is unknown.

7.6 Conclusions

The direction and sophistication of interruption and multitasking research in healthcare has started to change course. There is a continued need to move beyond descriptive studies to those that attempt to account for the complexity of these phenomena and the importance of the contexts in which they occur. Some observational studies have found associations between disruptive aspects of clinical work and errors in care delivery. However, there is some evidence of null effects, along with an emerging body of evidence demonstrating that interruptions, and to a lesser extent multitasking, may be effective strategies for dealing with a dynamic clinical environment and may contribute to greater organisational resilience. The mixed results partly reflect the diversity of healthcare, in that interruptions and multitasking may have different effects depending on the context, the specific scenario, and so on. The varied results may also represent the diversity in how interruptions and multitasking have been defined and conceptualised. By defining a broad range of interactions and behaviours under these terms, we then naturally observe a broad range of effects. Furthermore, evidence to date of the effects of interruptions and multitasking is based on studying the clinical work of individual clinicians. As yet, we have no clear evidence as to how these phenomena affect clinical work at the team or system level, which is an important topic for future research.

The literature suggests that efforts to support clinicians in managing the cognitive load of disruptive environments may be more valuable than blanket interventions to reduce interruptions (Westbrook et al. 2018). Identifying work practice and resource issues to avoid unnecessary interruptions should be considered, along with strategies which support recovery from interruptions such as the use of cues, and increased awareness of, and training about, how to effectively use these strategies to support safe and efficient delivery of care.

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Chapter 8
Reengineering Approaches for Learning Health Systems: Applications in Nursing Research to Learn from Safety Information Gaps and Workarounds to Overcome Electronic Health Record Silos

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8.1 Introduction

An effective learning health system can drive more efficient and safer care by adapting and aligning individual structures (e.g., applications) and processes (e.g., workflows) to optimize outcomes within a system of systems. Health systems engineering is an approach to effectively implement a learning health system. A learning health system is defined as a system in which "science, informatics, incentives, and culture are aligned for continuous improvement and innovation, with best practices seamlessly embedded in the delivery process and new knowledge captured as an integral

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by-product of the delivery experience." (The Roundtable 2012) Electronic clinical systems that are used to capture patient care data, for outcomes reporting, and to support safer care decisions, particularly in the hospital setting, are heavily reliant on nursing data capture and workflows. This chapter will outline 3 broad approaches that can be triangulated within a systems engineering framework to reengineer patient care workflows and overcome information silos by actively learning from safety information gaps and workarounds within a health system: (1) "In the lab" participatory design and usability evaluation, (2) "In the wild" observations, and (3) "In the metadata" models of health care processes.

Participatory design is a method for designing systems with end users, such as nurses, and is particularly important for designing clinical systems that are aligned with and embedded in clinical workflows. Within the clinical domain, efficient nursing workflows are essential processes that enable effective nursing practice and patient care. Consequences of poorly designed clinical systems for nurses are well-cited (Koppel et al. 2008) and are a barrier to achieving a learning healthcare system. Nurses have been described as particularly adept at identifying and utilizing workarounds to overcome poor system design, including information systems as well as hospital processes overall (Koppel et al. 2008). These workarounds can be observed "in the wild" by conducting observations of clinicians in the clinical setting, including time motion studies.

Workflows and workarounds are not limited to directly observable patient care activities; they also occur within documentation activities and can be modeled using metadata (data about data) from clinical information systems (Institute of Medicine (US) Committee on the Work Environment for Nurses and Patient Safety 2004; Collins et al. 2012). Documentation workarounds, as will be described in this chapter, can have unintended negative consequences, such as information loss. When analyzed quantitatively within a health systems engineering framework, workarounds can be leveraged as a source of information that signals expert patterns of care and knowledge to inform a Learning Health System. Evaluation of workarounds as an indicator of nurses' information needs and key data sources and expertise can also inform how to best balance structured data capture to maximize value and minimize documentation burden for each data point recorded.

Usability evaluation and observational studies of nurses using systems "in the wild" are important methodologies that complement participatory design to understand system and workflow dependencies and how to better align systems with nursing workflow. Further, analysis of documentation patterns can elucidate workarounds and corresponding practice patterns. The health systems engineering techniques that will be described in this chapter including participatory design, observational evaluations, and EHR (electronic health record) usage pattern analytics, can lead to key insights to inform system redesign. This type of approach may, for example, identify visualizations that bring together isolated data from the EHR into useful and patient-centered tools at the point of care to minimize information loss and support safe care, decision-making, and continuous learning. These techniques may also identify opportunities for optimizing patient-centered systems to decrease information and communication silos among care team members and patients. A health systems engineering approach promotes the use of these complementary methodologies for development and redesign of applications and their integration within a "system of systems". This chapter will provide an overview of participatory design and usability evaluation, workflow observations, and EHR documentation analytics to model health care processes within a health systems engineering framework and highlight how each method has been applied in nursing to promote learning, reengineering, and safer care to support a Learning Health System.

8.2 Background

The Institute of Medicine (IOM) Report "To Err is Human" called for a nationwide effort to stop preventable medical errors (Institute of Medicine (IOM) 1999). Among errors reported, it has been noted that 25% of medication-related injuries could have been prevented (Institute of Medicine 2007). Healthcare organizations have been tasked with addressing ongoing patient safety challenges and improving the quality of care. A variety of health information technology (IT) systems are increasingly being deployed within healthcare organizations to improve the safety and quality of care and support clinicians' workflows (Institute of Medicine 2003). Healthcare IT such as EHRs with clinical decision support (CDS), computerized provider order entry (CPOE) (Bates et al. 1998), electronic medication administration records (eMAR), and barcode medication administration (BCMA) have been touted as promising strategies for preventing medication errors (Bates 2000; CPOE 2003; Bates and Gawande 2003), and are particularly relevant to nursing care and workflows. For example, CPOE has been shown to reduce the incidence of serious medication errors by 55% (Bates et al. 1998). A systematic review conducted by Baysari et al. identified effectiveness of IT interventions (e.g., CDS, CDS with EHR or CPOE) to improve the appropriateness of antimicrobial prescribing in hospitals (Baysari et al. 2016). Barcode eMARs have been proven to support medication administration at the bedside for preventing medication errors (Scott-Cawiezell et al. 2009). One study performed by Paoletti et al. (2007) showed a 54% reduction of medication administration errors with BCMA and eMAR.

Although there is evidence for the improvement of medication safety with health IT systems, the IOM noted that health IT products are expected to improve patient safety only if the products are well-designed and strategically implemented (Committee on Patient Safety and Health Information Technology; Institute of Medicine 2011). Additionally, health IT systems could negatively impact organizational culture, workflow processes, siloed communication, and medical errors due to poor design and lack of integration with the clinical workflow (Campbell et al. 2006; Househ et al. 2013; Leslie et al. 2017). The integration of the health IT systems into nursing workflows is needed to optimize patient care delivery and to support safe care, decision-making, and continuous learning.

The need for a good fit between the health IT systems and routine clinical practice is recognized as essential (Bates et al. 2003; Ammenwerth et al. 2003; Beuscart-Zephir et al. 2001; Kuhn and Giuse 2001; LaDuke 2001; Staccini et al. 2001), and clinician time efficiency is one of the factors that is used to measure the successful implementation of the clinical system. Clinical data capture and documentation should be of high quality, efficient, usable, and clinically pertinent while supporting multiple downstream uses as a byproduct of recording care delivery (Cusack et al. 2013). Further clinical documentation should bridge information silos to enable shared decision-making and collaboration, enable collection and interpretation of information from multiple sources, and be automated whenever appropriate (Cusack et al. 2013). Clinicians spend a significant amount of time documenting, increasing the opportunity costs of using time for data entry versus knowledge generating activities and direct patient care (Poissant et al. 2005; Keenan et al. 2008; Mamykina et al. 2016; Hripcsak et al. 2011). When clinicians engage in task-switching and multi-tasking to manage their workload demand, documentation is deprioritized to enable a higher priority focus on direct care tasks (Walter et al. 2014). Decreasing clinician documentation burden—including nursing—is a priority of several professional organizations and government agencies, and a focus of the Quadruple Aim (Cusack et al. 2013; Agency for Healthcare Research and Quality (AHRQ) 2018; O'Brien et al. 2015; Payne et al. 2015). The first recommendation from AMIA's EHR 2020 Task Force Report was to decrease documentation burden (Payne et al. 2015). Our team found that on average, nurses perform 631–662 manual flowsheet data entries per 12 h shift (excluding device integrated data), averaging to 1 data point every 0.82–1.14 min in acute care (Collins et al. 2018). Other EHR log file analyses indicated nurses spend 21.4–38.2 min per day authoring notes, on average (Hripcsak et al. 2011); yet fewer than 20% of these nursing notes were read by physicians, and only 38% were read by other nurses (Hripcsak et al. 2011). In addition to the time quantified above for writing notes and documenting flowsheet data, nurses perform additional documentation including recording medication administration, documentation of patient education and plan of care, reviewing historical and current data, reading team notes, reading and sending electronic communications, and preparing the patient's discharge (Hripcsak et al. 2011). These activities are in addition to delivering direct patient care (Hripcsak et al. 2011).

In evaluating the impact of health IT systems on nurses' activities, some studies use documentation time as a primary outcome measure. A systematic review conducted by Poissant et al. revealed that the weighted average of the relative nursing documentation time with bedside terminals showed a 25% reduction in overall time spent documenting during a shift, and documentation time with a central-station desktop showed a 24% reduction (Poissant et al. 2005). Despite similarly weighted averages between bedside terminals and central-station desktops, the five studies that assessed bedside terminals were consistent and showed a time reduction while the two studies looking at central-station desktops had an increase (Poissant et al. 2005). Other studies conducted in critical care settings did not verify the reduction in documentation time after using EHR. (Marasovic et al. 1997; Menke et al. 2001)

Observational studies conducted by Westbrook et al. using the Work Observation Method By Activity Timing (WOMBAT) method also identified a distribution of the time spent on different nursing tasks and clinician's patterns of professional communication and documentation after introducing health IT systems (Ballermann et al. 2011; Westbrook and Ampt 2009; Westbrook et al. 2013). While qualitative data supported some improvement of time efficiency on nursing documentation, other studies pointed out a lack of user acceptance, and staff attitudes have been cited as a factor that hinders the implementation of health IT systems (Ash and Bates 2005; Ball and Lillis 2000; Robles and Karnas 2007; Clemmer 2004). For example, one study investigated nurses' perceptions of EHR and found that 64% of nurses perceived the EHR system did not decrease nursing workload. Additionally, only 44% of nurses thought the current system was optimally functional, and 61% indicated frustration with multiple EHR documentation workflows (Moody et al. 2004). When a misfit between the new IT system implementation and existing work processes occurs, it creates a frustration for healthcare providers and could result in workarounds while using the systems (Ignatiadis and Nandhakumar 2009).

Workarounds have been defined as alternative procedures employed by users to accomplish a task in response to a misfit between computer-based and existing clinical processes (Koopman and Hoffman 2003). Workarounds have been identified as creating negative consequences for the system implementation (Orlikowski and Yates 2006; Ash et al. 2007; Lapointe and Rivard 2005) and may lead to violations or deviations from safe operating procedures and standards, which can compromise a key objective of implementing these healthcare IT systems (Runciman and Walton 2007). Workarounds are caused by various reasons, such as inefficient process design, poor system usability, inadequate user training, and inflexible clinical guidelines (Edwards et al. 2008; Halbesleben et al. 2008; Vogelsmeier et al. 2008), and the efforts to eliminate workarounds are recognized difficult tasks (Hayes 2000). Various types of workarounds in various health IT systems have been identified in previous studies. For example, one study conducted by Koppel et al. identified causes and possible consequences of workarounds with an eMAR in a hospital (Koppel et al. 2005). In this study identifying the role of CPOE in facilitating prescription error risk, the study investigators found that workarounds such as post hoc documentation and the use of parallel paper systems for documenting medication administration caused confusion and the risk of information loss within the electronic system (Koppel et al. 2005). Another study conducted by Andersen et al. found a different type of workarounds such as transcribing medication orders from the computer to paper, while clinicians are using a range of computing devices to access a computerized provider order entry system (Andersen et al. 2009).

A study conducted by Poon et al. (2010) identified the noncompliance rate of scanning barcodes in BCMA and eMAR. Even though the study showed a 41% reduction in non-timing administration errors and a 51% reduction in potential adverse drug events from these errors, 20% of the drug administrations were given without the barcode scanning. Reasons for this noncompliance were the learning curve in the early stages of implementation and an early version of the software that required several improvements after the system implementation. That study concluded that the deployment of health IT should be thought of not as a single event in time but rather as an iterative process that requires modifications and improvements (Poon et al. 2010). When workarounds have been observed after implementing health IT systems, healthcare organizations need to re-evaluate the implementation and how the system fits in the current clinical practice in terms of improving patient safety, workflow efficiency, and perceptions of the clinical staff.

Workarounds that occur when related processes are not effectively reengineered also pose a risk to medication safety (Vogelsmeier et al. 2008). The effectiveness of these systems may be reduced when workarounds performed by users in response to the issues negate the system's benefits (FitzHenry et al. 2007). Therefore, we should assume new health IT systems will change the current workflows, processes, procedures, and policies. The re-design of workflows to preclude modified workflows of negative workarounds is required as preparation of the system implementation, as well as assessment of successful implementation after the implementation.

8.2.1 Health System Engineering: Participatory and User-Centered Design for Continuous Learning

The pace of adoption of IT in healthcare is rapidly increasing and the types of IT solutions vary widely. Nurses are a key clinician group who are facing challenges adapting to the use of clinical IT systems. A focus on the interrelationship between nurses, IT and the healthcare environment are fundamental to achieving a learning healthcare system. The need to investigate the impact of health IT from the socio-technical perspective has been broadly recognized (Sittig and Singh 2010; Westbrook et al. 2004, 2009), which advises that people-focused (socio) elements, organizational and human, and information technology elements (technical) are interdependent and must be evaluated together (Robertson et al. 2010). Several researchers have adopted socio-technical evaluation frameworks (Westbrook et al. 2004; Sittig and Singh 2010) using a range of methods (e.g. surveys, interviews, focus groups, task analysis, work sampling, results mapping, and outcome indicator data analysis) to understand the inter-dependency of these elements. Sittig and Singh (2010) outlined eight dimensions of assessment: (1) hardware and software computing infrastructure, (2) clinical content, (3) human-computer interface, (4) people, (5) workflow and communication, (6) internal organizational policies, procedures and culture, (7) external rules, regulations and pressures, and (8) system measurement and monitoring (Sittig and Singh 2010).

These frameworks illustrate the importance of addressing the interdependent relationship between the health IT and its social context where the health IT is implemented. Nevertheless, health IT usability and nursing workflow assessment are needed to ensure that health IT is compatible in existing nursing workflow, and any workflow changes do not result in unintended consequences from health IT implementation. A systems engineering framework includes the participatory design approaches commonly used to develop health IT applications and incorporated into the socio-technical models described above.

Reliable and computable data capture (i.e., data collected consistently and using standard formats) within commercially available EHRs is critical to building a Learning Health System (Collins et al. 2016) and achieving the Healthcare Quadruple Aim of improving patient experience, health of populations, reducing healthcare costs, and improving the work life of health care providers (Bodenheimer and Sinsky 2014). Reliable and computable data do not naturally emerge, even within the same clinical information system, without proper clinical governance and technical oversight that maximizes the value of data points captured by nurses while minimizing unnecessary burden (Collins et al. 2013a, 2016). Analytics of EHR metadata for usage patterns within a health systems engineering framework can identify nursing practice domains where EHRs impose a high documentation burden and domains where the data captured by nurses is: (1) siloed from other clinical data and (2) characterized by low reliability and computability for reuse.

A central goal of the Learning Health System is to generate knowledge rapidly and inform decisions to improve health (Friedman et al. 2014). To achieve these aims, nursing researchers are utilizing data science approaches to analyze large complex data sets to support nursing practice. Westra and colleagues in a recent review of the state of the science of nursing big data analytics, categorizes the current three main approaches of data science analysis—knowledge discovery, prediction, and evaluation (Westra et al. 2017), with most utilizing nursing-sensitive indicators (Montalvo 2007). The knowledge discovery studies attempted to find new meaning in patient specific factors (Lee et al. 2011, 2012; Merrill et al. 2015; Monsen et al. 2011; Topaz et al. 2016; Collins et al. 2013b), and identify associations or patterns of patient outcomes by utilizing data mining of electronic patient records and natural language processing (Topaz et al. 2016; Hyun et al. 2009). Prediction approaches sought to improve on existing algorithms or develop tools to predict risk factors or patient outcomes (Monsen et al. 2012; Cho et al. 2015; Kontio et al. 2014; Raju et al. 2015; Olson et al. 2014). Large data sets and big data analyses were utilized in evaluation studies to assess and evaluate new tools (Cho et al. 2013) or frameworks for patient outcomes, such as decision support systems (Bowles et al. 2015), care coordination (Topaz et al. 2017; Buis et al. 2013; Popejoy et al. 2015), or internet based portals (Shaw and Ferranti 2011). Within a systems engineering framework, data science approaches applied to EHR evaluation, particularly with an emphasis on knowledge discovery of novel documentation patterns and nursing sensitive indicators, can complement usability evaluation and observational studies to identify opportunities for reengineering nursing workflows, information silos, documentation burden, and safer patient care.

8.2.2 Fundamentals of Systems Engineering

The interdisciplinary field of systems engineering focuses on the design and management of complex systems over the system development life cycle: **problem analysis, design, development, implementation, and evaluation**. Systems engineering consists of a broad set of process analysis, design, and modeling methods that identify and prioritize potential high-impact problems, and implement system optimization solutions (Fanjiang et al. 2005; Mabry et al. 2010; Watts et al. 2013). Systems engineering methods can be applied to a broad range of healthcare processes to model workflow, data and information flow (Foster et al. 2010; Benneyan and Bond 2013; Peck et al. 2013; Benneyan et al. 2012). These activities optimize system design, prevent development of information silos, and ensure overall integration of health information technology (IT) components into a well-integrated "system-of-systems" (Mathews and Pronovost 2011; Pronovost and Bo-Linn 2012).

8.3 Systems Engineering Approaches for Health IT Applications

Health systems engineering approaches can be applied to support the development of health IT applications as well as their integration into a larger system of systems. Usability evaluation methods within a sociotechnical framework, such as workflow observations, task analysis, participatory design and usability testing are important systems engineering tools.

Usability evaluation methods are conducted where appropriate during each phase of the information technology (IT) development lifecycle, from conception through design and evaluation (Johnson et al. 2011; Schumacher and Lowry 2010; Saleem et al. 2009; Landman et al. 2014; Goodman et al. 2012; Johnson et al. 2005; Association UEP 2018; Kushniruk and Patel 2004). Integration of health systems engineering activities ensures that the role of the user (i.e., patients, family, healthcare providers) in system design is considered, specifically the user's relationship and interface with the environment, the technology, and the system as a whole. The goal is to understand the user's role and behaviors in identifying and mitigating risks in relationship to the system and the environment, so that workflow and IT system usability constraints can be addressed proactively. Specific theoretical and methodological usability evaluation frameworks will be discussed in detail later in this chapter. The following section provides an overview of systems engineering approaches and tools applied across all phases of the IT system development lifecycle, followed by case examples. Examples of systems engineering and human factor approaches that are useful across the system development lifecycle are included in Table 8.1.

Table 8.1 Systems engineering and usability tools by project phase

Problem analysis	Design	Development	Implementation	Evaluation
Systems engineering approaches				
• Process mapping and observation • Workflow analysis • Work sampling • Data analysis • Workflow observation • Critical incident Interviewing • Task analysis	• Engineering design methods/lifecycle • Reliability science design methods • Measurement alignment • Simulation and queuing models • Work, space, and flow design • Storyboards • Participatory design • Usability testing • Usability roundtables		• Learning and tests of change cycles • Compliance control charts and analysis • Lean and process simplification tools • Focus groups • Workflow observations	• Analytics of outcomes and usage data • Root cause analysis • Redesign 'what if' modeling • Control charts for local improvements • Critical incident interviewing • Surveys

8.3.1 *Problem Analysis*

8.3.1.1 Using Levels of Health IT Evaluation for Problem Analysis

Several models and frameworks have been proposed to identify factors influencing health IT usability (Yen and Bakken 2012). A stratified view of health IT usability evaluation (Fig. 8.1) (Yen and Bakken 2012) presents levels of health IT evaluation which incorporate both the system development life cycle (Stead et al. 1994) and socio-technical considerations. Level 1 of this model targets health IT specifications to understand user-task interaction to inform heath IT development. Level 2 examines the task performance to assess health IT validation and human-computer interaction. Level 3 addresses environmental factors to identify work processes and system impact in real-world settings. Task/expectation complexity, user variances, and organizational support are factors discovered during problem analyses and are factors that can influence the use of the health IT. Computer supported cooperative work (CSCW) (Pratt et al. 2004) and contextual design (Holtzblatt and Beyer 1997) involving structured observations and interviews of individuals and groups are used in the problem analysis phase to inform the design of health IT. Workflow assessment aims at detecting changes on the constructs of nursing practice.

To assess the impact of health IT on nursing practice, workflow assessment can be conceptualized from two perspectives: (1) workflow within the scope of human-computer interaction, and (2) workflow in the social context (environment). They can be represented by the Level 2 and Level 3 evaluation respectively in the stratified view of health IT usability evaluation model. Investigation with a clearer explication of interactions at the Level 2 and Level 3 evaluation help develop suitable solutions for issues discovered.

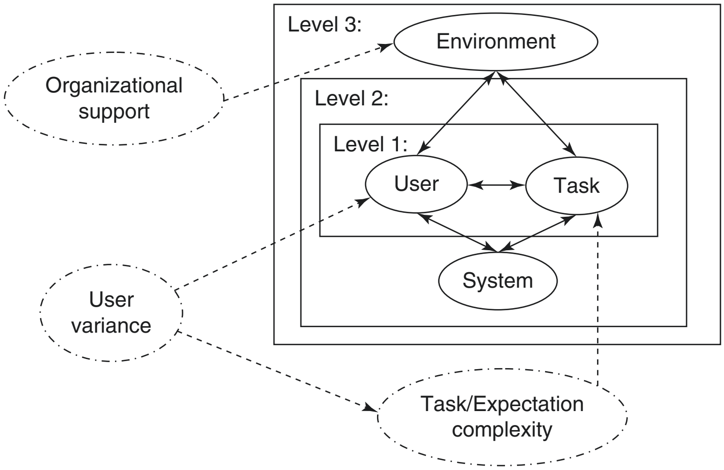

Fig. 8.1 Stratified view of health IT usability evaluation (Yen and Bakken 2012)

Assessing Nursing Workflow Within the Scope of Human-Computer Interaction

Human-computer interaction studies focus on the relationship between human and computers (or health IT). Cognitive walkthrough (Wharton et al. 1994) and Think Aloud Protocol (Jaspers et al. 2004) are two common usability methods, commonly referred to as human-factors approaches, to assess health IT (Jaspers 2009), and to discover the interactive workflow. Cognitive walkthrough identifies actions and goals needed to accomplish tasks, and is often conducted by HCI experts; Think aloud protocol, conducted by end-users, encourages end-users to express out loud what they are looking at, thinking, doing, and feeling, as they perform a task (Lewis 1982).

For example, one study evaluated an electronic perioperative nursing documentation system using cognitive walkthrough, and identified usability problems in the interactive process (Usselman et al. 2015). Another study extended the traditional cognitive walkthrough approach to groupwise walkthrough, and described the collaborative workflow between nurses and case managers in home care (Pinelle and Gutwin 2002). A systematic review of usability evaluation studies reported that cognitive walkthrough and think aloud protocol were used in 49 (26%) studies (Ellsworth et al. 2017). A think aloud protocol study evaluated a nursing information system (Rogers et al. 2013). In that study, participating nurses expressed their thoughts about the interactive process as well as how the system might impact their workflow, such as team communication, and the efficiency or effectiveness of their work. The study identified usability issues in the interface design as well as nurses' concerns about work processes (Rogers et al. 2013).

Assessing the human computer interaction process has become a standard process to identify interactive issues in health IT. Unified Modeling Language (UML) (Booch et al. 1998), a graphical representation approach, can be used to illustrate the interactive workflow between health IT and end-users and inform prototype design (Machno et al. 2015). As usability evaluation is an iterative process, problems identified at Level 2 should be addressed before moving on to the Level 3 evaluation. Once a health IT has been demonstrated to be usable at the human computer interaction stage, the Level 3 evaluation would further incorporate environmental factors to satisfy the socio-technical model where technology should be investigated within the social context.

Assessing Nursing Workflow in the Social Context and Clinical Environment

Interviews are used to elicit user's needs and preferences to provide a deeper understanding of their experience and identify additional social-technical factors. Workflow analyses can be used to validate interview findings and to explore opportunities for use of health IT applications in the current practice of care on patient care units.

Observational studies, such as time motion studies, inform how health IT is being used in practice as well as among other competing tasks. Time motion studies have been used to examine nurse' work pattern, workload, and time allocation of nursing activities (Westbrook et al. 2011, 2013). Through understanding the time allocation of nursing activities, new strategies could be developed to improve quality care (Mallidou et al. 2013). However, most time motion studies have not specified the time period of the observation (Westbrook et al. 2007, 2011; Abbey et al. 2012; Sakai et al. 2016; Wright et al. 2015). When the time period is underspecified, it is unclear if the data might be skewed due to observers' time availability, or if the observer's fatigue was taken into account for quality control if a long-hour observation (8–12 h) was required. In addition, although task definitions were provided, the start and the end time point of each activity are often not reported, thus limiting the replication of the study. Other methodological limitations also include randomly selected observation time (Westbrook et al. 2007; Tuinman et al. 2016; Gartemann et al. 2012), self-report approach (Hendrich et al. 2008), manual paper-based & stop watch data collection (Abbey et al. 2012), and focusing on a single nursing activity (e.g. documentation (Wong et al. 2017; Read-Brown et al. 2013), medication administration (Elganzouri et al. 2009; Qian et al. 2015, 2016), communication (Popovici et al. 2015), glycemic control (Gartemann et al. 2012)).

8.3.2 Design

Design is informed by findings from the problem analysis phase and may include definition of the content, display, and workflow integration strategies most likely to address requirements and overcome barriers identified in Phase 1. Participatory design should ensure that requirements for health IT applications address differing stakeholder (e.g., patients, family, nurse, physicians) goals and the tasks necessary to achieve those goals. Common themes for requirements specification are prioritized, mapped to new processes and tools, and used to inform the development of prototypes. Low fidelity prototypes of processes and tools are developed and iteratively refined in collaboration with stakeholders using develop-test-revise iterations to identify components to be included in the detailed design for high fidelity prototypes.

8.3.3 Development

Once the design of a tool is finalized, iterative testing and evaluation is conducted with stakeholders, including nurses. In this phase, initial testing may be conducted using focus groups and interviews iteratively refining the prototypes until a working prototype is accepted by the stakeholders. Testing and further development with stakeholders continues until the final product is developed. An iterative process of prototype refinement and usability testing whereby the prototypes are tested by representative users (Usability.gov 2018) continues until sufficiently mature and implementation-ready versions of processes and tools are developed and validated by stakeholders.

8.3.4 Implementation

Implementation may begin with a series of pilot implementations to continue learning and refinement within a Learning Health System. For example, health systems engineering methods and tools used as part of the piloting and implementation phase include process-flow mapping and analysis, work design and simplification, root cause analysis, workload estimation, and general principles from lean and six sigma to evaluate the impact and to refinement of the intervention on workflow and patient care. During this phase, the identification and understanding of the emergence of new tasks, procedures and workflow patterns provide an opportunity to enhance workflow processes to facilitate system use and to correct any “bugs” or unintended consequences of health IT that could lead to “workarounds” and impede adoption.

8.3.5 Evaluation

In the phases above we describe specific usability evaluation methods for workflow reengineering, which should be iteratively applied so that problems identified at Level 2 should be addressed before moving on to the Level 3 evaluation. Once a health IT tool is demonstrated to be usable at the human computer interaction stage, the Level 3 evaluation would further incorporate environment factors to satisfy the socio-technical model where technology should be investigated within the social context. In addition, interviews using methods described in the problem analysis phase can be applied to identify user perceptions and experience after reengineered workflows and tools have been implemented, informing a continuous learning cycle for optimization.

Within a broad health systems engineering framework, evaluation also includes a range of process and outcome measures. Such measures may include clinical outcomes, such as adverse event rates, or usage analytics to evaluate end-user engagement with the system being evaluated. A continuous learning cycle for iterative evaluation to comprehensively identify system weaknesses and inform optimization can be complemented with data science methodologies to understand the amount, quality, and metadata patterns of system usage and data captured within clinical systems. In studying nursing documentation workflows, data science methodologies evaluating usage data and documentation patterns provide valuable tools for the analysis of EHR interactions. Critical to this data science process is the contribution of nursing domain knowledge to provide context to these data (Westra and Peterson 2016).

As the title of Bakken and Brennan's work "Nursing Needs Big Data and Big Data Needs Nursing" (Brennan and Bakken 2015) asserts, while data science is useful for processing big data, nursing science and practice encapsulates expertise in diagnosis and treatment of human responses. Therefore, clinical nursing domain experts that understand nursing practice and workflows are essential when determining what data are appropriate and particularly helpful for clinical analytics.

Data science methods are essential to track patient states across settings, health professionals, and research databases, however these methods require common data definitions to group similar patients across sites and providers, enabling the identification and tracking of patient need and outcome patterns. Nurse-sensitive patient indicators are defined as "those outcomes that are relevant, based on nurses' scope and domain of practice, and for which there is empirical evidence linking nursing inputs and interventions to the outcome for patients" (Doran and Almost 2003). Nursing-sensitive quality indicators reflect the structure (e.g., nursing education or certification at an institution), process (e.g., nursing assessments, nurse job satisfaction), and outcomes (e.g., patient falls, pressure ulcers) of nursing care (Montalvo 2007). There are a number of nationally recognized quality indicators (Owens and Koch 2015), however the National Database of Nursing Quality Indicators (NDNQI®) (Montalvo 2007) is the most widely used and influential set of nursing outcomes. Capturing data on care and/or outcomes most impacted by nursing provides essential outcomes measurement to support Learning Health System analytics which should be a driving focus to standardize nursing data sets for capture in EHRs. Standardized (or minimum) data sets, can be used to represent EHR data, such as non-standard flowsheet data, and can be enhanced for capturing relevant documentation workflows that impact and enable effective data analytics (Ahn et al. 2015; Delaney and Westra 1991; Delaney et al. 2015; Ranegger et al. 2015; Williams 1991; Werley et al. 1991). Standardized data sets that identify a specific collection of data elements necessary to represent a given clinical domain or topic are referred to as a "detailed clinical model" or more simply a "reference model" (Moreno-Conde et al. 2015; Kim and Park 2011; Park et al. 2011). Openly available resources of existing reference models are available for use to guide iterative optimization of system design and analytics of clinical data (openEHR Foundation 2016; Intermountain Healthcare 2015; Health Level 7 International 2017; Hoy et al. 2009; Oniki et al. 2016; Pedersen et al. 2015).

8.3.6 Use Cases of Pragmatic Applications Grounded in Theoretical and Methodological Approaches Within Systems Engineering Framework

In the following sections we present use cases of pragmatic applications grounded in theoretical and methodological approaches within a systems engineering framework. Use cases will be presented from four studies:

1. **The Brigham and Women's Hospital (BWH)/Northeastern University Systems Engineering (NUSyE) Patient Safety Learning Lab**
   The BWH/NUSyE Patient Safety Learning Lab was established in order to apply a systems engineering approach to design safer and more reliable healthcare processes and to improve patient and family engagement in their safety plan during an acute hospitalization. Key stakeholders, in addition to patients and family members, were the care team members on the acute care clinical units targeted in this lab, including nurses and physicians. Using health systems engineering approaches, an electronic Patient-Centered Safety Plan (PCSP) IT infrastructure was developed to address patient safety threats in real-time and to support continuous learning. The PCSP IT infrastructure included the following: (1) A Patient-Centered Safety Plan Portal to provide patients and family with the core set of information needed to participate in their personal safety plan during a hospitalization, (2) A Patient-Centered Fall Prevention to engage patients, family, and care team members in the fall prevention process, and (3) MySafeCare, an application to facilitate patient reporting real-time safety concerns.
2. **Exploration of Nurses' Time Allocation and Multitasking: A Time Motion Study**
   To address the methodological limitations of time motion studies described previously, an example of a time motion study will be presented (Yen et al. 2016). The time motion study (Yen et al. 2016) shadowed registered nurses (RNs) during the regular working shift and used the TimeCaT tool which is an open-source comprehensive electronic time capture tool that was developed to support time-motion studies (Lopetegui et al. 2012; TimeCaT 2015).
3. **Analytics of Nursing Data to Identify Healthcare Process Models**
   We will describe work by Collins and colleagues (Collins et al. 2012, 2013b; Collins and Vawdrey 2012) that uses analytics of nursing data to identify health

care process models (HPMs) as an example of how data science methods can be used to evaluate health systems, including nursing documentation workflows, workarounds, and information silos. These HPMs are generated by EHR utilization data and embedded with information about clinical practice, can be applied to evaluation studies, and also used for predictive modeling that leverage HPMs as proxies of clinician concerns and decisions.

4. **Standardized Clinical Data Element Reference Models**
   Collaborative projects focused on defining standardized clinical data element reference models will be described to illustrate how they can both inform iterative optimization of system design and analytics of clinical data. These models define system implementation workflows and functionality that drive documentation practices, and ultimately data used for secondary analyses. We will describe case studies that highlight the use of these models for the evaluation and optimization of nursing documentation within EHR systems.

8.3.6.1 Problem Analysis: Use Case Examples

Interviews and Workflow Observations to Assess Nursing Workflow in the Social Context and Environment

In the BWH/NUSyE Patient Safety Learning Lab individual Interviews and Focus Group Sessions using semi-structured interview guides were used to learn about the needs and preferences of patients and healthcare providers and other social-technical factors related to patient engagement in developing their safety plan. The goals of the interviews and observations were twofold: (1) to inform investigators' understanding of the current state of patient engagement in developing their safety plan (e.g., formal plan to keep them safe during an acute hospitalization) and, (2) to identify core requirements for developing a set of tools and processes to facilitate routine engagement of patients in identifying areas of safety risk and a plan to mitigate risk (Fig. 8.2). The interviews informed the current state of existing processes of care from the perspectives of stakeholders. After conducting these sessions, project investigators followed basic content analysis methods (Krippendorff 2012) to interpret descriptive data obtained from the interviews. The focus group sessions were recorded, transcribed, and evaluated to identify perspectives about the degree to which patients are engaged in developing a safety plan in the current state, perceived barriers and facilitators to patient engagement, and core system requirements for tools to facilitate engagement.

A workflow analysis was completed to: (1) identify and document current workflow patterns, (2) consider how they might be impacted by technology, and (3) identify the types of tools and or processes needed to ensure end-user buy-in and workflow integration (see Fig. 8.3). This information was then used to inform the configuration of the intervention and to anticipate needs for training.

Within the BWH/NUSyE Patient Safety Learning Lab interviews and workflow analyses revealed that patients and family were not routinely engaged in their safety

Pt./Family Study ID#:______ Unit#:____ Interview Date:______ Interviewer:______

Topic 1 **Background Information**	To begin, we would like to learn some background information related to your knowledge about falls. - Could you tell me how often and what time of the day your family usually visits you in the hospital? a. PROBE: How engaged or involved are they with your care? - Have you fallen before and in what setting? a. PROBE: Did you suffer any injuries? b. PROBE: Has anyone close to you fallen before? - Are you afraid of falling at home or at the hospital? a. PROBE: Tell me what you do to actively prevent falls? - How many people do you think fall during a hospital stay each year? *(Comment #1: Researcher states that "1/3 of people above age 65 fall, and regardless of age being hospitalized increases risks for falling and fall injuries.")*
Topic 2 **Fall Risks**	Now, we would like to ask you about risks for falling. - Did your nurse communicate with you about your risks for falling? a. PROBE: When was this communicated and how often? b. PROBE: To what extent were you involved and in what way? c. PROBE: Was your family involved in any way? - Tell us your risks for falling as suggested by your nurse *(Comment #2: Researcher states "nurses fill out a fall risk assessment form upon your admission based on an established fall scale")* - Would you be willing to complete a fall risk assessment form with your nurse that would identify why you're at risk for falling and subsequently develop a fall prevention plan? *(Comment #3: If patient isn't willing to, then researcher explains "evidence from research shows filling out a risk assessment form with your nurse can reduce risks for falling at hospital" and asks "tell me your concerns about participating in the fall risk assessment")* a. PROBE: Would you be willing to do this every day? b. PROBE: To what extent would you want to be involved and in what way? c. PROBE: Would you want to involve your family in this process? - Tell us what your family knows about your fall risks. a. b. PROBE: Would you want the nurse to communicate the risks to your family?

Fig. 8.2 Sample interview guide

plan during an acute hospitalization. We learned that workforce training related to the value of patient engagement was needed. In addition, we learned that the Patient-Centered Safety Plan tools needed to be integrated with the electronic health record and patient safety event reporting systems to facilitate workflow. We also learned

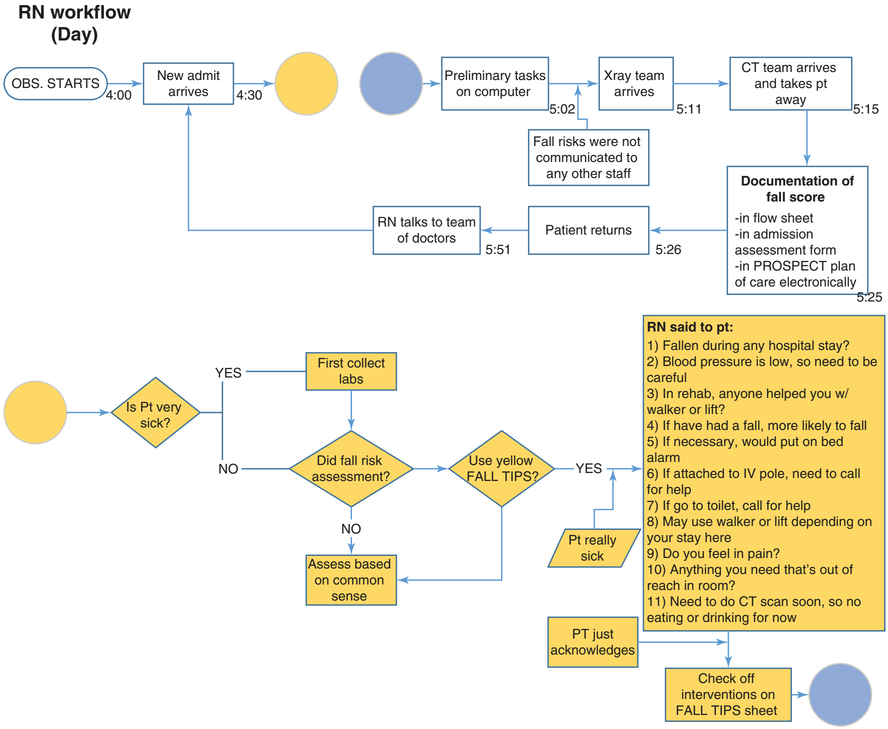

Fig. 8.3 Sample workflow observation related to patient engagement in 3-step fall prevention process

that a range of low (e.g., paper) to high technology (e.g., mobile apps, patient portal, electronic whiteboard) tools were needed to ensure that all patients, even those who were not willing to use technology, were able to engage in their safety plan.

TimeCaT Time Motion Studies to Assess Nursing Workflow in the Social Context and Environment

The example time motion study was (Yen et al. 2016) intended to address common methodological limitations of time motion studies described previously, such as data sampling issues. The study shadowed registered nurses (RNs) during the regular working shift. The observations occurred in the general patient care areas including the nursing station, hallway, medication room, patient room, and supply areas. The typical 12-h nursing working shift was split into three time blocks: 7 a.m.–10:59 a.m., 11 a.m.–2:59 p.m., and 3 p.m.–7 p.m. The 4-h observation time block minimized the chance of un-balance data if a 12-hour working shift has an unusual heavy or light workload. In addition, to ensure the data quality the study implemented a three-phase data collection process, including (1) trial phase—generate and confirm observable nursing activities, (2) training phase—establish inter-observer reliability, and (3) observation phase—data collection with confidence. The trial and training phases help introduce the study and study personnel to nurse participants as well as other unit personnel. The prolonged engagement could also minimize the Hawthorn effect.

TimeCaT (Lopetegui et al. 2012; TimeCaT 2015) a comprehensive electronic time capture tool was developed to support time-motion studies. TimeCaT records data in three activity dimensions: *communication*, *hands-on task*, and *location*. The *communication* dimension captures with whom nurses are interacting; *hands-on task* allows for recording of tasks that require nurses to physically touch the patient or care equipment required to perform a task (i.e. patient assessment); and the *location* variable allows capture of where nursing activities take place. This approach allows capture of information about the time spent on nursing activities as well as the phenomenon of multitasking in nursing practice. Figure 8.4 shows the sequence of nursing activities (nursing workflow) during a 4-hour observation. The data collected provide opportunities to analyze nursing activities quantitatively, as well as qualitatively by visualizing nursing workflows that reveal the context of nursing activities (hands-on tasks with information of communication and location) (see Fig. 8.5). With similar approaches, future studies investigating nursing workflow change before and after the implementation of a new health IT could discover the impact of health IT on workflow as well as identify environmental support needed for nurses.

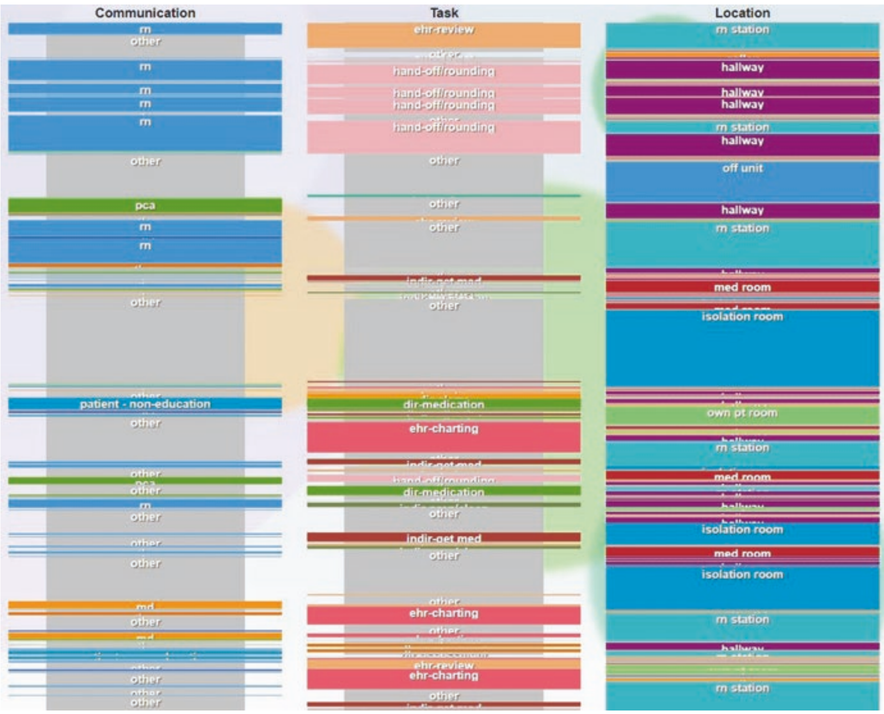

Fig. 8.4 Nursing workflow visualization

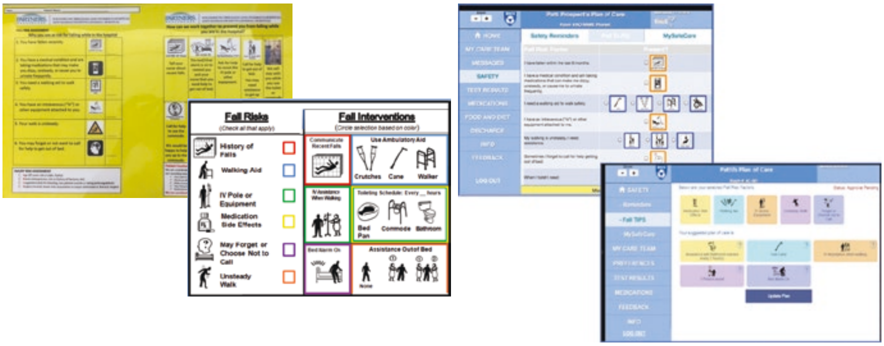

Fig. 8.5 A series of paper and electronic prototypes were developed to engage stakeholders in a discussion of the content, display and workflow requirements for engaging patients and family in their safety plan during an acute hospitalization

8.3.6.2 Design: Use Case Example

In the BWH/NUSyE Patient Safety Learning Lab, an interdisciplinary project team ensured that differing perspectives were captured in the design phase. Findings from Phase 1 were used to identify requirements for health IT applications that address stakeholder goals and the tasks necessary to promote patient engagement in their safety plan. As a part of the design process, team members defined the content, display, and workflow integration strategies most likely to address requirements and overcome barriers identified in Phase 1. Common themes were prioritized, mapped to the new processes associated with the planned intervention and then used to inform the development of the tool prototypes. An initial mockup of each tool was developed and refined by the project team. Prototypes were then further refined though focus group interviews with stakeholders (patients, family, and care team members) using develop-test-revise iterations to identify components to be included in the detailed design.

After this process, a detailed design was developed by mapping out the core and interdependent functions of the Patient-Centered Safety Plan tools along with the specific patient requirements. Prototype graphical user interfaces were used to engage with stakeholders and to get direct feedback from the users.

8.3.6.3 Development: Use Case Example

Once the design of the tools from the In the BWH/NUSyE Patient Safety Learning Lab were finalized, iterative testing and evaluation of the Patient-Centered Safety Plan tools were conducted with patients, family, and other stakeholders, including nurses. In this phase, a project team did initial testing using focus groups and interviews until a working prototype was accepted by the stakeholders. Testing and further developing with hospitalized patients continued until the final product was developed. An iterative process of prototype refinement and usability testing continued until sufficiently mature versions of the Patient-Centered Safety Plan tools were developed and validated by stakeholders. To perform usability testing, we developed

Fig. 8.6 The Patient-centered Safety Plan Sample "low -tech" and "high-tech" tools for engaging patients in their safety plan during and acute hospitalization

case scenarios that included a set of tasks associated with engaging patients in identifying safety risk factors and identifying an evidence-based prevention plan. We asked end users (nurses and patients) to use the tools to complete the tasks. The usability sessions were monitored by a research team member who observed the participants to see whether they could complete the tasks without instruction. The observer recorded areas of difficulty and asked questions about the process and use of the tools at the end of the session. Data from these sessions were used to refine the Patient-Centered Safety Plan tools. The final version of the Patient-Centered Safety Plan tools, which included both "low-tech" and "high-tech" tools was then formally implemented in Phase 4 (Fig. 8.6).

8.3.6.4 Implementation: Use Case Examples

Implementation of the Patient-Centered Safety Plan tools in the BWH/NUSyE Patient Safety Learning Lab started with a series of pilot implementations. The project team used systems engineering methods and tools including process-flow mapping and analysis, work design and simplification, root cause analysis, workload estimation, and general principles from lean and six sigma to evaluate the impact and to refine the Patient-Centered Safety Plan tools. For example, the project team looked for the emergence of new tasks, procedures and workflow patterns. The pilot implementation provided an opportunity to enhance the software and to correct any "bugs" that could lead to "workarounds" and impede adoption. The project team conducted a human factors evaluation regarding use of the Patient-Centered Safety Plan tools by patients, nurses, and physicians. The goals of these observations was to determine: (1) the facilitators of and barriers to effective use; and (2) how communication and collaboration process changed from the pre-intervention to intervention period. This information was used to refine the tools and educate patients and care team members about the tools over the course of implementation process. Failure Modes and Effects Analysis (FMEA) was used to analyze the potential failure modes, the effects of failure, and causes with evaluating their severity,

Table 8.2 Failure modes and effects analysis (FMEA) for the patient-centered safety plan tools

Item/function	Potential failure mode(s)	Potential effect(s) of failure	Severity	Potential cause(s)/mechanism(s) of failure	Probability	Current design controls	Detectability
Organization	Patient lack of education	Patient doesn't understand use of display	6	Delirium, clinicians not doing enough to educate, patients not always receptive to ed.; pt. might not 'receive' that the info has to do with them	7	Engagement rounds	7
Users	Patient not physically able to see the screen saver (visual impairment)	They can't see it/ understand their safety plan; fall	4	Physical impairment; environment; mobility issues	5	None	3
Environment	Screen facing away from the patient	They can't see it/ understand their safety plan; fall	3	Requested it off, moved it away, screen is also used for charting (competing priorities)	9	Staff trained to rotate screen toward patients	2
Technology	User Interface	Not understanding safety plan	4	Font size, colors, understanding	3	Usability testing	7

probability and detectability of the failures (Table 8.2). The pilot implementation also provided an opportunity to test the integrated system in the wild and identify both socio-technical factors to inform system versioning or unintended workflow consequences that may have been unrecognized that could limit effectiveness or create excessive work burden on care team members.

8.3.6.5 Evaluation: Use Case Examples

Evaluation of Heath IT systems can leverage analytics of usage data informed by clinical domain experts to identify and define Healthcare Process Models (HPM). Collins et al., have developed Healthcare Process Models of Clinical Concern (HPM-CC) which are generated from perceptions, interpretations, and recordings entered by clinicians (e.g., nurses, physicians), and are based on clinician decisions to observe and enter data in the EHR (Collins et al. 2012, 2013b; Collins and Vawdrey 2012). These HPM-CCs are used to identify nursing documentation workflows that are associated with a nurses concern about risk for patient deterioration. These types of models demonstrate that EHR utilization patterns are rich in information that can be used to understand and evaluate system design to support clinical care processes such as nursing surveillance activities and decrease information and communication silos (Hripcsak and Albers 2013). Collins and colleagues' data mining of nursing documentation workflows identified signals from annotations or comments placed in flowsheets that were associated with nursing surveillance patterns and patient outcomes (Collins et al. 2012). Triangulating those data with qualitative findings elucidated that nurses were utilizing free text comment fields as a documentation workaround to convey concern for a clinical change in patient state, and that these important data may be missed by other care team members (Collins et al. 2012).

Standardized Clinical Data Element Reference Models

Efficient documentation workflows often leverage EHR functionality that anticipate and facilitate clinicians in navigating to relevant modules within the EHR based on prior or current actions and selections, such as showing or hiding fields depending on prior data entered. When an EHR is well-designed, these documentation workflows can be effective in increasing the efficiency and completeness of documentation. As discussed previously in this chapter, improvements in time efficiency is a primary outcome used to measure the successful implementation of a clinical system. Usage analytics from clinical systems can be used to quantify documentation burden by calculating data points recorded by nurses as a complementary method to observational studies to understand nurses' documentation burden (Collins et al. 2018). EHR facilitated documentation workflows are particularly prevalent for nurses in the inpatient setting given the significant amount of patient assessment and intervention data documented in flowsheets by nurses (Penoyer et al. 2014). Secondary analysis of these data requires sufficient metadata to differentiate missing data from not applicable data. For example, information is needed to determine which fields: (1) were available in the nursing workflow and were completed (i.e., captured data), (2) were available in the nursing workflow but not completed (i.e., missing data), or (3) were not available in the nursing workflow and therefore were not completed (i.e., not applicable for a given patient) (Westra et al. 2015). Westra and colleagues described these challenges in a study modeling flowsheet data for quality improvement and research, and presented lessons learned including an overall need for standards to represent flowsheet data (Westra et al. 2015). When nursing documentation reference models are data-driven, informed by best practices, validated by domain experts, and openly shared, they can serve to standardize nursing workflows, decrease nursing documentation burden, and further enable data science in nursing. For example, a validated Pain Reference Model implemented in a vendor EHR specified the data elements used to capture which pain scale was selected and used by a nurse, and was designed to explicitly captured pain score data in one field for all scores that used a scale of 0–10 to support reporting of pain scores across patients, settings, and time (Collins et al. 2017). A reference model that captures relevant EHR implementation specifications, such as cascading logic and documentation workflows, informs consistent design and reliable and accurate interpretation of data for secondary analysis while supporting efficient EHR navigation.

8.4 Discussion

Implementing new health IT is often disruptive. Studies to promote health IT implementation have primarily focused on behavioral theories (Kukafka et al. 2003), such as technology acceptance model (Davis 1989), task-technology fit model (Goodhue and Thompson 1995), and diffusion of innovations (Rogers 1995). The measures of health IT implementation success primarily have relied on technology acceptance rate, usage, and clinical quality measures (Phichitchaisopa Naenna 2013; Venkatesh et al. 2011; Patel et al. 2013; Steininger et al. 2014). In addition, health IT implementation is a process and it requires active participation of individuals and the organization. Understanding factors that address cultural differences and communication within and between clinical professions or departments are essential, and should be understood in early phases of the system development lifecycle. It has been reported that most health IT evaluation studies have been conducted in the implementation or post-implementation stage (Yen and Bakken 2012; Ellsworth et al. 2017). Rather evaluation at all stages are useful and health IT vendors should conduct usability evaluation throughout the system development lifecycle, including the laboratory setting as well as larger scale process evaluations in live clinical settings. Failure to address multi-level perspectives (individual, departmental or unit, organization) iteratively may cause the misalignment of expectations and goals, and result in workarounds and disruption in nursing practice.

Nevertheless, conducting socio-technical evaluations iteratively or longitudinally is a challenge, due to a lack of agreement of socio-technical research on definitions and guidance, causing both practical and conceptual interpretation problems

(Cresswell and Sheikh 2014). Mixed-methods research with both qualitative and quantitative methods provides valuable multi-dimensional justification and data validation for reengineering changes in nursing workflow studies. Organizational culture and support, and how they affect nursing practice, are significant factors for health IT implementation success.

Overall patient outcomes are dependent on the complex relationship between the work activities and the systems used by the entire care team. To form a more relevant relationship between nursing activities, systems and processes, and patient outcomes, “nursing-sensitive” indicators were developed for both the inpatient and outpatient settings (Gallagher and Rowell 2003). These nursing sensitive indicators can be used to inform nursing documentation reference models that maximize the value of data points captured by nurses while minimizing unnecessary documentation burden, and can be used to incorporate nursing domain expertise into data science methods for evaluation of systems, as well as patient outcomes.

Despite activities described earlier in this chapter of nurse driven knowledge discovery using EHR data, there is still a lot to be discovered. From a nursing perspective, there still exist considerable knowledge gaps in Learning Health System analytics. To borrow a metaphor from Albers and colleagues (Albers et al. 2014), nursing practice and patient characteristics, including clinical outcomes, are not unified in the same way that engineers and physics are, even though nursing activities are integral to patient outcomes the same way that physics is crucial to building a bridge. The set of approaches needed to create this level of integration are both known and not known. Known approaches already in the literature, from other clinical contexts include more advanced natural language processing (Zhou et al. 2010), time series analysis (Albers et al. 2014; Hripcsak et al. 2015; Pivovarov et al. 2014a), automatic methods of analysis (Albers et al. 2014) and mitigating bias (Pivovarov et al. 2014b) in EHR related data. For example, Hripcsak et al. have developed deep models for understanding and characterizing the relationship between prescribers (i.e. physicians, nurse practitioners and physician’s assistants), and associated patient outcomes (Hripcsak et al. 2016). Deep understanding of these types of relationships can inform innovative system design. Some of the still unknown methods includes ways of dynamically characterizing or phenotyping (Albers et al. 2014) nurses by their workflow and their patients’ nurse-sensitive indicators to aid in knowledge discovery, prediction and evaluation. Health systems engineering provides a flexible, yet targeted, framework to understand the impact of new systems on nursing and patient care throughout the system development lifecycle, and can be used to incorporate novel data-driven models that evaluate user profiles, documentation workflows, data capture, and associated outcomes to inform optimization and reengineering of clinical systems for continuous learning.

8.5 Conclusion

Health IT evaluation is complex and requires empirical studies to explore barriers and facilitators. It is critical to address the interdependent relationship between health IT and its social context where the health IT is implemented. Inattention to workflow assessment results in low health IT acceptance and workarounds (Sheehan and Bakken 2012). Usability evaluation guided by a framework (e.g., socio-technical theory, stratified view of health IT evaluation model, or other framework) and observation approaches can assist in identifying problems in the interactive process and nursing workflow. Moreover, the use of a health systems engineering approach that leverages a range of methodologies (e.g., participatory design, usability evaluation, workflow observations, and documentation analytics methodologies) for development and redesign of applications promotes integration of health IT innovations within a system of systems.

In this chapter, we provide a series of examples that demonstrate the iterative nature of health IT evaluation. These examples highlight the complexity of nursing and patient care workflows and the significance of an iterative and multi-level approach to usability evaluation. This approach first identifies and resolves basic human-computer interaction issues before testing health IT systems in the context of clinical workflows, and then learning from EHR usage analytics. Evaluation of overall system effectiveness is conducted *after* usability and workflow issues are addressed.

Nevertheless, this chapter highlights the fact that even well-designed systems that adequately address socio-technical dimensions as part of the development process, require continued attention to workflow during and after implementation. Post-implementation attention to end-users' concerns and feedback provides an opportunity for system enhancement and refinement, prevents workarounds, and maximizes the likelihood that the intended system benefits will be realized. Secondary analysis of EHR data after system implementation can provide important clues about the degree to which the system is built to capture data in the context of nursing documentation workflows and minimize silos, and the degree to which the reference model differentiates missing data from data that is not applicable for a given patient. This context is needed to achieve a learning health care system and can be achieved if nursing domain experts work closely with data science experts throughout the system lifecycle to contextualize clinical analyses and help to successfully convert data into knowledge. Nationally recognized safety and quality indicators can be used to provide useful and relevant clinical and process outcomes for continuous measurement and to support Learning Health System analytics to promote learning, reengineering, and safer care.

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Chapter 9
Patient-Oriented Workflow Approach

Mustafa Ozkaynak, Siddarth Ponnala, and Nicole E. Werner

9.1 Introduction to the Patient-Oriented Workflow Approach

Existing research that focuses on designing, implementing, and assessing organizational interventions (such as information technology) in health care and improving care delivery have two important limitations: (1) care delivery is seen as a series of unrelated or independent (discrete) episodes (Elhauge 2010), and (2) the research focuses on individual care settings, predominantly formal health settings or daily-living environments, instead of the connections between settings. As a result, health-care delivery (particularly chronic disease management) is often not examined in an integrated, holistic way, and organizational interventions to improve healthcare delivery across settings can create challenges impeding optimal design and implementation.

An integrated understanding of workflow across settings is important to inform the design of health information technology (HIT) to support improved health outcomes (Ozkaynak et al. 2016a; Werner et al. 2017a). In general, workflow can be defined as "the flow of work through space and time" (Karsh 2009)—i.e. temporally organized activities that occur across settings. However, most workflow studies focus on limited boundaries, typically single settings such as emergency departments (EDs) (Fairbanks et al. 2007; Yen and Gorelick 2007), operating rooms (Kobayashi et al. 2005; Marjamaa et al. 2008), intensive care units (Malhotra et al. 2007), primary care settings (Unertl et al. 2009) or the workflows of individual

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clinician groups (physician's workflow, nurse's workflow) or individual care processes, such as barcode medication administration (Carayon et al. 2007a), that take place in a single organizational context. Capturing workflow within a defined boundary or a single setting or role is less challenging methodologically. However, health care occurs beyond a single setting (Walker and Carayon 2009; Werner et al. 2016, 2019). Incomplete understanding of workflow across diverse settings may result in failure to adopt new technology, localization (lack of context awareness), and operational ineffectiveness (Walker and Carayon 2009). For example, lack of adoption of personal health records by both clinicians and patients is likely if there is a gap between clinical workflow and patient's workflow at home (Tang et al. 2006). Extreme localization due to lack of understanding of workflow across diverse settings has been reported to be a barrier for health information exchange (Unertl et al. 2013; Ozkaynak and Brennan 2013a). Suboptimal operational effectiveness related to coordination challenges can occur when the interaction of activities that take place across diverse settings is ignored, and when activities are studied in each setting separately rather than holistically (Abraham and Reddy 2010).

Although workflow is a useful concept, identifying appropriate system boundaries is needed for its full utilization (Xie et al. 2016). We argue that patient-oriented workflow is an appropriate approach to study workflow holistically (i.e. capturing all essential activities and other elements in the health care of the patient). This approach re-conceptualises workflow so that it focusses on patients. In a healthcare context, this means decoupling workflow from the personnel who work in formal settings and coupling it, instead, to the patient (Ozkaynak et al. 2013), who is at the center of all work and who spans all settings, formal and informal.

The patient-oriented workflow approach allows us to re-define the system boundaries of healthcare activities (i.e., incorporating both clinical and daily-living environments). Identifying system boundaries precisely is critical to examining how health care delivery systems function in their entirety (i.e., with all essential elements) (Xie et al. 2016; Karsh and Alper 2005). Studying workflow enables an understanding of how work elements (including information, resources, and influence) are organized. Workflow models can help explain patient interactions (Unertl et al. 2009) and reveal design directions for HIT that supports user performance (Yen and Bakken 2012).

A patient-oriented workflow approach focuses on the three essential elements of workflow: activities, roles, and sequence (Ozkaynak et al. 2013; Ozkaynak and Brennan 2013b). We believe that a patient-oriented workflow model provides the "true flow of the work" perspective (Zheng et al. 2010) by including activities performed by the key players—patients, informal caregivers, "care partners" (Sarkar and Bates 2014), and clinicians—in the "coproduction of healthcare delivery" (Batalden et al. 2016). Patient-oriented workflow also captures the cooperative work that typically occurs across traditional organizational boundaries. In other words, the patient, rather than the clinician, drives the flow of work (Ozkaynak and Brennan 2013b). This approach to workflow follows the patient "out the door" of the formal healthcare setting rather than stopping "at the door". It allows us to study workflow across healthcare environments by including all relevant activities in all settings.

Patient-oriented workflow focuses on actual episodes or instances, rather than "typical" cases. By examining many individual episodes, patterns and variations can be analyzed (Ozkaynak et al. 2015). For example, in a study of five ED sites, the pattern of unique interactions among disciplines in the ED, could be graphically mapped (Ozkaynak et al. 2015). Variations (in terms of how various activities are conducted in a sequence) in care received, as well as those providing the care, could be identified. These patterns and variations can then potentially be related to their affect on health outcomes.

The holistic perspective that patient-oriented workflow provides, (Ozkaynak et al. 2013, 2016a) can inform the design and implementation of various interventions by: (1) accounting for multiple roles and their interrelated activities; (2) connoting continuity over time and between visits; (3) helping tailor care to patients' needs and preferences; and (4) capturing the relationships between patients and caregivers (Werner et al. 2019).

9.1.1 Patient-Oriented Workflow Informs the Design of Health Information Technology (HIT)

HIT literature indicates that explicating workflow across settings is essential to obtaining desired results (Moen and Brennan 2005; Brennan and Casper 2015; Kaufman et al. 2009; Valdez et al. 2015a; Ozkaynak et al. 2018a). Un-nuanced workflow models may lead to reduced adoption of new technology (Tang et al. 2006), lack of awareness of external health information (Unertl et al. 2013), mistrust (Ozkaynak and Brennan 2013a; Ross et al. 2010) and unintended consequences, such as medical error (Koppel et al. 2005) or coordination issues (Abraham and Reddy 2010).

Development of HIT has traditionally focused either on clinical settings (e.g., electronic health records [EHR]) or on consumer use (e.g., home glucose devices). The design of most clinical information systems aims to effectively use clinical information such as laboratory results and/or radiological/other tests to formulate a diagnosis or guide treatment. Consumer HIT systems, on the other hand, are generally designed to provide information to patients for self-management at home. Therefore, existing HIT generally fits exclusively into a clinical-solution bucket or a consumer-solution bucket. Patient-oriented workflow can be an effective approach to bridge clinical and consumer HIT (Ozkaynak et al. 2018a) and inform a collaborative HIT design, which jointly optimizes clinical and consumer informatics technologies (Valdez et al. 2015b).

As patient-oriented workflow eponymously focuses on the patient, it engenders a significant but undervalued healthcare-related work unit patient work (Werner et al. 2017a; Valdez et al. 2015a; Holden et al. 2015a). Examination of patient work can help identify information/data needs across diverse settings (Coleman et al. 2004), and identify the gaps between activities in diverse settings (Ozkaynak et al. 2018a). Patient-oriented workflow can make technology more user-centered by getting the right information to the right people at the right time. These "right's" are essential for effective use of HIT (Werner et al. 2017b; Campbell 2013). For example, clinical decision support systems (CDSS) can support antimicrobial stewardship efforts in EDs effectively only if they can support decisions at multiple points of care (within overall care delivery) and at multiple physical locations (Ozkaynak et al. 2018a). Patient-oriented workflow can inform the development of CDSS by identifying these points and physical locations.

9.1.2 Patient-Oriented Workflow Informs Organizational Design

Workflow studies are common at various stages of organizational (re)design of healthcare institutions. An important objective of these workflow studies is to ensure that technical and social components (or subsystems) are congruent with each other and that together, they are congruent with the environment. Patient-oriented workflow or patient-focused workflow (compared to traditional workflow methods), can potentially better inform organizational design by; (1) showing variability in how work is accomplished, (2) showing cooperation between involved parties, (3) identifying sources of problems, (4) facilitating communication and coordination, and (5) facilitating patient-centeredness.

Although some variability in healthcare work is inevitable lack of awareness of these variabilities in care can lead to poor outcomes. For example, treating patients with acute asthma with systemic corticosteroids within an hour of presenting to the ED significantly reduced admission rates, while administration of steroids later than 1 h after presenting to the ED may lead to poor outcomes (Rowe et al. 2001). Patient-oriented workflow can highlight the existence of inconsistencies during the delivery of care in health care settings. Likewise, in the setting of everyday living, a workflow pattern can capture inconsistencies in self-management. The patient-oriented workflow includes time-stamped information, enabling all relevant care-related activities to be closely examined. For example, Ozkaynak et al. (Ozkaynak et al. 2015) studied patient-oriented workflow in 6077 asthma-related patient care episodes in five EDs. They demonstrated how variability in events and timing occurred for patients presenting to EDs with a similar diagnosis. The work also quantitated the workflow in various sites showing differences based on ED, patient acuity, and arrival mode (ambulance vs. walk-in). Electronic health records (EHR), barcoding technologies, and Radio Frequency Identification (RFID) technologies can allow researchers to make connections between the number and types of individuals who performed activities based on their background (education, experience etc.) to patient outcomes. Patient-oriented workflow can also show how various individuals perform various roles at different times throughout a patient episode.

Ability to identify problems at their source is an important organizational design objective (Clegg 2000). Effective organizations can capture and mitigate the problem as soon as they occur before it propagates over time across the entire organization. In the context of healthcare, these problems can be in the form of inefficiencies, safety concerns, quality of care issues, reduced access to care, low patient satisfaction, and high cost of care. Current EHRs and other technologies (e.g. barcoding, RFID) can successfully track and record workflow steps and patient outcomes at multiple points. By capturing patient episodes across diverse settings and associated activities, roles and temporal relationships to patient outcomes can allow for problem identification at their source. For example, if nursing assessment prolongs assessment of the patient by physician, a workflow targeting nursing activities alone would not reveal this barrier and the actual source of the problem. Patient-oriented workflow will both reflect the variety of challenges experienced by patients and providers and capture deviations from optimal care management.

Self-management is an increasingly important aspect of both chronic disease management and post-acute care (Wagner et al. 2001). Although the term "self-management" refers to health activities in daily-living environments, these activities are not generally created in the home. Self-management protocols are often created in formal, clinical healthcare settings. An important barrier to effective self-management is the disconnect with events in clinical settings (Nagelkerk et al. 2006; Rogers et al. 2005). Thus, workflow study can reveal inconsistencies between clinical and daily-living settings, and the way these inconsistencies lead to challenges and deviations optimal care delivery and health management.

In short, because the communication and coordination needs of contemporary healthcare delivery go beyond the boundaries of single settings (Coleman et al. 2004), understanding these needs will reveal problems and provide the basis from which to improve communication and coordination. Patient-oriented workflow helps identify these needs by focusing on the patient, operationalizing her or his needs, and identifying reasons for unmet needs.

9.1.3 Patient-Oriented Workflow Informs Implementation and Evaluation

To successfully implement HIT, it is essential to understand the workflow in which implementation is to be integrated. Without an accurate understanding of current roles and activities, the implementation of HIT in healthcare delivery may alter the workflow in an adverse way, resulting in unintended consequences (Carayon 2012; Carayon et al. 2007b; Karsh et al. 2010). Because the focus of patient-oriented workflow is on the patient instead of the clinician, it can inform implementation practices across boundaries, personnel, and time (Werner et al. 2016). Implementation across boundaries is inevitable in some circumstances such as personal health records (Tang et al. 2006) and health information exchange initiatives (Unertl et al. 2013). Analysis of this type of workflow can highlight variations in practice and allow us to isolate an efficient or preferred workflow. For example, in the hospital, medication is typically administered by nurses, but when the patient leaves the hospital, the same task is performed by the patient or an informal caregiver. Clinician-centered workflow permits awareness of only hospital-based workflow, leaving out critical implementation barriers that may be relevant in the home. The patient-oriented workflow allows us to take a holistic view of workflow as it occurs across work systems and informs whether or not the implementation of an organizational intervention (such as HIT) is suitable for a longitudinal process rather than discrete episode of care.

Patient-oriented workflow can also inform evaluation research. An important reason for unintended consequences of interventions in healthcare, is the complexity of healthcare systems (Sittig and Singh 2010). Interdependence between various settings (e.g., hospital, primary care clinic, home, workplace) requires inclusion of relevant settings and cross-setting connections for a comprehensive evaluation. Patient-oriented workflow takes the interdependence between settings into account and highlights the connections and/or problems with these connections.

9.1.4 Limitations of Patient-Oriented Workflow Approach

Despite the benefits of gaining an increased understanding of patient-oriented workflow, such models are challenging to develop. There are difficulties in conducting workflow studies in both formal (e.g. clinical) and informal (e.g. home) health settings (Holden et al. 2015b). Methodological challenges include ensuring the reliability and validity of the collected data due to a high level of variability and complexity in health settings (Ozkaynak et al. 2018a; Chung et al. 2017). Theoretical challenges include the lack of comprehensive, robust conceptual frameworks that can be used to guide patient-oriented workflow studies (Ozkaynak et al. 2016b). Additionally, patient-oriented workflows involve a larger scope and more complex work phenomena. These workflows often rely on patient entry of data which may require technical literacy or written data input which often results in missing data. The home environment also will vary among individuals based on cultural, ethnic, and social factors etc. The inconsistencies across reported workflow studies have been attributed to the combination of these high levels of complexity as well as simplified modeling techniques (Zheng et al. 2011). More sophisticated modeling techniques are needed to address this escalated level of complexity.

9.2 Approaches to Study Patient-Oriented Workflows

9.2.1 Qualitative Methods

Both qualitative and quantitative methods have been used to model and evaluate patient-oriented workflows (Ozkaynak et al. 2016a). Traditionally, workflow evaluation has consisted of in-depth (ethnographic like) observations, interviews, and contextual inquiry that are leveraged to explicate individual workflows. These methods yield rich qualitative data that provides a depth of understanding to the multiple components of patient-oriented workflow (Ozkaynak et al. 2018a). However, several limitations are associated with this method. First, ethnographic work of this kind is resource intensive, often requiring time-consuming and costly data collection. Second, in-depth ethnography to explain workflows can be invasive and burdensome for study participants, requiring numerous prolonged interactions between study participants (clinicians and patients) and researchers. Third, as a result of the former limitations, sample sizes tend to be small and may lack representation of a broader context. Finally, qualitative methods yield descriptive findings that limit the ability to statistically associate workflow findings with outcomes.

Recent methods have been developed to quantify qualitative findings. For example, Epistemic Network Analysis (ENA) (Shaffer et al. 2009, 2016), a novel method of mixing qualitative and quantitative data, creates quantitative models of the qualitative data. ENA is a new analytical approach that combines principles from social network and discourse analysis, to identify and quantify connections among elements in coded data and represent them in dynamic network models (Shaffer et al. 2009, 2016; Gee 2014). A key feature of ENA is that it enables comparison of different networks, both visually and through summary statistics that reflect the weighted structure of connections. As such, ENA also provides a potential mechanism for quantifying workflow comparison.

ENA is based on an epistemic frame, which is a pattern of associations across knowledge, skills, and habits of mind along with other cognitive elements that characterize communities of practice. This data analysis method can be utilized to model interactions across work systems in healthcare delivery, and to better understand which cognitive patterns propagate through the patient journey. Wooldridge et al., have used ENA to study task allocation communication in primary care teams (Wooldridge et al. 2018). Qualitative data were collected through 15 h of observations of a high performing primary care team that included a physician, nurse, medical assistant, and unit clerk in task allocation communication. ENA was employed to build a quantitate model of the observation data specifically to evaluate sender, receiver, and synchronicity impact of task acceptance. From this analysis, the researchers learned that physician and unit clerks were most efficient in allocating tasks. ENA can be employed in other applications across work systems to identify patterns of barriers and facilitators for desired work system outcomes.

9.2.2 Quantitative Methods

Recently, quantitative methods have been applied to study patient-oriented workflows (Ozkaynak and Brennan 2012, 2013b; Ozkaynak et al. 2015; Chung et al. 2017). The quantitative data for patient-oriented workflow research includes structured observations and EHR data. Data typically includes time stamped activities and roles of individuals who conduct these activities. Quantitative methods, in particular temporal sequence analyses such as Markov modeling, provide a method of characterizing patient-oriented workflow in a way that allows for statistical comparisons (Ozkaynak et al. 2015). However, quantitative methods also have limitations; data from EHR needs to be validated in terms of completeness both within and across organizations (Dziadkowiec et al. 2016) and collecting the necessary quantitative data through field studies is resource-intensive.

The patient-oriented workflow approach in particular results in some unique challenges for data collection and analysis. Studying workflows as they occur across healthcare settings often requires data collection in a patient's home. In-home research typically limits researchers in the time they can spend in a house, the number of visits to a home, and may be restricted to a certain number of homes due to travel or cost limitations (Holden et al. 2015b). Novel methodologies that engage patients in collecting data such as journaling (Ozkaynak et al. 2016b) and photovoice (Wang 1999; Woda et al. 2015) can help overcome this challenge. Additionally, crossing organizational boundaries pose challenges associated with getting buy-in from multiple organizations, clinicians, and patients, as well as accounting for procedural and environmental changes.

Taking a patient-oriented approach inherently broadens the scope of the analysis, increasing the complexity of the workflow. Variability due to this increased complexity can lend itself to challenges in ensuring the reliability and validity of the data (Ozkaynak et al. 2018a). Patient-oriented workflow is more likely to involve incompatible data sources and challenges in aggregating data, due to the study across diverse settings using actual individual episodes. Quantitative methods facilitate statistical analyses of workflows that allow for associations. However the escalated level of complexity (e.g. involvement of multiple individuals (or entities) with activities at different levels of details, concurrency of activities and high level of variability across patient care episodes) can be problematic without thoughtful planning and resources such as statistics experts and other support personnel.

9.3 Case Studies

As mentioned above, the patient-oriented workflow approach has several applications in healthcare. To follow is a description of the application of the patient-oriented workflow, in four different care environments: EDs, daily-living environments, nursing homes, and skilled home health care.

9.3.1 Emergency Departments

The first author developed a preliminary version of a patient-oriented workflow in the context of EDs (Ozkaynak 2011). Although EDs represent a single setting, different roles are assumed in various subsettings of EDs. Patient-oriented workflow can be used to identify cooperative work in EDs (Ozkaynak and Brennan 2012, 2013b). Early stages of 108 patient care episodes were identified using structured observations in three EDs (Ozkaynak and Brennan 2012). Data were collected on time-stamped activities and roles of individuals who conduct these activities. Each episode was modeled as a workflow and included a sequence of activity-role pair. Data analysis yielded 96 different sequence patterns. Using data reduction techniques, such as multidimensional scaling and hierarchical cluster analysis, six patterns of care delivery were identified, differentiated primarily by whether the prescriber was a physician or midlevel clinician. Secondary differentiators included whether the patient arrived in the ED as walk-in or via ambulance, and in which ED patient care occurred. The high level of workflow variability reported in this study can inform the design of ED work systems. The variability in workflow could not have been captured using a strictly clinician-oriented approach (e.g. studying single type of clinician's workflow). The study concluded that work interventions should not limit EDs' flexibility to handle sequential variability in patient care.

In another study, patient-oriented workflow using EHR extracted data demonstrated factors that shape the workflow patterns and the relationship between workflow and patient outcomes (i.e. length of stay) (Ozkaynak et al. 2015). In this study, 6077 episodes for asthma patients were identified in five EDs in one calendar year. The data included time-stamped activity data. EHRs could track logs for many activities, the following activities were followed and used in the analysis; patient arrival, triage started, pain assessed, patient roomed, nurse/tech assigned, attending assigned, resident/fellow assigned and patient departed from ED. Using Markov models and visual analytic techniques, patient-oriented workflow yielded workflow patterns for each of the five EDs by aggregating the sequence of activities for each episode. These patterns were correlated with length of stay. Moreover, the workflow displayed variations for different arrival modes, settings, and acuity levels. Clinician-oriented approaches on the other hand, would not have been linked to patient outcomes such as length of stay, as they are generally linked to clinician outcomes (e.g. spent time on various activities, clinician activity patterns) (Ozkaynak et al. 2018b).

Both of these ED studies identified workflow patterns and factors that resulted in these patterns. Identifying the factors and linking patterns to patient outcomes, allows the redesign of ED systems that lead to better outcomes and discourage patterns that lead to worse outcomes.

As discussed previously, the patient-oriented workflow approach has been applied to study longitudinal processes of healthcare. Doutcheva et al. applied this method to study the workflow associated with older adults transitioning to the ED and then returning to their homes following hospital discharge (Doutcheva et al. 2017). Qualitative methods were used to identify: (1) the organizational boundaries crossed, (2) barrier/facilitator interactions across organizational boundaries, and (3) the patient work consequences that occur when patient work occurs across boundaries. Thirty-six semi-structured interviews were conducted with older adult patients who were discharged from a level 1 trauma center ED to their home. The goal of the interviews was to have patients describe their "patient journey" from their initial decision to go to the ED to their current state of care after being discharged home from the ED. Specifically, the SEIPS (Systems Engineering Initiative for Patient

Safety) framework was used to guide the directed content analysis of the interview data to answer the research question described above (Carayon et al. 2006; Hsieh and Shannon 2005). Results revealed that patient work crossed several organizational boundaries including the home, hospital, primary care facility, pharmacy, and community organizations. Further, barrier/facilitator interactions across boundaries were connected to either positive or negative consequence for the patients from their perspective. In this study, the use of a patient-oriented workflow enabled the researchers to trace cross-boundary barriers, facilitators, and post-ED discharge patient consequences related to those barriers that would otherwise not have been identified had the focus only been on the clinical setting. The results highlight that ED transitions happen longitudinally, that is, beyond the care that occurs within the ED, and extend into the community. As a result, the process is vulnerable to variances in the different work systems. Currently, interventions to improve ED discharge and transitions from acute care settings to the home have focused on the discharge process that occurs in the clinical setting, leaving out the potential to identify and subsequently address downstream effects. Use of the patient-oriented workflow approach in this case allowed for the ability to identify many of the issues associated with transitions in healthcare that happen after the patient leaves the clinical setting. As a result, subsequent system redesign can focus on supporting patient work across system boundaries to ensure successful care transitions.

9.3.2 Daily-Living Environments

The patient-oriented workflow approach has been applied to understand performance barriers related self-management in the home environment. Holden and Mickelson examined patient work among elderly chronic heart failure (CHF) patients in their homes (Holden and Mickelson 2013). A sociotechnical system approach was used to understand patient work associated with self-care for patients with CHF and their caregivers including: therapy related knowledge, motivation, tools/technologies, barriers/difficulties, strategies/resources, and social/physical environment. Thematic analysis of interviews with patients and their caregivers revealed several patient-reported barriers in the patient work system. These barriers included physical limitations, knowledge gaps, medication complexity, side-effects, lack of or overdependence on aids, lack of indoor gyms, sodium-rich food culture and, stairs. Patient-oriented workflow allowed the researchers to expand the patient's work system beyond the clinical environment and identify challenges that may inhibit the delivery of quality care at home.

Management of anticoagulation treatment in daily-living settings has been studied using patient-oriented workflow (Ozkaynak et al. 2016b, 2018a). This approach allowed for identifying gaps between the clinical workflow and healthcare activities the setting of daily-living. The term "gap" refers to a "break in continuity" between health-related activities across diverse settings. Gaps can disturb care delivery and lead to poor patient outcomes (Booth et al. 2013). These gaps can inform the design and implementation of gap-filling, collaborative health information technologies

(HIT) (Valdez et al. 2015a). Collaborative HITs can potentially allow patients to capture patient work (self-management practices, daily living routines and context) (Ozkaynak et al. 2018a) and to share with their provider. Clinicians can then have a better understanding of patients' barriers and obstacles for self-management at home and community settings for patient-centered care to address management issues.

9.3.3 *Nursing Homes*

Nursing homes entail distinct workflows (Morrill et al. 2016) that comprise the numerous daily-living activities of residents and asynchronous communication between team members. This asynchrony often occurs because, unlike hospital settings, some providers, such as medical staff, are often external to the facilities and thus not constantly available. This situation results in enhanced roles for nurses and other caregivers in clinical decision-making (Lim et al. 2014). Nursing homes comprise differing levels of clinical or residential support for clients. Residents with high level clinical needs depend on staff and resources for care and assistance in activities of daily living. Staff work within their scopes of practice, guided by regulations i.e., formal rules and licensure responsibilities. In low-care hostel or nursing home settings, residents are relatively independent and require limited clinical services but have the support of services such as housekeeping and social engagement activities, and have access to staff nearby if required. Although clinical and residential support activities have different dynamics, they need to coexist together and both residents' and clinicians' preferences should be factored in (Ozkaynak et al. 2018c). Patient-oriented workflow can be an ideal approach for studying the temporal organization of healthcare workflow, which lasts all day and interacts with the daily routines of residents. Workflow in nursing homes often crosses temporal (between shifts), organizational (e.g., hospital, lab, primary care, pharmacy) and institutional (clinical and daily-living) boundaries. Ignoring cross-boundary workflows in nursing homes can lead to safety and quality problems (Stokoe et al. 2016). Acknowledging cross-boundary workflows can lead to health IT and other interventions that ensure pertinent information (e.g. resident preferences, daily routines or medication list) is transferred across boundaries and is made available to the right people at right time.

9.3.4 *Skilled Home Health Care*

Another area where patient-oriented workflow has been applied is Skilled Home Health Care (SHHC), also known as community care services. SHHC is a formal, regulated program of care that provides a variety of skilled services such as nursing, physical therapy, speech therapy to patients in their home. Typical tasks involved in SHHC include wound care, physical therapy, and medication management, along with some house keeping and social support activities. Werner and colleagues applied the patient-oriented workflow to understand medication management (MM) during transitions from hospitals to SHHC (Werner et al. 2017a). Transitions in healthcare require the execution of several tasks distributed across multiple people, organizations, and time. Patient-oriented workflow allows researchers to study how processes are distributed across healthcare delivery settings through an analysis of interactions and emergent properties that would not have been possible at the task level. Werner and colleagues used interviews and observations with older adults, caregivers, and SHHC providers involved in care transitions from the hospital to SHHC (Werner et al. 2017a). The study identified: (1) key attributes of the MM process through the transition from the hospital to SHCC, (2) emergent properties of MM across system boundaries and related barriers, and (3) patterns of barrier propagation through the transition processes. The patient-oriented workflow approach facilitated identification of barriers to the process specific to crossing organizational boundaries. Additionally, barriers identified in one system of care were traced throughout the hospital to SHCC care transition. Barrier propagation across organizational boundaries was associated with negative work system outcomes such as process delays like missed medication, as well as frustration and increased workload for the SHHC provider. The use of patient-oriented workflow allowed researchers to conceptualize care as a continuous process across systems rather than a discrete care episode. The results suggested that work systems need to be aligned to support critical care processes across transitions to reduce the potential for process breakdowns.

9.4 Conclusion

Although workflow analysis in general, and patient-oriented workflow analysis in particular, has inherent challenges and limitations, the potential benefits for both care delivery processes and HIT design/implementation far outweigh the potential disadvantages. To successfully redesign healthcare delivery, as well as design and implement HIT that can account for care across the entire patient journey, healthcare delivery must be examined as an integrated system of a longitudinal process rather than a cluster of discrete tasks/processes in isolated environments. Patient-oriented workflow can provide the needed integrated perspective.

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Chapter 10
Workflow at the Edges of Care

Bradley N. Doebbeling and Pooja Paode

10.1 Introduction

In order to understand specific tension points related to workflow capture and measurement, one might revisit the turn of the last century. Here, two landmark reports highlighted gaps related to care quality and safety in the United States' healthcare system. First was the Institute of Medicine (IOM) report *To Err Is Human: Building a Safer Health System*. Written by the IOM Committee on Quality Health Care in America, this report emphasized that errors resulting in patient harm are properties of healthcare systems, not just the health professionals in the systems. It follows that patient safety is also a property of systems of care. Errors refer to "the failure of a planned action to be completed as intended or the use of a wrong plan to achieve an aim" (Donaldson et al. 2000). Errors that cause injury or harm lead to preventable adverse events.

Shortly afterwards, the National Academies of Medicine released their landmark report, *Crossing the Quality Chasm: A New Health System for the 21st Century* (Baker 2001). This report attributes rapid technological development, the growing complexity of healthcare, and fragmentation of care delivery as factors contributing to a healthcare system unable provide safe and high-quality care to all individuals in the system.

The care fragmentation described in the report disproportionately impacts high-need populations, including those with multiple or complex chronic health issues who experience frequent changes in health status and multiple transitions between care settings and providers, as well as patients at risk for multiple social and behavioral determinants of health. Workflow modeling can improve the integrity of the

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healthcare safety net, which currently exists as a loosely connected patchwork of safety net services, meant to support these individuals. Understanding workflow at the edges of care can prevent patients "falling through the gaps," lead to improvements in the overall quality of care and even suggest novel technological development in line with healthcare system and patient work.

The IOM committee provided ten general principles to inform care redesign efforts and mitigate errors. One of these principles emphasized improved collaboration and cooperation between clinicians and care institutions to promote information exchange and care coordination. Information exchange and care coordination between care systems, providers, and patients and their families are critical targets for workflow study at the edges of care.

Workflow measurement is largely linked to general quality improvement efforts in electronic health record (EHR) usage. In 2009, the Medicaid and Medicare EHR Incentive Program was established under the Health Information Technology for Economic and Clinical Health (HITECH) Act. This program helps support patient engagement with their personal health records. This has increasingly directed attention towards consumer health informatics (CHI) such as mHealth and easily accessible tools (such as blood pressure cuffs or pedometers) (Blumenthal and Tavenner 2010). During this time, Affordable Care Act (ACA) also incentivized the creation of accountable care organizations (ACOs) and formalized partnerships between social services and community-based organizations to improve the quality of transitions and post-hospital care (Nasarwanji et al. 2015).

10.2 Current State of Workflow Mapping at the Edges of Care

10.2.1 Transitional Care

According to the Centers for Medicare and Medicaid Services, a transition of care occurs any time a patient is transferred from one care setting to another (Mansukhani et al. 2015). These settings include primary care offices, specialists, pharmacies, home care agencies, acute care hospitals, emergency departments, in addition to social service institutions and the patients' own homes. Care transitions, sometimes called "handoffs," are vulnerable points in the care process. They possess a few types of **inherent error vulnerability** (complexity, communication breakdowns, and shifting responsibilities of care) which operate synergistically to contribute to errors (Cortelyou-Ward et al. 2012). In an example where a patient transitions out of a hospital to home care, those error vulnerabilities may manifest in the following ways:

– *Complexity*: Even with rapid consolidation of smaller practices and care systems, transitions often happen between high numbers of small, independent providers. They may include several members of a care team and involve the exchange of a large amount of information. A patient may interact with multiple providers and staff and be given significant, complex instructions and education for their post-discharge care. Changes to medication regimens also contribute to complexity during care transitions.

– *Communication breakdowns:* The transfer of patient information (i.e., charts, images, test results) between levels and locations of care helps to ensure care continuity. However, breakdowns of these processes and discontinuous information transfer between care teams and care settings lead to poor care transitions. Common issues include: information not sent from the primary care setting to the specialist (and vice versa), key information missing from EHRs, information included in EHRs but still insufficient for providers, unavailability of test results, a lack of follow-up arrangements made, and poor communication of discharge summaries between patients and providers. Most of these issues occur between different types of providers, patients and their families, hospitals, and other care settings.
– *Shifting responsibilities of care:* A patient's self-care responsibilities may markedly increase when transitioning from complete care by a hospital team to individual or assisted care at home or at a transitional care facility.

Together, these factors make care transitions vulnerable exchange points that contribute to high rates of health services use and spending (Kripalani et al. 2007). Error vulnerability leads to a higher relative incidence of systemic errors, adverse clinical events, healthcare waste, and prevents patients' care needs from being sufficiently met (Naylor et al. 2011; Coleman et al. 2005). Barriers to addressing these issues include overstressed primary care systems with large and diverse patient panels and tasks as well as an overall lack of integrated care systems (Bodenheimer 2008). Studying workflow across transitions in care, care teams, and care settings should be a high priority if we are to improve care quality and patient safety.

10.2.2 Care Coordination in Transitional Care

Workflows associated with **care coordination** across the healthcare continuum are high-yield opportunities to improve patient care. Care coordination can be broadly defined as the "deliberate organization of patient care activities between two or more participants (including the patient) involved in a patient's care to facilitate the appropriate delivery of healthcare services" (McDonald et al. 2007). Care coordination considers all resources, including personnel and information, required to carry out all required patient care activities. Improving care transitions and collaborative care of patients across settings requires the integration of care delivery processes across settings (Mansukhani et al. 2015). Meaningful metrics of care coordination that can be targets of workflow optimization include:

– provider, interorganizational, and interagency collaboration and communication
– meaningful use of health information technology (HIT)
– medication reconciliation

– discharge processes (ensuring access to care after discharge, communication of healthcare information during discharge)
– post-discharge follow-up (follow-up phone calls, post-discharge home visits)

At the edges of care, healthcare personnel must consider not only organization-wide, but also system-wide workflow. There is an increasing push to capture and crystallize processes occurring at these “edges” and map the workflow between these edges when possible. One result of these efforts to decrease fragmentation in transitional care focuses on reducing hospital readmission rates, a key metric tied to insurance reimbursement (Naylor et al. 2011). Common methods to study workflow in transitional care include multi-site ethnographic observation, semi-structured interviews, and the development of process maps, flowcharts, and activity diagrams. Currently, most workflow mapping in transitional care occurs in and around acute care settings and specific programs focused on costly and complex care, such as behavioral and medical health integration.

10.2.3 Types of Workflow Study in Transitional Care Settings

Qualitative analysis in behavioral health settings: Kaiser and Karuntzos previously reported a qualitative workflow study conducted with practitioners involved in SBIRT (Screening, Brief Intervention, and Referral to Treatment), an evidence-based practice focused on alleviating substance use disorders, focused on characterizing and better integrate workflow. The study team conducted direct observations (focused on workflow processes related to care delivery, documentation, information storage and sharing, and patient engagement), semi-structured stakeholder interviews to identify workflow variation, and document reviews. The interviews resulted in the development of observation-informed standard workflows to visualize patient and information improvement across care systems (Kaiser and Karuntzos 2016).

Lean methodology to standardize transitions from intensive to ambulatory care units: A tertiary care center identified variation and unpredictability in patient transitions between intensive care units (ICUs) and ambulatory care units (ACUs) as a contributing factor to patient harm and systemic inefficiency. In order to develop standardized processes to transfer patients between ACUs and ICUs, leadership engaged key stakeholders, used lean methodology including process mapping (swim lane flowchart), analyzed waste and opportunities to standardize processes. Stakeholders together selected an “ideal state” solution using of checklists as a tool to guide workflow adherence. While this workflow study resulting in improvements in perception of communication clarity and adequacy and duration of transition, it was an intensive effort, requiring extensive time dedicated to process development and evaluation. Keeping in mind this significant resource cost, this study may be a useful guide to institutions involved in patient care transfers (Halvorson et al. 2016).

Clinician-centered continuity of care approach: Abraham and colleagues utilized observations, shadowing, audio recording, semi-structured interviews, and artifact identification and collection to explore clinician workflow before, during, and after a patient handoff. Evaluating workflow through the lens of clinician work activities allowed the identification of interdependencies between different parts of a patient handoff. Because workflow was analyzed across a full continuum of care, they also developed a non-linear descriptive framework of handoff communication (handoff as a discrete communication activity) that accounted for emergent collaboration and interactions between individuals on the care team. In mapping these workflows, the team was also able to identify specific points of information breakdown at a high level of granularity (Abraham et al. 2012).

Activity log modeling for care coordination: Another approach used internationally to study care coordination utilizes workflow activity logs, a granular (specific and detailed) data collection method. Describing and collating a large number of workflow functions across a care coordination workforce working at a specific organization dedicated to care coordination across settings can help identify gaps in local capacity for care coordination and also stimulate intentional practice redesign (Heslop et al. 2014).

10.2.4 Small and Resource-Limited Care Settings

Small or rural primary care practices, community health centers, and community-based health organizations are all examples of resource-limited care settings or care settings experiencing significant barriers to engaging in quality improvement efforts related to workflow improvement. These practices, sometimes termed “priority primary care practices,” are high-priority areas for workflow and information technology optimization. Resource limitation in these settings is characterized by a lack of infrastructure, limited internal management or information technology expertise and little or no access to external expertise in these areas due to financial or geographical reasons. These smaller primary care practices, found often in densely populated urban areas with high need and rural areas, make up half of all primary care practices (Liaw et al. 2016; Wolfson et al. 2009; Ryan et al. 2013).

Workflow in small practices A report on the adoption gap of EHRs indicates that only a fraction of small physician offices has fully implemented EHR systems. Ramaiah and colleagues utilized an interpretive case study approach to evaluate factors influencing workflow automation in small primary care practices. This approach triangulated questionnaires, *in situ* work observations, and interviews to study tasks conducted from the beginning to the end of a patient’s visit. Workflow was mapped using Unified Modeling Language activity diagrams. Notably, most primary care settings had unique workflows, with distinct workflows used to achieve similar goals.

In general, workflows in low-resource primary care settings can be complex and highly variable. In a study of primary care workflow, Holman and colleagues calculated an average of 37 tasks performed per visit, in no predictable order (Holman et al. 2015). Evidence suggests that starting small, seeking help from local resources focused on HIT, such as Regional Extension Centers (funded through the HITECH Act to assist with EHR implementation), and participation in other government-funded programs that provide incentives to implement HIT and consider workflow can all provide external resources to assist smaller practices with information integration and workflow standardization (Ramaiah et al. 2012).

In an international review of quality improvement studies conducted in low-resource settings, most studies were case reports with a focus on adoption and implementation, observational inquiries (qualitative inquiry of user and patient perceptions), and secondary literature reviews. Workflow assessments made up only a small fraction of these studies, indicating that there is a real gap in use of workflow to improve care processes, despite its demonstrated benefit (Jawhari et al. 2016).

Although there is still much to learn about specific factors that facilitate workflow measurement in small practices, studies evaluating facilitators of overall quality improvement have noted that general quality improvement activities are successful when the following factors are present: a dedicated "practice champion," involved practice leaders, clear team goals, collaboration between providers and staff, a sense of shared responsibility, and access to external resources such as learning collaboratives. Time constraints, costs, issues with HIT, a lack of staff motivation, and a lack of financial incentives are common barriers to quality improvement work, including workflow mapping (Wolfson et al. 2009).

Workflow in community health centers: Green and colleagues used cognitive task analysis interviews combined with observations of HIT implementation and semi-structured interviews to detect emergent themes to better understand challenges and facilitators related to IT workflow and maintenance (Green et al. 2015). Updates to HIT inevitably disrupt workflow and practices should prepared to manage these disruptions and adapt to HIT transitions.

Barriers to implementation of quality improvement strategies (including workflow assessment) can be categorized into situational (time, adverse effects on efficiency, culture, incentives), cognitive (fear of change, low perceived value), liability (privacy, security), knowledge (lack of training or knowledge on prioritizing systems to target), financial (high costs and low actual or perceive return on investment), technological (technical support, a lack of interoperability, limited reliability), and workforce (skillsets, leadership, organizational support). While cost of resources and expertise are prohibitive factors for urban and rural community health centers, rural community health centers also experience issues related to geography, wherein critical resources are not only unaffordable, but may be simply absent (Green et al. 2015).

10.2.5 Consumer Health Settings

Consumer health settings include "locations of daily living (LDL) such as workplaces, parks, exercise facilities, grocery stores," and even drug stores. Consumer health informatics (CHI) applications are powerful tools in consumer health settings. They include mHealth apps, remote monitoring systems, personal health records, in-home monitoring devices, decision support systems, and online health resources. They provide individuals with easy access to personal health information, are a means of actively storing and monitoring patient health information and are an opportunity to engage patients beyond traditional healthcare settings (Cortelyou-Ward et al. 2012; Patrick et al. 2008; Radley et al. 1994). Widespread adoption of CHI is limited due to device inefficiency and their lack of patient-centeredness. Jimison and colleagues suggest adoption could be accelerated through improvements in usability, adherence to patients' mental models, and "better integration of CHI into patients' and families' daily routines," or workflows (Jimison et al. 2008). Historically, consumer health technology developers and researchers have considered the design and usability of these technologies through a highly medicalized lens that eventually accounts for personal behavior.

In order to leverage CHI and accelerate adoption, workflows in the consumer health setting must consider the more specific local contexts of information exchange. Zayas-Caban, Valdez, and their colleagues have explored a **patient work** framework, using human factors ergonomics (HFE) methods to build on existing medical-behavioral approaches and increase meaningful usage of CHI in the context of daily living (Valdez et al. 2015; Zayas-Cabán and Dixon 2010; Marquard and Zayas-Cabán 2012). At a minimum, a patient work framework should consider **physical, cognitive**, and **social-behavioral** activities in addition to **macroergonomic** (organizational) needs and constraints in consumer health settings (Marquard and Zayas-Cabán 2012). Consumer health workflows include:

– *Patient work activity*: These include family work and factors related to individual operation of and interaction with CHI. There are a few underlying assumptions behind patient work. First, both patient (and family) work and health professional work involve agency (implied opportunity to actively have a role in the performance of work), context, and activity. Next, patient work activity can be decomposed into illness work, everyday life work, and biographical work which are supported by coordination work. Activities can be visible (recognized and valued) or invisible (taken for granted and perceived by outsiders as less valuable).
– *Workflows*: These comprise the flow of health information across space and time and interactions with caregivers across space and time.
– *Patient work systems (context)*: The social and organization conditions and contexts in which health work is performed, including the structural components of task, technology, environment, and community. They can either constrain or facility work activity.

Take the example of using a pedometer application on a mobile phone. Physical ergonomics would include turning on a mobile phone's GPS or turning on the application within the context of a physical environment, such as a home or running track. Cognitive ergonomics considers factors related to processing information from the device's user interface (interpreting speed, calories burned, and distance walked or run). Macroergonomics considers the context within which the device is used. Design can affect one or more of the aforementioned human factors domains.

Viewing consumer health work through these categories can facilitate the design of better health technologies that support individual cognition. **Case-based human factors evaluation**, where patients or patient proxies record the nature and severity of challenges experienced while completing user tasks on a particular device, can assess the fit of a technology in a context of a patient's work and help to preempt important challenges in the usability of CHI.

10.3 Emerging Approaches to Workflow at the Edges of Care

Qualitative field-based methods such as interviews, observations, and activity log analyses, while rich in data, are time-consuming, labor intensive, and largely clinician-oriented. They also may not sufficiently capture information about patient experience and workflows across multiple care settings, particularly in consumer health settings. Still, these methods are widely used, particularly in transitional care environments. Moving forward, methods such as human factors engineering, social network analysis, patient-generated data, and use case-based human factors evaluation can augment current methods and make workflow assessment more efficient and high-yield for all individuals involved. We can also learn from complexity science and predictive modeling to better assess complex and variable workflows at the edges of care (Abraham et al. 2012; Goldberg et al. 2011).

10.3.1 Complex Adaptive Systems Approaches at the Edges of Care

Complex adaptive systems consist of individual entities, or "agents," which engage in dynamic, nonlinear interactions. The behavior of agents involved in a complex system cannot be predicted by the behavior of individual components. Furthermore, the self-organization and collective organizing behavior of components of a complex system contributes to our understanding of these systems as complex adaptive systems. Understanding the complexity of healthcare systems—where care is provided across multiple providers, multiple care settings, with significant variations across settings—is critical to our understanding of how we can improve care quality and patient safety in these settings, especially when considering workflow across institutions and care teams.

The nature of collaborative care delivery across multiple sites of services makes healthcare a complex adaptive system. As healthcare is a complex domain, complex adaptive systems (CAS) principles can and should be used to support healthcare management and improvement, specifically concerning workflow. A CAS approach encourages us to study issues and problems in terms not as isolated entities, but in terms of concepts (care providers, locations, information flows) and the rules of engagement for how the concepts interact within and across settings (Kuziemsky 2015; Kannampallil et al. 2011). Primary care is conceptualized particularly well as a complex adaptive system due to its inherent variability and unpredictability.

Malhotra and colleagues have previously utilized a complex systems approach using functional decomposition on a series of complex workflows in an ICU. Activities were decomposed into the individual and collaborative or cross-organizational level. Cognitive requirements associated with those activities were considered. Once activities are decomposed, temporal sequencing of critical zones was used to determine relationships between the work activities. This additional variable (temporal sequencing and designated "critical" zones in the ICU) added an important layer of meaning that accounted for the complexity of workflow activities that may be ordinarily be considered in a discrete and linear matter. The identified relationships were then used to identify sources of errors or breakdowns and improve care processes (Kannampallil et al. 2011; Malhotra et al. 2007).

10.3.2 Patient-Centered Approaches

Overall, the needs and work activities of patients and their families are not sufficiently integrated into or measured in workflow assessment and associated system redesign (Levine et al. 2010). Ozkaynak and colleagues highlight how patient-centered or patient-oriented workflow studies may provide a more integrated understanding of healthcare work in formal and informal health settings (Ozkaynak et al. 2013). Clinician-oriented workflows focus on the specific activities of a single individual (the clinician) and are limited in their ability to capture all of the collaborative work, including a patient's work, involved in a care system. Conversely, patient-oriented workflow "define care delivery from the patient's perspective" (Ozkaynak et al. 2013). Benefits of patient-oriented workflow, especially at boundaries between care systems, include the following:

– Patient experiences represent a more accurate common "field of work" for the cooperative work of multiple providers and care teams.
– Patient-oriented workflow models cross, but can also more meaningfully define, system boundaries. Meaningful boundaries can help capture emergent features of care delivery such as cooperation and articulation, thus reducing variability that must normally be accounted for in clinician-oriented workflows.
– Patient-oriented workflow models can characterize the spaces between the "edges of care" and can also improve our understanding of less-studied settings such as locations of daily living.

Valdez and colleagues synthesize how patient work frameworks used to assess work activities (integral to patient workflow) in consumer health settings can be integrated into user-centered design processes. This approach can improve capacity for problem analysis, conceptual design, development and formative evaluation, and summative evaluation and monitoring. Workflow analysis can then be used as a tool to integrate information sourced from CHI and better understand associated patient and family work (Valdez et al. 2015).

– *Problem analysis*: Field research in a patient's home and other community settings can help integrate patient and family perspectives and priorities into health technology design, especially since CHI technologies are used primarily outside traditional clinical settings.
– *Conceptual design*: Community-based or community-informed informatics interventions can provide more accurate information related to the contexts in which health technologies are used by patients and families
– *Development, evaluation, and monitoring*: Participatory design sessions with patients and families, especially high-need or vulnerable populations, can integrate multiple "interconnected participants" such as patients, their families, and providers, into the design process.

The health system Kaiser Permanente has utilized case study video ethnographies to study workflow in a novel way and improve care transitions (Neuwirth et al. 2012). Rapid video ethnography was used to study transitions between settings and complement workflow mapping. Their four-step process effectively triangulated qualitative and quantitative measurement strategies. It included planning and design based on a clearly defined project, fieldwork (interviewing, observing, and video recording), data analysis (paired with identification of improvement opportunities), and video editing based on key themes and selected improvement opportunities.

10.3.3 Human Factors and Ergonomics

Human factors and ergonomics (HFE) methods help us consider patient, family, and provider strengths and limitations in the design of healthcare systems and technologies. This approach has been used for decades to improve care quality and safety in healthcare. The Systems Engineering Initiative for Patient Safety (SEIPS) model is an HFE systems approach that incorporates Donabedian's Structure-Process-Outcome model of care quality (Donabedian 1988). It includes an individual's external environment (structure/work system), care and other processes (process), and patient, employee, and organizational outcomes (outcomes). The SEIPS conception of external environment includes persons, tasks, organizations, the physical environment, technology and tools. It is an adaptable model that accounts for multiple healthcare domains, emphasizes systemic impacts, is flexible across various work systems, and provides a broad view of processes incorporating multiple work system elements (Carayon et al. 2014).

10.3.4 Social Network Mapping to Prioritize Target Areas

Small network mapping is a method that used analyze and interpret small networks of providers and practices. Recent efforts have evaluated case studies relevant to the edges of care: one of networks of patient handoff communication and the other of networks of interorganizational ties in primary care. Simple validation techniques can address the variability inherent in small networks and compare across networks. Network mapping conducted between organizations, focused on transition points with particularly high vulnerability (as evidenced by patient outcomes such as adverse events), can be used to determine the presence of a central coordinator of specific activities. This approach could in turn provide a basis to more specifically study workflows, reengineer workflows and drive policy changes within networks (Dunn and Westbrook 2011). Other approaches have used social network analysis more specifically to characterize the frequency and type of communication patterns between providers and patients, as well as the network of communication patterns between providers and patients during transition processes (Pinelli et al. 2015).

10.3.5 Cross-Organizational Workflow

Promoting local health information exchange (HIE): HIE provides the promise of readily available relevant medical and social information that bridges care settings. It may eventually help patients and providers with adherence to treatment recommendations, reduce waste, errors, and previously discussed issues of missing information. Currently, data exchanged between HIE, hospitals, and other healthcare settings is minimal and still mostly inaccessible to patients and their families. Clinical information is still largely heterogenic and data sharing is not sufficiently collaborative. Understanding factors that promote or prevent HIE implementation at the edges of care could accelerate our transition to a system where HIE is easily available, accessible by patients, families, and their care teams, and accurate (Jensen 2013). Workflow implementation challenges have hindered HIE participation, although implementing HIE may provide the opportunity to add new or improve existing workflows. Accountable care organizations, which include multiple sites of service, are driven by federal policy goals to recognize the importance of health technology implementation and coordination across care settings. Workflow assessment of care management processes could improve care quality and safety for their patient populations (Rundall et al. 2016).

Process-oriented coordination of care across organizations: Tello-Leal and colleagues recently developed a methodology to integrate cross-organizational healthcare services between generalist and specialist care. The methodology utilized Model-Driven Architecture, Petri Net specification and definitions of clinical documents using HL7 Clinical Document Architecture, housed on a coordinated software platform. The methodology included three phases: first, healthcare organizations involved defined an "integration agreement," which identified requirements and goals, processes, and clinical documents required across organizations. An integrated technological solution was then used to design the identified processes, define clinical documents, and design integration processes. The methodology can guide organizations to more specifically define care integration, define artifacts required in care integration, and automate patient referrals across settings (Tello-Leal et al. 2012). Though complex and resource-intensive, this approach has the potential to directly integrate processes across boundaries of care. Further development of similar approaches using scalable technologies could be one day replicated in other care settings.

10.3.6 Leveraging Local Resources and Funding

The resource limitations currently faced by smaller primary practices and community health centers limit workflow assessment and implementation of HITs which can promote improvements to care quality and safety (Young et al. 2017). In addition to leveraging local and federal funding dedicated to EHR implementation and adherence to Meaningful Use guidelines (Regional Extension Centers), external partnerships with universities and large health systems may better distribute resources and expertise related to HIT and workflows. There is also a potential to train and engage non-clinical staff such as patient advocates and navigators in these efforts.

10.4 Conclusion

There is significant discontinuity and fragmentation between different sites of service within healthcare, but limited documentation of workflow (1) in low-resource care settings, (2) between care settings, and (3) outside of care settings. Workflow analysis, especially patient-oriented workflow, can be used as a tool to better characterize and address these gaps. To equitably improve quality and safety of patient care across different care settings, there is a need for automated and mixed-methods approaches that continuously leverage existing data, account for the nuances and resource limitations at the edges of care, and ultimately reach across the continuum of the healthcare systems. Health information exchange, interorganizational collaboration and cross-sectoral collaboration will all be required in order to map workflow across settings. At the end of the day, clinicians and researchers should and must leverage the fact that the patient is central to all care delivery.

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Part III
Research Methods for Studying Clinical Workflow

Chapter 11
Computer-Based Tools for Recording Time and Motion Data for Assessing Clinical Workflow

Danny Tzu-Yu Wu

11.1 Introduction

This chapter focuses on computer-based tools designed to facilitate field data collection for time and motion studies (TMS) conducted in healthcare settings. As a commonly used research method, TMS originated from industrial engineering with a goal to assess workers' time expenditure and physical movements when completing a task, a series of tasks, or distinct steps that constitute a task. In recent years, TMS have been widely adopted and frequently used to study clinical workflow, especially in the context of introduction of health information technology (IT) systems (Lopetegui et al. 2014). As of April 2018, a cursory search in PubMed[1] with the keywords *("time and motion study" OR "time motion study")* yielded a total of 337 papers. More than 75% of them were published after year 2000. For more details of TMS, please see Chap. 4 in this book, "A Review of Clinical Workflow Studies and Methods."

TMS usually require a person (i.e., "external observer") to shadow clinicians' work in order to continuously record when, where, and what clinical tasks are performed. Since early 2000s, Several computer-based tools have been developed to facilitate time and motion data collection with features specifically designed to accommodate capture of complex workflow behaviors, such as multi-tier clinical task classifications and the ability to record multitasking and interruptions. In this chapter, we describe three such tools that have been used in multiple TMS-based research studies with established validity and generalizability. Our choice of these three tools, however, does not suggest they perform better than other competing tools available, or are more generalizable.

[1] https://www.ncbi.nlm.nih.gov/pubmed

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11.2 Time Capture Tool (TimeCat)

The Time Capture Tool, or TimeCaT, was developed in 2012 with a focus on standardization, scalability, and dissemination. Its development began with a systematic review of the features and limitations of existing TMS tools at the time. Then, a pilot version of TimeCaT was created and tested through an empirical study conducted in an emergency medicine setting. User feedback was collected to inform refinement of the tool, leading toward a significantly modified version with improved usability and functionality. Lopetegui et al. (2012) provides more details on the history, design, and development process of TimeCaT (Lopetegui et al. 2012).

TimeCaT has a user-facing website available at http://www.timecat.org/. Its current version (v3.9) is capable of capturing multitasking and interruption events; and allows observers to correct data during the observation (Fig. 11.1). TimeCat uses UNIX-based timestamps to calculate task duration to avoid discrepancies due to time zone difference. It also provides several dashboards for administrative and real-time data reporting purposes (Fig. 11.2). It is worth noting that TimeCaT uses visualization techniques to compare between observations to help researchers assess inter-rater reliability and discover patterns of differences (Fig. 11.3). One exemplar study that used TimeCaT to quantify and visualize nursing clinical workflow was conducted by Yen et al. (2016).

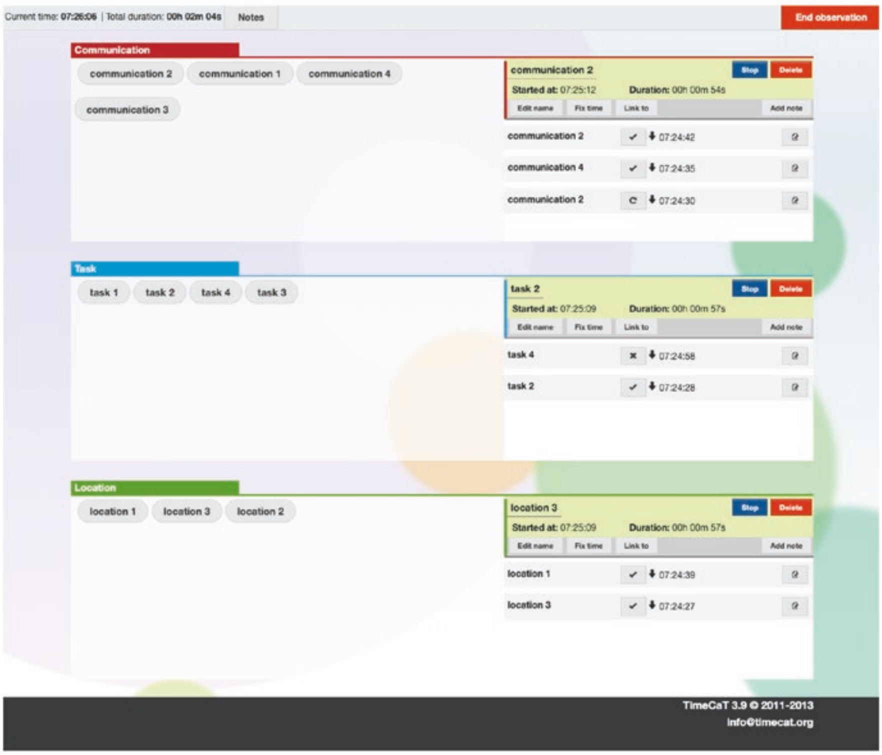

Fig. 11.1 TimeCat: Data capture and correction

Fig. 11.2 TimeCat: Real-time data reporting dashboards

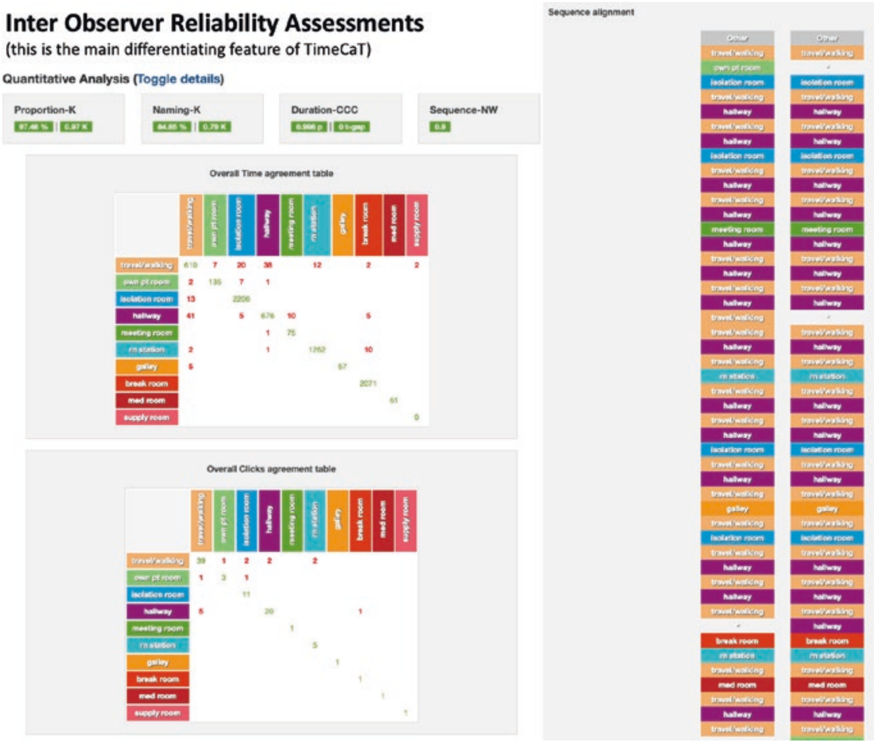

Fig. 11.3 TimeCat: Visual comparison to assist in evaluating inter-rater reliability

11.3 Work Observation Method by Activity Timing (WOMBAT)

WOMBAT was developed in 2008 by Johanna Westbrook and her colleagues at the Macquarie University, Sydney, Australia. Its design objective is to create a digital tool for efficient, accurate, reliable, and detailed TMS data collection to effectively capture health professionals' work and communication patterns. WOMBAT is capable of recording clinical work activities in four dimensions, namely *What*, *Who*, *How*, and *Where*; in addition to *When* which is automatically captured as computer-recorded timestamps.

WOMBAT was initially developed on the Personal Digital Assistant (PDA) platform and was later migrated to Android. Tablets with larger screen sizes (7″ or 8″ at the minimum) are recommended for optimal experience when using WOMBAT as a field data collection tool. In addition to the Tablet-based app, WOMBAT provides a web front to manage the app as well as to analyze time and motion data collected. Figure 11.4 shows a screenshot of the app (left) and the web front (right), respectively.

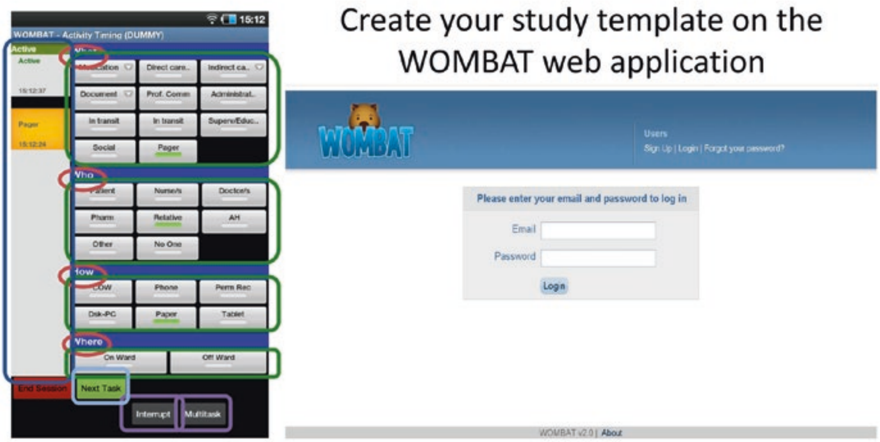

Fig. 11.4 Screenshots of WOMBAT Tablet (left) and web-based application (right) for data capture and tool administration, respectively

The initial version of WOMBAT was designed and evaluated through a nursing workflow study conducted by Westbrook and Ampt (2009) that involved four wards, 52 nurses, and 250 observation hours. The results of the study demonstrated that the nursing workflow data collected by WOMBAT accurately reflected known differences in clinical roles and tasks. WOMBAT was further validated in a study conducted in Canada in 2011 by Ballermann et al. (2011). This study observed clinicians' work in two intensive care units where a computerized clinical system was introduced. The study again demonstrated WOMBAT's utility in collecting high-quality workflow data to compare clinicians' time allocation before and after the system implementation. Since then, WOMBAT has been used in multiple TMS globally conducted by different research groups. A list of use cases of this tool can be found at http://aihi.mq.edu.au/content/wombat-case-studies.

The current version of WOMBAT can be accessed through its official website at https://aihi.mq.edu.au/project/wombat-work-observation-method-activity-timing. Of note, WOMBAT requires a license agreement for individual users. Once the license is obtained, WOMBAT can be used in any number of projects.

11.4 Time and Motion Data Collector

The Time and Motion Data Collector (the "TM Collector" hereafter) was developed in 2015 as part of a research project funded by the U.S. Agency of Healthcare Research and Quality (see Chap. 17, Examining the Relationship Between Health IT and Ambulatory Care Workflow Redesign) (Zheng et al. 2015). The tool was designed to capture both discrete clinical activities based on customizable task taxonomies, as well as multitasking and interruptions.

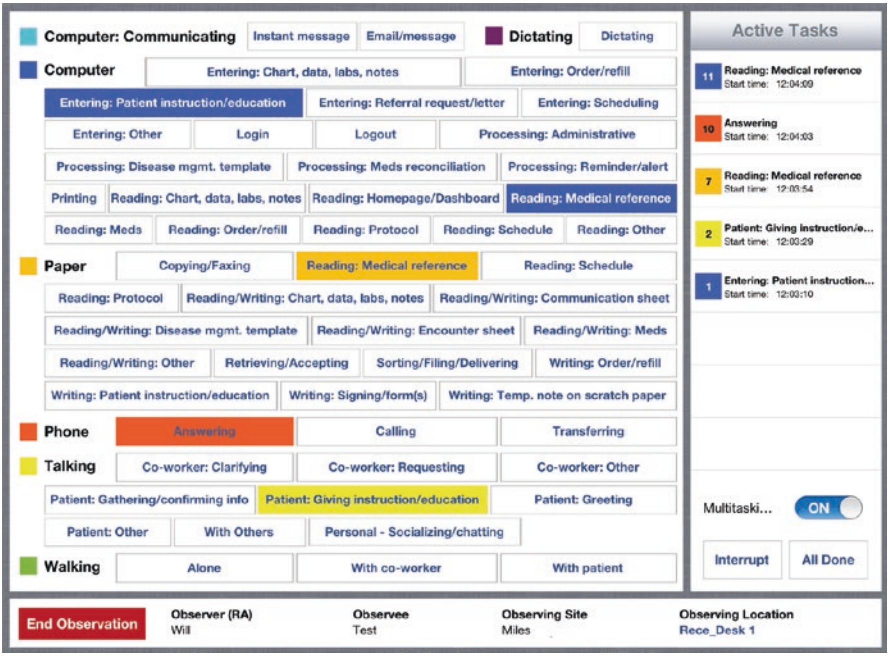

Fig. 11.5 Main data capture page of the T&M data collector

The TM Collector incorporates carefully designed features to accommodate recording of multitasking and interruption events (Fig. 11.5). Tasks being performed simultaneously by the observee can be handled with two approaches depending on the use scenario. In the first approach, overlapped task durations as a result of multitasking are grouped into new "composite" activities. In the second approach, overlapped durations are split and attributed proportionally to each of the tasks being performed at the same time. Take two tasks, A and B, as an example. Assume task A lasted 10 s, task B lasted 15 s, and there was a 5-s overlap between them. Using the first approach, a new composite task A/B would be created so that it produces a new event sequence of A (5 s) to A/B (5 s) to B (10 s). When the second approach is applied, the overlapped portion would be split and attributed equally to activity A and B, resulting in a new event sequence of A (7.5 s) to B (12.5 s). This distinguishing is important when certain measures, such as how clinicians distribute their time across different clinical tasks, are computed.

In addition to specifically developed features for accommodating the complex nature of clinical workflow, the TM Collector also has a web-based analytics platform for analyzing workflow data in real time using data mining and visualization techniques. Figure 11.6 shows the landing page of the analytics platform, which displays key descriptive statistics related to the duration of performance for each of the tasks or task groups. Users can then choose to conduct drill-down analyses at different levels. The platform also supports data analyses

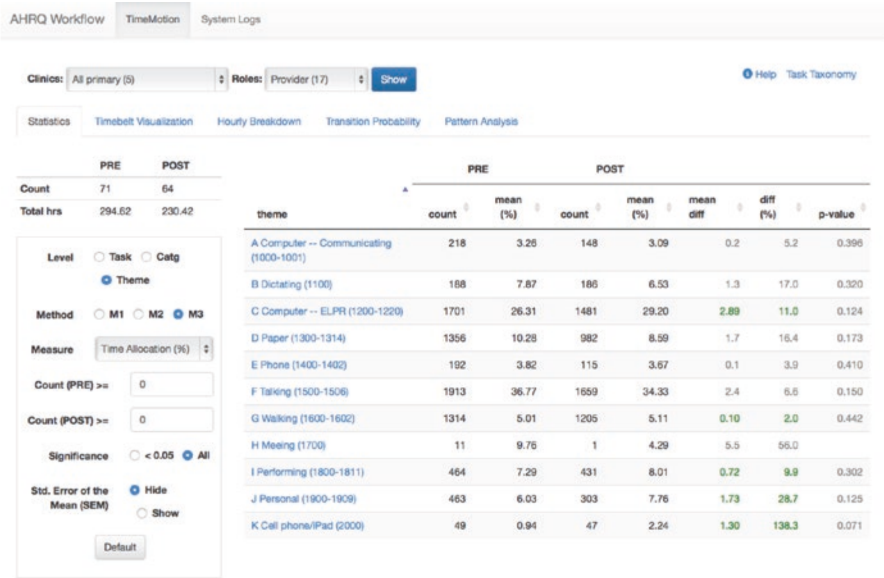

Fig. 11.6 Statistical summary of task allocation and continuous time on the analytics platform

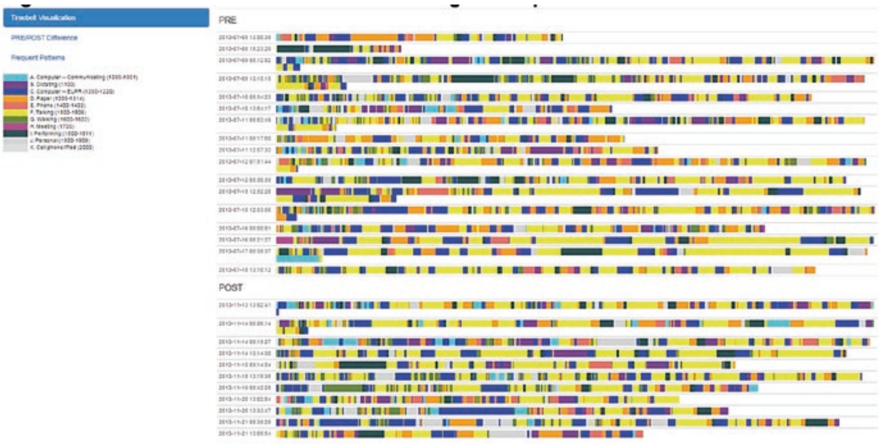

Fig. 11.7 Time-belt visualization on task sequences

for *before-and-after* studies. Pre- and post-data can be separately uploaded, which will be automatically compared using common statistical procedures such as paired or unpaired *t*-test and chi-square test. The analytics platform also provides a variety of visualization options to help researchers discern patterns of potential interest from the visual representations of their data. Figures 11.7 and 11.8 exhibit two examples.

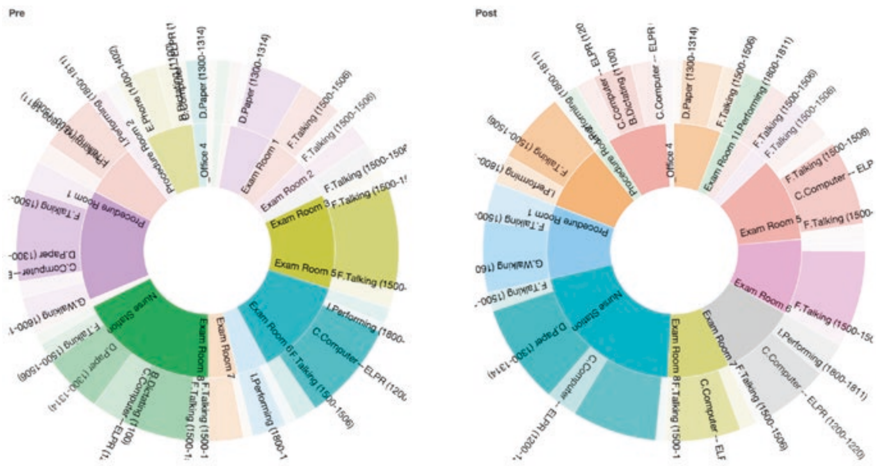

Fig. 11.8 Location-task analysis using a sunburst graph

The TM Collector has been recently adopted by two researcher teams to conduct TMS outside its original development context, demonstrating its generalizability. In the first study, it was used to record workflow data in an emergency medicine setting at an academic medical center in the U.S. to inform the design of a computerized clinical decision-support system (Ozkaynak et al. 2018). In the second study, the tool was used to collect behavioral data on how bedside nurses used a mobile app in Geneva, Switzerland (Ehrler et al. 2018).

11.5 Methodological Challenges and Potential Solutions

While TMS have been considered the "gold standard" approach for quantifying clinical workflow, it has its own limitations. First, collecting time and motion data requires a significant amount of resources, from hiring and training external observers to coordinating observation sessions with busy clinicians. Second, the quality of TMS data collected by human observers can be variable depending each individual's capabilities and biases. For example, an observer might deem an activity unimportant, or not clinically related, and therefore did not record it; yet the activity might turn out to provide crucial information for answering some research questions down the road. Moreover, the granularity of TM data and proper classification of activities require a thorough understanding of the clinical work being observed. This can be difficult for external observers who do not have relevant background. Further, TMS involving external observers is inherently intrusive. Study participants' behavior while being observed may deviate considerably from how they usually conduct their work.

Another critical limitation of TMS is that it is very difficult to compare results across different TMS studies due to the inconsistent methodologies they apply (e.g., how external observers are trained, how inter-observer reliability is assessed and calibrated, and whether the same observer is assigned to observe the same study participant across different study stages such as before and after an intervention is introduced). To address this issue, Zheng et al. developed a checklist called Suggested Time And Motion Procedures, or STAMP, based on a review of relevant TMS studies (Zheng et al. 2011). The STAMP list outlines 29 essential elements that need to be carefully considered in designing TMS and in reporting TMS-produced study results and research findings. These 29 elements are organized in eight key areas, including (1) intervention, (2) empirically setting, (3) research design, (4) task category, (5) observer, (6) subject, (7) data recording, and (8) data analysis.

Zheng et al. also provided a new perspective on how to analyze time and motion data. Specifically, they argued that the prevalent method that focuses on the "time expenditures" measure (e.g., how clinicians allocate their time across different tasks) is limited, and can generate conflicting or misleading results. Alternatively, they argued workflow studies should focus on investigating the "flow of work" instead. Through an empirical study, they demonstrated that this could be achieved by introducing using new workflow measures and new analytical approaches, such as workflow fragmentation assessments, pattern recognition, and visualization. These new measures and new analytical methods could collectively contribute to uncovering the "hidden regularities" embedded in clinicians' work and workflow (Zheng et al. 2010).

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Chapter 12
Understanding Clinical Workflow Through Direct Continuous Observation: Addressing the Unique Statistical Challenges

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12.1 Background

12.1.1 General Introduction

The nature of healthcare as a dynamic human process occurring within complex socio-technical systems means that there is no unique or standard way to examine its inner workings. Rather, a range of observational methods drawn from multiple disciplines have been used to study workflow *in situ* (McCurdie et al. 2017). Areview of methods used to study and model workflow across different industries, including healthcare, identified qualitative approaches such as ethnographic observation and interviews, along with quantitative methods including structured or timed observations, and surveys (Unertl et al. 2010).

Analogous to timed observations, the term *time and motion* is applied in many studies of workflow in healthcare. This umbrella term encompasses a range of methods and designs with the common feature of directly observing an individual's activities and recording aspects of that action, usually in a quantitative way. Zheng et al. (2011) reviewed time and motion studies used to assess the effect of interventions, especially technology-related interventions, on workflow in healthcare settings. From their synthesis, they developed the STAMP checklist (Suggested Time and Motion Procedures) to promote consistency in design, conduct and reporting of time and motion studies. Lopetegui et al. (2014) took this theme

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further by reviewing the distinct methods used in healthcare under the banner of 'time and motion studies'. The many variations they identified were categorized into three groups: those involving external observers shadowing participants, those using information self-reported by participants, and those that employed automated data recording such as GPS devices or accelerometers. Of the first type, they identified a method employing continuous observation and coined the term *workflow time study* to describe it as a distinct but increasingly common approach. This method constituted 26% of all time and motion studies reviewed, and over 60% of all studies that involved continuous observation by an external observer. Also, the proportion of studies employing continuous observation was noted to have increased over the review period.

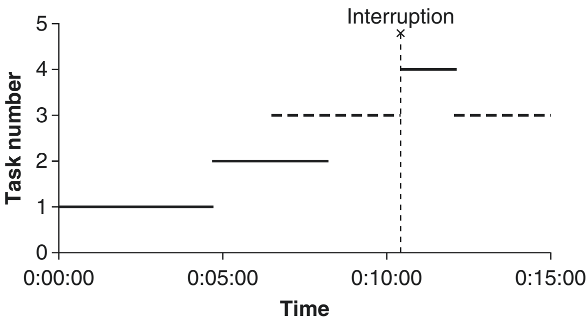
Although the workflow time study approach is one among many observational approaches, it offers many advantages over other quantitative methods, and its growing use in healthcare is a testament to this. This method itself involves observers shadowing individual clinicians and continuously recording time-stamped data about an individual's tasks and interactions (see Sect. 12.1.2 for more detail). Workflow time studies capture more of the fine-grained complexity of clinical work than methods such as work sampling, and the temporal continuity of the data forms the most complete record of an individual's workflow of any observational technique, barring audio-visual recording which is often not acceptable in a clinical environment. Workflow time studies have great potential to help us understand clinical work and workflow and can be applied to a diverse range of research questions and professional groups (Walter et al. 2015). This includes descriptive analyses that examine the way clinicians distribute their time between different tasks, between patients, between locations, and so on (Westbrook et al. 2008; Li et al. 2015; Richardson et al. 2016). It also supports assessment of the impact of interventions on workflow, such as the introduction of new technological systems, policies or practices (e.g. Georgiou et al. 2017). Furthermore, workflow time studies enable interrogation of more complex questions such as the way clinicians sequence, prioritize and interleave tasks. They can also examine associations between clinicians' work and safety-related outcomes, such as factors that contribute to errors of task omission and commission (e.g. Westbrook et al. (2018).

Capturing a more complete record of the complexity of workflow in healthcare settings is necessary to generate valid and relevant insights about everyday clinical work within a quantitative paradigm. However, this also introduces some unique methodological challenges in all aspects of the study process including design, data collection, analysis and interpretation of findings. Despite the importance of applying appropriate quantitative methods, methodology in the area is still evolving, and there is a tendency to apply conventional statistical methods to data that are inherently non-standard. This chapter examines the critical quantitative and statistical challenges with which workflow time studies are confronted, including reviewing methods applied in studies to date and suggestions for methodological improvements. Many of the aspects discussed in this chapter may also be relevant to the quantitative study of workflow more generally.

12.1.2 Defining Workflow Time Studies

The original definition of workflow time studies referred to those studies involving periods of continuous observation of a participant where "the observer records the occurrence and duration of unpredicted instances of tasks, producing a data schema of time-stamped tasks, which accounts for task fragmentation, interruptions and work variability" (Lopetegui et al. 2014). There are several features that distinguish this technique from other observational methods. First, the fact that observers continuously shadow participants sets it apart from approaches such as self-reporting of work activities (Ampt et al. 2007), work sampling or multimedia recording. Second, although carrying out detailed observations over extensive periods of time has parallels with ethnography, observers in workflow time studies apply predefined categories of task attributes at the time of observation, as distinct from ethnography where grouping of types of observed action into categories or themes occurs during the analysis phase (e.g. Malhotra et al. 2007). Third, the recording of time stamped intervals for each task generates data that represents a temporally complete record of the observed activity. In other words, at every time point during observation, action is assigned to one category or another, or, equivalently, no time in the workflow is unaccounted for. This contrasts with other methods where the observer may continuously shadow the participant but may only record data at certain times or on particular activities.

The data generated by workflow time studies is essentially a set of time intervals, each defined by a start and end time, and having any number of categorical attributes such as task type, location where the task was performed, with whom it was performed, and so on. Figure 12.1 provides a simple illustration of tasks plotted over time, in addition to one possible way to represent the raw data. The intervals can be contiguous where one task ends and another begins, as between tasks 1 and 2 in the figure; or they can overlap where two types of action occur in parallel (commonly called multitasking) as with tasks 2 and 3. When intervals represent fragmen-



Task ID	Start time	End time	Type	Interrupted by
1	0:00:00	0:04:40	A	
2	0:04:40	0:08:10	A	
3	0:06:30	0:10:25	B	4
4	0:10:25	0:12:05	A	
3	0:12:05	0:15:00	B	
...	...	...	...	

Fig. 12.1 Example of four tasks observed in a workflow time study, represented as intervals on a time line and as records in a dataset

Table 12.1 Examples of dimensions and categories used in workflow time studies

Dimension	Category
Task type	Direct care
	Indirect care
	Documentation
	Clinical communication
	Management communication
	Social communication
	Prescribing
	Other
With whom	Specialist (consultant)
	Fellow (registrar)
	Resident/intern
	Nurse
	Relative
	Patient
	Paramedic
	Other
	No one

tation of tasks that are suspended due to interruptions and later resumed, this can be indicated with categorical labels, as shown by the 'interrupted by' column in the figure. Some studies also augment with data from other sources such as patient load, self-reported measures or participant characteristics, in an effort to include factors at multiple system levels (see for example Westbrook et al. (2018).

The task attributes mentioned above are termed *dimensions*, each of which may have several *categories* (Westbrook and Ampt 2009). In workflow time studies, a dimension is an aspect of clinical work that is relevant to the research questions of a study. In the example in Fig. 12.1, 'type' is the main dimension which has categories 'A' and 'B'. In clinical settings, dimensions may be the type of task performed by the participant (usually the main dimension), the location where the task is performed, or with whom the participant interacts with while performing the task. In the language of quantitative analysis, dimensions can equivalently be thought of categorical variables, and the categories represent all the potential values that a variable can take on. Table 12.1 illustrates two dimensions and their categories from a study of emergency doctors in Australia (Walter et al. 2017).

12.2 Sampling Strategies

The first major methodological challenge in conducting a workflow time study is how to approach data sampling. The sampling strategy naturally depends on the study design. As it is impractical to cover the sampling strategies for all possible workflow time study designs within this chapter, we limit our discussion to the following three major study types: (1) descriptive studies that provide a snapshot of the clinical work process, (2) intervention studies that assess change in workflow over time as a result of an intervention, and (3) association studies that aim to link aspects of clinical work to patient safety or quality of care outcomes.

One aspect of the sampling strategy that impacts all three study types is that there is a limit as to how much one observer can continuously observe without a break. However, much of health care, particularly critical care, occurs around the clock. Although in an ideal situation we may wish to observe all clinicians at all times throughout the study period, this is simply not practical. Thus, the data in workflow time studies are often collected across many separate observation sessions, wherein each session typically consists of a few hours of shadowing with a single participant. The data from these sessions are then combined together to form a collection of workflow samples on multiple participants.

The nature of clinical work varies with time-related factors: time of day, day of the week, time of year, etc. (Walter et al. 2014). It also differs between clinician roles or seniority (Westbrook et al. 2010), and between the idiosyncrasies of individuals (Walter et al. 2014). Oversampling at certain times or among certain roles can therefore influence the study results, underscoring the need for an appropriate sampling strategy to avoid biases. Descriptive studies generally aim to generate a set of samples that, when combined, are representative of clinical work in a certain setting, among a particular professional group, or during a given period of the working day. For example, Arabadzhiyska et al. (2013) studied the work of resident physicians on night shifts (10 pm to 8 am) on general hospital wards.

Generating a representative sample is usually accomplished by applying a time-based sampling scheme to collect approximately equal amounts of observation time balanced across known factors that may influence summary measures such as proportions and rates. To illustrate, the rate at which clinicians' work is interrupted is known to be higher for those who are more senior (Walter et al. 2017), during weekends (Richardson et al. 2016) and is related to workload (Weigl et al. 2012) which varies throughout the course of the day. If there is unintentional oversampling of senior clinicians, Saturdays and Sundays or busy periods, it could then inflate the interruption rate to be observed. In contrast, balancing observation time across such factors provides an interruption rate estimate that is more representative of the 'average' workflow within the study population.

Such a sampling scheme was used by Richardson et al. (2016) who conducted a descriptive study of junior physicians working on day shifts during the weekend. The study population was from a single professional group of the same seniority; and a sampling scheme was developed to ensure balance in observation hours over time of day (between 8 am and 5 pm), day of the week (Saturday and Sunday) and also over the 13-week observation period (Table 12.2).

Another major source of variation in workflow is between individuals. A study of how clinicians in three hospital settings respond to interruptions found that significant variation between individuals persisted after adjusting for many task-level and temporal factors (Walter et al. 2014). Attempting to average individual differences by balancing (as shown in Table 12.2) would mean an unrealistically large increase in required sample size and hence observation time. For example, the Richardson et al. study had 16 participants, so to observe each of them, during every time of the

Table 12.2 Sampling schedule used by Richardson et al. (2016) to study junior physicians working on day shifts over the weekend

	Saturday A	Sunday A	Saturday B	Sunday B
Observation time	Week 1, 3, 5, 7, 9, 11, 13	Week 1, 3, 5, 7, 9, 11, 13	Week 2,4, 6, 8, 10, 12	Week 2,4, 6, 8, 10, 12
0800–0950	Observing			Observing
0950–1140	Resting	Observing	Observing	Resting
1140–1330	Observing	Resting	Resting	Observing
1330–1520	Resting	Observing	Observing	Resting
1520–1710	Observing	Resting	Resting	Observing
1710–1900		Observing	Observing	

day, day of the weekend and week of the study period, it would require an increase of the total observation time from 132 h to more than two thousand hours. Randomisation offers a way to average out the effects of temporal factors and individual differences with a more realistic sample size. For each observation session the participant is randomly selected, as is the time of day, day of the week, and so on. Sessions can be assigned in this way until a sufficiently large sample is attained.

In practice, it is not always possible to implement either a balanced or randomised sampling scheme exactly as planned. Finding a certain participant at a particular time can be difficult, especially in a hospital setting where staff rosters change and clinicians swap shifts at the last minute. While it is important to have a sampling plan, it may be necessary to modify it over the course of the study period to compensate for imbalances introduced by unanticipated deviations from the schedule. If logistical constraints cause the final sample to be unbalanced, it is possible to adjust for this in the analysis phase using multivariate regression. For example, to calculate the interruption rate across task type categories (as in Table 12.1) when there has been oversampling of senior clinicians, Poisson regression could be applied with the main covariate as task type, but also including, say, time of day and participant seniority as additional variables. This does not preclude the need for a sampling plan, but rather provides a way to mitigate the effects of compromised implementation of the plan.

For studies assessing the impact of an intervention using a pre-post design, an additional consideration is to use a consistent sampling strategy for each time period. While studies of this type should ideally use a control group to capture any pre-post changes not attributable to the intervention, the controls may not necessarily capture pre-post differences due to sampling. For example, if senior clinicians are oversampled post-intervention for the intervention group, but not for the control group, then the intervention effect will be muddied with sampling effects, with no completely satisfactory way to separate them during the analysis.

For association studies, the sampling priority is somewhat different as the aim is not to generate representative summary measures of workflow, but to assess statistical associations between aspects of clinical work. Where descriptive studies use a sampling strategy based on observation time, association studies build sampling around the units of analysis (tasks, events, etc.). To examine associations in an observational study it is necessary to adjust for confounding factors (in the epidemiological parlance) to derive the least biased estimate of the association of interest, usually done through multivariate modelling. The variables generated by workflow time studies are typically categorical, so an important consideration is whether there will be sufficient outcome data in each category. Small numbers in certain categories may cause issues with model fitting, so it may be desirable to oversample certain times of day, certain professional groups, and so on, to avoid this issue. In a study by the authors (Walter et al. 2017) on physicians' response strategies for dealing with external prompts (i.e. interruptions), the original analysis plan involving both categorical outcome and covariates was not possible due to some outcome categories never occurring at the same time as certain covariate categories. This caused implausible or nonsensical model outputs for some variables even after collapsing of some categories, and an alternative analysis approach was necessary. Therefore, for association studies, the sampling strategy must necessarily be developed in parallel with dimensions and categories.

12.3 Inter-observer Reliability

A fundamental aspect of generating high quality data from observations of clinical work is to ensure consistent application of dimensions and their categories between different observers. This is often called inter-rater reliability, a term taken from psychology, although in this context we use the term inter-*observer* reliability (IOR) since we are interested in observations as a more varied set of judgements, as opposed to ratings which tend to involve assigning a single value or category at a time. The fact that workflow data recorded at task-level have time stamps, involve temporal order and feature multiple categorical attributes makes it rather complex to compare between two or more observers who are following the same participant. To date, there has been persistent use of simple methods borrowed from other contexts that are not well suited for their purpose, and this is somewhat of an 'elephant in the room' in quantitative observational studies of clinical workflow.

A range of methods have been applied in workflow time studies to assess IOR and a review of these identified seven different approaches among the 27% of studies that provided some details of their IOR assessment (Lopetegui et al. 2013). The most common was Cohen's kappa, a well-known method used in psychology to quantify the level of agreement between two or more raters assigning units to a set of categories, such as assigning exam papers to either pass or fail (Cohen 1960). In workflow time studies this approach seems to be treated as somewhat of a gold standard, while at the same time most studies gloss over the details of its application to IOR assessment (Lopetegui et al. 2013). There are several issues with kappa, and other similar measures, that mean assessments of IOR are limited at best, and may even be misleading in that high kappa scores can be achieved even though significant observer differences are present.

Table 12.3 Example data from two hypothetical observers shadowing the same participant

Observer	Task ID	Start time	End time	Task type	Performed with nurse
1	1	0:00:00	0:04:30	A	0
1	2	0:04:30	0:07:00	B	1
1	3	0:06:30	0:10:25	B	0
1	4	0:10:25	0:12:05	A	1
1	5	0:12:05	0:15:00	B	0
1	6	0:15:00	0:20:00	A	1
2	1	0:00:00	0:04:40	A	1
2	2	0:04:40	0:08:30	A	1
2	3	0:06:30	0:10:25	B	1
2	4	0:10:25	0:12:05	A	0
2	3	0:12:05	0:15:00	B	0
2	5	0:15:00	0:20:00	A	0

The first main limitation is that for time-stamped and time-ordered tasks with multivariate attributes, identifying pairs of tasks from two observers that refer to the same observed action cannot be done with any certainty. Table 12.3 shows some example data from two observers shadowing the same physician. Task 2 recorded by the first observer lasted two and a half minutes, was of task type B, was performed with a nurse, and overlapped with the next task for 30 s. In contrast, task 2 recorded by observer 2 lasted almost 4 min, was of type A, was performed with a nurse and overlapped with the next task for 2 min. Given the disagreement on several attributes, it is not possible to conclusively decide if task 2 for each observer refers to the same observed action, and to decide they *do* agree based on only some agreeing attributes introduces unreasonable assumptions, or even outright guessing.

The second main limitation is that most methods used for assessing IOR only apply to one variable at a time. This may be acceptable for descriptive studies reporting summary measures of individual variables but is likely inadequate for association studies involving multivariate analyses. In one of our prior studies (Walter et al. 2014), a reanalysis of the data collected from three hospital settings found significant observer effects in multivariate models despite high univariate IOR scores.

12.3.1 Nonparametric Hypothesis Testing for IOR Assessment

In this chapter we look at two broad approaches to addressing these limitations. The first approach compares summary measures at an aggregated level using hypothesis tests. For example, the proportion of time spent performing tasks direct care tasks could be compared between observers shadowing the same participant. This method ignores temporal order and thus does not require matching at either task or time window level, making it applicable only for descriptive studies where reliability at such an aggregate level is sufficient. This approach assumes that the data from different observers should be the same and that any observed difference in summary measures is due to observer effects. Rather than generating an IOR score, this method provides a p-value where we hope to find a non-significant (large) value indicating no evidence of a difference in time proportions for data collected by different observers (as in Westbrook et al. (2018).

Proportions of time are the most common measure in descriptive workflow time studies, however, since these are proportions of a continuous variable they require unique methods (see Sect. 12.4.2.1 for more details). For this purpose, nonparametric resampling tests, specifically permutation tests, offer several advantages over conventional parametric options. Of the parametric tests, it is possible to aggregate the data into subgroups or clusters (e.g. by observation sessions) and to use a logistic transformation on the proportion for each group. This is appropriate where the subgroups or clusters are fixed (Warton and Hui 2011), however, in workflow time studies the choice of subgroups, such as observation sessions or individual participants, is not necessarily clear.

Permutation tests avoid the issues with distributional assumptions and sampling units. This approach involves reordering observer labels in the task-level data, cycling through all possible combinations and calculating the statistic of interest each time (such as the difference between proportions for two observers). These resampled values form the null distribution against which the actual difference can be compared. The proportion of null values more extreme than the 'true' difference provides the p-value. For large samples, the Monte Carlo permutation test uses many random shuffles of the labels to generate a p-value without having to calculate every possible label combination, thus reducing computation time. Good (2010) provides a comprehensive discussion of these methods. Applying a permutation test to the data in Table 12.3 to compare proportions of time spent on task types A and B and time spent working with a nurse yielded p-values of 0.61, 0.73 and 0.45, respectively. In other words, there was no evidence of a difference between observers in terms of time proportions.

12.3.2 Conventional IOR Measures Applied to Time Windows

The second approach addresses the time alignment issue by reformatting the task-level data into small time windows. This idea originated with Bakeman et al. (2009) who discussed applying Cohen's kappa in this way for timed-event sequential data, which is similar to workflow time study data. When comparing data from two observers shadowing the same participant, we can assume that during a given small time window they were observing the same activity, and this circumvents the issue with temporal alignment at the level of tasks described earlier in this section. Existing IOR methods, such as Cohen's kappa, can then be applied to the aligned time windows.

The time window approach then allows us to encompass the multivariate nature of data from workflow time studies. Janson and Olsson (2001) developed an IOR assessment method analogous to Cohen's kappa that is applicable to multivariate categorical data (pp. 282–283). When applied to two observers and one variable it is equivalent to Cohen's kappa, but can be generalised to any number of observers and variables. When applied to time windows, this is the best currently available approach for IOR assessment in workflow time studies. It is represented by the Greek letter iota, ι, (the letter before kappa).

Applying univariate kappa to the example data shown in Table 12.3 with time windows of 1 s (i.e. 1200 windows) we get scores of 0.57 for 'task type' and −0.45 for 'performed with nurse', indicating 'good' agreement for the former and moderate disagreement for the latter. If we apply Janson and Olsson's method to both variables we get a score of $\iota = 0.04$. This can easily be extended to include a third binary variable that represents multitasking (yes or no) in each time window. This has a univariate kappa score of 0.38, while the iota score for all three variables is 0.08.

The results for the 'task type' variable were consistent between the two methods, but were contradictory for the 'performed with nurse' variable. Also, the low agreement shown by the multivariate iota score did not concur with the high univariate kappa score for 'task type' alone. These results from the two general approaches highlight some key points about IOR assessment. First, the utility of any IOR measure must be considered relative to the analysis. The motivation behind assessing IOR is to identify and minimise observer biases in the data, however, IOR measures do not necessarily quantify the extent to which results are biased due to observer differences. For example, if there is good agreement on the overall proportions of individual categories between observers, but poor agreement at task level when multiple task attributes are considered together, then an analysis that aims to simply summarise proportions would not be biased, while a multivariate regression model would be. A corollary of this issue is that IOR measures have limited comparability between studies, such that it only makes sense to compare IOR results when the IOR method *and* the analysis are the same.

Second, a high univariate IOR score, as is typically reported in workflow time studies, does not tell us much about agreement levels in the whole dataset. Unless the analysis only uses one variable, it is imperative to take a multivariate approach to IOR assessment and to pursue development of customised methods for workflow time studies. More generally, it is therefore important to move away from the idea that any existing approach is the gold standard for IOR assessment, to have more transparent reporting of IOR in workflow time studies, and to have more open discussions of the limitations of existing methods and how they can be improved.

A final consideration is that IOR is not the same as accuracy, as a high IOR score could simply mean two observers are both wrong in the same way. The lack of a true record of the observed activity necessitates assessment of IOR, but also makes it impossible to assess accuracy. While we would expect some correlation between IOR and accuracy, there will always be uncertainty about data accuracy that cannot be overcome by any IOR method.

12.4 Analysis

12.4.1 Summary Statistics

The descriptive studies discussed in this chapter use a range of measures to characterise observed workflow. Of these, we focus on the most commonly used measures: proportions of time, and rates of events per unit time.

12.4.1.1 Proportions of Time

Proportions of time are a key metric in workflow time studies, providing an indication of how participants distribute their time across various activities, locations, or between the different people with whom they interact. They are a mainstay of descriptive studies but are also useful in intervention studies as an indicator of changes in work patterns. The summation of time intervals tends to be non-trivial, due to the presence of multitasking which creates overlap and hence multiple counting of time. While sums of time are not usually reported directly, they are part of the calculation of other frequently used measures such as proportions and rates.

Quantifying the uncertainty around estimated proportions in the form of confidence intervals (CIs) is important for interpreting results. For proportions of countable units, such as people or events, constructing a CI is a well-trodden path described in most statistics textbooks: the CI for a binomial proportion. However, for proportions of time—a continuous measure—the binomial methods do not apply. Surprisingly, there is little methodology for calculating CIs for proportions of continuous variables. In the early 1980s Gilchrist (1982) noted the lack of discussion in the literature despite such proportions occurring frequently, and this is still the case more than 30 years later. Only a few papers to date have discussed analysis of continuous proportions using parametric assumptions (Warton and Hui 2011; Stephens 1982), but they do not directly tackle CIs. A simple modification of the CI for the mean of a normally distributed variable has often been used (Li et al. 2015; Arabadzhiyska et al. 2013), which is expressed in the following form:

$$\frac{T_c}{T} \pm z_{1-\alpha/2} \frac{s_c \sqrt{n_c}}{T}$$

where T_c is the time spent doing tasks from category c, T is the total observation time, s_c is the sample standard deviation of task times for category c, and n_c is the number of tasks in that category. In addition, $z_{1-\alpha/2}$ is the standard score from a normal distribution, for example for a 95% CI, this would have the value $z_{0.975} \approx 1.96$.

A drawback of this method is that what constitutes a task depends on the definitions of dimensions and categories and to some extent on interpretation of those definitions during observation. For example, if a task is completed in two fragments due to an interruption, should this be counted as one task or two? That is, choices regarding task definition affect the term n_c, and hence the CI width is at the whim of these choices. Also, the normal assumption is only likely to be satisfied when samples of tasks (T_c) are at least 30, and in some cases it may generate values for the CI that are outside the plausible range, e.g. below zero or above one.

A natural alternative is to take a nonparametric approach, namely to use bootstrap CIs (as in Bellandi et al. 2018). This does not require parametric assumptions, which addresses the limitations just mentioned, making it an optimal choice for continuous proportions. DiCiccio and Efron (1996) offered a thorough discussion of the various approaches that can be used to construct bootstrap CIs. Below, we provide a brief description of the basic method.

For a dataset with n tasks, a random selection of n of these is drawn with replacement. Even though the new sample has the same number of tasks as the original data, it will not necessarily be the same dataset since the random selection *with replacement* means that in the new sample some tasks will appear multiple times while others may not appear at all. The proportion of interest for the resampled data is then calculated. This procedure is repeated many times to generate a large number of resampled proportions. The simplest way to generate an interval is to then take the 2.5th and 97.5th percentile of the resampled proportions (for a 95% CI) as the lower and upper limits of the confidence interval.

We use a simulation study to illustrate the utility of the bootstrap approach by comparing the normal approximation method to the simple bootstrap. We also apply the bias-corrected and accelerated (BC_a) bootstrap which accounts for asymmetry in the CI. A sample of tasks was drawn with time durations from either an exponential, gamma or normal distribution. A random subset of 5, 10 or 20% of tasks was selected to represent some category of interest. For that 'category' the proportion of time was calculated along with its CI according to the three methods. This was repeated 1000 times and the proportion of CIs containing the true value, the coverage probabilities, are shown in Table 12.4. By definition, a 95% CI should cover the true proportion 95% of the time for a large number of repeated studies (or simulations in this case), so the expected coverage probability is then 0.95.

Table 12.4 Coverage probabilities for confidence intervals of proportions of time generated via three methods

Total	'True'	Normal approximation			Simple bootstrap			BC_a bootstrap		
tasks	proportion	Exp	Gamma	Normal	Exp	Gamma	Normal	Exp	Gamma	Normal
10	0.05	0.070	0.049	0.013	0.384	0.398	0.406	0.391	0.404	0.404
10	0.5	0.786	0.782	0.501	0.892	0.905	0.925	0.938	0.931	0.946
10	0.95	0.987	0.982	0.946	0.375	0.394	0.396	0.386	0.398	0.394
100	0.05	0.671	0.654	0.381	0.830	0.881	0.905	0.851	0.895	0.925
100	0.5	0.934	0.882	0.587	0.940	0.951	0.950	0.948	0.952	0.954
100	0.95	0.999	1.000	0.980	0.831	0.867	0.903	0.853	0.882	0.924
1000	0.05	0.830	0.732	0.452	0.933	0.947	0.942	0.946	0.950	0.945
1000	0.5	0.946	0.877	0.584	0.948	0.941	0.952	0.951	0.942	0.956
1000	0.95	1.000	1.000	0.993	0.926	0.927	0.948	0.931	0.939	0.949

Both bootstrap approaches appear to perform better than the normal approximation method when the true proportion is near the lower boundary of the possible range of values (true proportion $\pi = 0.05$) or in the middle of the range ($\pi = 0.5$), especially for small and medium samples. The normal approximation performs particularly poorly for small proportions and small samples, with coverage probabilities less than 0.1. Towards the upper end of the range ($\pi = 0.95$), however, the normal approximation seems to perform better for small to medium samples, although proportions of this magnitude are rarely reported in the literature. Study samples are typically in the several thousands, and the results generated by the bootstrap method are consistently closer to the expected coverage probability of 0.95 for samples of that size. This suggests that the bootstrap CI is generally preferable to the normal approximation, which can be quite inaccurate. Further, the BC_a method consistently has slightly better coverage for all scenarios compared to the simple bootstrap and hence represents a better choice for calculating CIs of time proportions among the methods considered here.

12.4.1.2 Rates of Events Per Unit Time

Discrete events occurring at different points in time are common in clinical work and can be easily captured in workflow time studies. The most common example is interruptions. Since the number of such events is proportional to the length of time observed, they are generally analysed as rates per unit time, such as interruptions per hour. This quantifies the intensity of events while being independent of the amount of observation time. Descriptive studies tend to report rates in this form along with their CIs (Li et al. 2015; Walter et al. 2014; Westbrook et al. 2010). A common and simple approach for generating CIs is to assume that event counts, λ, are drawn from a Poisson distribution and to then generate a normal approximation CI in the form of:

$$\left(\lambda \pm z_{1-\alpha/2}\sqrt{\lambda}\right)/T$$

where T is the observation time. However, the Poisson assumption that the mean and variance are equal is not always met in workflow time study data and once again bootstrap CIs provide a more robust alternative.

We illustrate this through another set of simulations comparing the normal approximation method to both simple and BC_a bootstrap. This was done for task lengths drawn from two different distributions (exponential and normal), for small and large samples (n = 10 and n = 1000), for two different rates representing low and high rates relative to the typical range that appears in the literature on interruptions. We also simulated events to arrive according to either a Poisson or negative binomial distribution, where the former assumes that mean and variance are equal while the latter does not.

Table 12.5 Coverage probabilities for confidence intervals of rates per unit time generated via three methods

Total tasks	'True' rate[a]	'True' event distribution	Normal approximation		Simple bootstrap		BC_a bootstrap	
			Exp	Normal	Exp	Normal	Exp	Normal
10	3	Poisson	0.546	0.550	0.541	0.538	0.535	0.529
10	30	Poisson	0.919	0.921	0.868	0.904	0.865	0.903
1000	3	Poisson	0.939	0.960	0.940	0.961	0.938	0.961
1000	30	Poisson	0.932	0.948	0.930	0.944	0.933	0.944
10	3	NB[b]	0.533	0.567	0.529	0.561	0.521	0.553
10	30	NB	0.818	0.865	0.841	0.874	0.843	0.876
1000	3	NB	0.935	0.931	0.943	0.938	0.944	0.939
1000	30	NB	0.862	0.920	0.944	0.959	0.945	0.959

[a]Events per hour
[b]*NB* negative binomial

In the first part of Table 12.5, the simulated data satisfy the assumptions of all three methods and thus there is minimal difference between the three methods. The coverage probabilities are markedly lower for the small sample size scenarios, particularly when the underlying rate is also low. In the lower section of the table, the simulated events follow a negative binomial distribution. The differences in coverage between the three methods due to sample size and rate are similar, but a key difference can be seen for the scenario with large sample and high rate, in which the coverage for the normal approximation is lower than 0.95 while for the bootstrap method it is very close to the expected value of 0.95. This difference is amplified with increasing rate, such that for a rate of 300 events per hour the coverage for the normal approximation drops to 0.63 at best, compared to 0.96 for both bootstrap methods (data not shown in table). While the performance is comparable across most of the scenarios considered, the fact that the bootstrap approach is at least as good as, and in some cases clearly better than, the normal approximation method suggests that it may be considered a better choice to calculate CIs of rates.

12.4.2 Assessing Associations

12.4.2.1 Two Group Comparisons

Comparing outcomes between two groups is another common research goal in workflow time studies. For example, Richardson et al. (2016) (Table 3) compared both proportions of time and interruption rates between three studies of physicians, where each study used similar observational methodology and task definitions. Such comparisons in workflow time studies come with some important caveats, and some unique considerations are required for calculating significance.

Hypothesis testing was developed within the experimental paradigm in which factors extraneous to the effect of interest are controlled, such as randomly assigning subjects to one group or another. Any remaining difference in the outcome measure can then be attributed to the main effect. In other words, confounding is controlled through design. In observational studies of clinical work, this level of control is not possible, which means that the data represent a mixture of effects from many different factors, both known and unknown. When applying two group comparison tests to such data, it becomes difficult to definitively attribute the effect to any one factor. A study of physicians and nurses in surgical units (Bellandi et al. 2018) made such comparisons (adjusted for multiple testing), however, the authors appropriately refrained from attributing apparently significant differences to particular factors. Two-group comparisons in workflow time studies thus must be applied with caution.

As seen with calculating CIs, there is little methodology for analysing proportions of continuous measures. The calculations for parametric hypothesis tests involve the sample size, which, as seen several times in this chapter, can be open to interpretation. In the case of hypothesis testing, choices about what constitutes a task can then influence the sample size in the calculations and consequently the level of significance, which could result in incorrect conclusions, whether unconsciously or not.

Following on from the hypothesis testing approach used to assess IOR in Sect. 12.3.1, a way around these issues is, once again, through nonparametric methods. Permutation tests, or their Monte Carlo variation (Good 2010), can not only be applied to comparisons of typical measures in workflow time studies such as proportions of time and rates per unit time, but also to comparing means and counts. Rather than resampling the data as in the bootstrap method, the permutation tests randomly shuffle the group labels and calculate the difference between groups for each shuffle, e.g. the difference between proportions. This generates a null distribution for the observed difference and a p-value can then be determined as the proportion of permuted differences larger than the observed difference.

Again, we use a simulation to illustrate the efficacy of this approach. Tasks with durations following an exponential distribution were generated for two separate groups. For each group, a certain proportion of tasks (the 'true' proportion) were assigned to the category of interest and the difference between the group-level proportions of time for that category was calculated. The Monte Carlo permutation test was then applied to derive a p-value for the observed difference. This process was repeated 1000 times, from which the proportion of significant results was obtained using $\alpha = 0.05$. When there is a true difference, this proportion represents the power of the test. For a fixed proportion ($p1$) in the first group, the proportion in the second group ($p2$) was varied through a range of values and the power calculated each time as described above. This was done for $p1 = 0.05$ and $p1 = 0.2$, and also for sample sizes of 100 tasks (50 per group) and 1000 tasks (500 per group).

Figure 12.2 shows the estimated power for these four scenarios. Both plots show that power increases with greater true difference between groups and that this increase is more rapid for higher proportions (dotted lines for $p1 = 0.2$ versus solid

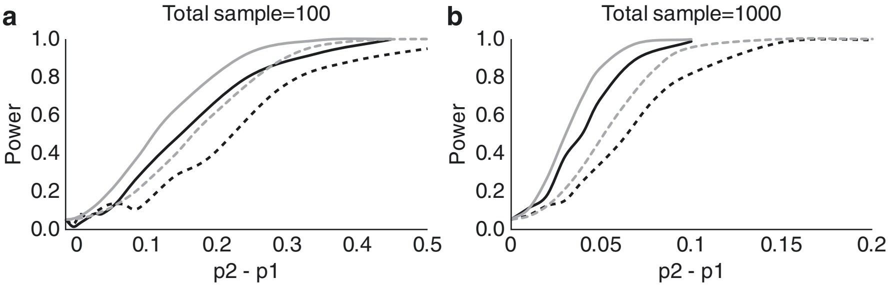


Fig. 12.2 Simulated power of the Monte Carlo permutation test to detect difference between two proportions of a continuous variable, for (**a**) a total sample of 100 tasks and (**b**) a total sample of 1000 tasks. The solid black line represents $p1 = 0.05$; the dashed black line represents $p1 = 0.2$. The computed power for equivalent differences in binomial proportions is shown as grey lines for reference

lines for $p1 = 0.05$), and for larger samples (plot **b** versus plot **a**). The two groups were simulated to have equal sample size. In additional simulations, it was found that keeping the same total sample size but allowing imbalance in group size reduced the power. The grey lines indicate power curves for the difference between two independent binomial proportions generated using the G∗Power program (Faul et al. 2007). While there is clear similarity, the power for the simulated permutation tests (black lines) are systematically lower. Nevertheless, the fact that they are in the same region and that the permutation test is applicable to proportions of continuous variables while binomial proportion methods are not, supports the permutation test as a reasonable choice for comparing proportions of time in workflow time studies.

An alternative testing approach, as outlined in Sect. 12.3, is to aggregate the data into subgroups. A proportion can be calculated for each subgroup, then the set of subgroup-level proportions can be analysed as continuous data, using methods such as t-tests or linear regression. We assessed this approach through simulation and compared it to permutation testing. To replicate a two-group comparison, we simulated 500 tasks per group (with exponentially distributed task duration) and divided the task in each group into either 10 subgroups of 50 tasks each, 50 subgroups of 10 tasks each, or six subgroups of eight or nine tasks each. In one group the underlying proportion of interest was set at 20% and for the other group this varied between 20 and 40%, that is, the difference between groups ranged from 0 to 20%. A t-test was applied to the subgroup-level proportions and the whole process was repeated 1000 times to obtain power estimates for the range of group differences.

The results of these simulations are shown in Fig. 12.3 where the power curves for t-tests applied at different levels of subgroup aggregation are relatively similar (all black lines). Although having fewer subgroups reduces the effective sample size of the tests, this seems to be counteracted by a proportional decrease in variance. The somewhat surprising result of which is that the power is not greatly affected by the level of aggregation. The grey line in the plot shows the power for the permuta-

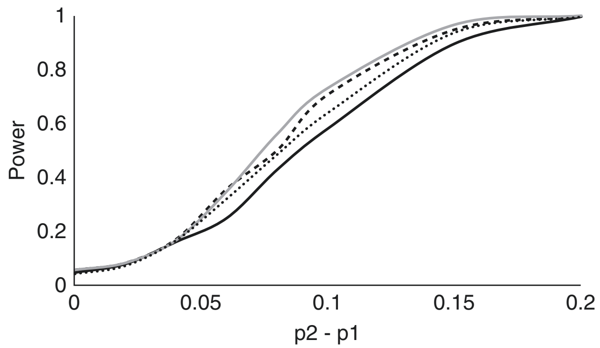


Fig. 12.3 Simulated power for *t*-tests applied to subgroups-level proportions for 50 subgroups of 10 tasks each (solid black line), 10 subgroups of 50 tasks each (dashed black line), and 6 subgroups of 8 or 9 tasks (dotted black line). The total sample of tasks was 1000 (500 per group), the underlying proportion of the group 1 was $p_1 = 0.2$ and proportions for group 2 ranged from 0.2 to 0.4. The power for a permutation test is shown for comparison (solid grey line)

tion testing approach. This is consistently as good or better than *t*-tests applied to aggregated data. The choice of units over which to aggregate data (e.g. observation sessions, clinicians, etc.) is not necessarily obvious in workflow time studies. Combined with the fact that permutation tests are at least as powerful, then once again a nonparametric approach is the better option.

12.4.2.2 Multivariate Analyses

There are many ways to apply multivariate methods in workflow time studies. Indeed, there is a strong case to make that most association studies should take a multivariate approach to better understand the factors operating at multiple system levels and minimise the bias in particular effects by adjusting for other influential factors. We have discussed general considerations of multivariate analysis in workflow time studies in our previous work (Walter et al. 2015). In this section we extend the theme of nonparametric analysis into the multivariate arena.

There are several ways to apply nonparametric methods to multivariate analyses. First, when fitting garden variety parametric models, such as linear regression, it is possible to use bootstrapping to determine the significance of the model estimates or to generate CIs for the estimates. This is essentially an extension of what we have discussed earlier regarding CIs and hypothesis tests, and similarly this may be an appropriate alternative when the data do not satisfy parametric model assumptions, as is often the case.

Second, there is a wide range of nonparametric multivariate modelling techniques that do not rely on assumptions about the distributional form (normal, Poisson, etc.) of the data. Some can be used as explanatory models, such as generalised additive models or spline regression, that can describe non-linear associations. In the study of

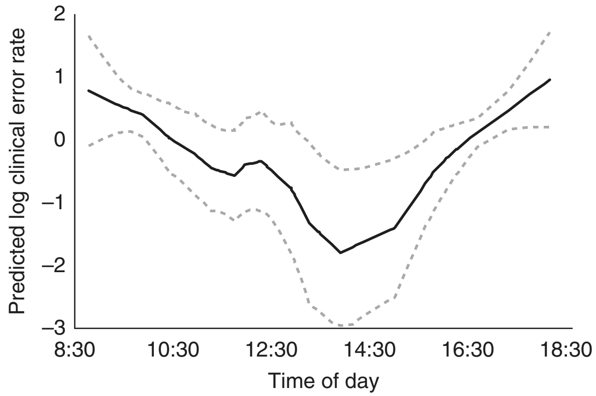


Fig. 12.4 Nonparametric estimate (LOESS smoother) of the relationship between time of day and clinical prescribing errors. The black line represents the predicted clinical prescribing error rate on the log scale and the dotted grey lines are the 95% confidence limits. This smoothing component for time of day had a p-value of 0.014

prescribing errors among ED physicians, Westbrook et al. (2018) found no evidence of an effect of time of day (categorised into 2-h blocks) on error rates using a Poisson regression model. However, Fig. 12.4 shows that fitting a nonparametric model (LOESS smoother) reveals a significant and distinctly non-linear relationship. Another explanatory approach is the classification tree, a version of which was used by Walter et al. (2017). In that study, discussed at the end of Sect. 12.2, the lack of data in certain categories necessitated a change from the original analysis plan. The alternative analysis used was a nonparametric model called a conditional inference tree, which iteratively splits the data into groups such that each group has a distinct outcome profile. Finally, in the area of predictive nonparametric models there is now a vast and growing collection of methods, such as Bayesian networks and random forests, that would be applicable to answering appropriately framed research questions in workflow time studies.

12.5 Discussion

Workflow time studies are an important type of research for generating knowledge about both the functioning of clinical work and workflow at a fine-grained level, and about the workflow-related factors that influence patient safety and quality of care. The data generated by such studies, and likely other types of time and motion studies, are not always amenable to conventional statistical methods. In this chapter we have highlighted some of the non-standard aspects of the data and offered alternative approaches that draw heavily from the family of nonparametric analysis techniques.

This chapter is somewhat technical, and it may be tempting for readers to form the impression that workflow time studies are overly complicated. The basic concept of these studies is, in fact, straightforward, but the complexity largely comes from the contexts in which they are applied. Clinical work is undeniably complex, and to understand its inner workings and interrelationships we must embrace that complexity into study design and data analyses, challenging as it may be. To design studies and analyses that fit within conventional approaches is to essentially shy away from or ignore those challenges. The methodological discourse in this chapter takes some steps towards tackling the intricacies of conducting quantitative studies of clinical work but is intended as a starting point for ongoing discussions rather than a definitive account of best practices.

Some recent studies have begun to employ more sophisticated methods such as multilevel models (Walter et al. 2014; Grundgeiger et al. 2010), transition state models (Carayon et al. 2015; Myers and Parikh 2019), and nonparametric models (Walter et al. 2017). However, explicit discussion of quantitative methodology appropriate for workflow time studies remains relatively rare. As we have highlighted in this chapter, there is an imperative to develop innovative approaches even for fundamental analyses such as IOR assessment, confidence intervals and hypothesis tests. Improving both our understanding of clinical workflow and the integrity of the workflow time study literature will require ongoing methodological innovation.

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Chapter 13
Clinical Workflow and Human Factors

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13.1 Introduction to Human Factors Engineering

Human factors engineering is a well-established scientific discipline that studies the functional capabilities and limitations of humans in order to design and optimize systems, processes and technology to reliably obtain a desired outcome (Lee et al. 2017). It incorporates principles and methods from disciplines such as industrial systems engineering, cognitive psychology, and computer science to analyze and model human-system interactions and to support system designs which meet quantifiable needs of the users and which support work in ways that are effective, efficient, and safe.

Human factors engineering has had a major influence on the design of systems and workflows in a wide range of safety critical industries including nuclear power, military and defense, and aviation. By understanding human capabilities, limitations, and common pathways for error, systems can be designed to prevent errors and—importantly—mitigate their effects, thus reducing harm to users and others who may be affected. In health care, the benefits of human factors engineering design approach extend to keeping patients free from error-based harm, to improving care through more efficient and effective workflows, to protecting staff members from fatigue and injury. Human factors engineering is particularly important in the successful integration of new technology into an existing work system. Recent

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examples include the use of drones in military and civilian applications and the emergence of self-driving cars that may share the road with human-driven cars. In each case human factors methods and principles are being applied to analyze the implications for the humans in the system, and to design effective user interfaces and work flows to enhance overall safety of operations (Casner et al. 2016; Roth and Pritchett 2018).

An important strength of human factors engineering is the focus on a broader context within which a system workflow or device operates (Carayon 2006). This includes describing specific physical, cognitive, and perceptual capabilities and limitations of the populations of system users involved; understanding and formally modeling the purposes and tasks being performed; mapping task requirements to human-system capabilities; and considering relevant aspects of the physical environment and work situations in which the system will be deployed. For example, a portable intravenous pump undergoing testing may work flawlessly in a simulated environment with experienced intensive care unit nurses, however that same pump may present significant hazard when an alarm goes off at home with a patient that misplaced their reading glasses.

This chapter introduces core concepts and methods from the discipline of human factors and describes how they can be applied to the study and improvement of clinical workflow. We begin by presenting a set of core human factors concepts (or human factors 'lenses') that are important to adopt when trying to identify sources of problems and opportunities for improvement to healthcare-related workflows. This is followed by description of specific human factors methods that can be used to analyze and improve workflow.

13.2 Applying Human Factors Lenses to Workflow Analysis and Design

When considering the application of human factors to the healthcare environment including health IT systems it is important to have a context within which to work. The following core Human Factors concepts and theoretical perspectives will aid the reader in applying a human factors lens when analyzing or trying to identify improvements to specific workflows and situations. These include situations where healthcare organizations may be trying to understand the factors that are contributing to performance problems or errors and how they can be mitigated; as well as situations where organizations are trying to develop and/or introduce new health IT and monitor and manage its impact on performance and satisfaction. There can be many points where there is value in adopting a 'human factors lens'—early in the process when requirements for a health IT system are being defined, during design in determining whether the system being developed will work as imagined, and after implementation, to understand and address human performance problems that emerge (e.g., near misses, adverse events, productivity bottlenecks).

13.2.1 Supporting 'Work as Done' Versus 'Work as Imagined'

A core precept of human factors is that it is important to begin any analysis or design project by studying how work is actually done, in all its messiness. Too often there is a significant gap between the way in which leaders believe the work is performed at the front line, and the way in which it actually occurs. Some authors refer to this as the different between 'work as imagined' and 'work as done' (Hollnagel et al. 2013; Braithwaite et al. 2017). Clinical work is fundamentally collaborative, involving multitasking, frequent interruptions, time-pressure, and incomplete, ambiguous, time-lagged information. Problems arise when there is a disconnect between the realities of the work 'as done' and the assumptions underlying the Health IT system (i.e., work as imagined). A case in point is decision-support tools where the implicit assumption is often that of a single decision-maker deciding at a particular point in time, with the all the information in hand. This contrasts with the demands of actual work practice, with the result that such tools are less likely to be adopted in real clinical settings (Wears and Berg 2005).

The rapid adoption of electronic health records in the United States since the Health Information Technology for Economic and Clinical Health Act (HITECH) in 2009 has introduced technology with variable degrees of success and unintended consequences (Bernstam et al. 2010). Often problems arise because of a mismatch between the implicit model of the work inherent in the HIT and the actual complexities of the clinical work environment. As Wears and Berg (2005) put it, the problem is not one of 'not developing the systems right' but rather of 'not developing the right systems'.

Good design and implementation needs to go beyond a narrow focus on the technology to be implemented. A sociotechnical lens is required that includes examining the characteristics of the organization to be supported (the people, values, norms, and culture), the technical environment in which the new system is to be inserted (the equipment, processes, procedures, and physical facilities), and the work demands and complexities that healthcare practitioners face. Only through this type of broad perspective will the gap between work as imagined and work as done be narrowed.

13.2.2 Addressing Context Independent vs. Context Dependent Design Elements

One of the significant challenges when introducing technology into any complex environment is addressing both its usability and usefulness. Usability is defined as how intuitive a tool is, how easy it is to learn and to use by the intended user. In contrast, usefulness refers to the extent to which the device, technology or workflow provides meaningful improvement in performance by the intended user under anticipated working conditions. To highlight the differences between usability and usefulness, one can imagine a new application within the electronic health record

(EHR) is tested in a lab and found to be intuitive to use with few errors by the user (usability). But when used by nurses in the emergency department who are frequently interrupted and multi-tasking across many patients the application becomes burdensome to enter data and found to have limited usefulness in the clinical environment due to missing critical information from other parts of the EHR.

Usability is generally affected by context independent features of a design often framed as design "heuristics" including making system status visible, providing meaningful and rapid feedback, maintaining consistency in indications and actions, using language and labels, and supporting error recovery (Nielsen 1995). These design principles are largely independent of the content and context of the interface or device being investigated. A recent human factors review of electronic medical record and electronic health record systems found that there were extensive usability issues (Zahabi et al. 2015). These authors noted that these often resulted from a lack of application of standard human factors usability guidelines including: using simple natural dialogue, speaking the user's language, minimizing memory load; providing feedback and good error messages; maintaining consistency in design and error prevention (Molich and Nielsen 1990).

Human factors engineering provides extensive guidelines for identifying and correcting these 'context-independent' aspects of design. There are well established rules and guidelines that have been agreed upon for decades in the human factors and associated literature regardless of the application, from medical device to electronic airplane dashboard. For example, yellow text on a white background provides less contrast than black text and will be more difficult for the user to interpret. In addition, providing a list of choices on a display that are only separated by one pixel is more likely to lead a user to make an accidental selection if they are distracted or slip. While the rush to implement health IT systems may not followed many of these guidelines, the incorporation of User-Centered Design principles and human factors engineers in the design and certification of EHRs in the United States has begun to standardize the approach and remove these basic design errors that can lead to patient harm (Tolley et al. 2018).

In contrast to usability, usefulness of a health IT system is based on context -dependent design considerations that rely on an understanding of the purposes of system implementation, user goals, and context of use (Hettinger et al. 2015). For example, when placing an electronic order for a patient, providers frequently need to refer to previous laboratory values to make the most appropriate choice. A well designed computerized provider order entry (CPOE) system would not only allow the user to view previous orders while placing a new order, but may make specific values more salient based on the current order selections. For example, a radiology test with intravenous contrast requires normal kidney function to prevent serious adverse events. Relying on the provider to remember the results of prior tests of kidney function or requiring them to navigate away from the ordering screen and potentially get distracted on another task will lead to the predictable error of ordering the wrong test or a delay in care. It would be preferable to display prior kidney function values on the screen used to order radiology tests.

Context dependent design is much more challenging and requires in-depth study of the users and their workflow in the environment where the work will be performed. This entails anticipating the needs of the users based on the context of use and making it easier for users to make the correct decision or action. Effective design requires consideration of both context independent and context-dependent aspects, and an interactive process that allows both usability and usefulness in context to be assessed.

13.2.3 Engineering for Resilience

Resilience Engineering offers a complementary human factors lens through which to examine clinical workflow (Fairbanks et al. 2014). Instead of focusing on the rare errors and failure modes, it encourages examining the adaptive behavior of individuals in the everyday context that keep things from going wrong, and how these behaviors can be better supported and more widely adopted (Braithwaite et al. 2015).

The basic premise of Resilience Engineering is that healthcare is a very complex process that presents multiple challenges. The different policies, procedures, patients, staff members and other various components interact in such a manner that there are often unanticipated outcomes when trying to change clinical workflow and that no one individual in the system has a clear understanding of all the components and how they interact with each other. However, humans are incredibly adaptable and often serve to hold the system together. For example, if a particular component in the system is not working correctly, e.g. the CT scanner stops working, then it is the humans that will develop the work arounds to get other testing, transfer patients to a facility that has the necessary equipment or delay the testing in those patients that have less time sensitive conditions until the equipment is working again. Without humans, the brittle interconnected system of electronic orders and medical equipment would grind to a halt until the equipment could be repaired, causing potential serious delays in acutely ill patients.

Resilience Engineering seeks to learn from the positive everyday behaviors of the humans in the system that keep the system going and prevent harm. In effect, instead of focusing only on the rare cases of errors and system breakdowns, it asks why more errors aren't happening and what can be done through better designs and workflows to enhance positive behaviors across users and not just the individuals that are anticipating the hazards through previous experience and institutional knowledge (Braithwaite et al. 2015).

13.2.4 Guiding the Co-evolution of Technology and Work Practice

A core Human Factors precept with extensive empirical support is that when new technology is introduced it inevitably changes work practice, sometimes in unanticipated ways. People adapt to the new health IT and learn to use it in ways that were not necessarily envisioned by the system developers. These new and unanticipated uses can in turn trigger a need for new technology development. This dynamic cycle of technology development and user adaptation has been referred to as the task-artifact cycle, to emphasize that how tasks are performed and the artifacts that support them co-evolve over time (Carroll and Rosson 1992; Carroll and Campbell 1998). This implies a need to continue to track the impact of a new health IT system after it is introduced to identify emerging practices and changing needs.

New technology cannot simply be 'dropped' into a work context. Rather, its impacts on the larger work context and organization needs to be tracked and unanticipated reverberations need to be recognized and addressed (Woods 2002). As Wears and Berg (2005) noted, the introduction of new health IT cannot be thought of in isolation, but rather as part of the larger context of organizational change. This includes recognizing that there will be a period of exploration and mutual learning involving users and system developers (Wears and Berg 2005). New workflows will emerge and additional support needs will be identified. This in turn will trigger new design cycles—be it through changes in training, workflow or design changes to the IT system. For example, the patient tracking boards (i.e., dry erase white boards) in emergency departments (EDs) originally were developed independently across organizations by the front line users. For example research by Bisantz et al. (2010) noted that with the transition to electronic information systems (EDIS) that attending physician workflow with resident physicians and students was no longer supported. Specifically, the method by which case presentation, attending exam and final note had been tracked on the dry-erase board with a series of colors and symbols was no longer supported (Bisantz et al. 2010). Attending physicians adapted by using paper notes kept in the pocket to track this information (new 'home grown' artifact). Because the information was no longer publicly displayed, residents and nurses were not able to maintain awareness of where the attending physician was in their workflow. An unintended consequence was that patients were sometimes discharged before the attending physician evaluation and plan was complete. This task-artifact loop spurred EHR design changes. More recent EHRs used in clinical practice have been observed using these findings to incorporate the tracking of resident/attending workflow and note status in a more comprehensive manner.

13.2.5 Adopting a Patient Safety Transformational (PST) Prevention Model

Human factors approaches are intended to anticipate and prevent or mitigate the use errors before they can occur and cause potential harm. This is analogous to the patient safety transformational (PSF) model that has been used in cardiovascular care. The PST model distinguishes primary prevention—prevention before the hazard occurs; secondary prevention—prevention after the hazard occurs but before the patient is harmed; and tertiary prevention—prevention after the harm event has occurred but during the critical time that an intervention could improve a patient's outcome. The aim is to design for primary prevention whenever possible, followed by secondary, and then tertiary prevention.

Cardiovascular care for patients has undergone major changes since the 1950s when researchers were just starting to understand the link between heart disease and risk factors that we now take for granted like diabetes, hypertension and hypercholesterolemia (Dawber et al. 1951). As a result of this improved depth of understanding and new methods for diagnostic testing, medicine went from a model of waiting for patients to have heart attacks to actively trying to prevent cardiovascular disease through life style modification (primary prevention) and aggressive management of chronic disease (secondary prevention). While there is still significant effort in tertiary prevention, reducing the long term impact of the heart attack once it occurs through rapid cardiac angioplasty and bypass surgery, there is considerable effort to prevent the patient from ever needing those dramatic efforts.

In stark contrast to changes made in cardiovascular disease, healthcare safety and operations often focus on the critical events that demonstrate breakdowns and try to improve their systems from one adverse event to the next. Using processes like Root Cause Analysis (RCA) often lead to brief analysis of adverse events that culminate in short term fixes such as disciplining those involved and training the other team members to vigilant instead of implementing sustainable and effective changes to the clinical workflow of the front-line staff (Hettinger et al. 2013). By taking a similar primary/secondary/tertiary prevention approach as that taken in cardiovascular care, the hazard under investigation may be designed out of the system. For example, a surgical department investigates a retained piece of medical equipment despite performing a surgical count of equipment and a post-operative x-ray at the completion of the case. In an effort to prevent future cases the organization decides to apply the PST prevention concept instead of a traditional model of referring the involved staff to their respective peer review committees and sending a memo to staff to be more vigilant. They find multiple pieces of equipment and disposables that are not visible on x-ray and develop a plan to replace them, removing them from circulation in the operating rooms (primary prevention). Furthermore, they investigate technology that will allow wireless scanning and counting of surgical equipment to remove a foreign body before the end of surgery (secondary prevention). Finally, after reviewing clinical data they determine that most retained foreign body cases are in surgical cases that are either long duration or complex with many pieces of equipment. They develop a clinical workflow so that these cases are pre-operatively identified as high risk and streamline a process for getting post-operative x-rays looking for foreign bodies before the patient leaves the operating room (tertiary prevention).

The PST prevention model can be embraced in the health IT system development process, before any adverse event has occurred. For example, the use of robust user centered design processes during the formative development period is likely to prevent many hazards from making it into the system (primary prevention) or catch the hazards during usability testing with representative end-users (secondary prevention). The use of EHR safety surveillance during the post implementation period for health IT system can then catch hazard and harm events where the contribution of the health IT system may be unrecognized (tertiary prevention). One of the benefits of human factors approaches is that it provides methods to catch and correct problems during different phases of design and implementation—before there is opportunity for harm. Without designing for primary, secondary and tertiary prevention in clinical workflow, individual healthcare providers are destined to make the same errors over and over again.

13.3 Human Factors Methods for Analyzing and Improving Workflow

Evaluating, designing andoptimizing clinical workflow is a critical part of providing safe and effective care to patients. The section above presented some core human factors concepts that are intended to provide guiding perspectives when trying to identify sources of problems and opportunities for improvement to healthcare-related workflow. A common thread across the multiple lenses presented is the need to understand the broader context of work, the complexities that can arise, and the cognitive and collaborative demands they impose, when trying to understand or improve workflow. This includes cases where an organization is trying to understand why problems or errors are occurring and develop mitigations. As well as cases where an organization is trying to design new health IT or insert new systems developed by vendors so as to improve performance.

In this section we provide brief descriptions of some core human factors methods that can be used to analyze the context of work and the impact of new technologies on work. These include methods that can be used early in the analysis process when one is trying to understand sources of performance problems and define requirements for more effective support, methods that can be used during design when a team is trying to determine whether the health IT system being developed will work as imagined, and methods that can be used after a system is implemented to understand and address human performance problems that are identified (e.g., near misses, adverse events, productivity bottlenecks). As we introduce each method we will highlight the types of analyses and stages of technology design and introduction for which they are best suited. We will also briefly describe their strength and limitations.

The review of human factors methods provided below is necessarily selective. We focus on methods for uncovering information about workflow and the context of work, particularly the cognitive and collaborative demands of work that can lead to performance problems, as well methods for evaluating and guiding the design new HIT systems as part of the development cycle. Broader surveys of human factors methods and more in-depth descriptions of the methods described below can be found in the literature (Bisantz et al. 2015; Bisantz and Roth 2008; Hettinger et al. 2017; Lee et al. 2013; Lowry et al. 2014; Stanton et al. 2017).

It is important to note for the reader that while each of the methods are covered individually below, in practice researchers will use a combination of methods to obtain a richer picture of the workflow of interest and the broader context in which it is imbedded than would be possible with any single method. For example researchers will often combine interviews and focus groups with observational studies (Militello et al. 2014) as well as with artifact analysis (Xiao et al. 2010).

These methods can be effectively used by multiple types of organizations and stake-holders and tailored to the scope, size, and budget of the project. This includes technology vendors who may be trying to develop and upgrade health IT systems for applications across multiple hospitals, clinical organizations (e.g. ambulatory clinics, hospitals, larger healthcare systems) that might be trying to roll-out and manage new health IT systems to minimize error, and improve performance, satisfaction and safety, as well as individual healthcare researchers or leaders who may be trying to examine sources of problems or errors and identify appropriate solutions.

13.3.1 Interviews and Focus Groups

Interviews and focus groups are among the most common methods for learning about workflow and obstacles to effective performance (Bisantz et al. 2015). They are particularly useful during the early stage of information gathering to get an overview of the ideal workflow and obtain multiple perspectives on challenges and barriers to effective performance that may result in a disconnect between work as imagined and work as practiced. Interviews and focus groups can also assist in tertiary prevention when analyzing an adverse event that has occurred and safety experts are attempting to assess the severity of hazard for future patients and the potential frequency with which they may occur.

Interviews using human factors methodologies frequently employ a semi-structured format to ensure that key topics (e.g., previously identified key pieces of a workflow or known work-arounds) are discussed, while remaining flexible enough for the interviewer to discover new information and allow the participant to guide the discussion based on their experience with the process, system and culture. This facilitates learning the true work as performed versus work as imagined discussed previously. As one example, McDonald et al. used a semi-structured interview approach to map the clinical workflow for high-risk patient monitoring at five specialty clinics (pulmonary medicine, breast cancer, gastroenterology, urology and otolaryngology). Based on the interviews they were able to identify (1) the steps that were most critical, time-intensive, and risky from a patient-safety perspective; (2) critical data elements needed for effective monitoring of high-risk patients; and (3) candidate technical and organizational interventions to address the identified workflow vulnerabilities (McDonald et al. 2017).

Focus groups also employ semi-structured interview questions but allow the participants to clarify and build upon each other's comments, enabling a richer, more nuanced, construction of the workflow. A critical decision is whether to mix individuals from different backgrounds (e.g., different job positions; experience levels; status in the organization) in one focus group. An important consideration is to ensure that everyone feels free to express themselves openly. One example where this concern came up is in a focus group conducted seeking to understand communication patterns between nurses and physicians (Benda et al. 2017). In this study, separate focus groups with nurses, residents and attending physicians were chosen because of anticipation of different perspectives based on both roles and experience level between and among nurses and physicians. Indeed during focus group interviews residents and attending physicians expressed very different views. Attending physicians were more likely to discuss the importance of two-way communication and listening to nurses as their eyes and ears within the ED. In turn nurses talked about strategies for guiding less experienced residents, given the formal hierarchy relationship.

Interviews and focus groups, in general, require less expertise and time to conduct than some of the following methods. However, lack of appropriate preparation for both techniques are likely to result in less helpful data collected. Further, focus groups often require two moderators—one to conduct the focus group and one to record the discussions. The use of audio and/or video recording devices can help reduce the number of personnel used but require a significant amount of resources to turn the recordings into usable data. Audio/video recordings can also negatively impact the participant's willingness to share more controversial views and observations.

13.3.2 Critical Decision Method

One of the most powerful methods for learning about the demands in the environment and the strategies that people have developed for coping with them is to ask them to describe a specific past challenging situation they personally experienced and how they handled it (Flanagan 1954). The critical decision method (CDM) is a widely used structured interview technique that builds on this approach (Klein et al. 1989). It was initially developed to understand the decision making process of firefighters when making rapid decisions with limited access to information that could have life-threatening consequences. It consists of a trained individual in the method conducting a structured interview with a single participant, typically an expert in the workflow under consideration. The method involves having the individual go through the incident in progressively deeper passes to understand the decisions that were made, the information that was used and alternative events that could have occurred and how they were avoided (Crandall et al. 2006).

CDM has been used in multiple high-risk settings, including urban and wild land firefighting, military command and control, and software engineering. It has been extensively used in health care, including to study the perceptual cues used by experienced neonatal intensive care unit nurses; (Crandall and Getchell-Reiter

1993) and to compare the strategies employed by physicians of different levels of expertise for early recognition of sepsis (Patterson et al. 2016). The results have been used to propose improvements to workflow, new forms of decision-support, and new training.

More recently a variant of CDM has been developed as a means to identify resilient behavior and workflows by healthcare providers. For example, Hegde and colleagues are developing a lesson-sharing tool called Resilience Engineering Tool to Improve Patient Safety (RETIPS) based on CDM interviews of nurses and physicians that focus on examples of resilient behavior (Hegde et al. 2014, 2015). The intent was to collect a corpus of cases that demonstrate how people adapt in everyday clinical work to perform effectively and avoid harm to patients under challenging conditions as a means of generating safety lessons.

While CDM is powerful method for collecting information on workflow challenges and the adaptive strategies that individuals develop in response, it has some limitations. In particular it requires significant training and expertise to conduct CDM interviews. Often CDM interviews are conducted by trained human factors consultants and there are short-courses offered in the methodology. In addition there have been efforts to adapt the methodology to on-line questionnaires (Hegde and Jackson 2017).

13.3.3 Observations

One of the most useful human factors techniques for studying workflow is to conduct observations in the actual work context or in a close analogue such as a high fidelity simulator (Roth and Patterson 2000). Observing individuals and teams working in their work environment allows the analyst to document the range of complexities that arise that challenge work flow and the various adaptations and work arounds that individuals have developed to cope with demands, overcome obstacles, fill in gaps and otherwise contribute to the overall safety of the system (or not).

Observational studies involve having one or more observers unobtrusively shadow individuals as they go about their work. The goal is to observe the activities and communications that occur without getting in the way, serving as a source of distraction, or otherwise influencing the behavior of the individuals being observed. The observer typically records their observations in real time either in free form or using a predefined set of coding categories (Bisantz et al. 2015). These are then analyzed after the fact using qualitative grounded theory methods and/or quantitative methods (e.g., recording and analyzing the frequency of different types of occurrences).

Often the observational team will include a behavioral scientist (e.g., a human factors specialist) with knowledge and skill in observational methods, and a second individual with knowledge and expertise in the domain of practice being observed (e.g., a physician or a nurse in studies of health care environments). For example, a study examining workflow challenges in complex surgeries had a two-person observation team in the operating room that included a practicing surgeon and a human factors specialist (Christian et al. 2006). The surgeon could draw on their surgical knowledge to interpret what was observed while the human factors specialist could draw on their cross-domain knowledge of human performance drivers and systems challenges to point to patterns of behavior and systems problems whose significance might not be recognized by the surgeon. Both took notes in real-time during the surgery being observed which were then combined to obtain a more complete and accurate description of what took place.

Whenever feasible, observations are coupled with opportunistic interviews that occur during periods of low workload or at the end of a shift. This allows for the subject to answer clarifying questions or provide elaborations or confirmations of what was observed without interfering with the work. In some cases, if the environment allows, the sessions are audio or video recorded for later review and analysis. For example, a study examining inter-operative deviations in care had video-recordings made of ten high acuity operations. These were then transcribed and analyzed by a multidisciplinary team consisting of surgeons and human factors specialists (Hu et al. 2012). This resulted in more complete data capture than would be possible when relying solely on real-time observations. In another study, Tiferes et al. used video- and audio-recordings of robotic assisted surgeries to code and characterize verbal and non-verbal communication among members of the surgical team (Tiferes et al. 2018).

Observational studies are useful early in an investigation when trying to understand the work as actually done (as opposed to the work as imagined). This includes situations where human performance problems have been identified and there is a need to understand why they are occurring and what can be done to reduce the problem. One good example was an observational study that was conducted to understand the 'counting protocol' used by nurses to keep track of surgical objects (needles, sponges, instruments) during operations in order to reduce the risk of leaving a foreign object in the patient (Dierks et al. 2004). Hospital leadership wanted to understand why surgical objects were sometimes left in patients in spite of having the counting protocol. The observational study showed that the counting protocol was difficult to perform and documented multiple factors that contributed to challenges in maintaining an accurate count (e.g., incomplete surgical kits; shift changes in the middle of surgery; differences in counting conventions across nurses). Further it showed that the counting protocol itself had unanticipated negative consequences that in some cases compromised patient safety. Complications in the count, which occurred in six of the nine observed surgeries, triggered activities to reconcile the source of the inconsistency. This drew attention away from the ongoing surgery, resulting in delays and additional risk to the patient. The study led to numerous recommendations for improving performance ranging from increasing standardization to eliminating the count through use of new technologies for keeping track of surgical objects.

Observational studies are also useful after a new system is put in place to understand the impact of the new system on practitioner workflow. This includes tracking whether the system is being used in the manner envisioned by the developers, whether it is having the positive effects anticipated, and whether any new issues are emerging. For example, an observational study was conducted to understand use of Electronic Health Record (EHR) systems in primary care outpatient clinics (Flanagan et al. 2013). The study identified mismatches between the EHR system designs and the demands of outpatient settings that led to a variety of work arounds (some paper-based and some computer-based) intended to improve efficiency and support memory and awareness of the healthcare practitioners. These pointed to limitations of the EHRs that contributed to their lack of use and opportunities for improvement. Another study examined the impact of the introduction of EHRs on nurse physician verbal communication in emergency departments (Benda et al. 2017). The goal was to understand the content and pattern of physician-nurse communication given the availability of EHRs. Among other things the study identified the situations where verbal communication continued to be needed in spite of the availability of the information in the EHR. For example, verbal communication was used to draw the attention of the provider to important patient status information that might otherwise not be salient, as well as to confirm that the provider was aware of the information. The results pointed to opportunities to improve EHR systems.

Observational studies have also been used to examine the impact of new technology such as surgical robots, on operating room workflow, teamwork and patient safety. For example, observational studies have been used to document workflow disruptions in robotic surgeries, the factors contributing to them and the impact on safety (Catchpole et al. 2018). Catchpole and colleagues observed 89 robotic surgeries and documented 4229 flow disruptions, defined as deviations from the natural progression of the operation. The researchers found that flow disruptions rates due to problems in communication and coordination were comparable to those for other types of surgeries. In contrast flow disruption rates due to equipment problems (e.g. improper insertion of the camera; fogging of the endoscope) were much higher pointing to opportunities to improve performance through changes in training, equipment or workflow.

Observational methods have also been used to explore verbal and non-verbal aspects of team communication in robotic surgery where the surgeon sits at a robot console away from direct view of the patient on the operating table (Tiferes et al. 2016). The authors documented numerous types of verbal and non-verbal interaction between the surgeon and the physician assistants located by the patient. This included use of the robotic tool itself as a means of non-verbal communication (e.g., positioning and zooming the camera to draw the attention of the physician assistant to a particular location). This last example illustrates how new technology results in new adaptations and uses unanticipated by the system developers. The authors pointed to how the results could be leveraged to design more effective team training for robotic surgeries.

While observational studies are a powerful tool for understanding the actual demands of work, they have some limitations. First they are time and labor intensive, both in terms of the time required to conduct the study and the time required to analyze the results. Second, they require expertise in performing observational studies. Their success depends on the skills of the observers and the representativeness of the sample of observations (Roth and Patterson 2000). Third, there is a potential that the presence of the observer to impact the workflow or get biased results, for example if the individuals being observed are concerned that they are being evaluated or that they may be reported if they deviate from prescribed policies and procedures. Finally, while the approach is useful for studying every day work, it is not suitable for studying rare events that by definition would be unlikely to be observed during any particular observation period.

13.3.4 Artifact Analysis

One of the best ways to gain insights into how work is actually performed and the requirements for more effective support is to examine the tools ('artifacts') currently in use (Xiao 2005). Artifacts include formal aids provided and sanctioned by the institution such as procedures and checklists (e.g., formal OR checklists) as well as 'home grown' artifacts that practitioners have developed on their own initiative to support their own work (Xiao et al. 2009).

'Home-grown' artifacts developed by practitioners can highlight mismatches between the formal systems in place and the requirements of the work (Bisantz et al. 2010; Xiao 2005). They provide a window on the cognitive and collaborative aspects of work that need to be supported and the information needed to effectively support work. Artifacts can be simple, low tech, items such as 'sticky-notes' and paper-based 'cheat sheets' (also sometimes called 'brain sheets') that practitioners routinely use to support memory and situation awareness. Increasingly one also finds highly sophisticated computer-based visualizations and decision aids developed by computer-savvy practitioners to facilitate their own work (Xiao et al. 2009). For example, Roth and colleagues examined work practice in a military airlift organization (Roth et al. 2006). They documented a variety of new computer-based visualizations; local databases; and decision-aids that were developed as 'home-grown' artifacts to compensate for limitations of the formal computer-systems in place.

Analysis of participant-developed artifacts can provide a rich source of information to guide design of new HIT. For example, Bauer, Guerlain and Brown studied the use of paper-based patient flow sheets in pediatric intensive care (Bauer et al. 2006). Positive features identified included that it was portable, that it supported easy comparison of information and that it allowed for free-form annotation. Based on these observations the researchers were able to specify important functions that electronic system s should continue to support including the need to allow for flexible rather than sequential data entry; the need to allow users to optionally leave data fields unfilled; and the need to support unstructured annotations. At the same time the researchers were able to identify ways that an electronic system could improve on the paper flow sheets, including automatic calculations that were done manually with the paper form.

Similarly, Gurses, Xiao and Hu studied the paper-based clipboard created by nurse coordinators to compensate for inadequate support of the formal hospital information system (Gurses et al. 2009). Nurse coordinators painstakingly created clipboards that synthesized and reorganized information obtained from multiple disparate sources to better support their fast-paced work demands. The authors recommended modifications to the hospital information system to allow users to create and print tailored single page views that could provide 'at a glance' summaries of key information.

One of the most studied home-grown artifacts in healthcare is the dry erase white board (Wears et al. 2007a; Bisantz et al. 2010; Pennathur et al. 2011; Patterson et al. 2010; Xiao et al. 2007). Dry-erase status boards arose spontaneously and became ubiquitous in the ED in the mid 1980s as a means to track patients (Wears et al. 2007a). Dry erase status boards have largely been replaced by electronic systems, however, as mentioned above, not all of the functions supported by the dry-erase status board were successfully transferred to the electronic versions. While the electronic versions support basic information exchange functions (e.g., patient demographics; location; caregiver assignments), they are less effective at directing attention, maintaining awareness of provider work flow status, and coordinating work across providers (Bisantz et al. 2010; Pennathur et al. 2007). For example, as mentioned earlier, attending and resident physicians used hand drawn symbols to track (and allow others to see) their patient specific workflow status with the dry erase status board but this was not supported with the electronic version. Similarly, with the dry-erase status board it was possible to provide information about the overall ED (e.g., whether an ED pharmacist) and to annotate and track aspects of medical care by making annotations outside the matrix structure (e.g., notes at the top, lines along the side). This flexibility was no longer supported by the electronic versions.

Comparison of dry-erase status boards and electronic versions led Bisantz et al. to draw several conclusions and recommendations (Bisantz et al. 2010). Most importantly, it is not sufficient to reproduce the literal format of an existing technology. Mimicking the matrix format and basic information of the dry-erase status boards failed to support the variety of cognitive and collaborative functions that the dry-erase status boards supported. System developers need to gain a deeper understanding of the demands of the work, how existing artifacts support work and where they fall short in order to develop a firm foundation for new health IT design. In particular, the fact that dry-erase boards are highly flexible, easy to tailor, and easy to simply walk up to and input information of any kind without having to first log in, and without being limited with respect to what can be entered and where it can go, turned out to be critical elements contributing to their success (Wears et al. 2007b). The results of the analyses provided the foundation for a more extensive project to design and evaluate improved display concepts for ED status displays (Guarrera et al. 2015).

Artifact analysis provides an important window on the multiple, often subtle, demands of work. As such it is a valuable tool for health IT developers trying to gather user support requirements. Its primary limitation is the risk of adapting too literally superficial aspects of the artifact (e.g., the particular format used; the specific bits of information included) without fully appreciating all of its functionality and the full range of cognitive and collaborative support it provides. This risk can be mitigated by coupling artifact analysis with other human factors techniques such as work practice observations and practitioner interviews to obtain a richer understanding of the demands of the work environment, how the artifact supports work, and limitations of the artifact that can be overcome through effective use of new technology (e.g., automating computations, synthesizing information).

13.3.5 Work Oriented Evaluations

Health IT systems are often plagued with usability problems that make them difficult to use adding to inefficiency and potential for error (Zahabi et al. 2015). Of even greater concern, they may not provide effective support for the cognitive and collaborative work of the healthcare providers. One way to overcome this problem is to encourage multiple work-oriented evaluation cycles as part of the system design process.

Traditionally a distinction has been made between two types of user evaluations: *formative evaluation* and *summative evaluation* (Neilsen 1994). Formative evaluations are designed to provide feedback with respect to what aspects of the system design work well and which can be improved—that is they are intended to be learning opportunities. There are a variety of approaches to formative evaluation ranging from fast and relatively low-cost heuristic evaluations that consist of structured reviews by usability experts, to more formal usability tests that bring in representative users to exercise the system. Usability tests typically collect both performance data (e.g., number of key strokes, time to complete a task, errors) and user feedback data (e.g., via structured questionnaires). S*ummative evaluations* are designed to provide an overall assessment of the system. They are typically conducted at the completion of a system development process to establish that the system meets predefined evaluation criteria.

A work-centered evaluation is an example of a usability test approach that is work-oriented (Truxler et al. 2012; Roth and Eggleston 2010). The focus is on insuring that the health IT supports the cognitive and collaborative work of the healthcare practitioners. Work-centered evaluations are designed to be *diagnostic*. They are intended to not only provide an overall assessment of the usability and usefulness the health IT system, but to also provide detailed a detailed assessment of: (1) which cognitive and collaborative activities the health IT supports well and which less so; (2) which features of the health IT system are useful to the health practitioners and which less so; and (3) which features of the health IT are easy to use (usable) and which less so. These provide important information to guide health IT design course correction.

Work-centered evaluations couple elements of both formative and summative evaluations (Roth and Eggleston 2010). From a summative perspective the aim is to evaluate the design against a predefined set of *cognitive performance support objec-*

tives that the system is designed to meet (Clark et al. 2017). For example a cognitive performance support objective might be ‘identify hold-ups in the care of an individual patient’. Work-centered evaluations include explicit metrics to establish whether these cognitive performance support objectives have been met. These metrics include performance on test cases that are representative of the cognitive and collaborative challenges that arise in that work context that the HIT is intended to support. For example, if an HIT system is to support ‘identifying hold-ups in the care of an individual patient’ then one or more of the test cases would involve recognizing that there is a ‘hold up’ preventing progress in the flow of care of a particular patient and being able to identify what that hold up was (e.g., the attending is waiting to hear back from a consulting physician). Work-centered evaluations also collect direct user feedback on whether that cognitive performance support objective has been met. This feedback is typically obtained via rating questions on a final questionnaire that is administered after all test cases have been completed. For example, the test participant might be asked to rate on a nine-point scale whether they feel that the health IT effectively supports ‘Identify hold-ups in the care of an individual patient’.

Work-centered evaluations also include a *formative* evaluation aspect—an opportunity to discover need for additional improvement. The evaluations are designed to catch any usability problems that need to be addressed prior to final implementation. This is accomplished by identifying any confusions, difficulties or usability errors that test participants make during the test cases portion of the evaluation, as well as via usability rating questions included on the final questionnaire. Work-centered evaluations are also designed to probe for additional work demands not previously identified that may signal new cognitive performance support requirements and propel further design innovation. Previously unrecognized work demands and additional cognitive performance support requirements are typically elicited via open-ended questions on the final questionnaire as well as via end of session verbal debriefs. This includes explicitly asking participants to consider situations beyond the ones sampled in test cases, and indicate any ones they feel the health IT might not handle well, as well as any situations where the health IT would be particularly helpful.

A work-centered approach was used to evaluate an Emergency Department information System (EDIS) prototype designed to support awareness of the overall ED state and flow of patients through the ED, patient care, staff workload, and available resources (Clark et al. 2017). Participants performed patient planning and orientation tasks using the EDIS displays. They then rated the ability of the EDIS to support the work-oriented cognitive needs of emergency clinical staff that were identified as part of the cognitive analysis that drove the system design (i.e., the cognitive performance support requirements). The questionnaire employed a nine-point rating scale with ‘9’ indicating ‘extremely effective’. Example cognitive performance support questions include ability to ‘Identify bottlenecks or holdups preventing overall patient flow through ED’; ‘Maintain awareness of overall acuity of patients waiting and currently being treated’; and ‘Provide support for prioritizing your tasks’. The participants also rated the usability, usefulness, and predicted frequency of use of specific system components.

Overall mean ratings were positive (i.e., mean above 5) for cognitive performance support objectives, usability, usefulness, and frequency of use, indicating that the EDIS prototype would provide effective cognitive support for emergency medicine staff. At the same time, the evaluation generated diagnostic information regarding which aspects of the EDIS displays were most useful, where there were issues in usability, and the extent to which the displays supported the cognitive work of different types of providers. For example, in some cases mean usefulness scores were significantly higher than mean usability scores (e.g., for the waiting room and patient progress displays) suggesting that while waiting room and patient progress information is useful to ED staff members, the information could be displayed better.

The study also illustrated the diagnostic power of cognitive performance support oriented questions. For example, the question ‘provide support for prioritizing your tasks’ received significantly lower mean ratings (5.9 on a nine-point scale) than many other of the questions (all with mean ratings above 7). This result made sense because while the researchers identified the need to support individual task prioritization as an important requirement for the ultimate full system, this particular cognitive task was beyond the design goals of the prototype being tested. The evaluation also revealed that Nurse and Physician provider roles had significantly different perceptions of the usability and usefulness of certain EDIS components, suggesting that they have different information needs while working.

In summary key elements of work-centered evaluations include: (1) An explicit articulation and test of the *cognitive performance support requirements* underlying the aiding system that are used to guide the selection of test cases and test measures; (2) test participants that are representative of the target user population; (3) test cases that reflect the range of cognitive and collaborative complexity that arises in the work context; and (4) multi-faceted assessment measures, including objective measures of performance as well as a final user-feedback questionnaire that addresses usability and usefulness of the aiding system. A main strength of the approach is its work-oriented focus. A primary limitation is that it can be resource intensive to design, implement, and analyze.

13.3.6 Task Analysis

There are a variety of human factors task analysis methods used to formally describe work activities. These methods decompose work in terms of goals, tasks, and sub-tasks. Requirements for successful task completion are identified, including knowledge or skills, equipment, or information needs, and opportunities for error or other performance limiting factors are made explicit. The granularity of decomposition depends on the needs of analysis, and can range from high-level activities (e.g., “order medication”) to keystroke or mouse-click level actions. In some cases, time estimates are associated with activities in order to predict task completion times.

Hierarchical Task Analysis (HTA) is a common task analysis method that begins by decomposing task goals, hierarchically, into subtasks and actions (Kirwan and Ainsworth 1992; Stanton 2001). A distinguishing feature of HTA is the articulation of plans, which describe the manner in which subtasks and activities are executed. For instances, activities can be performed sequentially, subject to if-then or branching conditions, or performed iteratively until some stopping condition is met. Each node that has been decomposed into lower level actions is provided with a plan. The HTA method therefore supports a description of activity in a way that is reflective of predictable situational conditions or more flexible choice of strategy.

The family of GOMS task analytic methods (task Goals, Operators or actions, Methods or sequences of actions, and Selection rules to choose the appropriate Method) includes operators that describe cognitive, perceptual, and motor actions at the keystroke level of detail along with the times associated with the operators. GOMS models can be used to model predictable sequences of actions, including interactions with health IT systems such as electronic health records (John and Kieras 1996). Models can be used to compare task times across different systems (during procurement) or to understand impacts of operational change. A number of architectures influenced by GOMS have been implemented which support computational modeling of human activities (Byrne 2009).

Data necessary to complete task analyses (regardless of form) comes primarily from observation or interviews to allow the work tasks, performance indicators, and support requirements to be identified. Task times can be obtained through measurement, and in some cases (e.g., perceptual, cognitive, or keystroke level GOMS operators) from the published literature. Results for task analyses can be used in design (i.e., to insure critical information is present, to identify and mitigate likely sources of error, to understand when activities exceed perceptual capabilities), in system procurement (i.e., to compare times or skill requirements for critical activities), and in training (i.e., to document required knowledge and skills). For example, hierarchical task analysis was used to compare interactions with across two different drug infusion pumps in order to predict potential user errors (Chung et al. 2003). Importantly, however, task analyses are limited by the degree to which tasks are predictable a priori, and therefore are best applied to well-defined, repeated tasks (e.g., entering a medication order) rather than complex higher level tasks (e.g., diagnostic decision-making). Such complex work activities should be analyzed using other methods, such as the critical decision methods (described above) and related cognitive task analysis techniques (Bisantz and Roth 2008).

13.3.7 Cognitive Informatics Techniques

The development of cognitive informatics presents new opportunities to interface with human factors engineering principles. Whereas many of the previously mentioned methods and techniques can be challenging to gather data on more than

10–20 participants, the use of cognitive informatics can allow for observations across thousands of users and millions of interactions. Cognitive informatics goes beyond just measuring clicks and mouse movements, but seeks to both identify and understand the circumstances of a particular action or outcome across large numbers of users. Adelman et al. were able to identify instances of where medical providers ordered a test on a wrong patient by creating algorithms based on provider workflow (Adelman et al. 2013). The authors were able to significantly reduce the incidence of these errors by having ordering providers re-identify their patients with each order. Follow up work by Green et al. was able to replicate the work, but noted that the change in workflow increased workflow by 4.1–4.9 s per order. A reduction in wrong patient orders of almost 25% was sustained at 2 years after the implementation (Green et al. 2015). Yet further analysis of their implementation, extrapolated across the national healthcare system would require 400 additional full time emergency physicians and 900,000 extra hours of checking to make sure that the order is placed on the correct patient (Wears 2015). While the intervention is effective, future research is needed to better understand the human factors engineering principles behind why users order on the wrong patient. It could due to patient names on the screens being next to each other, interruptions, or errors in the health IT systems that route users to the wrong patient despite making the correct selection or some combination of other causes. Each of these require different interventions and improvements to the EHR workflow to design the errors out of the system. For this problem and many others, the use of cognitive informatics with human factors engineering is critical to identifying the underlying reasons for the errors and inefficiencies, and to help prioritize the most frequent and potentially catastrophic events from impacting our patients and clinicians.

13.4 Conclusion

This chapter provided an introduction to human factors perspectives and methods. Key methods include semi-structured interviews and focus groups, critical incident analyses, observational methods, artifact analyses and cognitive informatics approaches. Multiple health care examples of applications of these methods were provided to illustrate the power of studying work as practiced to identify sources of complexity that create risk as well as adaptive behavior of healthcare providers that contribute to system resilience and enhance safety. The examples also illustrated how human factors methods can be leveraged to identify opportunities for improvement whether through training to disseminate and reinforce effective strategies or through technology enhancements. A key point is the need to include multiple opportunities to collect information on the usability and usefulness of new technologies throughout the development process, up to and including fielding of systems in the actual work environment.

An important point to stress is that the human factors methods are appropriate for use by multiple types of organizations and stake-holders, and can be and tailored to the scope, size, and budget of the project. This includes technology vendors who may be trying to develop and upgrade health IT systems for applications across multiple hospitals, clinical organizations (e.g. ambulatory clinics, hospitals, larger healthcare systems) that might be trying to roll-out and manage new health IT systems to minimize error, and improve performance, satisfaction and safety, as well as individual healthcare researchers or leaders who may be trying to examine sources of problems or errors and identify appropriate solutions.

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Chapter 14
Automated Location Tracking in Clinical Environments: A Review of Systems and Impact on Workflow Analysis

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14.1 Background and Motivation

The impact of workflow on clinical error and consequently on patient safety has been widely known for some time (Frisby et al. 2017). While it may be convenient to blame human error for the findings presented in the report "To Err is Human," this is not a view shared by a majority of patient safety researchers (Henriksen et al. 2008). A more accepted view is to consider the complexity of a medical environment, where errors are typically caused by failure of one or more aspects of the system, leading to a sequence of further failures, which ultimately impact patient safety. Errors more often result from our lack of understanding of the environment and its bottlenecks than from a specific individual within the environment. To that end, thorough analysis of health care professionals' clinical workflow is essential to build a knowledge base of the areas of potential bottlenecks that may compromise patient safety.

Since the publication of the above report, research in clinical workflow has increased significantly. An important approach to studying complex environments is ethnography (Malhotra et al. 2007; Patel et al. 2008; Vankipuram et al. 2011). Ethnography pertains to the study of the individuals that make up the environments and how their biases and interactions affect the outcome of that setting. Ethnographic observations combined with surveys, interviews, and questionnaires are all techniques that help piece the puzzle of an environment together. However, each data

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collection method has its own limitations. Specifically, these methods rely heavily on single or multiple human observers processing multiple, and at times parallel, streams of information (Vankipuram et al. 2009). Increasing the number of observers can help in such a situation, but this can also quickly lead to logistical issues as accounts are combined.

Our goal in writing this chapter is to summarize an important modern technological advancement that can potentially help enhance our understanding of the intricacies within clinical environments and processes. We will present an overview of automated location tracking technologies followed by related research on the efficacy of the technologies. We then look at case-studies from our own work to elucidate the potential impact of location tracking in the medical domain. We break down the case-studies into analytics derived from location tracking data and data visualization techniques that can help present this information to relevant target users (i.e., clinicians and researchers).

14.2 Automated Location Tracking Technologies

Automated tracking of entities in a clinical environment has gained popularity over the past decade, with uses ranging from equipment tracking in clinical environments to research. Automated tracking refers to the use of technological advancements to continuously track clinical personnel, patients, and equipment with minimal human supervision. The methods associated with automated tracking were inspired by those in the field of aviation. Specifically, by considering tracking of processes in a complex medical environment to be comparable to a black box in aircrafts (Vankipuram et al. 2011). In this analogy, the black box continuously monitors various aspects of flight, such as pilot communication, altitude, cabin pressure, and relays this information to the ground or recorded for post-flight analysis and in case of emergencies. Clinical environments can be similarly monitored to reveal underlying process bottlenecks or sources of error.

One of the most popular techniques to achieve automated tracking is the use of sensors. Several examples of such technologies exist, including Radio Frequency Identification (RFID), Bluetooth, ZigBee, and Wi-Fi (Vankipuram et al. 2018). The efficacy of these various methods depends greatly on the nature of the environment itself and the constraints (safety protocols, lead-lined walls, inference from other medical devices) placed on signal transmission in medical environments. As a result of these constraints, RFID and Bluetooth have become the most popular technologies for automated tracking (Vankipuram et al. 2018). Lee and colleagues (Lee et al. 2007) compared the various safety protocols discussed above, and while they determined that the suitability of a protocol was most dependent on its use-case, Bluetooth and ZigBee were the most suited protocols for low data, low battery use applications. Near-Field communication was effective for much shorter distances than would be convenient for tracking. Wi-Fi, while a popular method, was found to interfere with existing hospital networks.

14.2.1 Radio-Frequency Identification (RFID)

RFID tags are typically carried by the subjects being monitored and they relay their information at regular intervals to a central receiver. Typically, multiple receivers are needed in larger areas. Information, such as proximity of tags to the receiver, is used to determine interactions between subjects. This helps build a model of interaction that can be used to analyze the impact of interventions or general workflow. Figure 14.1 shows an early version of RFID tags provided for clinical tracking purposes. These earlier technologies suffered from a significant amount of interference leading to a loss of data quality. Data collection over wireless networks also posed a challenge and often the data collected was stored at a central location by the vendor and had to be specifically requested as a data file when needed. Obviously, this was a significant barrier to adoption due to the circuitous and time-consuming collection process, but, more importantly, resulting from an inability to restrict ownership of potentially sensitive data, especially when dealing with patient tracking. Therefore, these technologies were rarely, if ever, used on patients. Additionally, the receiver stations shown in the figure were meant to be placed, manually, at the most appropriate locations and since they were ground stations it meant that they had a higher probability of interfering with the normal clinical workflow and could be distracting or concerning for patients and physicians.

Fig. 14.1 SNiF® RFID tag (Vankipuram et al. 2011)

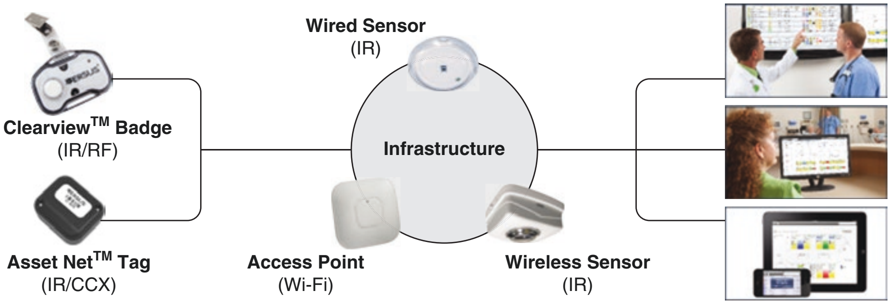

Fig. 14.2 Versus RFID-RTLS system

A modern version of an RFID system is shown in Fig. 14.2 (Versus Technology, RTLS Technology | Accurate, Reliable IR-RFID RTLS | Versus RTLS n.d.). The technologies have been updated to conform with the standards required of medical data including security. In the case of the Versus system, a reduction in the size of the receivers along with an improved tag detection mechanism has allowed the system to improve the efficacy of collected data. While the Versus system is used as an example here, there are several vendors who use variations of similar techniques and achieve similar effectiveness. Additionally, medical organizations have also begun to implement their own solutions because RFID tags and receivers tend to cheap and easily available.

There are two broad classes of RFID technologies that are available:

1. Passive RFID: The tags have no power source and only transmit a signal when they are within range of a receiver. This typically leads to a longer lifespan and passive tags can last up to 10 years. However, due to a lack of onboard power their detection range is within 40 ft. The receivers are often more expensive than active RFID owing to a need to transmit radio frequency energy.
2. Active RFID: These tags are battery powered and continuously transmit a signal. They have a detection range of over 300 ft but have reduced battery lives (3–8 years depending on the range). Receivers are cheaper than their passive counterparts.

Choosing between these technologies is largely based on the characteristics of the medical environment in which they are implemented as well as organizational concerns, such as safety and cost.

14.2.2 Bluetooth

Bluetooth based tracking solutions are a more modern approach to clinical tracking. The technique was originally introduced, and is most often used, in non-medical settings (e.g., keyless entry for houses) (Andersson 2014). Bluetooth offers certain advantages over RFID, especially in terms of cost and battery life (Frisby et al. 2017).

The Bluetooth tracking setup is similar to RFID and relies on receivers and tags on tracked entities/personnel. An additional advantage of this technology is its increased compatibility (compared to RFID) with mobile devices and PCs (i.e., most devices can receive and process Bluetooth signals without purchase of a specialized receiver). Bluetooth tracking setups can therefore be more cost effective than the equivalent RFID systems. However, to maximize the efficiency of data collection and minimize the cost, a higher level of technical knowledge is required for setup and maintenance of ad-hoc solutions. Bluetooth technologies are classified by their versions. The latest version of Bluetooth, released in 2016, was Bluetooth 5.0. Each subsequent revision of the Bluetooth standard has led to an increase in communication range and a reduction of power/cost. In version 4.0, an associated technology called Bluetooth Low Energy (BLE) was released. This version greatly reduced power consumption of Bluetooth devices while having a comparable communication range. Figure 14.3 shows an example of the Bluetooth tag (beacon) by Estimote (n.d.), which is an example of a BLE device. The Estimote tags and similar BLE sensors were estimated to have an increased battery life, making them more efficacious for automated tracking solutions.

As mentioned earlier, Bluetooth signals can be received by a range of commonly found devices, such as mobile phones and laptops. Raspberry Pi (low cost processors used in mobile devices and computers) have also been used as receivers (Frisby et al. 2017).

14.3 Efficacy of RFID: A Research Perspective

Clinical workflow analyses are especially important when attempting to assess the impact of an intervention or other modifications to everyday processes. An example of such an intervention, and potentially the most relevant to modern medicine, is the introduction of technology into typical clinical workflows. Zheng and colleagues (Zheng et al. 2010) assessed the impact of health information technology implementations (specifically for Computerized Physician Entry (CPOE) forms) on clinical workflows. They introduced a set of new analytics for assessment of impact and demonstrated a means to use data visualization to make complex data more decipherable and useful for quicker assessments. Drawing from this work, Vankipuram and colleagues (Vankipuram et al. 2009) introduced a Hidden Markov Model based approach to capture and analyze interactions using RFID tag based data.

Fry and Lenert (2005) implemented a system called MASCAL that used RFID technology to track personnel, patients, and equipment in mass casualty events such as natural disasters and other catastrophes. MASCAL involved the use of RFID tags in combination with receivers set around the hospital to track the various resources in real-time at times of emergency. There are two different kinds of RFID tags,

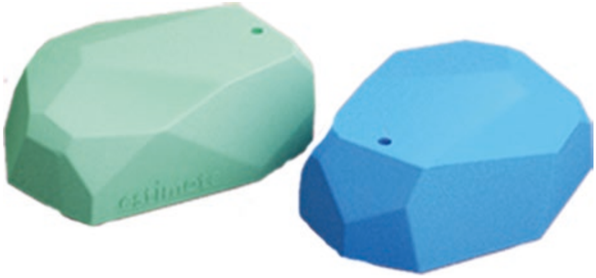

Fig. 14.3 Estimote® Bluetooth Beacons

active and passive. Active tags constantly broadcast a signal and passive tags wait until they are near a receiver. Ohashi et al. (2008) compared different RFID systems typically employed by hospitals and found that in general both passive and active were affected by the environment. Active tags are battery powered and therefore have a set lifespan whereas passive tags need to have a local receiver to be used.

A study by Elnahrawy and colleagues (Elnahrawy and Martin 2004) compared localization algorithms for tracking precision and found that the uncertainty associated with tracking was likely fundamental and any approach (i.e., Wi-Fi, RFID, Bluetooth, etc.) would suffer from the same issues. Frisby and colleagues (Frisby et al. 2017) implemented a similar system using a beacon to track physicians in the emergency room at the Mayo Clinic hospital, using Raspberry Pi as a receiver. In this study, six receivers and fourteen beacons were used in the hospital.

14.3.1 Case Studies: Emergency Room (ER)

In this section we present our work using location tracking data, specifically, RFID data, in deriving workflow-related analytics in an ER.

14.3.1.1 Automated Location Tracking for Clinical Performance Analysis

Positional tracking can be used to derive additional metrics that may function to benchmark emergency room performance. The Center for Medicaid and Medicare Services (CMS) enacted several performance measures that needed to be enacted beginning in 2012 (Blumenthal and Tavenner 2010).

The measures that can be analyzed using location tracking data include:

- Door to Diagnostic Evaluation by a Qualified Medical Professional
- Median Time from ED Arrival to ED Departure for Discharged ED Patients
- Median Time from ED Arrival to ED Departure for Admitted ED Patients
- Admit Decision Time to ED Departure Time for Admitted Patients

Welch and colleagues (Welch et al. 2011) elucidated, in detail, the performance measures for emergency rooms and the salient timestamp or time-interval measures were as follows:

- Treatment space time: Time taken to acquire a bed or room
- Provider contact time
- Arrival to provider time (door-to-doc)
- Arrival to treatment space time
- Length of stay: Arrival to departure

Continuous tracking of these attributes can provide emergency rooms with the ability to continuously monitor and improve their processes.

14.3.1.2 Location Tracking Data Collection

To understand the implementation of techniques to analyze clinical workflow and processes using location tracking, we need to understand the structure of tracking data. Most commonly, tracking data is stored in a tabular format. When tracking tags are within the range of a receiver, a single data point is written into the table which may be a locally stored or network relational database. An additional concept to understand is that most effective tracking systems require a high level of coverage (i.e., receivers placed in the environment to achieve a reasonable level of granularity of location data). The data table, therefore, typically has low dimensionality (i.e., few columns, but is usually large since data is recorded per instance of tag detection and this can happen several times a minute per tag that is within the receiver range). It is not uncommon to collect several gigabytes worth of data in a year for a sufficiently large system, such as the one we are describing in this case study. It is therefore incumbent on organizations attempting to implement similar systems to understand their baseline technical requirements and to plan for the growing needs with each year of the system's operation.

Table 14.1 shows two rows of the RFID data collection for a single tracked clinician in the ED. The columns of the recorded data are as follows:

- Location: The location of the ceiling mounted receiver.
- Start: First instant of time when the tag is within range of the receiver
- End: Instant of time when the tag moves outside the range of the receiver
- Duration: Time spent within range of the receiver

Additionally, each RFID tag was associated with a unique ID which was stored by the receiver, once per row (Table 14.1). The ID could be, therefore, used to

Table 14.1 Structure of location tracking data from the ED (Vankipuram et al. 2018)

Location	Start	End	Duration
Office	11/20/2016 12:04:09 AM	11/20/2016 12:06:44 AM	0:02:35
Physician Workspace	11/20/2016 12:06:47 AM	11/20/2016 12:12:11 AM	0:05:24

identify each tracked clinician. It is worth noting that while this case study deals with RFID data, Bluetooth data will likely need to be similarly structured.

14.4 Data Analytics

Having understood the type of data being collected we can now consider the types of analytics that can be performed on the data. The value of automated techniques over manual observations can best be described by considering methods that require large and higher fidelity datasets, such as the ones we can create using an automated system with good coverage.

14.4.1 Entropy (Degree of Randomness)

A valuable goal of tracking tasks and movement in a fast-paced, concurrent environment like the ED is to be able to map the inherent structure or lack thereof of the various processes that make up clinical workflow. To that end, we can use the location data to compute the entropy or degree of predictability of processes. Structured processes should have a lower level of entropy or unpredictability since they are, by nature, a series of repeating patterns of movement or behavior. Computing entropy can allow researchers and clinicians a birds-eye view of workflow in an environment like the ED. The entropy of a sequence of movements that underlie a process can be compared to a baseline of truly random movement to get a relative degree of predictability. The associated methods are described in detail in our previous work in the Mayo clinic ED (Vankipuram et al. 2018).

14.4.2 Discrete Event Simulations (DES)

Demonstrating clinical utility of location tracking data is incumbent on deriving meaningful metrics and relevant ways to present those metrics to the relevant target clinical users. Location tracking data has been used in the creation of new workflow metrics for the ED from RFID data (Vankipuram et al. 2018). As part of this, the clinical environment was modeled using movement transition probabilities to capture its underlying uncertainty. This type of probabilistic model may be visualized to derive specific workflow-related insight, but it can also be used to simulate parameters of interest in the system (Rutberg et al. 2013; Asamoah et al. 2018). These system simulations can be used to assess impact of specific processes or as a predictive model to assess trends.

DES is a technique used to model complex systems by simulating it in action to estimate or predict parameters and outcomes of interest (Rutberg et al. 2013). Systems are typically represented as a series of states, events, and transitions, each of which have a cost associated with them. The net cost of moving through the system in various scenarios is typically then used to estimate the value of the resource that one is looking to optimize. In the medical domain, examples of this could be queue length or wait times for patients (Vankipuram et al. 2018). Traditionally, the costs associated within the system are set based on clinical expertise. Additionally, the movement through the system in the case of branching (concurrent) processes is determined randomly. While this is reasonable approximation of uncertainty, various medical environments may demonstrate varying levels of uncertainty. It is also possible that uncertainty levels may vary during a shift due to cognitive and physical stress (Patel et al. 2008). Using probabilistic models generated from RFID data, we can represent the uncertainty of the system in a way that better represents the actual workflow. One way to progress through a probabilistic system is to use the Monte-Carlo method which has been shown to work in DES (Rutberg et al. 2013).

The task of estimating the underlying distributions associated with parameters of interest in a medical environment has been researched (Asamoah et al. 2018). With automated tracking, we can enhance our understanding of the underlying structure of the uncertainty.

Figure 14.4 represents a simplified view of a clinical movement probability model. Such a model can be utilized to simulate outcomes of interest. Figure 14.5 shows the results of DES for three behaviors in ED (providers tracking). The time computed represents predicted time to exam for a physician over 1000 simulated runs. The transition probabilities were used to pick the next location to

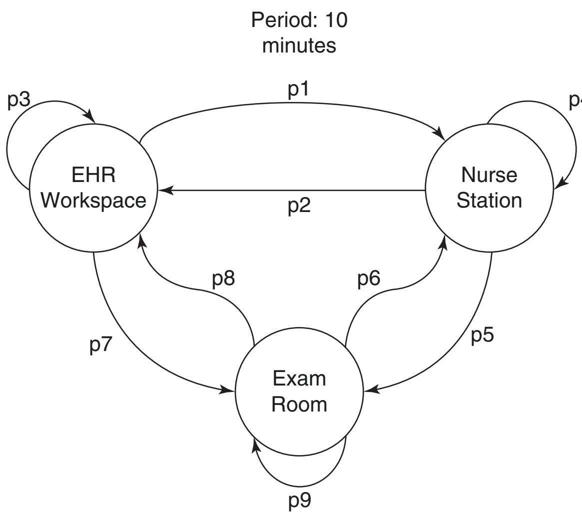

Fig. 14.4 Simplified probability model of the ED (actual model contains all 59 locations)

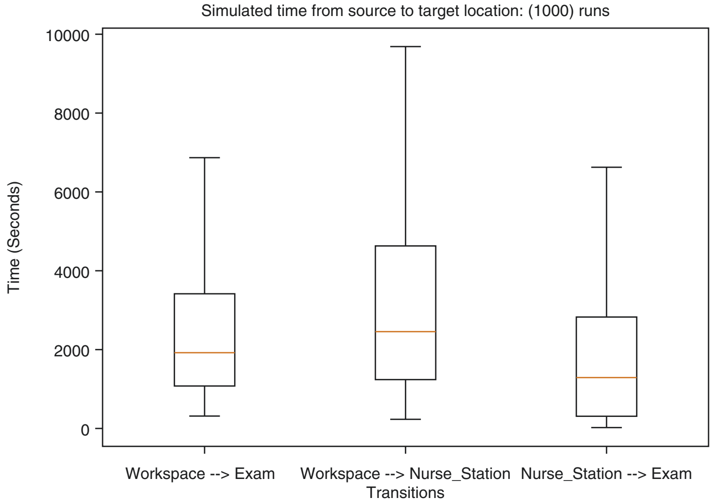

Fig. 14.5 Result of DES for three cases of interest in ED

move in the simulation. To pick the duration at each location, we compute the skew for each duration and generate a random number from a distribution with the same mean, std, and skew. Figure 14.6 shows the time distributions generated using tracking data that form the underlying models used in this sample simulation.

14.5 Data Visualization

Utility of analytic techniques are the greatest when derived information can be presented to target users in meaningful ways. In the medical domain, users may include clinicians, administrators, or clinical researchers. The theoretical foundations for this space are provided by the science of visual analytics. Visual analytics is the "science of analytical reasoning facilitated by interactive visual interfaces" (Thomas and Cook 2006). Visual analytics can aid in the deeper exploration and insights derived from data and the presentation of this information to specific types of end-users. In this section, we present some example of visualizations created using the ED location tracking data to illustrate the value further. At the end of the section, we provide a sample workflow dashboard which is used as an example of an idealized outcome of an integrated location tracking analytics system in an ED or similar clinical environment.

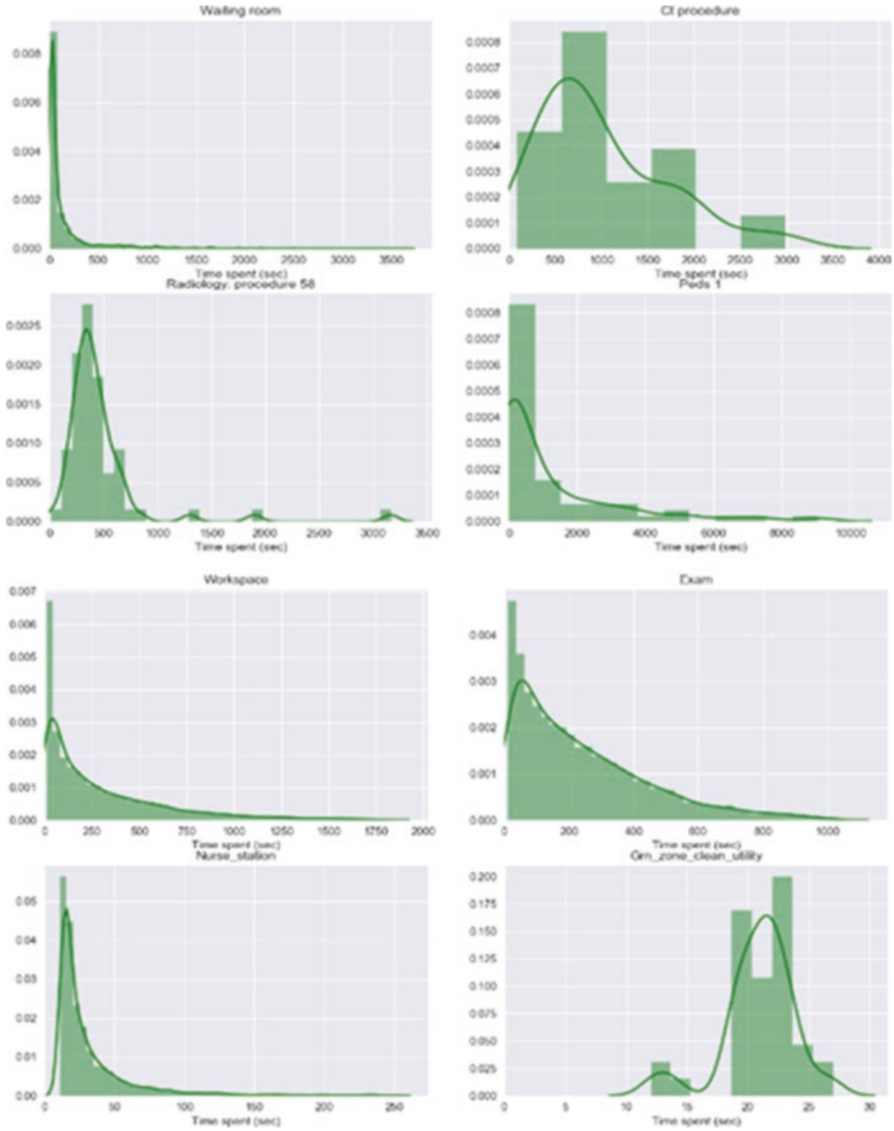

Fig. 14.6 Time distributions for four sample locations in two EDs

14.5.1 Chord Diagram

Figure 14.7 is a representation of the net duration of interactions between clinicians. Interactions are defined as an event where the clinicians were co-located for a length of time. The practical value of this is its use in process management to provide

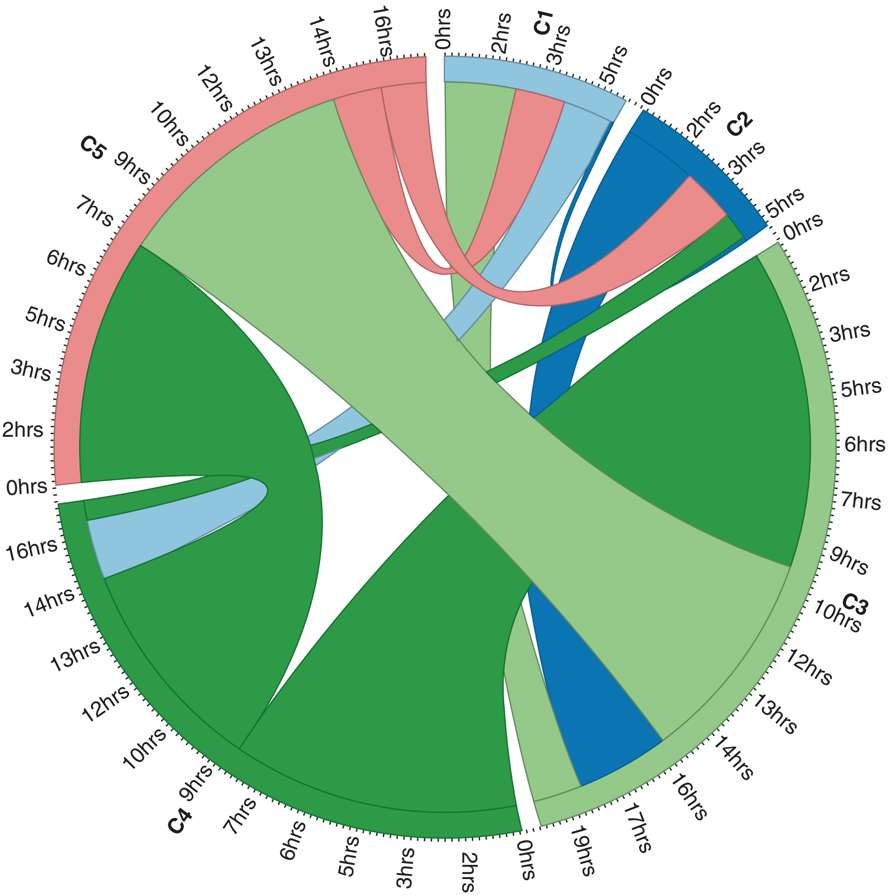

Fig. 14.7 Net duration of interactions between tracked clinicians at Mayo Clinic

circumstances that maximize interactions and to find pairs of clinicians who are more likely to interact and study them further.

The chord diagram (Fig. 14.7) shows duration of interactions between clinicians. Each colored segment on the boundary represents a different clinician (C1–C5, respectfully). The chords connecting the segments represent a pairwise link and the width of the chord represents the net duration of interaction (the axis of the boundary can be used to estimate the duration).

14.5.2 Longest Common Subsequence

The longest common subsequence (LCS) is a computational problem that deals with finding the longest common set of sub patterns within two series. An example of this is to find the longest common sequence of nucleotides in two gene sequences. By treating movement data as a series of location sequences, we can compare two sequences of movement, either by time or by tracking personnel, to derive additional insight into behavior.

LCS can be computed for each tracked clinician and visualized as seen for one clinician in Fig. 14.8. This can also be used for process management, but additionally may be used to compare clinicians with varying expertise. The figure shows a movement graph of the most common movements a single tracked clinician makes during a shift. This can be potentially used to compare novices and experts and see if the experts' movement allows them to manage time better or mitigate certain types of error.

The blocks on each axis represent a move within the location (e.g., 'Workspace' to 'Workspace,' with the arrows representing direction of movement). This chart can be compared over lengths of time or between a specific pair of clinicians (e.g., novice vs. expert). It is also possible to use the chart in Fig. 14.8 to view arbitrary length sequences for any clinician, but in this case, we use it to view the LCS of movement across all shifts of a clinician.

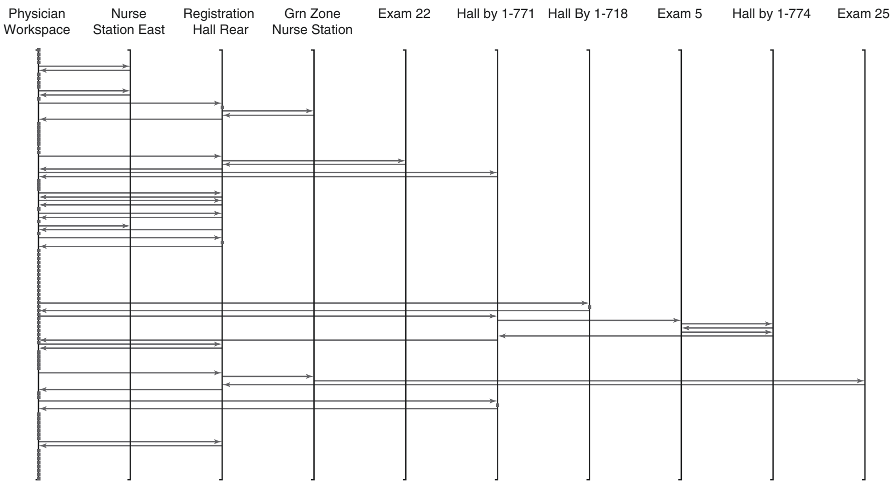

Fig. 14.8 Longest common subsequence for a single clinician over 7 months at Mayo Clinic

14.5.3 Network Graph-Based Visualization

Relationships and probabilities can be represented as a network graph, as seen in Fig. 14.9, which gives the probability of a clinician's next location. The radius of each colored circle represents the time spent in that location. The strength of the relationship is represented by the number of the links between locations (i.e., more links indicate stronger relationships). These links also show the probability of the physician's next locations from any origin point. This type of graph eliminates any overlapping edges to provide a clearer interpretation of the relationships between locations. Network graphs work well in a dynamic setting, such as an interactive dashboard.

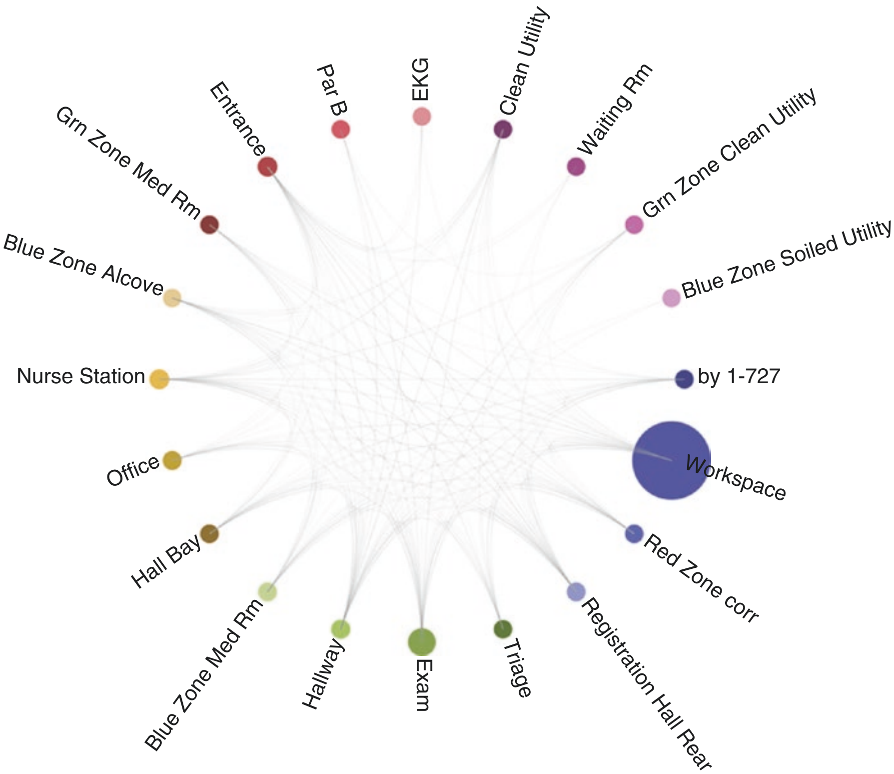

Fig. 14.9 Probability of clinician's next location at Mayo Clinic

14.5.4 Radar Chart

A radar plot/chart is a form of visualization that is a good way to represent a single discrete axis. It is a popularly used plot in gamification research, which is the introduction of video-game elements into visualization dashboards to enhance clarity and intuitiveness. Below (Fig. 14.10) we look at an example of a radar plot generated to display the probability of the physician's next location from any origin point.

The radar chart is a useful representation of clinical movement as a Markov process (i.e., when we model the system as a Markov chain where the probability of the clinician being in the current location is only dependent on the immediate previous location). Markov process are usually a good approximation of complex processes and can be further used in methods like the discrete event and Monte Carlo simulations described earlier. Radar charts are an effective way to convey Markov systems.

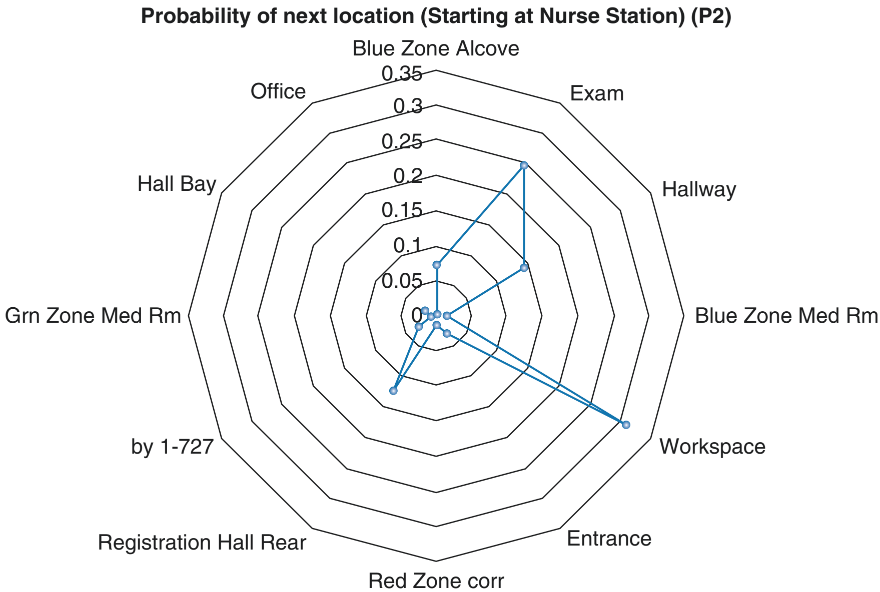

Fig. 14.10 Probability of next physician location, with nurse's station origin. The axis of a radar plot is categorical giving a discrete representation

14.5.5 Clinical Workflow Dashboard

As mentioned previously, an ideal goal of visual analytics work is to provide a platform for clinicians and researchers to receive feedback on the results of data analysis. Below we present a proof-of-concept dashboard developed using ED location tracking data. Figure 14.11 shows a sample dashboard for a single physician based on measures derided from location tracking. The top row shows instances of direct patient care (movement from workspace to exam room), multiple patient

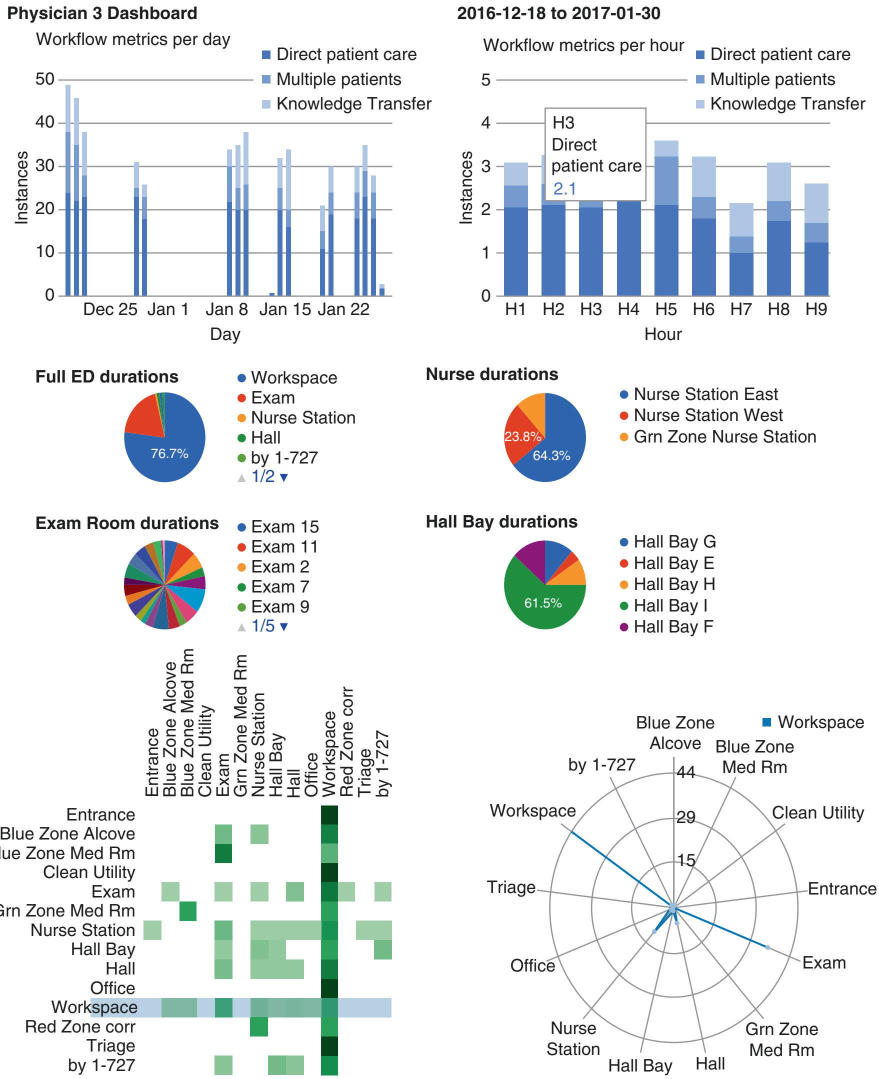

Fig. 14.11 Location tracking analytics visualization dashboard

exam room visits, and knowledge transfer (movement from workspace to nurse stations). The plot of the left shows the net count of each of the above metrics per day. The plot on the right shows a single day as selected on the stacked plot (left). This plot is shown per hour of the shift.

The second row shows a set of pie charts representing time spent in various locations within the ED. EHRs have been a disruptive influence on clinical workflow and clinicians are often concerned with time spent with patients compared to other areas and activities. These plots can convey the proportion of time spent in exam rooms compared to other areas in the ED.

Finally, the transition probabilities described in the radar chart section is represented in the final row. Transition probabilities for a single physician represented as a heatmap (left). The darker squares represent a higher likelihood of movement from location on the column to the location on the row. Useful for presenting net behavior. The radar plot on the right is populated by selecting one of the location in the heatmap and presents probability values for movement from that location.

Figure 14.11 is an example of an interactive dashboard and can be updated to display measures for any arbitrary length of time. A possible use for such a dashboard could be to observe trends in these measures across time to assess the impact of technological or process interventions.

14.6 Conclusion

In this chapter, we described automated location tracking technologies and associated analytical methods in medical environments. Clinical workflow is inherently complex, and the techniques described above were developed to complement other quantitative methods typically used in the analysis of clinical workflow. Derived measures can assist researchers and clinical stakeholders as they identify bottlenecks which can be further investigated in greater detail using ethnographic techniques. We believe that the most effective way to study workflow is to use a combination of available methods. Our goal in this chapter is to present the utility of, what we believe is, an efficacious modern method to supplement workflow study.

There are also additional sources of data that can be leveraged to create a more holistic picture of clinical processes which we have not included here, but are equally important. Location tracking provides just one dimension of qualitative data. Another example of a valuable data source is EHR trace/usage log files. EHR logs are collected by most mainstream vendors, which includes the use of the system by various authorized personnel. Including this data in clinical workflow analysis can increase the granularity of our view into the medical environment to provide more context to movements and related activities, and thus improve the depth of our automated monitoring capabilities.

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Part IV
Applications and Case Studies

Chapter 15
Health IT-Enabled Care Coordination and Redesign in Ambulatory Care

Jonathan S. Wald and Laurie Novak

15.1 Introduction

Studying workflow and health information technology (IT) adoption is complex because there are many contributing factors and confounders. Research attention to the study of workflow has intensified in the U.S. since the rollout of the meaningful use (MU) program by the Office of the National Coordinator for Health IT (ONC) in 2009. The mounting interest in better understanding clinical workflow in the context of health IT implementation reflects a realization from early pioneer health IT studies, which is that factors such as site leadership, workflow optimization prior to automation, team communication, and attention to many details of practice and health IT design and use, can lead to successful adoption of new technology when aligned, or can limit the adoption if gaps are present and remain unaddressed.

The misalignment between workflow and health IT may arise from many contributing factors. These include mismatch between health IT design and the workflow that predated the implementation, insufficient training of users, and inexperienced technical staff responsible for configuring health IT. In addition, health IT often brings together changes in clinical and administrative activities, such as how clinical activities are documented and how billing processes are managed. These, and other sociotechnical challenges, add to the complexity of health IT adoption and implementation research.

Subtle configuration and implementation-related decisions can hurt or help with user experience, such as how users are assigned to system-defined user roles with different levels of access privileges. For example, a mid-level role such as a physician

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assistant or nurse who functions as a population health manager may perform both clinical and administrative tasks, which doesn't always "fit" the roles pre-defined in health IT systems. Flexible health IT design is therefore needed to accommodate unanticipated task sequences, workflows, and roles. Decisions on how to configure systems for the local context may also introduce usability or workflow challenges, and also may limit the flexibility of the software as clinical redesign takes place.

Many decisions related to user training may also impact health IT adoption. For example, training that uses simulated test environments may not correspond closely to the live environment, although differences may not be apparent until after go-live. Also, many of the more technical users, especially clinicians, may be paired with trainers who lack specific skillsets needed to train certain users. Finally, the generic, *one-size-fits-all* design, which is popularly found in today's health IT systems, may be insufficient for supporting complex tasks when there is a significant amount of variation in how they are performed in day-to-day clinical practice.

15.2 Background

15.2.1 Gaps in Prior Research on Workflow

The widespread adoption of health IT to manage electronic patient data and support care delivery has expanded the role that technology plays during work systems redesign in healthcare. However, the anticipated benefits of health IT are difficult to achieve unless implementation and workflow challenges are identified and addressed (Ash et al. 2009; Blumenthal 2011; Dorr et al. 2007; Novak et al. 2012; Holden et al. 2013). Health IT–workflow interactions are best understood through a human factors and sociotechnical framework (Novak 2010), but large gaps in systematic research of ambulatory care workflow still exist (Carayon et al. 2010).

In 2010, the U.S. Agency for Healthcare Research and Quality (AHRQ) published a comprehensive literature review study that looked into existing research and evidence about the impact of health IT on workflow, its linkage to clinician adoption, and its linkage to the safety, quality, efficiency, and effectiveness of patient care delivery. The study showed evidence of variable quality, little generalizability to non-academic and ambulatory settings, and limited focus on the sociotechnical context of health IT implementation including potentially conflating or mediating factors such as training, technical support, and organizational culture (Carayon et al. 2010). Existing research reviewed in the AHRQ study also did not address redesign of ambulatory care settings, though this is an important aspect of health systems change.

In addition, the AHRQ study identified significant gaps in understanding the interactions between health IT and workflow, and advised that more systematic research was needed, both to establish causal relationships and to produce highly generalizable knowledge in the study of health IT and workflow interactions

(Carayon et al. 2010). Accordingly, the study that we describe in this chapter was designed to address two major gaps in the literature:

- **Rigorous research focused on workflow**. This study used a combination of methods (Carayon et al. 2012) specifically designed to understand workflow in the context of a work system implementing new health IT. These adapted methods were implemented by experts in sociotechnical systems research in partnership with clinical subject matter experts in order to provide an understanding of workflow phenomena that are typically ignored or underspecified in prior studies, including: adaptation of health IT, the role of health IT in team-based work, and the coevolution of health IT and workflow.
- **Attention to sociotechnical context**. This study approached workflow as an interactive sociotechnical work system of: (1) people; (2) tools, technologies, and other artifacts; (3) tasks and task characteristics; (4) organizational structures and characteristics; and (5) the surrounding physical, social, and political environment. Data collection and analysis focused on these five factors, alone and in interaction, and how they relate to (for example, constrain or enable) the studied work processes. Attention to the sociotechnical aspects permitted this study to both describe this context and allow comparisons to other contexts. It also permitted the research team to understand what specific contextual factors influenced workflow-related phenomena—for example, the circumstances in which implementing the same health IT system in two or more settings might lead to divergent workflow changes, and why.

15.2.2 Theoretical Framework

The study's theoretical framework was informed by two compatible models that have been applied to workflow research: the adapted SEIPS (Systems Engineering Initiative for Patient Safety) model (Carayon et al. 2006; Karsh et al. 2006; Carayon 2009) and the Workflow Elements Model (WEM) (Carayon et al. 2012; Unertl et al. 2010), depicted in Figs. 15.1 and 15.2. The SEIPS model defines the work system as the interaction of people, tools/technology, tasks, organization, and environment. This work system (structure) shapes workflow (process) that in turn shapes patient and clinician outcomes. The structure-process relationship requires that workflow be studied in the context of the interacting work system. In addition to understanding workflow as process steps or patterns, it must be specified who is involved or not involved (**people**), what artifacts are used or not used (**tools/technologies**), what characteristics such as goals or task demands constrain work (**tasks**), what structures or policies are in place that govern people and processes (**organization**), and where the work takes places (**environment**). This adapted model shown in Fig. 15.1 builds on the SEIPS and related systems models to illustrate workflow as the product of a sociotechnical work system that is transformed by new health IT as well as adaptations over time.

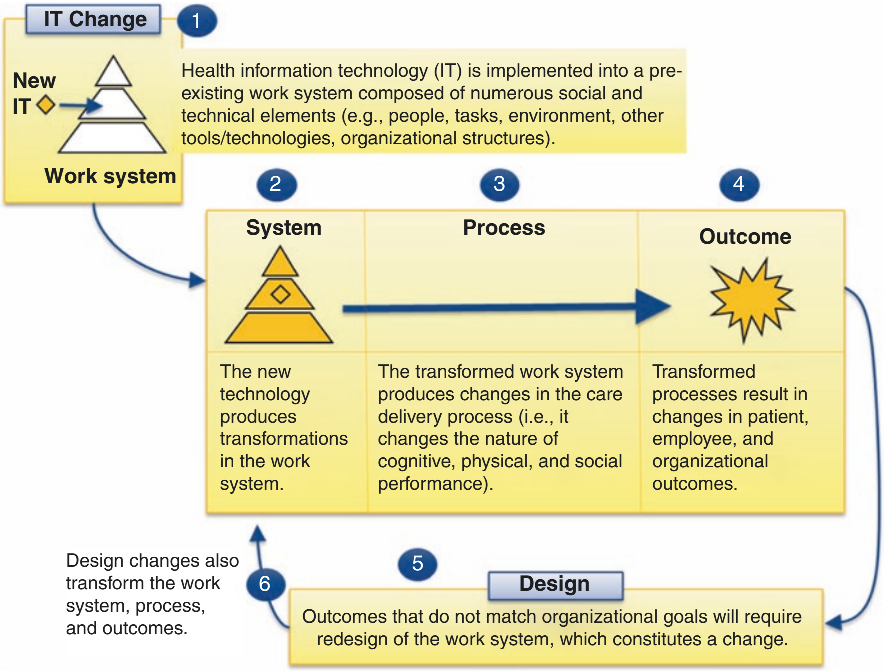

Fig. 15.1 The Adapted SEIPS Model. Source: Holden et al. (2011). Note: This graphic is reprinted under a Creative Commons license

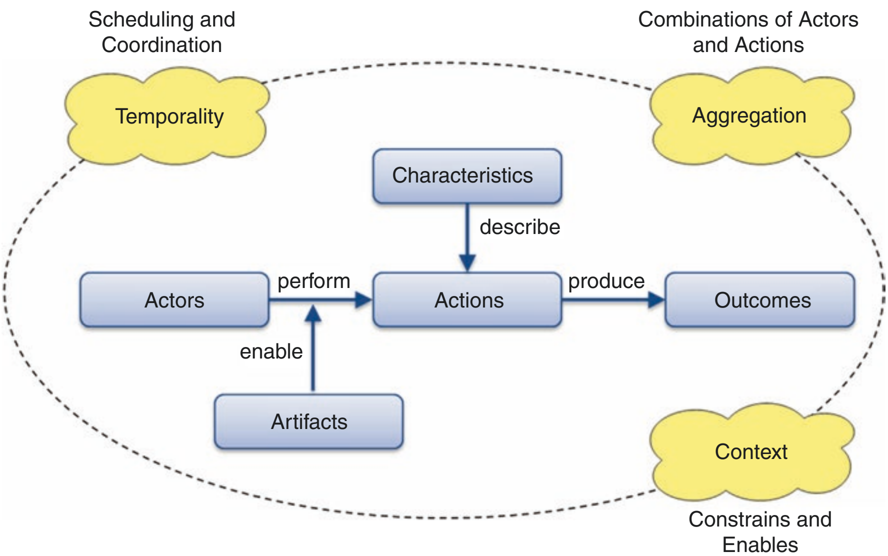

Fig. 15.2 Workflow Elements Model. Source: Unertl et al. (2010) with permission from Oxford University Press

WEM is a broad synthesis of prior workflow research and adds to and refines how one might apply SEIPS generally to the study of workflow (Carayon et al. 2012). WEM specifies three pervasive properties of workflow that shape outcomes or the end products of workflow. First, workflow is dynamic (**temporality**): it occurs across time, changes from moment to moment, depends on a context that may change over time, and often emerges from the activity of individuals and groups working asynchronously in different locations. Second, workflow is collective (**aggregation**): work is carried out by multiple individuals as well as collectives working separately or in concert, synchronously or asynchronously, and toward goals that may converge or diverge. Processes, too, are subject to aggregation and can be delineated into tasks or patterns or seen in combination or as emergent properties of work. Third, workflow occurs in **context**, including work system elements—such as people and technologies—and any other factors that constrain or enable workflow. Examples of contextual factors not explicit in SEIPS include extra-organizational culture, standards, legislation, pressures, and workforce characteristics (Karsh et al. 2006).

The two models in combination guided the data collection of this study in the following ways:

1. Both models promote capturing and analyzing data on sociotechnical system factors (such as people, technologies, and task characteristics) that are relevant to studied processes and steps or patterns.
2. SEIPS specifically promotes capturing and analyzing data on people, tools/technology, task, organization, and environment factors—as well as interactions between the factors—related to parts of or whole processes.
3. WEM specifically promotes capturing and analyzing data on temporality, aggregation, and contextual properties of parts of or whole processes.
4. Both models promote a focus on processes and related work system factors and pervasive properties that shape key outcomes such as successful, coordinated health and disease management.

15.3 Our Study

15.3.1 Health IT Studied and Empirical Setting

The My Health Team at Vanderbilt (MHTAV) program was initially developed in 2010 by the Vanderbilt Medical Group to be an innovative, ambulatory health care delivery model for a small group of patients with three chronic conditions, diabetes, hypertension, and congestive heart failure, among pilot physicians in one clinic. Vanderbilt received external funding through a U.S. Centers for Medicare & Medicaid Services (CMS) innovations contract in 2012 to greatly expand the program with revised goals: to improve chronic disease management, care coordination, and transition management for all Vanderbilt patients with the three chronic medical conditions.

The expanded MHTAV program was centrally administered and implemented, although the implementation of the program varied somewhat across clinics based on the experience of the care coordinators and the composition of the clinical teams. The MHTAV program included intensified patient engagement and dedicated care coordinators (CCs). CCs were registered nurses who helped coordinate care for patients.

Major IT system components were developed or used in support of care coordination activities, including: (1) the Vanderbilt electronic health record (EHR) system (StarPanel), (2) cross-patient dashboards for diabetes, hypertension, and congestive heart failure, (3) worklists for use by CCs, (4) a shared view of the patient's plan of care (POC) among clinical staff, (5) alerts and reminders related to care coordination activities, (6) the disease control form, (7) patient portal secure messaging, (8) an interactive voice response (IVR) system, (9) the clinic scheduling system, and (10) online patient education and materials.

A number of health IT components were created or used primarily for MHTAV, including the dashboards, worklists, the POC, and the IVR system, collectively referred to as My Health Team (MHT) tools or the MHT system. A key goal of the MHT system was to support structured, bidirectional, and closed-loop communication among members of the care team, including the patient and caregivers. In the context of MHTAV, the providers and clinic nurses provided direct care to patients. CCs managed the MHTAV panel of patients and were supported by MHTAV medical assistants who assisted the CCs with patient education, collection and summaries of patient home monitoring data (blood pressures and blood sugars), and administrative tasks. MHT tools included a range of information that could be viewed for an individual patient or at the population level. At the patient level, this included demographic information, the patient's condition or disease, and a POC. At the population level, a dashboard showed aggregated statistics for selected indicators. Care coordinator activities were driven by a worklist which showed patients with alerts that were either clinically driven (such as an elevated home blood pressure reading) or process driven (such as a patient who was due for an annual foot exam).

The empirical study involved six study site teams in five office locations (see Table 15.1). These included a single on-campus medical office (medium-sized; 35 part-time clinicians) and four off-campus primary care offices (small; 2–11 clinicians). All of them are located in Tennessee and staffed with providers (physicians, nurse practitioners), clinic nurses, clinic secretaries, and clinic medical assistants.

15.3.2 Methods

15.3.2.1 Study Design

A formal mixed-methods approach was designed, employing direct observation, patient and staff interviews, surveys of staff and patients, artifact and spatial data collection, software use monitoring, and impact on process outcomes for the six site

Table 15.1 Study sites

Site team	Attending MDs	Resident MDs	NPs	Setting	MHTAV adoption[a]	CC proximity
1	35	93	0	Urban	April 2010	In separate office, 5 days/week
2	2	0	0	Rural	March 2014	On-site, 2 days/week
3[b]	4	0	3	Urban	November 2013	On-site, 5 days/week
4	10	0	1	Suburban	October 2012	In office on different floor, 5 days/week
5	11	13	0	Suburban	May 2013	In separate office, 5 days/week
6[b]	4	0	3	Urban	November 2013	On-site, 5 days/week

MD physician, *NP* nurse practitioner, *MHTAV* My Health Team at Vanderbilt, *CC* care coordinator
[a]At initial observation, MHTAV site teams were already Live at sites 1, 4, 5; MHTAV-adopting site teams 2, 3, and 6 began use of MHTAV after initial study observation
[b]Two different teams were observed at the same clinic

teams at primary care clinics in different phases of adopting MHTAV. Data collection occurred over a 12-month period to capture health IT–workflow interactions over time, and across clinics in various implementation phases.

Care coordinators in this study were licensed as RNs who functioned in the CC role rather than the clinic nurse role, and worked with a care team composed of a provider (i.e., a physician or nurse practitioner), a clinic nurse (i.e., a registered nurse [RN] or licensed practical nurse [LPN]), a medical assistant (MA), and sometimes a scheduler.

Three site teams were already “live” with MHTAV and a CC at the start of the study, and three site teams were introduced to the CC and MHTAV program after the 12-month observation period had begun. Observations and data collection occurred at time zero, after 6 months, and after 12 months for each site team.

CCs in the study were primarily focused on identifying and managing hypertension-associated risks in their panel of patients, and worked to mitigate those risks and help their patients reach blood pressure goals, enabled by health IT. In the last few months of data collection, use of the MHT tools for diabetes-associated risk was added.

Recruitment of the six site teams occurred following approval of the study by both RTI’s and Vanderbilt’s Institutional Review Boards (IRB).

15.3.2.2 Data Collection and Analysis

Data collection activities included: (1) project orientation meeting with staff from each clinic site, (2) direct observation of staff work, (3) individual staff interviews, (4) individual patient interviews, (5) staff surveys, and (6) patient surveys. In addition, the Vanderbilt University Medical Center IT department provided utilization data for the MHT system, and diabetes process outcome data were obtained for the providers participating in the study. These data collection methods are summarized in Table 15.2.

Table 15.2 Data collection activities

Data collection activity	Source of data	Data description
1. Staff orientation meeting	Practice staff	Notes of practice staff discussion of practice operations, including health IT support of care coordination issues and challenges
2. Direct observations of care coordination	Care coordinator (if identified); patients; other individuals in the practice responsible for care coordination key workflows including: (a) registering patients, (b) sharing care plan, (c) handling alerts and reminders, (d) compiling and interpreting data from at-home monitoring, and (e) communicating with patients between visits.	Field notes of workflow steps, information flow steps, and other information required to create workflow and information flow models; description of health IT components and capabilities relating to care coordination
3. Staff semi-structured interviews	Practice staff participating in direct observations	Responses to interview guide questions gathered from practice staff
4. Patient semi-structured interviews	Patients with diabetes contacted through direct observation or introduced by their physician	Responses to interview questions from patients
5. Staff surveys	Practice staff	Responses to modified Technology Acceptance Model (TAM) survey (Davis 1989); modification includes responses to additional survey questions focusing specifically on care coordination
6. Patient surveys	Patients	Responses to Patient Activation Measure (PAM) 13-item instrument (Hibbard et al. 2004); and Summary of Diabetes Self-Care Activities (SDSCA) 10-item instrument
7. Artifact and spatial data collection	Researcher or study participant	Items identified as relevant by researchers during direct observations; examples include: a template of a shared care plan; an appointment reminder postcard, or printed lists used by care coordinators to monitor their work each day
8. Software use monitoring	Data extracts developed for My Health Team (MHT) reporting	Audit logs

Meeting notes and narrative data were entered and analyzed using Dedoose™ through a process of (1) open coding, (2) axial coding, and (3) workflow modeling. Dedoose is a web-based qualitative and mixed-methods data analysis cross-platform application designed to support collaborative data analysis activities. To further support the analysis, we scored staff and patient survey responses and tracked software module use. Quantitative and qualitative data, together, supplemented one another to help us identify complementary themes, resolve conflicting findings, and provide rich detail to support conclusions about health IT–workflow interactions—in general and across implementation phases.

15.3.2.3 Coding

During Open coding, data captured after each observation period were reviewed to identify coding elements for "chunks" of textual data, and the coding structure was refined over time as observations were added and higher-level themes were identified.

Next, axial coding was performed to add depth and structure to the constructs (codes) from the open coding phase, synthesizing lower-level constructs into a more integrative theory (Saldaña 2009). During axial coding, all qualitative data were reviewed again and categorized according to the SEIPS model combined with the WEM. The combination of SEIPS and WEM provided the structure for assigning data and codes to the elements shown in Table 15.3.

Applying this framework to hypertension care, primary care providers (actors) perform preventive care and screening procedures (actions) during routine patient care visits, leading to a patient being current on all recommended preventive health care services (outcomes). Health care providers use artifacts in accomplishing their work, including EHRs, paper forms, and paper education materials. Characteristics describing the actions include descriptors such as "routine," "screening," "preventive," and "recurrent." The work of routine preventive care takes place in a specific sequence on a schedule defined by evidence-based guidelines. Routine preventive care work also occurs during days the clinic is open (temporality) and relies on administrative staff and nurses for assistance and information contributions from other health care providers to develop thorough understanding of patient status (aggregation). Permeating all of the workflow processes is the context of the work—the health care organization, the physical space available, the family and support structure for the patient, and the organization's policies and requirements.

15.3.2.4 Stage 3: Workflow Modeling

The final element of qualitative data analysis involved development of graphical representations of workflow processes, called workflow models. The workflow models were similar to flow charts but contained more detailed documentation of work practices and capture actual work processes as opposed to idealized ones.

Table 15.3 Workflow elements model Categories guiding axial coding

Element	Definition	Examples from data
People (actors)	Individuals engaged in work	Care coordinator, medical assistant, physician, clinic nurse, patients
Process (actions)	Steps that actors take to accomplish work	Care coordinator work, medical assistant work, patient work
Outcomes	End results of work	Diabetes adherence, patient education
Tools and technologies (artifacts)	Tools used in work	Message Basket, the EHR, MHT system, Plan of Care Support tab
Tasks (action characteristics)	Descriptions of the work	Patient education, response to alerts/reminders, personal interactions with patients
Temporality	Time-based factors, including scheduling and coordination	Alerts/reminders, patient appointment times, meeting patients in clinic
Aggregation	Collective work across actors and actions, including collaboration	Coordination with multiple providers (including external), coordination with call center, coordination with clinic nurses
Context	Setting for the work, which constrains and enables work activities	Spatial proximity to clinic/providers, technology constraints
Interactions among elements	Phenomena that are the result of interactions among the elements described above	Creation/modification of Plans of Care

The modeling process is based on concepts from soft systems methodology (Checkland and Scholes 1999) and hierarchical task analysis (Shepherd 2001). Similar to hierarchical task analysis, during model generation, each larger task is divided into subtasks and each subtask is further divided until a detailed diagram of workflow is generated. For example, the overall work process this project studied is care coordination. Subtasks involved in this overall task may include physicians taking notes in the EHR system, nurses measuring a patient's vital signs, CCs contacting patients directly via phone or e-mail, or many other subtasks. The subtask of CCs contacting patients directly may be further broken down into steps taken to identify patients requiring contact, obtaining contact information, contacting the patient, discussing relevant information with the patient, and documenting the outcomes of the discussion with the patient. All subtasks are captured in the graphical workflow models.

Using the output of earlier data analysis stages, researchers identified the overall flow of CC work and each sub-process involved in it and manually developed workflow models. Workflow models represent physical space, artifact use, roles, decision points, process variation, organizational policy, and other aspects of workflow related to CC work as necessary. For example, the support activity of "Search for Information" was depicted using a diagram that highlighted information flow and artifacts, rather than focusing on physical space, given that most of the activity took place at the CC desk using the computer, notepad, and phone. The modeling process highlights the specific role that health IT plays in CC work and the impact of new health IT functionality on workflow.

15.3.2.5 Staff Survey Data

Survey data collected from each individual who was interviewed was used to consistently capture additional user information beyond qualitative data such as those obtained through observations and interviews. Responses to the adapted Technology Acceptance Model (TAM) survey were used to evaluate user perceptions and acceptance of technology (Davis 1989). Specifically, the TAM measure includes ease of use and usefulness. Descriptive statistics (for example, mean, standard deviation, and median) were calculated using Microsoft Excel, adding context in interpreting staff perceptions related to health IT.

15.3.2.6 Patient Survey Data

The patient survey data consistently captured additional information about patient characteristics, such as diabetes self-monitoring measures and levels of patient activation. These measures were analyzed in SPSS to produce descriptive data about the patients surveyed at each site (for example, mean, standard deviation, and median) in order to understand participant differences across the various clinic sites. Quantitative analysis beyond simple descriptive statistics was not performed because of the small number of patients surveyed and the primary qualitative approach.

15.3.2.7 Data Synthesis

Data synthesis compared and contrasted all health IT and workflow-related data gathered across six sites during two or three (depending on the site) observation periods over 12 months. As detailed earlier, data collection spanned clinic groups in different phases of MHTAV program implementation (already using MHTAV or in the process of adopting MHTAV). Findings gathered from multiple sources with qualitative and quantitative methods were therefore used to examine the strength of support for the identified themes, conflicts in the findings, and the development of final conclusions. Table 15.4 describes the research products that address the research question. Three categories of research products were identified and described: (1) workflows, (2) health IT design elements, and (3) interactions between the workflows and health IT elements.

Table 15.4 Description of research product(s) for each analysis activity

Analysis activity	Source of data	Product
A. Workflow diagramming to identify and describe workflows	Semi-structured staff discussion Direct observations Staff interviews Patient interviews	Set of workflows and workflow elements
B. Identification of health IT design elements used in support of care coordination activities	Semi-structured staff discussion Direct observations Staff interviews Patient interviews Staff surveys Usage data Diabetes outcome data	Set of health IT design elements
C. Identification of interactions between workflow and health IT design elements	Analysis activities A and B Underlying source data	Set of interactions, health IT barriers and facilitators to care coordination workflows
D. Analysis of interactions across implementation stage (MHTAV, MHTAV-adopting) and time	Analysis activities A, B, and C Underlying data	Interaction results by implementation stage

15.3.2.8 Interactions Between Health IT and Workflow

The data analyses described above would help us derive a "technology matrix" to capture clinical workflows that comprise care coordination; and the health IT features or components that either support, create barriers for, or have a neutral impact on the workflows. "Good alignment" describes a positive interaction between health IT and workflow. "Neutral alignment" is neither positive nor negative. "Poor alignment" describes a negative interaction. The overall "fit" of a health IT feature in supporting or impeding workflow can be then assessed by looking at the alignment of the feature with individual workflows of a work activity.

15.3.3 Findings

15.3.3.1 Health IT Impact on Workflow in Key Work Domains

Our study identified seven domains of activity central to the work of care coordination, and around which the study results are organized. Five of these activity areas addressed the primary work of the CCs:

1. Establishing and maintaining relationships with patients
2. Establishing and maintaining a POC
3. Collecting and analyzing home monitoring data
4. Educating and coaching patients
5. Coordinating with other clinicians and patients

The remaining two *supported* the primary work of CCs:

6. Searching for information to support decision making and action
7. Prioritizing tasks and planning work

In this section, we present the findings from two of these seven work domains, namely "establishing and maintaining relationships with patients" and "coordinating with other clinicians and patients." For each of them, we include a *description,* a *workflow diagram* of activities observed and/or discussed in interviews, a *technology matrix* that depicts the level of alignment of health IT features with the workflow, and a summary of findings. We chose to provide a detailed report on only two domains in order to fully explain the methodology we used to analyze and depict the data. We direct readers interested in the additional findings to the final report of the study published by the AHRQ, accessible at https://healthit.ahrq.gov/sites/default/files/docs/citation/hit-enabled-care-coordination-and-redesign-in-tn-final-report.pdf.

15.3.3.2 Establishing and Maintaining Relationships with Patients

Initial engagement of the patient in the care coordination program. As the MHTAV program was initiated in each clinic, potential patients were displayed on the MHT system worklist, based on dynamic registries using existing EHR data, behind the scenes. The registries used a risk stratification schema that represented two dimensions: (a) disease control and stability (for diabetes patients, "level 1" criteria were: documented HbA1c less than 8, fewer than 3 medications for diabetes, no complications OR mild stable complications AND followed by a subspecialist, without severe or frequent hypoglycemia or hypoglycemic unawareness); and (b) complexity of primary disease and related comorbid conditions. Initially, the registries were used to populate a worklist of patients that CCs needed to enroll manually into the program, with a face-to-face meeting in the next provider visit. Later, to accelerate enrollment, the decision was made to move to an auto-enrollment model, whereby patients whose records were identified by the registry were automatically enrolled into the MHTAV program and placed on the CC worklist. With this change, face-to-face meetings in the clinic became uncommon, as CCs moved to telephone-based outreach to meet and set up the POC for each patient.

In the early phases of the program, a clinician initiated the patient enrollment meeting with the CC, which typically took place face-to-face in the clinic during a scheduled clinic visit. One CC noted that 10–11 patients per day were enrolled at first; then after the first few months the number dropped substantially to approximately 7 per week since the majority of eligible patients were already enrolled. At a later point in the MHTAV program, an auto-enrollment process was implemented through which patients who met certain clinical thresholds (for example, HbA1c > 8) automatically became part of the MHTAV program population. CCs were then expected to create a POC for each patient who was auto-enrolled, even without a face-to-face meeting. A CC who described this process pointed out the impact on establishing and maintaining the relationship with the patient: "I can see that it's made a difference. I feel like they, you know… you build that rapport so they trust you and they, they try to… do what you're asking them to do and you know I have a lot of them, [who] take their readings and do, and keep, record that stuff regularly."

Ongoing engagement. The CCs reported that engaging the patients in an ongoing way over time was an important aspect of their work. Developing and maintaining strong relationships with patients helped with obtaining home readings (blood pressure and blood glucose), following up on medication effects, identifying hospital admissions, and monitoring other clinical events. Fostering a friendly and collegial relationship was especially important because CCs could learn about patients' jobs and families, explore with patients what made adherence to clinical recommendations difficult, and share experiences with patients (such as a shared joke), all of which helped establish rapport and trust. For example, one CC could not reach one of her patients for approximately 1 year, but once the patient met with the CC face-to-face during a clinic visit, she began communicating with the CC regularly about her medical care. Another CC described how the care team was able to keep a patient out of the hospital through education, medication, and diet management. She mentioned the face-to-face communication as key during this process, as both the CC and the patient were able to see and discuss the positive changes as they occurred.

Care coordinators maintained contact with patients through calling on the telephone, messaging through the patient portal, and meeting face-to-face in the clinic. CCs used the clinic schedule to determine if one of the patients they were following would be visiting that day.

However, advances in technology did not always support maintaining patient relationships. For example, when auto-enrollment replaced the need for a face-to-face enrollment meeting with the patient, the CCs felt that their ability to initially engage the patient, and maintain strong engagement, suffered. They stated that the ability to see patients face to face on a regular basis is helpful for maintaining engagement. One CC suggested that Skype or FaceTime may be an alternative strategy for communicating with patients. CCs also noted variation in communication preferences based on a patient's age. They commented there appears to be a cohort of patients (aged approximately 40–50) who prefer to use the messaging function through My Health at Vanderbilt rather than the telephone. The CCs speculated that these patients are employed full time and have more constraints on their time, making online communications easier to accomplish.

Relationship-building activities. The CCs used several strategies to build relationships with patients. These strategies included setting reminders to see patients while they were in the clinic; making notes in the POC Support tab for future reference (memory cues); and providing educational materials to patients. CCs mentioned that having patients visit with them in-person in the clinic helped to create and maintain rapport. For patients who were difficult to engage, CCs described introducing themselves again when the patient came in for an appointment, offering them information and log sheets, and any other assistance to try to reconnect with them.

During our observations, CCs mentioned that reduced in-person contact with patients, either because CCs visited multiple clinics or because their office was outside the clinic building, changed the nature and strength of their relationships with patients. As mentioned previously, CCs also felt that auto-enrollment may be a barrier to establishing strong relationships with each patient.

Figure 15.3 and Table 15.5 present the workflow diagram and technology matrix for establishing and maintaining relationships with patients. Figure 15.3 illustrates

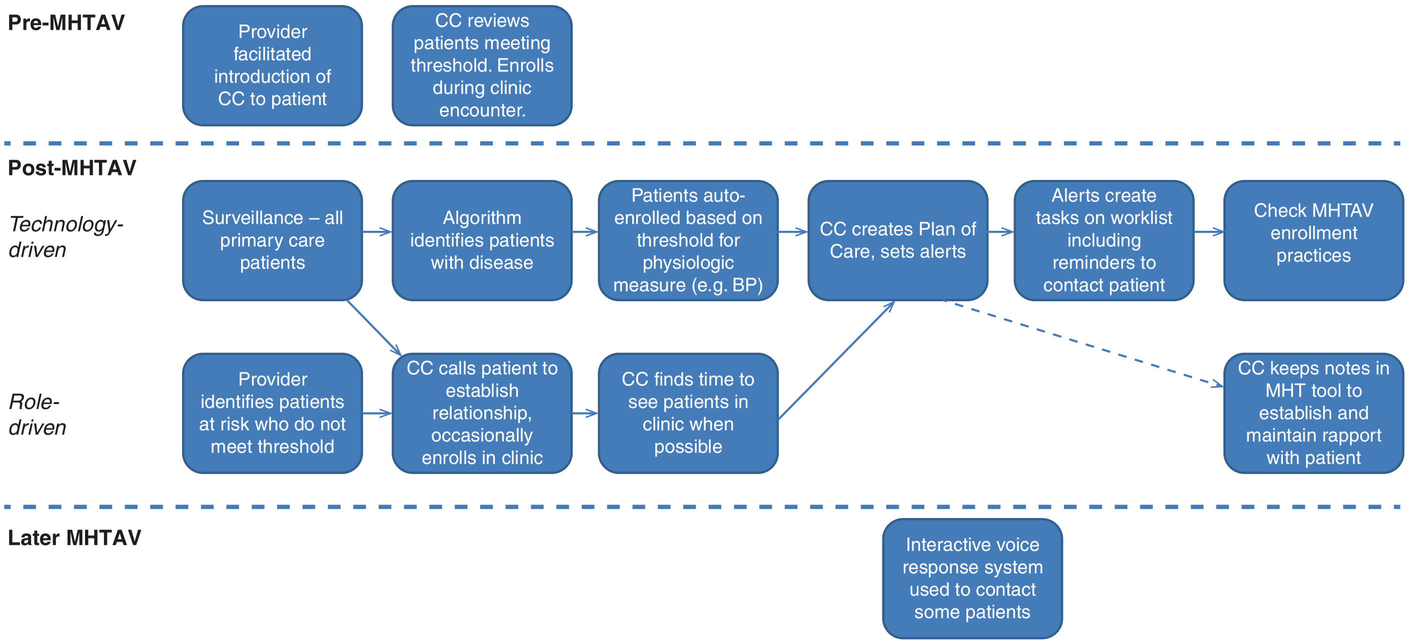

Fig. 15.3 Workflow diagram: establishing and maintaining relationships with patients. *CC* care coordinator, *BP* blood pressure, *MHT* My Health Team, *MHTAV* My Health Team At Vanderbilt

Table 15.5 Technology matrix: establishing and maintaining relationships with patients

Relevant IT resources or attributes	Workflow: establishing and maintaining relationships with patients	
	Activity: enrollment/auto-enrollment	Activity: building rapport with patients
Alerts and reminders populate the CC worklist	Reminders are used to connect with patients during clinic appointments. This can assist in educational goals, as well as supporting the patient by providing monitoring equipment, validation of monitoring equipment. ***Good alignment***	Reminders to call/message patients or connect with them in clinic. Opportunity for CC to build rapport via face-to-face communication. ***Good alignment***
Disease Control Form (DCF)	Displays information about patient, including the next appointment. ***Good alignment***	DCF shows status of patient and allows CC to update status based on information received from communications with patient. ***Good alignment***
POC Support tab	Records activities involving initial patient contact, and assists in establishing the POC for the patient. ***Good alignment***	Enables ongoing communication with patient, as well as input of possible pertinent information about the patient home environment ("Red Flags": Activity, Diet, Foot care, Emotion coping skills, Disease monitoring, Unable to reach patient, Physical activity, Medication adherence, Medication reconciliation, Tobacco cessation, and Other categories). ***Good alignment***
POC Support tab (continued)		"CC Actions" are entered here, and a history is maintained in the "POC Support Hx." CC Actions contain information about education/coaching given to patient, and also monitoring equipment status (that is, validation of existing equipment or providing one to patient). These serve as memory cues to establish and build rapport with patients. ***Good alignment***
Auto-enrollment process was implemented in later stages of MHTAV	Patients enrolled without meeting the CC in the clinic, minimizing CC work. ***Good alignment***	CCs reported face-to-face meetings with patients were important to rapport-building. ***Poor alignment***

CC care coordinator, *DCF* disease control form, *POC* plan of care, *Hx* history, *MHTAV* My Health Team at Vanderbilt the change over time that occurred before, during MHTAV, and later in data collection. As technology was introduced to identify, enroll, and later, contact the patients, direct CC initial contact with many of the patients decreased.

The middle section of the diagram in Fig. 15.3 illustrates the two ways in which relationships are established and maintained within the MHTAV program. Technology-driven refers to the MHT system itself, including algorithms used to trigger alerts and set the status of patients in the MHTAV program. Role-driven refers to ways in which CCs engage patients and establish relationships on a more personal level. Before MHT tools were introduced, CCs were introduced to patients by a provider or clinical team member. This continued, though reduced, after the MHT tools were introduced.

15.3.3.3 Coordinating with Other Clinicians and Patients

As the MHTAV program was implemented, it took time for the clinic teams to embrace the CCs as key members. Initially, a team member sometimes inadvertently duplicated the effort of another team member (for example, LPNs sent messages to the provider and/or patient not realizing the CC also called and/or sent messages about the same topic). Over time, other team members (providers and clinic nurses) learned about the CCs' capabilities and role and learned how the CCs could significantly contribute and efficiently function on the team. However, CCs who were off-site or part-time with the clinical team lacked daily contact with providers, who were in turn less aware of the various tasks and activities that CCs performed. Some CCs reported having to actively promote their abilities, such as assisting with patient education, reviewing home measurement techniques, and spending time responding to patient questions, especially those who relied on electronic communications and telephones to reach physicians/NPs and clinic nurses they did not interact with face-to-face.

The care team often wanted the CC to meet with patients immediately before or after a patient saw his/her provider at a visit, requiring communication. This was challenging when a patient was newly identified for inclusion in MHT, for example in the cases of new patients whose diabetes was not known by the clinic until the initial visit, new laboratory results that indicate diabetic status shortly before or during the visit, a patient who shows low adherence and the need for further education, or cases in which a patient requests more information or education regarding the self-management of their chronic illness. However, it was not easy for the CC to figure out which patient needed to be seen, to know when a patient was actually done seeing a provider, or to receive a provider message that they should see the patient, despite multiple communication technologies. The EHR message basket (or email) could be helpful if the CC was at her computer; the online schedule helped the CC prepare for the patients visiting each day; and the online whiteboard assisted the CC in knowing when a patient arrived and checked in. However, messages were not always used to notify the CC, up-to-date information was often missing from the schedule, and the whiteboard often lacked accurate information about when the patient was actually being seen by a provider, making it difficult for CCs and providers to coordinate a face-to-face meeting for the patient with the CC. As a result, CCs often learned later that they needed to schedule a separate appointment to meet with the patient.

MHT worklist alerts, whether system triggered or created by the CC, provided valuable information to the CC in monitoring and acting on "to do's" for each patient. There were a lot of activities to manage, such as requesting and following up on laboratory tests, checking on the patient experience using a new or changed medication, and following up on teaching. CCs reported good alignment between these tools and their work coordinating future activities for patients.

Coordination activities were also observed to vary among teams from urban, suburban, and rural areas. The rural clinic CC interacted with a variety of non-Vanderbilt affiliated hospitals and clinicians, frequently exchanging information via fax. In contrast, CCs in the suburban and urban clinics more often only interacted with Vanderbilt-affiliated hospitals and providers, reflecting real variation in the information ecologies within which the teams worked.[22]

Figure 15.4 and Table 15.6 present the workflow diagram and technology matrix for coordinating with other clinicians and patients.

15.4 Discussion

15.4.1 Lessons and Insights

The rigorous, mixed methods study of six site teams at various stages of adoption of health IT to support new care coordination team-based care generated a large amount of data and was itself a complex undertaking. To assess the interaction between technology and the work system for care coordination, with its multiple workflows, actors, tasks, and multidirectional influences between technology and workflow, we identified and examined seven broad areas of work. Those seven areas included the routine use of technologies by the care coordinator, clinical teams, and patients. Many more use cases were partially addressed or not addressed in this research study, in part due to time and budget limitations. The research team observed that many other factors such as cultural, physical, policy, and social environments played an important role in the health IT–workflow interactions we observed, making it important to situate our specific questions about health IT and workflow within a broader context.

15.4.2 Health IT Design

Our main finding, that the overall impact of health IT on workflow was mixed, was not surprising. It made sense that multiple work activities, roles, and technologies interacting in the real-world environment of primary care practices

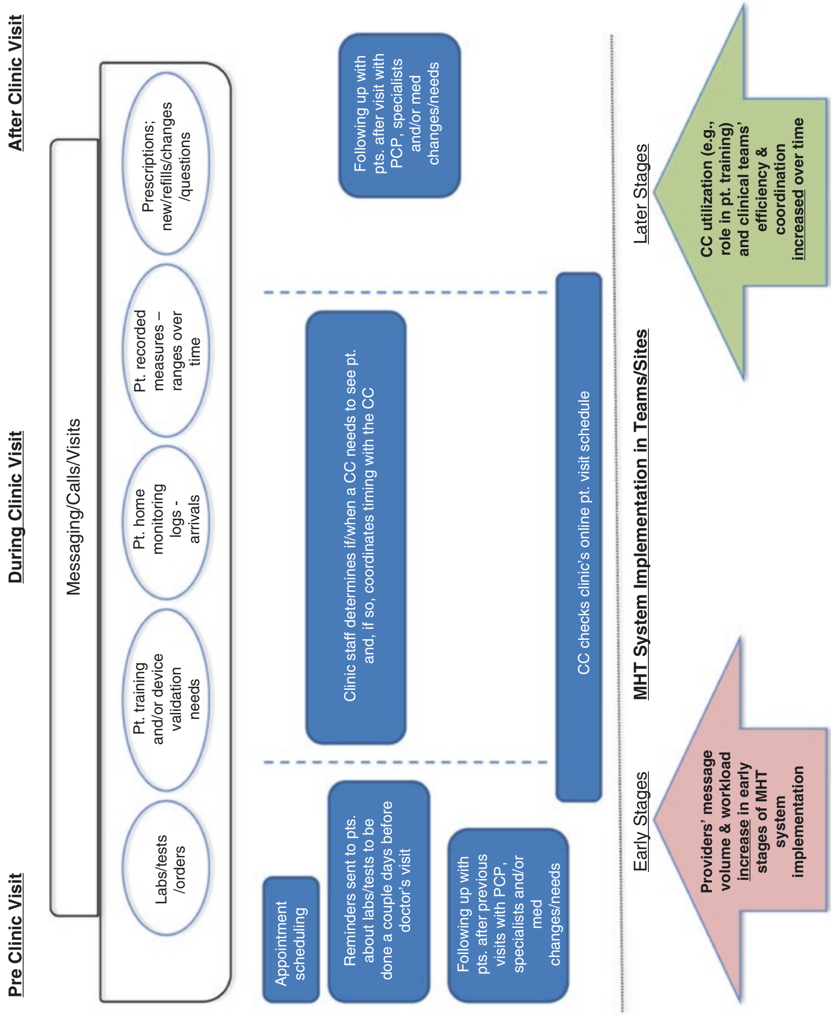

Fig. 15.4 Workflow diagram: coordinating with other clinicians and patients

Table 15.6 Technology matrix: coordinating with other clinicians and patients

Relevant IT resources or attributes	Workflow: coordinating with other clinicians (nurses & PCPs) Activity: messaging	Activity: medication changes and refills	Activity: prompts to CCs and patients
MHT worklist alerts and reminders		Notify CCs (or IVR system) to follow-up with patients about new or changed medications on a certain date. ***Good alignment***	Reminders are used to notify patients to come in for a lab/test a few days before their doctor's appointment *Good alignment* Alerts and reminders notify CCs when a patient's status (readmitted to hospital) has changed, a medical appointment has or will soon occur, and/or CCs need to follow up with the patient to see how they are doing and/or how an appointment went. ***Good alignment***
Electronic communications: In-basket/MHTAV messages	Convenient method for CCs to notify clinicians when they need to act (such as to review a patient's BP or blood glucose data, or that a patient needs training or a monitoring device validated). ***Good alignment*** Clinicians having a large number of messages sent by the CCs can feel overwhelmed and wish the technology helped to alleviate this. ***Poor alignment***	Prescription requests and/or information and questions about medications can be e-mailed among CCs and the clinicians. ***Good alignment***	Electronic messaging (MHAV and/or e-mail) has helped CCs when scheduling appointments with patients. ***Good alignment***
	Messages sent/received to coordinate the best time for the CC to see the patient are often not received in time. ***Poor alignment***		

Table 15.6 (continued)

Relevant IT resources or attributes	Workflow: coordinating with other clinicians (nurses & PCPs) Activity: messaging	Activity: medication changes and refills	Activity: prompts to CCs and patients
Clinic schedule for viewing by CCs			The online schedule is unreliable due to delays, early arrivals, cancellations, and/or no-shows. CCs often must schedule another appointment to see the Pt at a different time. ***Poor alignment***
Interactive voice response (IVR) system asks patients, about new or changed medications (if patient has consented)		IVR system only asks generic and broad questions that often lack specific and contextual information. ***Poor alignment***	Since the IVR system is not always reliable, the CC doesn't get sufficient or reliable information and must call the Pt to ask about their new/changed med. ***Poor alignment***
CCs schedule or availability status is not accessible remotely/ electronically			Clinic staff are unable to easily and quickly coordinate a face-to-face encounter between a patient and the CC. Instead, staff go to the CC's office or call her, if they have time. ***Poor alignment***

BP blood pressure; *CC* care coordinator, *HR* heart rate, *IVR* interactive voice response, *MHTAV* MyHealthTeamAtVanderbilt, *MHT* My Health Team, *Pt* patient

would surface many examples in which workflow was supported by, as well as at odds with, health IT.

The observed differences in alignment of health IT and workflow at different practice sites, and over time, were a strong reminder that technology redesign and practice redesign are both ongoing. Whether technology changes are secondary, made in response to other changes such as new staffing roles, new workflows, or patient direct use of technology, or primary, such as a new dashboard for monitoring population health, our findings suggest that plan-do-study-act (PDSA) steps to observe the actual effects of changes in health IT on workflow are important. Redesign work is best performed by a team of individuals combining their expertise in health IT, workflow, and clinical care. It is not unusual for redesign work to progress through a series of iterations to introduce new features and test their impact. This is especially useful when adapting complex systems where changes in multiple areas are common.

15.5 Conclusion

In this mixed methods study assessing the workflow impact of implementing health IT-enabled care coordination in six ambulatory primary care clinics over a 12-month period, we used a human factors and sociotechnical framework that identified five areas of primary work and two areas of supporting work. This approach revealed a complex picture with multiple workflows and varied IT systems used alone and in combination to support those workflows.

Our findings support the WEM assertion that context, aggregation, and temporality can impact the alignment of health IT and workflow. Stronger satisfaction with care coordination tools and processes was noted when there were well-defined workflows, tools designed to fit the workflow, adequate training, good team communication, physical co-location of CCs with other care team members, stronger team relationships, and time to allow the new work system to stabilize and for learning to take place. This study shows that the work of care coordination is broad, complex, and varied. It also demonstrates that even when a specific health IT-enabled program is implemented in a consistent IT environment, its impact varies substantially depending on the physical, social, and policy environment. Alignment between health IT and workflow is dynamic rather than fixed because the implementation of care coordination is changing over time from a narrow scope (a primary focus on the introduction of the new CC role and a few conditions) to a much broader one (a greater focus on team-level communication, multiple contributing roles, and more conditions).

Through the study, we also explored the use of the health IT alignment matrix as a tool to communicate to what extent system components aligned with functional and workflow requirements, and "scoring" of the overall alignment for a work system. Future work is needed to improve the way multiple contributors are identified and tracked during health IT adoption and its redesign over time.

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Chapter 16
Turning "Night into Day": Challenges, Strategies, and Effectiveness of Re-engineering the Workflow to Enable Continuous Electronic Intensive Care Unit Collaboration Between Australia and U.S.

Cheryl Hiddleson, Timothy Buchman, and Enrico Coiera

Safe and effective care of critically ill patients requires a team of professionals including intensivists and critical care nurses experienced in providing care for patients in the intensive care unit (ICU). While critical illness can strike at any time and demands continuous attention, allocation of scarce staff follows a predictable pattern. The night shift is more likely to have disproportionately newer and thus less experienced nurses, and the experienced nurses on that shift are engaged in providing care to their own set of patients (Claffey 2006; Floyd 2003). At times this leaves them unable to sufficiently supervise the newer staff. There is also evidence of increased risks at night time with higher in-hospital mortality for admissions at night (Coiera et al. 2014).

There is also a maldistribution of intensivists in the United States with the south-eastern region experiencing a greater need, and there are no intensivists present at many hospitals during the overnight hours. This combination leaves most ICUs in our region struggling with less experienced and diminishing numbers of staff at night with less physician support. There are fewer resources in many departments of the hospital during nighttime hours, requiring these staff to be more independent and resourceful in providing vital care. These novice nurses are not yet prepared for autonomy and are less sure of themselves and of where they might turn for advice or counsel.

To mitigate that nighttime challenge, Emory Healthcare (EHC) supports bedside caregivers with remote guidance from senior intensivists and critical care nurses using an efficient telehealth system, "eICU™" (Lilly et al. 2014). This platform

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allows the remote caregivers to observe, collaborate and prescribe at 10 ICUs in 5 hospitals from a single clinical operations room (COR) located in Dunwoody, Georgia. The Emory eICU program has data flowing from the electronic medical records and bedside monitors allowing the remote staff to have continuous access to all patients. The novel displays of data and the corresponding alerts driven by Boolean and trending algorithms in the eICU™ system, augments situation awareness and allows early detection when a patient veers off of the expected trajectory.

Every eICU nurse (eRN) has a minimum of 5 years hands on experience at the bedside and each is certified as a critical care nurse (CCRN) by the American Academy of Critical Care Nurses (AACN). They provide the novice night nurses in the ICUs with "just in time" education and support during hours when onsite resources are not readily available. The bedside nurse pushes a button on the wall in a patient's room to access the eRN who comes on camera in about 15 seconds. The eRNs provide the newer nurses with insight and support that comes from the in-depth knowledge they acquire after years of providing bedside care to critically ill patients.

The physicians in the eICU are Emory faculty, all board-certified intensivists, have acquired additional training in critical care after completing specialty training in their field of choice. The intensivists in the eICU also provide many forms of support to bedside staff that might otherwise be delayed or not occur at all. That support ranges from just in time education about a drug the staff has never previously had prescribed or administered, to providing support to patients and families approaching the end of a prolonged course of illness.

The caregivers in the eICU are challenged to provide outstanding care throughout the night despite the obvious disruption in their normal wake-sleep cycles. Working through the night time hours exposes clinicians to adverse alterations in their physical, emotional and cognitive abilities. Night shift workers have been shown to exhibit detrimental changes in their health and wellbeing, with the WHO even classifying night work as a "probable carcinogen" in 2007 (Gu et al. 2015). Though these detriments to health have been widely acknowledged, solutions for mitigating the effect on caregivers have not been sufficiently explored. In an attempt to further innovate and mitigate these deleterious effects on our staff, Emory proposed, piloted, and established a solution: "Turning Night into Day" (https://clinicaltrials.gov/ct2/show/NCT02895997).

Thus, Emory clinicians that provide remote eICU coverage on the night shift were relocated to the opposite side of the world. From the Antipodes, they would deliver their nighttime care to the patients served at the Emory eICU site, but they would do so from daylight in Australia. (The remote monitoring platform used allows for distance communication and connection with ICUs as far away as 250 miles, so repurposing that platform for ultra-remote coverage 12,000 miles away was technically possible.) A 6-month pilot research study was proposed to explore the effects on clinicians providing the eICU services when they are moved to a different time zone. Could a geographically dispersed clinical team create quality outcomes for patients as well as increase quality of life for those clinicians? The decision was made to focus on an English-speaking country, with a specific initial focus on a destination familiar to Americans. We were able to leverage a personal connection to establish a relationship with Macquarie University (MU) in Sydney Australia. That university is also home to the Australian Institute of Health Innovation, so it was an ideal location to form a partnership for this forward-looking study. Meetings were scheduled with administrative leadership there to assess the feasibility of this project. There was mutual interest in exploring the project, so the planning phase began.

There were three primary areas of focus for developing this new clinical workflow; how to manage the people, how to manage the legal aspects and how to choose the technical solutions to be used.

16.1 Managing the People

Study development and design was a cooperative effort between EHC and MU. The Emory eICU clinicians would be the study subjects and an application for an IRB was completed that focused on studying how the change in location and night/day hours would affect them physically, emotionally and cognitively. Study subjects were chosen on a volunteer basis and would travel to MU for a time of 6–9 weeks while performing specific physiologic tests and wearing a heart rate and activity monitoring device. The subject travelers also completed surveys on quality of life and mood status in addition to performing validated tasks to measure efficiency.

Once the study design was complete the focus turned to providing what the clinicians would need to perform effectively in the new environment. The decision was made to send two clinicians. Sending two Emory clinicians would lend to assuring a shared sense of purpose and understanding of the primary objective for the study and the Emory eICU Center. This laid a foundation for the primary component of building the dispersed teams. Relocating our own clinicians instead of employing services of local Australian clinicians ensured that the possible obstacles of competing goals and objectives by clinicians from different backgrounds and countries would be avoided (Crowley 2005).

The site in Australia was built to echo the site in Atlanta to help increase clinicians’ level of comfort working there. Tools to communicate with the team at home in Atlanta in a seamless and timely manner were needed so there would be no delays in patient care. A video conferencing tool was installed in parallel with the patient-centered eICU tool so clinicians could launch a sidebar video call. This sidebar video conferencing system allowed all clinicians to maintain the perception of being physically collocated, yet they were still thousands of miles apart. To further the sense of teamness, a large screen television/monitor was placed in the MU monitoring room that had a live feed of the Australian COR running for the duration of the shift. A reciprocal monitor was also placed in the COR in Atlanta. In all, there were three video channels used by staff: the video channel embedded in the eICU application facilitating communication between eICU staff and the bedside; the sidebar video link so eICU staff could speak with each other; and the full-room continuous video link providing a sense of “looking into the other room” on the other side of the globe.

16.2 Legal Aspects

There were many questions related to liability, insurance, professional credentialing, indemnity and more that had to be answered to arrive at a mutually acceptable contract. Agreements would be governed by Australian law so a contract dispute among the parties would be litigated in Australia. For this reason, EHC chose to hire outside legal counsel in Australia to assist with navigating these questions. Making decisions about how operations function in another country involves being as informed as possible to protect traveling clinicians, Emory Healthcare and the patients treated.

The Australian legal team consulted with the NSW medical and nursing boards to determine what the requirement would be for the clinicians while they worked there. We were informed that Emory’s physicians and nurses were not required to apply for registration as health practitioners, apply for licensure or fulfill credentialing requirements in Australia during the six (6) month Project. Even if the Emory employees did not have to register, they were required to comply with relevant codes of conduct for Australian practitioners. They could not provide any type of medical services including consultations to Australian patients at all. All clinicians had to adhere to their scope of practice guidelines and codes of conduct for their place of practice, Atlanta Georgia. Emory clinicians had to comply with EHC employment and HR policies and US laws and regulations. As the Emory employees would not have an Australian employer the Australian minimum conditions, such as pay rates, would not apply during their Australian assignments. However, as they are performing duties in Australia relevant U.S. employment laws would apply, including anti-discrimination, harassment and work health and safety (which in turn covers workplace bullying). Emory had to take reasonable steps to ensure that the Australia workplace is safe for the Emory employees.

They determined that Emory employees could apply for standard visitor’s visas electronically online instead of any type of work visa. MU sponsorship was not required because Emory individuals would not be employees or contractors of MU. This was determined because the clinicians would remain Emory employees for the length of their work assignment there and not employed by an Australian entity. They also found that EHC would not need to register with the Australian Securities and Investment Commission as a company doing business in Australia because of the temporary nature of the trial and the fact that it would not be hiring Australian employees. General sales tax would also not be paid because the Emory team would not be generating revenue while there.

To ensure uninterrupted insurance for the clinicians, Emory verified their plan for medical, dental and life insurance had global coverage. There are very different limits and restrictions related to malpractice between the U.S. and Australia, so indemnity had to be granted to the Australian parties involved. The malpractice insurance for all participating clinicians from EHC had to be verified and outlined in the legal contract.

Emory privacy guidelines had to be reviewed with each participating employee before deployment to the Australian site. Any visitors to the Australian site had to complete forms for compliance with HIPPA guidelines around patient confidentiality and privacy. After some preliminary investigation the determination was made that an end to end connection from Emory to the distant site in Australia would be the best solution for ensuring adherence to HIPPA guidelines and ensure security for protected health information (PHI).

16.3 Technical Aspects

Emory needed to have a connection back home that was private, secure and reliable. The IT team made the determination that an end to end circuit was the best option to achieve all three. A multiprotocol label switching (MPLS) network was chosen for the circuit type. This type of circuit could be configured to originate in Atlanta at EHC and terminate at MU in Sydney. This circuit is private and does not involve any transfer of information from one site to another. All the patient data remained on the Emory network, eliminating concerns about adherence to HIPPA guidelines or violation of security of patient information. All patient information remained the property of EHC. The telephones placed in the MU site were also internet based on the EHC network. This offered our clinicians in Atlanta and Australia the ability to make the same local calls with the same numbers and dialing protocols thus avoiding confusion.

The circuit is composed of a fiber connection extending from the U.S. to the street outside the MU building the operations room was located in. Once the fiber was installed, the line then had to be connected to the building and up to the COR where it would terminate. There were three vendors that had to be employed for the completion of the build of the fiber line. The line was then connected to a router which was connected to a switch. The switch had network jacks that allowed the computers in the room to connect to the Emory network. All phases of this process had to be managed by the specific vendor and checks had to be made to ensure the access was complete and live. It is essential when developing this type of connection that all vendors are engaged early on, so they can partner and make the process as seamless as possible.

The decision was made that the Emory IT team would purchase and configure the CPUs to be used in Australia. Then the units were shipped to the site at MU. This was another step to ensure patient confidentiality and protection of patient information. Once the computers arrived in Australia, the IT team used remote desktop access to log into the computers and ensure functionality. This remote access also allowed the Emory IT team to apply updates and needed changes to the computers in Australia. There was no need to train or depend on staff at MU to perform those functions thus adding to the reliability of the systems' performance. The computers were also configured using local Atlanta time in order to avoid any confusion or error in documentation by the Australia based clinicians. Upon arrival, the computers were set up by an outside party with Emory IT checking functionality remotely.

The MU site was a locked room with access granted only to Emory staff and essential IT and emergency MU staff. Once again reinforcing protection of PHI and the clinicians themselves that worked weekends when other employees were not present. The computers remained powered on but clinicians logged off after each shift. This action not only added a layer of PHI protection but leaving them on and accessible allowed changes or trouble shooting by Emory IT to be performed remotely.

The "sidebar" video sessions were performed via a standard commercial video conferencing tool. This tool was loaded on the secondary computer the clinicians use and also had separate speakers to allow the verbal communication needed. When a nurse in Atlanta called the nurse or physician in Australia they had an open instance of the video tool and made a call. This resulted in an indicator popping up on the receiving clinician's monitor and they could then answer the call. Network phones were installed and active, and this was the primary means for our staff to communicate back and forth with the staff in Australia.

A 42-in. monitor was installed on the wall in the COR in Atlanta and in Sydney. This monitor had a mini CPU connected to it, and a live video feed from one side of the earth to the other was established. This feed was the best option for allowing the staff at both sites to have the feel of being collocated. When a nurse in Atlanta had a question or task for the physician to follow up on this live feed allowed them to see what the physician was doing. If the physician was involved in a conversation with another clinician, the nurse in Atlanta could communicate with the nurse in Australia to ensure the question would be answered in a timely manner.

As patient populations change there is a need for healthcare to adapt to provide the care needed to those patients. The Emory eICU represents another option for managing the demands of care delivery for this critically ill population. The expertise and knowledge that might not be available locally to some hospitals can be leveraged through this medium, thus providing patients access to the care they need. The Australia approach affords the clinicians delivering that essential care another option for preserving a quality of life that isn't available while working during night time hours. The audio-visual base of the program affords the ability to put novel workflows in place regardless of the distance between the clinicians and patients. As tele medicine models grow in use, these types of options will increase for clinicians.

We also analyzed qualitative data collected from the clinicians that were study subjects. The model allowed clinicians at the remote site to forge friendships and a level of closeness neither of them expected, and they reported that made the work even more rewarding for them. The clinicians felt more awake and alert while being in Australia because they were able to maintain regular sleep/wake cycles instead of trying to rest ahead or make up for sleep missed working at night. One of our clinicians wrote "The communication from Australia to stateside seemed to be a non-issue when it came to the workflow of the eICU. Personally, it was a chance of a lifetime. I was able to complete my shifts on the weekends and during the week, my time was mine to do as I wanted. The most significant aspect for me, was the change from working nights to working days. I felt like I had more time. When working nights, you can either sleep when your get home, or stay up all day and change to a day routine. Either way, your feel tired, and exhausted, especially working 3 or 4 12-h shifts in a row. In Australia, I completed my assigned shifts, went home and slept. The next morning, I was able to accomplish whatever I had planned. I was not exhausted and did not lose a day just to make the transition from nights to days". Emory Healthcare leadership fully supports their staff and makes efforts to ensure the clinicians are cared for as well as the patients. This program allowed those clinicians a once in a lifetime experience in another country while having the security of continuous employment and financial stability.

As the next phase of the project, we are launching an Emory eICU installation in Perth, Western Australia. Perth is the largest city antipodal to Atlanta and offers the advantage of being either 12 or 13 h out of phase with Atlanta (depending on whether Atlanta is on daylight or standard time.) Our initial experience in Perth will be reported in 2019.

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Chapter 17
Encoding Clinical Pathways: The Impact Beyond the Target

Edward H. Suh and Gina T. Waight

17.1 Introduction

The past several years have seen the long-predicted convergence of two trends in modern medicine: the standardization of care and the computerization of the clinical environment. Now, in many care settings, practice improvement has become virtually synonymous with efforts to encode clinical behavior into the electronic health record (EHR) and computerized prescriber order entry (CPOE) systems.

The Emergency Department presents a particular challenge for the implementation of health IT systems with computerized decision support. There is tremendous clinical heterogeneity and diagnostic uncertainty in the patients and their presentations; yet care must be delivered with constrained resources and compressed timescales. In the field of emergency medicine, there has been a particular push to incorporate clinical pathways into the workup and treatment of certain "high acuity" diagnoses such as stroke, acute coronary syndromes (ACS), and sepsis. Because of the acuity of these diagnoses, the pathways developed to date tend to be both labor-intensive and perceived as critical. Due to the great effort devoted to completion of the pathway, at any cost, this perversely can lead to negative ramifications of implementing a pathway at all.

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17.2 Narrative

A 79-year old man is brought to the ED by his family. Family members tell the nurse in triage that he has had a few hours of vomiting, abdominal pain, as well as some weakness on the left side. The triage nurse requests an immediate evaluation by a physician as she recognizes that unilateral weakness is a possible sign of a cerebrovascular accident (CVA). The hospital is an academic institution with a stroke program that is known for aggressive intervention. Criteria for "stroke protocol" activation are intentionally set as broadly as possible, in order to capture all possible cases of acute stroke. The nursing staff have received extensive training focusing on the importance of early identification of these cases in order to meet the standards for stroke care that are both subject to regulatory scrutiny and are part of the neurology department's preferred approach to CVA management.

On the initial evaluation by a resident physician, a history of waxing and waning mental status along with left sided weakness is rapidly obtained from the patient's family members. The resident's cursory first examination reveals a patient with unwell appearance, difficulty following commands, and possibly some limb weakness. She requests the patient elevate both arms symmetrically to check for "pronator drift", a sign of unilateral weakness, but the patient is unable to comply with her instructions. It is not clear whether the difficulty was due to global weakness, an alteration of mental status, inattention, or other factors. When the resident asks the family how long these symptoms have been present, they report that they found the patient in this state approximately an hour and a half ago. They also note that the patient had been recently suffering from some sort of arrhythmia, and that the cardiologist subsequently placed a pacemaker.

While the resident physician is conducting her exam, the nurse checks the patient's vital signs and obtains a fingerstick blood glucose. None of those values are found to be abnormal. The patient has been in the ED for 4 or 5 minutes at this point. The resident identifies that the patient meets the entry criteria for the hospital acute stroke protocol. The resident verbally orders the clerk to call the hospital page operator, who sends simultaneous pages activating all members of the stroke team. Another ED resident assists by entering the "stroke protocol" order set in the CPOE. Orders for blood work, monitoring, and neuroimaging are automatically generated.

A multidisciplinary team assembles at the patient's bedside. The team includes a neurology fellow, resident, research coordinator, and pharmacist. The laboratory supervisor calls in by telephone to announce that the laboratory is standing by to process the bloodwork. The CT technician removes the patient who was on the table in preparation for the possible stroke patient. Labs are drawn and an ECG is obtained. The patient is attached to the cardiac monitor and transported by the team to the CT scan, which is located in the ED.

The neurology resident performs a focused history and examination while the patient is being wheeled on the gurney to the scanner. He obtains a similar history of waxing and waning mental status, with possible increased weakness on the left side, over the past hour and half. A past medical history of congestive heart failure, chronic obstructive pulmonary disease, hypertension, and hyperlipidemia is also noted. A stat non-contrast CT scan of the head is performed and appears negative for an acute bleed. The team decides to administer the "clot-busting" stroke medication, tPA. The pharmacist opens the sealed medications and begins to mix them in preparation for administration.

Twenty minutes have passed since the patient first arrived at the ED. Four patients were in the process of being triaged when the stroke activation was triggered. An additional six patients had been triaged and were waiting to be seen in different districts of the ED; overall the ED held approximately 150 patients in various stages of evaluation when the stroke patient arrived. Since that time, three more patients have walked into the ED, in addition to the arrival of two more ambulances. One of the patients who had been waiting for triage, a well-appearing 50-year old woman, is now getting vital signs performed by the nursing assistant. The vitals are notable for fever to 38.2 °C orally, as well as tachycardia to 120 beats per minute. The oxygen saturation is 95% on room air and the blood pressure is normal. These measurements are automatically fed from the machine into the EHR.

On the status board display of the EHR, which gives an overview of all the patients currently in the ED, the patient's name begins to flash in purple and yellow. The vital signs have triggered a medical logic module designed to identify patients at risk for sepsis by notifying clinicians when a patient meets the systemic inflammatory response in sepsis (SIRS) criteria. This was put into place after a review of patients admitted for severe sepsis and septic shock revealed a substantial number of cases, in which the treatment and evaluation did not meet state-mandated guidelines. As the state sepsis guidelines were developed in a relatively algorithmic fashion, the hospital quality committee decided to encode the algorithm into the EHR in the form of automated alerts and order sets in addition to focused education. While initially physicians were concerned that the care pathway left little room for autonomy, measurements of compliance with the state guidelines have improved dramatically in the year since the initiative was rolled out.

The patient name, flashing in purple and yellow on the computer tracking board, alerts a nurse monitoring patient flow through triage to send out an electronic message through the EHR to the senior resident physician who is assigned the responsibility for managing acute cases. The resident receives the notification of a potential "code sepsis" on her mobile device. She finishes entering the tPA orders on the stroke patient, which only requires one click and entry of her password. She switches over to the potentially septic patient's electronic medical chart. She notes the vital signs and the history obtained in triage of a cough and fever, and furthermore sees that the past medical history field contains the diagnoses of hypertension, diabetes, chronic obstructive pulmonary disease, and chronic renal insufficiency. The tracking board indicates that the patient had been in the ED for 40 minutes already. Sensing the need to expedite things, she opened the sepsis order set and signs off on the routine panel of tests, interventions, and nursing orders.

The patient's status board entry now indicates the patient is a "code sepsis". The orders entered on her automatically rise to the top of the work list for the nurse assigned to the patient. These include drawing blood in cultures, blood gas, venous lactate, as well as a general electrolyte and cell count panel. There are also orders automatically included to obtain urine for analysis and urine culture, a chest X-Ray, as well as treatment with both antipyretic medications and intravenous fluids. Before the CPOE system will process the orders, it produces a series of prompts and hard stops that the resident must clear one by one, checking for proper patient identification, asking that the results of a pregnancy test be entered before the radiology examination, and asking for entry of a patient weight to calculate the intravenous fluid volume.

Meanwhile, the stroke patient's first bolus of intravenous tPA finishes. As the second dose is starting to infuse, he appears acutely uncomfortable. He is retching and attempting to sit up, and appears confused. The nurse attending the patient shouts for help and both the emergency medicine and stroke teams arrive at the bedside. One provider notes that the cardiac monitor is demonstrating what appears to be ventricular tachycardia, but it resolves before intervention and the patient's mental status improves. There is discussion between the neurology and emergency medicine teams on the question of whether to suspend or continue the tPA infusion. After a few minutes, the neurology stroke fellow elects to terminate it.

The patient remains stable in the ED, but the disposition of the patient is now unclear. The neurology team requests a cardiology consultation and is advocating for admission to the cardiac care unit. When the cardiology fellow arrives, he disagrees with this assessment. The dispute is escalated to the attending physicians of the two consultative services, and the patient is ultimately admitted to the neurological intensive care unit for monitoring. Interrogation of the patient's pacemaker would eventually reveal that he had been suffering from intermittent episodes of rapid atrial fibrillation, as well as occasional episodes of ventricular tachycardia throughout the day. His pacemaker precludes an MRI, but after stabilization of his dysrhythmia no further focal neurological symptoms are noted.

During this time, the code sepsis patient finishes a liter of normal saline infusion and is starting on a second liter. She has not had her chest X-ray taken; but her blood work is undergoing analysis in the laboratory. The resident physician finds time obtains a more in-depth history, which includes fever, cough and wheeze for the past several days. Her examination is notable for diffuse expiratory wheezing, so the resident orders nebulized albuterol and oral prednisone to treat a potential COPD exacerbation. The chest X-ray and the majority of the bloodwork eventually return unremarkable, with the exception of a moderately elevated venous lactate. The attending physician is able to evaluate the patient a few hours after arrival. The elevated lactate is noted, and as this is flagged as a critical result, the team makes a plan to repeat the test. The patient, however, has symptomatically improved and is concerned about several pet animals that she has left alone at home. She refuses the repeat blood draw for the second lactate and instead asks for discharge papers. The emergency medicine team, faced with the elevated lactate in a high-risk patient, discharges the patient with significant consternation. They provide prescriptions for oral antibiotics that could cover community acquired pneumonia, as well as oral steroids for COPD.

It is now 5 hours after the stroke alert has been activated and five and a half hours since the potentially septic patient has arrived. The ED has received over 60 more patients during that time, which is average considering the time of day and day of week. Triage processes had returned to normal as soon as documentation on the stroke patient is completed, but the few minutes of delay has led to a queue forming outside of triage. This in turn has led to some unrest among patients waiting to be evaluated, further increasing pressure on the nurses in triage as people begin approaching them to ask when they will be seen. By prioritizing the stroke patient for his CT scan, normal ED flow is further disrupted. The radiology staff have to bump a patient who is about to have a scan because of the stroke alert. In addition, there have already been some delays in the normal turn-around time for CT orders because of difficulty coordinating transportation between the clinical areas and radiology for several moderately sick patients. This leads to median times between CT order and test performance to stretch to more than 90 minutes, well above the average for the department. The nursing staff working in the ED also have trouble keeping up with the orders being entered on other patients. Although there is some re-distribution of patients to other districts because of the burden of these two acute cases, there is not enough excess capacity in the nursing group to fully 'catch up' with the patients being evaluated by the medical staff. As a result, average time between first evaluation and disposition decision increases significantly on several patients. This has led, in turn, to significantly increased crowding in the clinical areas. The conditions continue to negatively affect the care until past midnight, when arrivals to the ED finally taper to the point where the queue of pending work could be completed.

Two days later, the potentially septic patient's blood cultures grow gram positive cocci in one of the two bottles. The patient is asked to return for re-evaluation and she reluctantly complies. On her second visit, she is clinically much improved, and it is felt that the positive culture is likely due to contaminant rather than true infection. The patient is discharged again with strict return instructions.

17.3 Analysis

In a system with an aggressive stroke program, the push to adhere to the timed steps in the pathway can overshadow the clinician's primary responsibility to perform a thorough evaluation of the patient. When a complex patient presents with multiple complaints or with an unclear clinical picture, focusing on the one sign or symptom that can justify the stroke activation and place the patient on a predetermined pathway may induce the clinician to simplify the case. As illustrated in this case, focusing on the patient's unilateral weakness leads the clinician to standardize her evaluation and treatment plan at the expense of a fuller understanding of her complaint. The system, designed to optimize care for stroke patients, lures the clinician to make a premature diagnosis and thereby limits the likelihood that the patient would receive the appropriate evaluation and treatment for her true ailment. Though the outcome is favorable, the patient's evaluation in the ED is prolonged while her disposition is debated between several services and leadership, resulting in admission to an intensive care unit not specialized in the care of cardiac patients. Thus, the patient is exposed to increased risks (misdiagnosis, administration of tPA), while the ED is exposed to the risks of increased crowding and management of critically ill patients.

Similarly, a patient with sepsis may indeed derive benefit from a standardized approach, when it enforces compliance with established "best practices". Yet at the same time, many tests or interventions that show some evidence of benefit when studied in a population may be less advantageous for a particular individual. In this case, while strictly speaking the patient may have met recognized criteria for severe sepsis, both the likely physiological processes as well as the patient's own preferences make the algorithmic approach far less efficacious. The patient is unlikely suffering from the distributive vascular dysfunction and poor tissue perfusion that the sepsis protocol is designed in part to address. In addition, a conversation with the patient reveals strong preference on her part to return home as quickly as possible. Without the flashing patient name, to pressure the clinician to abide by the standardized treatment plan, she may have otherwise obtained a more detailed history and physical that could have led to a more focused care plan, relieving the patient and the system from the burden of unnecessary testing.

These types of encoded, computerized clinical pathways not only place boundaries on the clinician's approach to the individual patient, but also add new burdens and limitations on the local system as well. Every emergency department has some areas of constraint, and most have reached a sort of resource equilibrium that forces them to operate at or near maximum capacity. In this setting, even seemingly minor perturbations can cause significant downstream effects on workflow which may emanate far beyond the initial event. The delay in CT scan turnaround time caused by one stroke patient, or the backing up of orders to be carried out on other patients while a nurse is called to first attend to a possible sepsis emergency, can result in a significant slowdown in the care of other patients, compromising their outcomes. On a broader level, it can lead to increased ED crowding, which has its own deleterious effects on clinical outcomes.

17.4 Conclusions

Our experience as practicing physicians in the ED leads us to believe that for informatics innovations to be truly successful, we must disseminate the understanding that technology-based interventions must align with the patient-centered perspectives and the context within which they are operating. To date, much of the literature on computerized decision support tools has focused largely on the performance of these systems with respect to the diagnosis or process that they are designed to address, rather than clinical outcomes or local real time impacts. We strongly believe this "diagnosis-centered" or "process-centered" approach is woefully inadequate in assessing the true impact of the intervention. Rather, these tools need to be also evaluated from both the perspective of their overall impact on the care environment into which they are being inserted, as well as their customizability to best fit the individual patient's experience of care.

As new technologies continue to take even more of decision making out of the hands of clinicians, it is of critical importance that developers are aware of the potential negative implications of each tool. It is difficult to imagine near-term products that are truly fully "optimized" to achieve every healthcare system and individual patient care goal at once. It is therefore necessary to design them with an approach that supports the clinician's ability to balance factors and needs that may not be well anticipated. Software designers will need a little humility, understanding that a particular approach, while possibly very well constructed and capable of achieving its internal goals, may not be right at any given time.

Furthermore, hospitals, healthcare systems, regulators, and providers also need to develop an awareness of this issue. Implementing a technological "solution" has an obvious appeal, as these lend themselves well to standardization and efficiency. However, such solutions can only succeed when the problem that they are designed to address is well defined, and the scope of the impact is well understood. Further, evaluation of such solutions should not simply focus on the rate of compliance, but also on the overall impact to the care system.

We are confident that the current phenomenon of encoding clinical care into health IT systems will continue. The advantages and utilities may seem abundant. However, unless those responsible for developing and implementing these pathways fully grasp the limitations of the current process-centered approach, we have far less confidence in the overall benefit of this advancement.

Chapter 18
Cognitive Disconnect and Information Overload: Electronic Health Record Use for Rounding and Handover Communications in a Pediatric Intensive Care Unit

R. Stanley Hum

18.1 Introduction

Bedside working rounds can be one of the most cognitively complex situations in clinical medicine. Team members develop a mental model of the patient synthesizing electronic health record (EHR) information and information that is verbally transmitted during shift-to-shift communication. Each provider must synthesize and filter a large amount of information, which can be error prone. Rounds are also prone to interruptions. Despite interruptions, because the EHR allows for each individual provider to interact with the patient chart and there is an expectation that each team member fulfills a different role for the same patient, the team should develop a shared mental model to enable optimal workflow and provide optimal care. In this case study describing the bedside working rounds in a pediatric intensive care unit (PICU), we will explore each of these issues in depth.

18.2 Case Background

When you think about critical care medicine, you think about a team of healthcare providers frantically performing cardiopulmonary resuscitation on a patient whose heart has stopped. While these situations happen, the more common situation is a critical care team participating in a discussion about a complex patient. In medicine, these discussions are called "rounds". What a description of patient cases during rounds may fail to convey is the time pressure imposed on providers. In a typical unit with 14 patients, completing rounds within a 3-h period is not uncommon.

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Hence, a patient presentation from start to finish needs to be in the order of 10–15 min. During this time, the team discusses a single patient, but interruptions are inevitable. Other patients may be deteriorating, new patients may be coming in, and stable patients may need to be discharged to maintain patient flow. This time constraint leaves little time for reflection and contemplation even in the absence of interruptions.

18.3 Case Presentation

Fourteen patients ranging from 2 months through 18 years of age are admitted in a 16-bed PICU. Around 9 AM, the healthcare team is starting to see patients. Standing and gathered in front of the patient's room is the PICU attending physician ("the attending"); the PICU fellow physician ("the fellow"); four resident physicians ("residents"); and the bedside PICU nurse. The patient can easily be seen from the outside and the patient's parents have come out of the room to listen and participate in the discussion.

The attending, working on a workstation on wheels (WOW), is logged into the patient's electronic health record (EHR). The others are waiting for the attending to finish opening a new physician note for this patient. Using a combination of copying and pasting from yesterday's attending note, acronym expansion and direct data substitution, the attending is finally ready to hear the presentation.

There are three residents on the team today. Each of them is carrying a stack of stapled paper printouts and each is standing in front of a WOW. These printouts were created just before the shift-to-shift communication ("handover") at 7 AM and are summaries of their respective assigned patients including the medication orders, last 24-h of laboratory results and fluid status summaries. They received handover from the overnight resident at 7 AM who has left the unit. Each printout also included handwritten notes including "To Do" reminders, corrections and events which the overnight resident did not enter in the handover document. Each resident also carries a mobile internal phone so that they can be contacted individually.

The resident assigned to this patient ("the presenting resident") starts to report the patient's summary and major events of the last 24 h. Simultaneously, the attending is typing the pertinent information into the interval history section of the patient's EHR note. The attending interrupts the resident as some of presented patient events were reported on the previous day. The resident realizes that some of the handover document events had not been updated. Upon completion of the 24-h events, the attending adds an additional event, which the resident was unaware. After the interval events are described, the bedside nurse ("the nurse") starts their report.

The nurse is standing next to the bedside computer with the patient flowsheet. The nurse has a paper-based written handover aid sheet. The sheet has been updated by the overnight nurse. To ensure consistency, the nurse follows the protocol of reading through the handover sheet in the following order: major 24-h events, neurologic status including sedation, analgesic and muscle relaxant infusions and boluses; cardiovascular status including vasoactive infusions; respiratory status including respiratory rate ranges, ventilator settings and the most recent arterial blood gas as it is written on a sheet by the bedside; fluid balance status; and other systems including skin. Some of the information on the sheet is incorrect, and the nurse reports the correct information. There is also some missing data that has not been updated. Some of the information reported contradicts the resident presentation of the events. The attending asks the team to try to clarify the events. There is no one present with firsthand knowledge of the event in question. Using the bedside computer, the nurse checks the flowsheet data or a nursing note in the EHR but there is no further explanation. The resident checks the handover document interface on the patient's record, but no further information is available.

Simultaneously, while the resident and nurse are presenting, several events happen. First, a nurse pulls the fellow aside because of a deteriorating patient. The fellow returns after the completion of the nurse report, and continues to listen. The fellow has their own sheets on all the patients in the unit. The fellow also received handover at 7 am from the overnight fellow.

Second, one of the other residents' internal phone rings. It is another patient's nurse. That patient's medication is due to be given and the nurse would like clarification about the order. The resident steps aside and looks up information on their handover sheets. The nurse asks the resident to update the order. The resident changes to the appropriate patient, enters the order and returns to the discussion.

Once the nurse report is completed, the presenting resident continues by describing their findings on physical examination, followed by the laboratory results. The presenting resident's phone rings. The presenting resident passes the phone to a third resident who answers the phone and steps away. It is one of the consulting services regarding another patient. The third resident takes a message and returns to rounds.

Meanwhile, to save time, another resident has pulled up the patient's chest X-ray (CXR) of this morning along with yesterday's CXR while the presenting resident continues. The attending asks about the CXR and all eyes move to the display which has been turned so the entire team can see the CXR. The endotracheal tube (ETT) is in a little high. The resident measures the exact distance that the ETT needs to be pushed inwards. The attending confirms that the ETT should be advanced inwards by that distance. Both the presenting resident and the nurse take note as this procedure will need to be performed after the rounds.

The presenting resident the discusses their impression and plan of care. Intermittently, as the resident is corrected by the attending, the presenting resident writes down "To Do" reminders on their handover printout. Since there is minimal time, the handover screen will need to be updated later in the day. One of the other residents starts to enter orders on the patient. As part of the order entry system, there is an alert to notify if the resident is accessing the correct patient's chart which forces a brief period of waiting. Fortunately, the resident notices that the wrong patient's chart has been accessed. In fact, it was the patient that the resident was asked for a medication clarification. The order is cancelled, and the resident switches to the patient being discussed, and the order is re-entered. After waiting, the system allows the order to be finalized.

The other resident continues to enter orders as they are being presented. Another resident is modifying a portion of the handover screen in the EHR. This portion of the handover screen is reserved for the daily checklist. The checklist for the previous day's goals are removed and current goals are entered. The parents are asked if they have any questions. They do not, and the team moves to the next patient of the day.

18.4 Analysis of the Case and Discussion

This case illustrates a typical process preparing for and participating in patient rounds. Upon examination of the case, we will discuss a couple of themes: first, the development of a shared mental model including the effect of technology and use of artefacts to overcome constraints imposed by time and the nature of EHRs, and second, the occurrence of interruptions.

18.4.1 Shared Mental Models

In a recent systematic review, there is a significant body of evidence supporting teamwork in the intensive care unit to provide high-quality care (Donovan et al. 2018). In this example, the work during rounds is distributed across multiple providers with each provider having a different role. Lane et al. (2013) concluded that a successful communication strategy during patient care rounds included standardized rounding structures and processes with explicit roles for healthcare providers. Ideally, each of the providers should maintain a shared mental model of the patient and the goals of care (Page et al. 2016; Weller et al. 2014; Westli et al. 2010; Reader et al. 2009; Haig et al. 2006; Mathieu et al. 2000). In our example, each of the providers receive their initial patient mental model individually from their overnight counterparts who are not present during rounds. The process of rounding serves to synchronize and reconcile conflicting understanding about the patient amongst the providers as well as to make explicit the goals for the day (Lane et al. 2013). Ideally, the entire team, overnight and daytime, would gather on rounds to handover but these have become increasingly difficult because of duty hour restrictions (Philibert and Amis 2011; ACGME 2017).

With the implementation of reduced duty hours and the increased importance of the healthcare team, handovers to provide continuity of care has become essential (Arora et al. 2014). Handovers have become an increasing important topic of study and handover tools have become more common (Hoskote et al. 2017; Cochran 2018; Mardis et al. 2016, 2017; Keebler et al. 2016; Davis et al. 2015; Abraham et al. 2014). During these handovers, the goal is not only to communicate information but a mental model of the patient in question (Reader et al. 2009; Jiang et al. 2017). Discrepancies between a provider's firsthand knowledge and that which is documented in EHR should be reconciled (Davis et al. 2015).

Sources of error in the EHR can lead to discrepancies in the provider's mental models (Collins et al. 2011; Embi et al. 2004). These sources include incorrect original documentation, incorrect interpretation of an event, copy and pasted information which no longer is accurate and missing information. Based on a provider's expertise and familiarity with the patient, these errors can be accommodated. Unfortunately, in the case of electronic handover tools, which can be a combination of summarized prose by providers and automated summaries extracted from observations documented in the EHR, these errors can lead to incorrect summaries, and can create serious misunderstandings in the mental model developed by inexperienced providers or providers that have never cared for the patient (Davis et al. 2015).

Beyond errors, the amount of information stored in the EHR is immense and can lead to information overload (Farri et al. 2012). Inexperienced providers do not necessarily understand which information is significant and which can safely be ignored and as a result they tend to convey all the information which can impede a succinct description of the patient. Rarely are EHR summaries context-aware as to filter out unneeded information. While advances in EHR summarization is being investigated (Pivovarov and Elhadad 2015), mostly, the summaries are aggregators and it is up to the provider to interpret the summary (National Academy of Sciences 2009). In fact, Varpio et al. (Varpio et al. 2015) found showed differences between paper and EHR data summarizations and cognitive loads with EHR data summarization being detrimental to clinical reasoning.

Despite the promise of EHRs, many providers still use personal (usually paper) artefacts, such as handover sheets to make up for the deficiencies in the electronic reporting (Kelley et al. 2013; Blaz et al. 2016; Collins et al. 2012; Rosenbluth et al. 2015). In the dynamic environment of the intensive care unit, information about a single patient varies from provider to provider leading to diverging mental models throughout the workday (Mamykina et al. 2014). Some of the unintended consequences of healthcare technology include workarounds such as deferred data entry by first documenting on personal artefacts and then subsequently transcribed into the EHR if time permits which can negatively impact documentation quality (Kelley et al. 2013; Blaz et al. 2016; Zheng et al. 2016).

In the previous section, we discussed the discrepancies of information content that needs to be effectively reconciled to develop a shared mental model and how these discrepancies can cause incomplete shared mental models which may lead to suboptimal care. In our case, each of the healthcare providers is situated behind a computer so there is potential for a physical divide between team members. The lack of face-to-face communication and physical barriers is thought to negatively impact rounding effectiveness (Lane et al. 2013; Gharaveis et al. 2018; Morrison et al. 2008). Additionally, each provider is interacting with the computer and thus, their attention is divided between the EHR interface and the group discussion.

While each provider has the overarching goal to provide the best care for the patient, each provider has their own set of priorities (Donovan et al. 2018). Effectively, each handover (nursing, resident, fellow, attending) concentrates on specific sets of information and not all are overlapping (Jiang et al. 2017; Collins et al. 2011; Mamykina et al. 2014). There is a distributive nature of the division of work in rounds. Each provider must have a similar understanding about the patient to be able to most effectively perform interrelated tasks (Page et al. 2016; Weller et al. 2014; Westli et al. 2010; Mathieu et al. 2000). Information from each of the providers must be taken into context, information must be evaluated in terms of being most representative of what occurred. Discrepancies must be reconciled so that a shared mental model can be established. Despite this shared mental model, each provider must augment that mental model to suit the needs and requirements of their own priorities.

18.4.2 Interruptions

Smartphones or rather instant access communications (voice or text) are increasingly common in the clinical workplace (Tran et al. 2014; Wu et al. 2010) and have been shown to improve communication efficiency (Ighani et al. 2010). The ability to immediately contact a remote provider is clearly important and helpful but it can also be a source of increased interruptions and potential interprofessional conflicts (Aungst and Belliveau 2015; Wu et al. 2013a, b; Vaisman and Wu 2017; Quan et al. 2013). If there are differing interpretations of the significance of a clinical event, then the provider who is being interrupted can become frustrated or experience increased stress (Weigl et al. 2014). With a paging system, it is the provider being interrupted who controls the timing of the communication, whereas, with personal mobile communications, a phone call or text message is generally returned immediately (Lo et al. 2012). In addition to increased interruptions, text paging and smartphones can have negative effects on decreased communication quality compared to face-to-face interactions and potentially leading to weakened interprofessional relationships (Wu et al. 2011, 2012, 2014).

These interruptions can be a source of increased cognitive load due to task switching (Li et al. 2012; Skaugset et al. 2016). Interruptions can lead to gaps information flow (Laxmisan et al. 2007). In our case, the face-to-face interruption and the phone call interruptions require task switching. Providers involved in the interruption must change their focus to another patient and they may miss important information that contribute to shared understanding. These external interruptions are a potential source of rounding efficiency (Anderson et al. 2015) and detrimental to team understanding (Laxmisan et al. 2007). However, Rivera-Rodriguez et al. (Rivera-Rodriguez and Karsh 2010) suggests that not all interruptions are should be considered detrimental. For example, when a presenting member is interrupted by others to clarify information then the mental model remains focused on the same patient and discrepancies can be reconciled and contributing to better shared mental models.

In addition to the effect on information flow, interruptions can be a cause of medical errors (Skaugset et al. 2016). In our case, an interruption was the potential cause of a near-miss with ordering. Several authors have suggested the importance of interruption management such as using physical cues or conscious times to delay or reject interruptions to mitigate errors (Ratwani et al. 2017; Coiera 2015) as well as the importance of error recovery (Patel et al. 2015). Unfortunately, a systematic review of interventions to reduce interruptions showed that the evidence that these interventions reduced errors was equivocal and that further study was needed (Raban and Westbrook 2014).

18.5 Conclusions

The time of the individual provider delivering care is past and teamwork is essential to delivering optimal healthcare. Effectively developing a shared mental model is important in teamwork. Rounding in the intensive care unit is a cognitively complex task involving multiple members of the healthcare team. Participation in rounding serves to distribute work and cognitive load as well as to help solidify shared mental models. The development of shared mental models is affected by the handover process, by handover tools including those that involve EHR systems, by discrepancies in the experiences of individual team members, and by errors in the EHR systems. In addition, the demands of using EHR systems at the point of rounding can change the physical environment so that team dynamics are sub-optimal for shared mental model creation. Rounding is also affected by interruptions. Technology can also mediate provider-to-provider communication and be a source of interruptions. Personal communication devices have been shown to make care more efficient but the technology can also lead to increased interruptions and potentially interprofessional conflicts. These interruptions can be a source of medical error. Recovery from these errors and interruptions is an important process.

18.6 Recommendations

Current processes and workflows, particularly involving handover and rounding, need to be re-evaluated in the light of the distributive nature of work and cognition in the intensive care unit. Processes need to optimize development of shared mental models and support effective teamwork. Implementation of technology needs to be reviewed in this context as it can both be a benefit and a hinderance (for example, smartphones can improve unit efficiency but can also contribute to increased external interruptions or EHR use on rounds can be a cause of distraction and worsening shared mental model development).

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Chapter 19
Clinical Workflow: The Past, Present, and Future

Kai Zheng, Johanna Westbrook, Thomas G. Kannampallil, and Vimla L. Patel

As evident from the discussions throughout this book, workflow plays a central role in ensuring smooth functioning of all clinical activities—from patient encounter to medication administration to population health management. Any disruption to workflow can result in severe, adverse consequences such as decreased time efficiency and greater patient safety risks. In the recent two decades, the most systemic disruption to clinical workflow across the globe is associated with the widespread implementation of health IT systems, electronic health records (EHR) in particular.

In the EHR era, coordination of clinical workflow increasingly relies on the use computerized systems. However, it has been well recognized that current generation EHR systems "appear designed largely to automate tasks or business processes," providing limited support for clinical workflow and the cognitive tasks of clinicians (National Research Council 2009). Disruption to workflow as a result of EHR implementation is thus common, which is a manifestation of a wide range of design

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and implementation problems including poor software usability, complex intersystem dependencies, and the lack of sociotechnical integration of software systems into their complex use environments.

Understanding the impact of health IT on clinical workflow has been a key focus of the research on health IT-related unintended consequences (Bloomrosen et al. 2011; Zheng et al. 2016). In this body of the literature, there has been a general consensus that the top-down approach in the prevalent EHR design, which predominantly emphasizes administrative efficiency, is responsible for many of the adverse effects observed (National Research Council 2009). Because newly introduced health IT systems often fail to adequately support clinical workflow, clinicians are forced to develop or maintain their own workflow processes deviating from the 'recommended' practice, which as a result could increase workload and introduce new threats to patient safety.

There have been some efforts to address this issue. For example, the U.S. Agency for Healthcare Research and Quality (AHRQ) funded a project to develop a toolkit to help small and medium-sized outpatient practices more effectively manage their workflow (Carayon and Karsh 2010); and subsequently launched a funding program, "Using Health IT in Practice Redesign: Impact of Health IT on Workflow," to specifically support research that studies the causal relationship between health IT and workflow processes (Zheng et al. 2015a; Wald et al. 2015; Carayon et al. 2015). Further, the U.S. National Institute of Standards and Technology (NIST) issued a guideline in 2014 recommending the use of human factors modeling methods to better align EHR design with ambulatory care clinical workflow; and to move away from a billing-centered design to a patient-centered design in order to support better workload management and more flexible flow of patients and tasks (Lowry et al. 2014).

However, as several chapters in this book point out, there remain significant knowledge and methodological gaps in clinical workflow research. Even though disruption to workflow is a topic frequently discussed in the literature, very few studies actually measure workflow changes directly. Instead, most studies speculated that workflow might have been modified because of differences observed in outcomes-oriented measures (e.g., improved guideline adherence and reduced patient safety events) (Carayon and Karsh 2010). Even among studies that have attempted to directly quantify health IT's impact on workflow, many focused on changes in time utilization (e.g., average total time spent in direct patient care activities vs. using the computer), rather than 'flow' of the work (Zheng et al. 2010). This distinction is important because the spirit of workflow lies in the chronological organization of clinical tasks and the temporal (inter)dependencies among them.

In the literature that directly measures workflow, the most commonly used approaches are qualitative methods, such as ethnographic observations, interviews, and focus groups, and quantitative analysis of data collected from self-reported questionnaire surveys. While such approaches provide an important means for studying workflow and understanding the disruptive effects of health IT, they often fall short of measuring the magnitude of the impact; and their results are susceptible to prejudices (e.g., clinicians' negative emotions due to reluctance to change rather than shortcomings of health IT) and biases (e.g., cognitive heuristics, recall errors).

Quantitative studies on workflow that do not rely on self-reported data usually employ a pre-post observational design to assess changes in workflow. Time and motion is the most commonly used approach, which collects workflow data by having human observers observe clinicians for a continuous period of time to record how they perform their clinical tasks (what, when, for how long) (Zheng et al. 2011). Compared to alternative methods (e.g., work sampling and self-reported questionnaires), the time and motion method is considered the most accurate way to quantify workflow. However, conducting time and motion studies is resource demanding, and their results are subject to many limitations, such as small sample size, observer bias, and the Hawthorne effect (when being observed, clinicians may demonstrate different behavior from their usual practice) (Zheng et al. 2011).

In recent years, several new methods have emerged for studying workflow using data automatically collected through software tools (e.g., screen capture software) or sensor technology such as eye tracking devices, 3D infrared laser projectors (e.g., Microsoft Kinect), and radio-frequency identification (RFID) (Calvitti et al. 2017; Kannampallil et al. 2011). These methods, collectively referred to as "computational ethnography," present an automated and less obtrusive means for collecting *in situ* data reflecting real end users' actual, unaltered behaviors in real-world settings (Zheng et al. 2015b). These methods have the potential to substantially reduce the resource requirement for conducting workflow studies while producing more granular data than what could not be captured by human observers.

Log analysis of security audits, in particular, can be a valuable solution to enabling large-scale workflow studies at a very low cost. In the U.S., mandated by Health Insurance Portability and Accountability Act (HIPAA) and the Meaningful Use criteria, all computerized systems in healthcare must implement security auditing mechanisms for detecting malicious access to, or alteration of, protected health information. These security logs record each and every clinical activity and the associated metadata (when, by whom, the nature of the action, and the IP address or geocode of the device used), providing very rich information on how medical work is conducted. Such data are also highly structured, and can be readily analyzed to reveal insights into workflow through reconstruction of the spatiotemporal distribution of clinical activities. While still limited, workflow researchers have started to tap into this rich data resource. For example, Zheng et al. studied clinicians' workflow in an EHR system using automatically recorded access logs (Zheng et al. 2009); and Tai-Seale et al. and Hirsch et al. used EHR audit trail logs to examine physician workflow and time utilization in primary care practices (Tai-Seale et al. 2017; Hirsch et al. 2017).

In conclusion, understanding and reducing disruption to clinical workflow as a result of health IT implementation is of vital importance, because of its critical patient safety consequences and the broader concerns about inefficiency and clinician burnout that may result from suboptimal workflow. To develop a systematic solution, it requires a collective effort from multiple stakeholders and an evidence-based approach. This includes regulatory oversight, continued effort by the industry to improve the design of their products, and development of new, patient- and clinician-centered implementation models to better incorporate software systems into clinical workflow. It should also be recognized that there does not exist a *one-size-fits-all* solution, especially considering the complexity of medical work and the variability across specialties and settings. More adaptable software designs are therefore desired, to better respond to the dynamic nature of clinical workflow to allow changes and deviations both during and after system adoption. In addition, clinicians' knowledge of and expectation for health IT also need to be updated to accommodate technological interventions. Clinicians need to develop a more informed understanding of the new methods of medical work enabled by computerized systems, and the limitations thereof, to better leverage technology in their clinical practice. Through this book, we hope to establish a solid foundation toward these goals by compiling a collection of high-quality scholarly works that seek to provide clarity, consistency, and reproducibility, with a shared view of clinical workflow and its relevance to health IT design, implementation, and evaluation. We also hope that the discussions presented in this book will lead to actionable, pragmatic insights for informatics practitioners in designing, implementing, and evaluating workflow changes to better accommodate the adoption and use of health IT.

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