# Chapter 2
# Cognitive Behavior and Clinical Workflows

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## 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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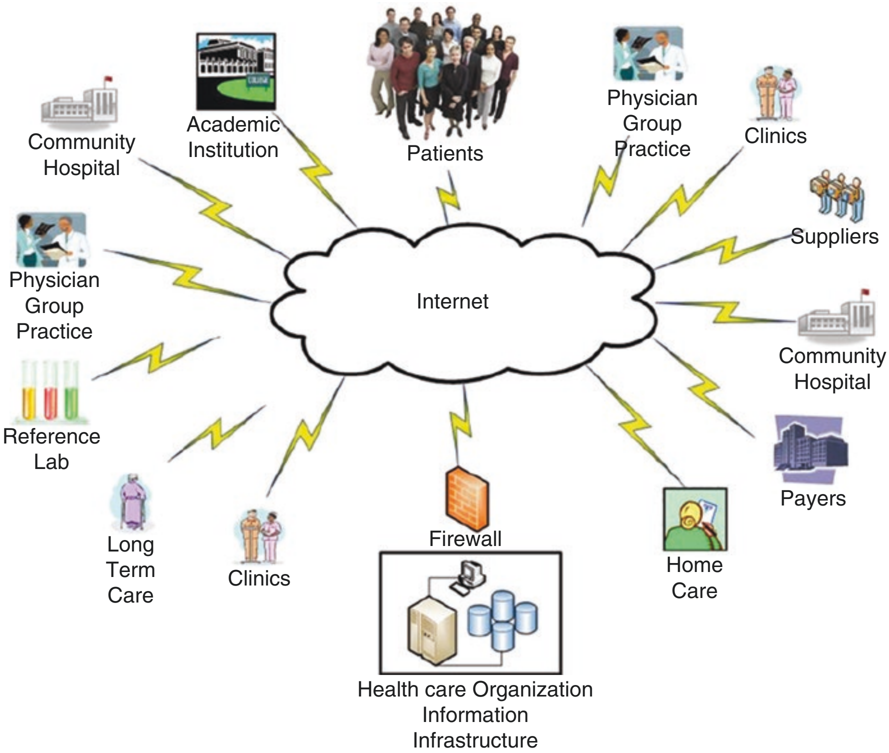


**Fig. 2.1** Major organizational components of integrated healthcare industry. Reprinted from Vogel LH. Management of information in healthcare organizations. In: Shortliffe EH, Cimino JJ, editors. Biomedical informatics: computer applications in healthcare and biomedicine. London, Heidelberg, New York,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