CHAPTER

# Cognitive Considerations for Health Information Technology

# 22

**Amy Franklin and Jiajie Zhang**

## 22.1 Introduction

Health information technology (HIT) has great potential to increase care quality, efficiency, and safety through its wide adoption and meaningful use. An example of the importance of this goal is that it is the major rationale behind the United States (US) national HIT Initiative, started by President Bush in 2004 and strengthened by President Obama in 2009 with the $19 billion HITECH Act under the American Recovery and Reinvestment Act (ARRA) (see Chapter 1), to have every American's medical records on computers by 2014. However, there are huge gaps between the status quo and the potential of HIT, mostly due to cognitive, financial, security/privacy, technological, social/cultural, and workforce challenges. Among these, the 2009 National Research Council (NRC) report on "Computational Technology for Effective Health Care: Immediate Steps and Strategic Directions" (Stead and Lin, 2009) identified "cognitive support" as an overarching research grand challenge for HIT.

Cognitive support for HIT is intended to assist clinical problem solving and decision making such that the care for patients can be maximized along the Institute of Medicine's six dimensions of quality (safe, effective, timely, efficient, equitable, and responsive) (Institute of Medicine, 2001). Thus this chapter is devoted to exploring the methodologies of cognitive science as they are applied to more fully understanding the stresses of the clinical environment to aid in developing clinical decision support (CDS) to meet these needs. Much of the stresses come from the nature of health care itself, the burdens of the information and knowledge explosion, the multiplicity of diagnostic and therapeutic choices available, the time pressures, and the fragmentation of care, which led to the demand for CDS in the first place. The need to better understand cognitive considerations is especially true for more complex care, when the patients themselves are more complicated, multiple participants are involved in the health care team, and often the environments themselves are stressful – such as in the emergency department, operating room, or critical care unit.

**Clinical Decision Support.**

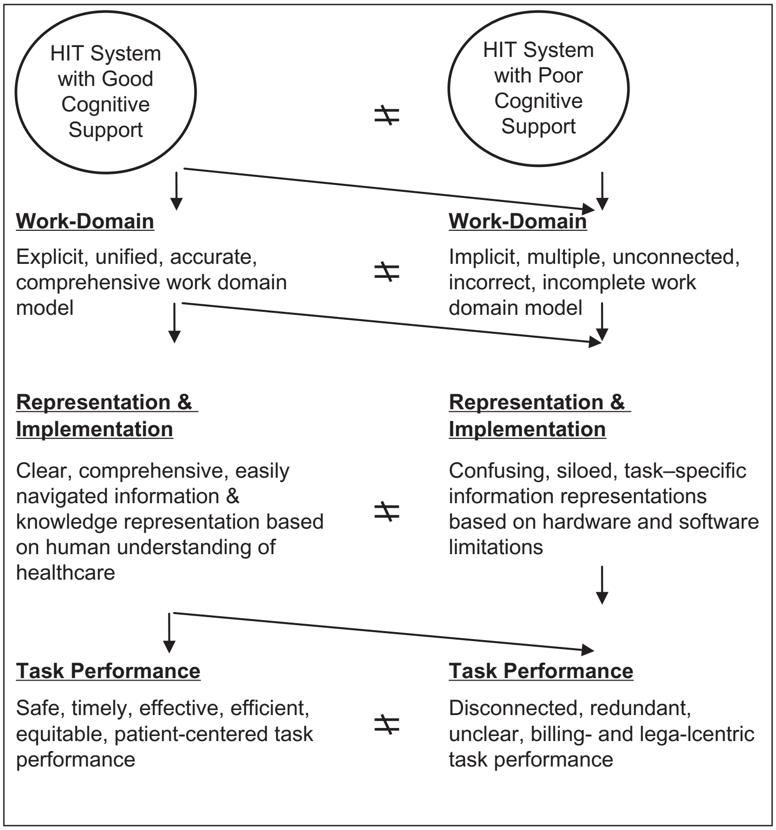


**FIGURE 22.1**

Cognitive challenges for Health IT are characterized as the gaps at three levels between HIT systems that have good and poor cognitive support.

The National Center for Cognitive Informatics and Decision Making in Healthcare (http://www.sharpc.org), funded by the Strategic Health Advanced Research Projects (SHARP) grant program under the Office of the National Coordinator for Health IT (ONC), characterizes the cognitive challenges for HIT as the gaps between HIT systems with good and poor cognitive support at three Levels (Figure 22.1). (a) At the **work domain level**, HIT systems with good cognitive support should have an explicit, unified, accurate, and comprehensive model that reflects the true ontology of the work domain, which provides a clear understanding of the care that is independent of how systems are implemented. What this means for HIT is that the systems should be developed with a work domain ontology for health care that reflects all the goals, needs and challenges of clinical care. Such a model should hold across sites regardless of the implementation (e.g. which electronic health record system is in place, or if providers are physicians or nurse practitioners.) HIT systems with poor cognitive support typically suffer from having models of the work domain that are implicit, multiple, unconnected, disparate, incomplete, and often inaccurate. (b) At the **representation and implementation level**, HIT systems with good cognitive support are characterized as having clear, comprehensive, easy to navigate information and knowledge models optimized for human users. That is, the systems should be useful, usable, and satisfying for the end users. HIT systems with poor cognitive support usually have representations that are based on hardware and software features, which make them confusing, siloed, task-specific, difficult to use and learn, and hard to navigate, because they do not match human needs and expectations. (c) At the **level of task performance**, HIT systems with good cognitive support are characterized by having "built-in" safe, timely, effective, efficient, equitable, patient-centered task performance (Institute of Medicine, 2001). HIT systems with poor cognitive support often have disconnected, redundant, tedious, and unclear user models based on business and legal requirements that interfere with task performance. These gaps between good and poor systems highlight some of the issues the ONC named in their call for proposals for the SHARP programs. Strong cognitive support within a well-designed HIT system is built on appropriate models of how clinician make decisions, provides information display and visualization to increase situation awareness, facilitates decision making under stress and time pressure, improves communication among clinicians, patients, and teams, and operates within highly usable systems.

## 22.2 Challenges for cognitive support in health care

"Too much to find and buried too deep."

Physicians need to perform life-critical tasks that require the acquisition, processing, transmission, distribution, integration, search, and archiving of significant amounts of data in a distributed team environment in a timely manner. While HIT provides opportunities for support in these environments, there are also concerns regarding the impact of such technology on clinical performance. With the introduction of Electronic Health Records (EHRs), increasingly augmented with further data from health information exchange, data comes at physicians in large volumes. Clinicians must not only manage potential information overload (Hall and Walton, 2004; Van Vleck et al., 2008; Singh et al., 2009 Sep 28), they must also make efforts to ensure that the abundance of data in EHR systems and the unintended consequences of such technology do not lead to error (Ash et al., 2004; Ash et al., 2007; Sittig et al., 2006; Horsky et al., 2005; Koppel et al., 2005).

With the increasing role of HIT and electronic data repositories in clinical settings, it is relevant to evaluate the role of technology in supporting (or impeding) clinical reasoning and decision making (Patel et al., 2000). Increases in information can lead to overload if, as Bawden (Bawden et al., 1999) suggests, "information received becomes a hindrance rather than a help when the information is potentially useful." For example, in a survey of 229 general practitioners, Christensen and Grimsmo (Christensen and Grimsmo, 2008) found 37% of the group sometimes gave up searching for information simply because it was too time-consuming. Significant redundancy in data and the sheer volume of information make it difficult to both isolate individual pieces of data and also, at the same time, problematic to gain an appropriate overview of the patient's entire record. Kannampallil et al. (2013) find that information seeking is challenged by both the cognitive limitations of clinicians, such as memory capacity and the aforementioned overload, as well as limitations imposed by technology. Intensive care physicians in this study (Kannampallil et al., 2013) were observed iteratively swapping back and forth between electronic and paper resources (as well as within different segments of single sources such as the EHR) as they worked to find and re-find information. Implications from this additional cognitive burden include negative impacts on their ability to filter information for reasoning and decision making (Patel et al., 2009; Patel and Kaufman, 1998).

### 22.2.1 Unintended consequences

Some of the identified unintended consequences of HIT, particularly for computerized provider order entry and CDS, include changes to work and workflow (including increases in volume of effort), changes in roles and responsibilities, negative alterations to communication, new types of errors, and additional cognitive burdens such as alert fatigue and management of misleading content (Ash et al., 2004; Ash et al., 2007; Sittig et al., 2006; Horsky et al., 2005; Koppel et al., 2005; Campbell et al., 2006; Ash et al., 2007; Southon et al., 1999).

Despite reports on the consequences of poor EHR usability (Koppel et al., 2005; Han et al., 2005; Johnson, 2006; Karsh et al., 2010; Viitanen et al., 2011), historically more attention has been directed to the financial and technical aspects of EHR development and use than to EHR usability and integration into the clinical work environment. However, HITECH regulations not only incentivize HIT use but are requiring, as part of Stage 2 certification, evidence of usability as an aspect of safety-enhanced design. The American Medical Informatics Association Task Force on Usability recently put forth a statement (Middleton et al., 2013) regarding enhancement of patient safety and quality of care through usability, including policy, industry/vendor, and end-user recommendations. Improvements in usability can amplify the cognitive support of HIT systems.

### 22.2.2 Complex team environments

HIT with poor cognitive support disconnects tasks from the desired focus on patient-centered care by using representations that are not intuitive or are limited by the technology. Often such systems indicate a poor understanding of the work domain by their designers. Research on teamwork in complex environments has been going through a new and major challenge due to the explosive growth of information technology. The role of HIT is much more than the transformation of cognitive labor from people to machine. Information technology has become an inherent part of the complex work system, which includes passive artifacts, active agents, communication tools, workflow processes, and information and knowledge bases. Information technology also modifies the structures, processes, and outcomes of the complex work system. It not only changes how individuals and teams perceive, act, solve problems, reason, make decisions, communicate, and interact with other people but also determines these processes to a higher and higher degree.

Research on teamwork has been very active in several areas of social and behavioral sciences, such as industrial and organizational psychology, social psychology, organizational behavior, and management science. Research in these areas has focused on interactions among team members, individual mental structures and shared mental models, psychological processes and mechanisms, and influences of cognitive, personality, motivational, emotional, social, organizational, and cultural factors on team performance and dynamics (Mathieu et al., 2000; DeChurch and Mesmer-Magnus, 2010; Cooke et al., 2012; Salas and Fiore, 2004; Arrow et al., 2000). The role of information technology in teamwork has been investigated in these areas (Bolstad and Endsley, 1999; Ho and Intille, 2005), although their emphasis is on psychological and behavioral issues, not on information technology. Needs with respect to information technology were discussed by a panel at the Human Factors and Ergonomics Society Conference in 2012, which focused on patient-centered communication, its role in patient outcomes, and the absence of attention to teamwork as managed by EHR systems (Zachary et al., 2012). Additional support for team work and the cognitive demands of group effort are required.

## 22.3 Developing cognitive support: distributed cognition

The study of distributed cognition is a scientific discipline that is concerned with how cognitive activity is distributed across human minds, external cognitive artifacts, and groups of people, and how it is distributed across space and time (Hutchins, 1995; Norman, 1991; Zhang, 1997; Zhang, 1998; Zhang and Norman, 1994; Holland et al., 2000; Patel et al., 2000; Patel 1998). In this view, people's cognitive behavior results from interactions with other people and with external cognitive artifacts (including information technology), and people's activities in concrete situations are guided, constrained, and, to some extent, determined by the physical, cultural, social, historical, and organizational contexts in which they are situated (Clancey, 1997). The unit of analysis for distributed cognition is an entire distributed system, composed of a group of people interacting with external cognitive artifacts, as depicted in Figure 22.2. Such a distributed system (e.g. emergency department in a hospital or airplane cockpit) can have cognitive properties that differ radically from the cognitive properties of the components (Hutchins, 1995). In general terms, the components of a distributed cognitive system are

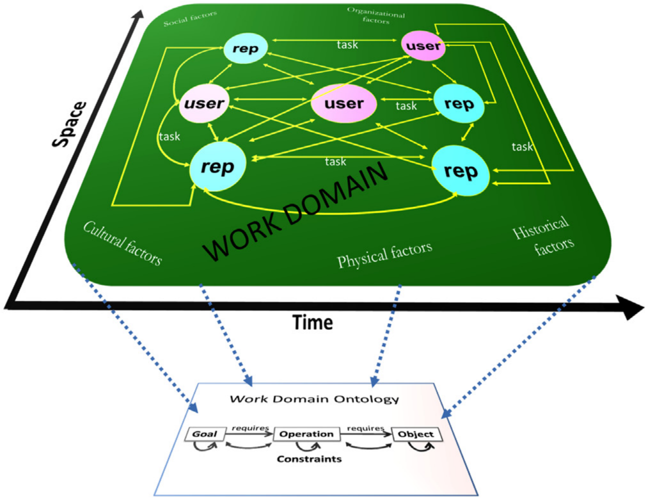


**FIGURE 22.2**

The theoretical framework of distributed cognition. The upper part shows how cognition is distributed across users (internal representations) and representations (external representations), across space and time, and situated in social, cultural, physical, organizational, and historical backgrounds. The lower part is the abstract structure, called the work domain ontology, is an implementation-independent description of the work domain.

described as internal and external representations. Internal representations are the knowledge and structure in individuals' minds; and external representations are the knowledge and structure in the external environment (Zhang, 1997; Zhang and Norman, 1994).

### 22.3.1 Distributed cognition between individuals and artifacts

Many complex information-processing tasks require the processing of information distributed across internal minds and external artifacts (Zhang and Norman, 1994). External artifacts are defined as objects (e.g. buttons on a medical device), symbols (e.g. vital signs on a patient chart), tools (e.g. BMI calculator), and other entities that support or modify human cognitive behavior. It is the interwoven processing of internal and external information that generates much of a person's intelligence. Let us consider multiplying 965 by 273 using paper and pencil. The internal representations are the meanings of individual symbols (e.g. the numerical value of the arbitrary symbol "5" is the quantity five), the addition and multiplication tables, arithmetic procedures, etc., which have to be retrieved from memory. The external representations are the shapes and positions of the symbols, the spatial relations of partial products, etc., which can be perceptually inspected from the environment. To perform the multiplication task, people need to process the information perceived from external representations and the information retrieved from internal representations in an interwoven, integrative, and dynamic manner.

### 22.3.2 The power of external representations

One important aspect emphasized by distributed cognition research is that external representations are more than inputs and stimuli to the internal mind. External representations have many nontrivial properties that empower human cognitive capability (Zhang, 1997). External representations make information displays and visualization (such as dashboards for the ED or ICU) into powerful aids to human cognition due to the following features: they provide information that can be directly perceived and used, such that little effortful processing is needed to interpret and formulate the information explicitly (Zhang and Norman, 1994; Gibson, 1979); they support perceptual operators that can recognize features easily and make inferences directly (Larkin and Simon, 1987); they stop time to make invisible and transient information visible and sustainable (Tweney, 1992); they provide short-term or long-term memory aids so that overall memory load can be reduced; they provide knowledge and skills that are unavailable from internal representations (Reisberg, 1987); they anchor and structure cognitive behavior without conscious awareness (Zhang and Norman, 1994; Norman, 1988); and they change the nature of a task by generating more efficient action sequences (Norman, 1991).

### 22.3.3 Distributed cognition across individuals

Cognition can also be distributed across a group of individuals. For this type of distributed cognition, there are two different views. The reductionist view considers that the cognitive properties of a group can be entirely determined by the properties of individuals. In this view, to understand group behavior, all we need is to understand the properties of individuals. In contrast, the interactionist view considers that the interactions among the individuals can produce emergent group properties that cannot be reduced to the properties of the individuals. In this view, to study group behavior, we need to examine not only the properties of individuals but also the interactions among them. Examples of emergent group properties include group affect (George, 1990), collective efficacy (Bandura, 1986), and transactive memory systems (Wegner, 1987).

One important issue in distributed cognition across a group of individuals is the group effectiveness problem (Foushee and Helmreich, 1988). A group of minds can be better than one (process gain), because in a group there are many more resources, task load and memory load are shared and distributed, errors are cross-checked, and so on. The performance of a group can also be worse than that of an individual (process loss), because in a group communication takes time, knowledge may not be shared and different strategies may be used by different individuals.

This phenomenon has been demonstrated in a clinical environment where people work face-to-face, sharing tacit knowledge (Patel et al., 2000) and at a distance. It was also demonstrated empirically that whether two minds were better or worse than one mind depended on how the knowledge was distributed across the two minds (Zhang, 1998). The issue of group effectiveness is especially important in health care and has received some attention (Patel et al., 1996).

### 22.3.4 Cognitive work in distributed system

From the distributed cognition perspective, cognitive work can be viewed in two different ways. From the individual user perspective, cognitive work is measured by the performance of the individuals in terms of time-on-task, success rate, error rate, etc. From the system perspective, cognitive work is measured by the performance of the distributed system composed of both users and technology. Information, knowledge, processes, and constraints can all be distributed across users and technology in various ways.

For a distributed system, there is an ontology of the work domain (see the lower part of Figure 22.2) that the distributed system entails. The ontology of the work domain is the basic structure of the work that the system together with its human users will perform. It is an explicit, abstract, implementation-independent description of that work. The work domain ontology is composed of goals, operations, objects, and constraints. Correctly identifying the ontology of a work domain is essential for identifying the information needs for the design of user-centered information systems. More details of work domain ontologies are described in Section 22.4 about TURF (see also Table 22.1).

### 22.3.5 Organizational memory

Organizational memory is an important research topic for distributed cognition as well as for the field known as Computer-Supported Collaborative Work (CSCW) (Baecker, 1993). Organizational memory is the collection of knowledge embedded in individuals, artifacts, and processes in a team setting. It is the collective long-term memory of a team in a complex environment. It involves individuals, artifacts, organizational culture, organizational transformation, organizational structure, institution manuals, filing systems, databases, stories, etc. Its encoding, storage, organization, retrieval, and transmission are all potentially important factors for team performance.

Designing information systems' infrastructures for the capture of organizational memory and the distribution of this knowledge across a team requires not only an in-depth understanding of the numerous technical knowledge management activities, but also, more importantly and often omitted, an understanding and inclusion of the social, cultural, organizational, and cognitive aspects that not only occur within an individual or group of individuals but also occur across individuals and artificial agents. In general, any information system that supports organizational

**Table 22.1** The TURF framework and its components

| TURF Components | |
|---|---|
| User Analysis | Clinical roles<br>The process of identifying the types of users and the characteristics of each type of users.<br>Types of users: physicians at various levels (e.g. attending, fellow, resident, medical student); nurses with different responsibilities (e.g. charge nurse, floor nurse,).<br>User Characteristics: experience and knowledge of EHR, knowledge of computers, education background, cognitive capacities and limitations, perceptual variations, age related skills, cultural background, personality, etc. |
| Functional Analysis | Work domain ontology<br>The process of identifying the ontology of the work domain. The work domain ontology is the basic structure of the work that the system, together with its human users, will perform. It is an explicit, abstract, implementation-independent description of that work.<br>Components of the work domain ontology: goals (e.g. treating high glucose level in a pre-diabetic patient), operations (e.g. writing a medication prescription), objects (e.g. patient name, doctor's name, diagnosis, medication name, dosage, frequency, duration, route), and constraints (e.g. the relation between the operation "write a medication prescription" and the objects "Metformin" and "500 mg") |
| Representational Analysis | The process of evaluating the appropriateness of the representations for a given task performed by a specific type of user, such that the interaction between users and systems is in a direct interaction mode.<br>Examples of Representations: user interface objects such as icons, lists, tables, graphs, views, and windows.<br>Methods for representation analysis: isomorphic representations, affordance analysis, heuristic evaluations, etc. |
| Task Analysis | The process of identifying the steps of carrying out an operation by using a specific representation, the relations among the steps, and the nature of each step (mental or physical).<br>Methods for task analysis: key-stroke level modeling, user activity logs, workflow analysis, observations and interviews, etc. |

memory for a team or organization should have the following properties (Walsh and Ungson, 1991) (Davenport et al., 1997):

- Provide a means for collaborative communication
- Capture informal knowledge
- Organize knowledge as searchable data

- Frame formal knowledge within context
- Increase search and retrieval capabilities
- Increase information sharing across team members
- Minimize repeated problem solving with routine tasks
- Decrease interruptions
- Redirect one-to-one to team communication patterns

### 22.3.6 Group decision making and technology

Groups have many functions: to communicate, share information, generate ideas, organize ideas, draft policies and procedures, collaborate on report writing, share a vision, build consensus, make decisions, etc. Nunamaker et al. (1991) used an electronic meeting system for teams to demonstrate how information technology can affect team dynamics in significant ways. They considered the following factors for the design and evaluation of the this system: group factors such as size, proximity, composition, and cohesiveness; task factors such as activities required to accomplish the task and task complexity; context factors such as organizational structure, time pressure, evaluative tone, and reward structure; and outcomes factors such as efficiency, effectiveness, and satisfaction. This system showed a number of positive effects on team performance: it increased many process gains and decreased many process losses that typically occur as a result of team behavior. The process gains that were increased included increases in information, synergy, objective evaluation, stimulation, and learning; and the process losses that were decreased included air time fragmentation, attenuation blocking, concentration blocking, attention blocking, memory failure, conformance pressure, evaluation apprehension, socializing, domination, etc. The system has some drawbacks. Some process losses were increased, among them information overload, slower feedback, free riding, and incomplete use of information. Studies such as this one show that many of the properties of teams identified from behavioral studies of their operation without interactions with technology can be changed, eliminated, or transformed in systematic ways by introducing information technology. This also demonstrates that teams in a distributed system with technology do not behave in the same way as teams in a distributed system that is only composed of people, even if the tasks that are performed in the two systems are the same.

### 22.3.7 Group decision making in clinical contexts

Shared decision making involving the patient in conjunction with the clinical team is one area in which group decision making and HIT has received significant attention. Shared decision making (SDM) is defined as "…a formal process or tool that helps physicians and patients work together to choose the treatment option that best reflects both medical evidence and the individual patient's priorities and goals for his or her care (American Medical Association, 2012)." Technology in the form of decision aids is explored in patient-physician decision making, often with a focus on patient's access and ease of use (Bass et al., 2013), patient knowledge gain (Vlemmix et al., 2013) and changes in patient's decisional conflict (Stacey et al., 2011). (See Chapter 27 for more discussion of consumer aids to decision making.)

Cognitive interventions for other group contexts aim to support decision making by easing the burden of group meetings, increasing adherence to protocols or supporting individuals as components of the traditional team process (Kraemer and King, 1998). Although care may be provided by a group, much of the literature on decision making in health care domains focuses on communication gaps and interventions (Abraham et al., 2012), mutual agreement on treatment plans (Have, 2013) or individual and/or role-based differences within a team (Kannampallil et al., unpublished).

Although not representing forms of group decision making per se, there are other ways that the power of the masses is being incorporated into HIT solutions, ranging from translation of SNOMED terms (Schulz et al., 2013) to crowd-sourcing the identification of relationships between clinical problems and medications (McCoy et al., 2012), surveillance (Ranard et al., 2013), and using the wisdom of the crowds to develop diagnostic decision support systems (Hernández-Chan et al., 2012).

## 22.4 Building systems with distributed cognition in mind

### 22.4.1 TURF: A framework for HIT usability and cognitive support

TURF (Zhang and Walji, 2011) is a cognitive framework originally developed for the evaluation, measurement, and design of EHR usability. However, its principles and methods can also be applied to address the cognitive factors for workflow and decision making in complex team environments. TURF stands for Task, User, Representation, and Function, which are the four core components of user-centered design. Table 22.1 describes these four components for the clinical environment. To develop good cognitive support for clinical care through HIT, we need to consider all four components. Different users have different needs, capabilities, and constraints. Therefore, HIT systems developed for different users should be customized. An ontology of work is a foundation for designing effective cognitive support. If the ontology of work is not correctly and completely identified, HIT systems developed may have overhead functions that are not essential for the work, interfere with the execution of the required work, and potentially induce errors. The representations, or user interfaces, of HIT systems should follow human-centered principles to maximize the effects of cognitive support and reduce usability problems. Also, tasks are sequences of activities that are carried out by specific users, using certain representations to achieve the goals in the work domain. An understanding of the tasks is essential for optimizing the workflow and decision support. This four-part harmony builds cognitive support through good usability into HIT systems.

## 22.5 Developing tools to support cognition

The presentation of information to clinicians has the potential to profoundly influence their decision making (Patel et al., 2000; Dumont, 1993; Patel et al., 2002; Mark, 2008). However, current systems often present information in a fragmented fashion, splitting a single patient record across screens and tables in different formats (Bourgeois et al., 2010; Lindwarm Alonso et al., 1998; Pieczkiewicz et al., 2007). Disjointed records, redundancy of information, and the sheer volume of data to be sifted through can prove challenging to users of HIT. The opportunities for support through technology and automated methods are being explored in data presentation or visualization and ways in which information can be clustered or aggregated to decrease human cognitive efforts.

For example, medication reconciliation is a complex task requiring the consideration of multiple streams of disparate and potentially incomplete information. The physician must assimilate and reconcile all the patient's medications from all available sources (e.g. hospitalizations, specialists, over-the-counter medications) into a single active medication list. To facilitate this process, Plaisant and her research team (Plaisant et al., 2013) have created Twinlist, a collection of interface designs for this purpose. The features of Twinlist include the use of spatial layouts that highlight and separate the sources of medications as well as a multistep animation that visually highlights the reconciliation process by indicating the movement of medications from each list as well as the drugs requiring management.

Within this display, columns separate unique, similar (e.g. generic versus brand-name drugs, different timings of administration, varying dosages), and identical medications not requiring reconciliation. Each column is dedicated to a source of the lists (as seen in Figure 22.3, showing intake versus hospital medication records). As a physician views the animation process, he or she can select between the medications that are similar and indicate to the system which medications


**FIGURE 22.3**

Twinlist screen.

(and their formulation, instructions, etc.) should be included in the final list. Visual indicators such as color coding highlight the medications that have been reconciled. Through this design, Twinlist seeks to improve the speed and accuracy of medication reconciliation by supporting the cognitive needs of the users.

### 22.5.1 Situation awareness

Situation Awareness (SA) is a theory that evolved out of the aviation industry and military decision making and is used to understand decision making and error. Endsley (Endsley, 1995) describes situation awareness as *the perception of the elements in the environment in a volume of time and space, the comprehension of their meaning, and the projection of their status in the near future*. These components are linked to different levels of decision making, as they exist under the influence of task or system factors. Taken together, the distributed system and the situation awareness of individuals within it contribute to quality of decision making. In health care, this framework has been applied and extended (Singh et al., 2006) to four levels: information perception, information comprehension, forecasting of future events, and choosing appropriate action (resolution) based on the first three levels. Understanding current circumstances "what's going on" while projecting to "what's next" is critical to this fourth level of decision making. Gaps in SA can lead to error; as Singh et al. (Singh et al., 2006) points out, there are many levels at which situation awareness may falter, and missing situational understanding can be propagated throughout the distributed team. Failures leading to compromised SA have focused on misperception, shortcuts in reasoning and factors such as fatigue, stress or interrupted workflow (Woodward, 2010; Yule et al., 2008). Improving situation awareness as a means of improving safety and care has been embraced by anesthesiology (Fioratou et al., 2010) and in operating rooms (Parush et al., 2011), and SA has been deemed a critical human factors topic for patient safety by the World Health Organization (World Health Organization, 2009).

Information dashboards are one way in which improving situation awareness has been approached in health care. Dashboards have become important business intelligence tools for many industries (Few, 2006), and similar information systems arising from whiteboards and later electronic boards are seen in diverse settings from emergency care (Aronsky et al., 2008) to labor and delivery (Simms et al., 2013). The intent of such systems includes facilitating group communication and team situation awareness (Parush et al., 2011), efficiency (France et al., 2005), general care, and administrative processes such as bed location monitoring (Aronsky et al., 2008). One of the intents of such systems is to externalize some of the demands placed on clinicians to recall the details regarding all patients under their care.

For example, a dashboard in the Emergency Department might display a patient identifier, location or room of the patient, chief complaint, clinical team caring for the patient, status of treatment and testing as well as measures such as length of stay in the unit and the time elapsed from bed assignment to seeing a provider.

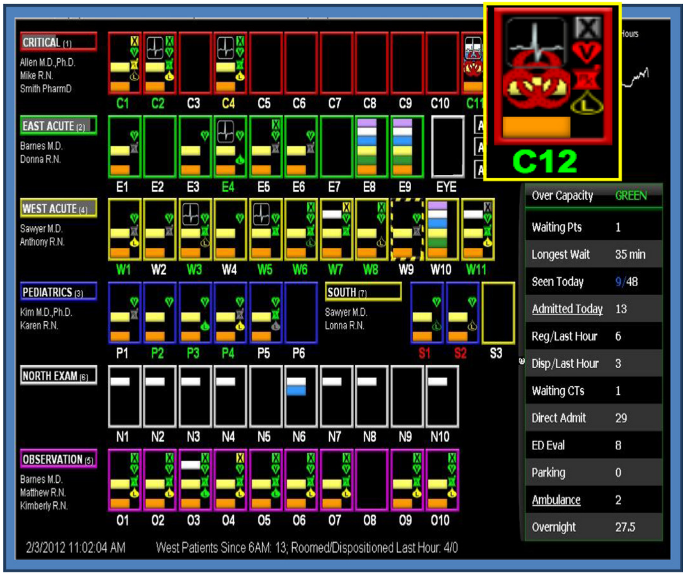


**FIGURE 22.4**

Patient locator board used in a large (50+ bed) emergency department (the Yes-Board application in use in Mayo Clinic, Arizona, courtesy of Vernon D. Smith, MD, Mayo Clinic). Shown are key personnel working in each area (names are fictitious), room occupancy, patient deterioration warnings, departmental metrics and messages. Icons indicating each of these types of information are portrayed in color on the actual dashboard, and/or flashing based on urgency. The inset shows a close-up of a room showing location name (C12), availability and criticality of testing results (X-Ray,V-itals,Rx-Orders,L-abs), ongoing monitoring (QRS Complex) and patient status (Biohazard).

The intent of these systems is to help clinicians manage patient care, maximize ER throughput, and make appropriate selections in their course of action based on needs at that time. Dashboards can also be used to highlight at-risk patients by indicating changes in vital signs, lab results or other critical values as shown in Figure 22.4. Shifting demands in the environment, such as forecasting overcrowding conditions or a need for diversion can also be improved through displays that increase the situation awareness of clinicians regarding bed availability, wait times, patient needs, staffing conditions, and trends such as patients leaving without being seen. Additionally, communication demands are eased through increased information available on such systems such as the status of labs or patient dispositions. Dashboards and other electronic information sources have been proven to increase patient throughput (Farley et al., 2013) and improve individual task completion times (Koch et al., 2013).

### 22.5.2 Data aggregation

The development of such support systems has the potential to improve decision making, reduce memory burden, and improve the quality of care. For example, one way quality may be improved is to bolster the performance of trainees so that they function more like experts. Patel et al. (Patel and Groen, 1991) suggest that the process of clinical comprehension differs between expert and novice clinicians with respect to selective filtering, pattern recognition, and accuracy of inferences generated. Experts use knowledge structures called *intermediate constructs* that represent clinically meaningful clusters of observations that lead toward specific diagnoses. In contrast, although non-experts may possess a large knowledge base, they tend to be less organized. Information aggregation *built into the system* can provide information to end users at an *intermediate* rather than raw level. For example the Psychiatric Clinical Knowledge Enhancement System (PSYCKES) (Cohen et al., 2004) presents information at the level of intermediate constructs through clusters of relevant information. This has been shown to lead to improved comprehension by residents when compared to current nonaggregated practice (Dalai et al., 2013).

Such aggregation and presentation of information to clinicians at the right time and in the right format underlies efforts in clinical summarization. Ranging from discharge summaries to daily progress notes, patient handoffs at change of shift, and oral case presentations, there are a variety of efforts to generate, automate, and standardize tools to improve information exchange while reducing data loss or gaps (Stelfox et al., 2013; Abraham et al., 2013).

The ***AORTIS*** model of Feblowitz et al. (2011) provides a conceptual model for the process of clinical summarization and provides a framework for various types of clinical summaries along with methods that could be employed to shift from human- to machine-generated summaries. AORTIS has five stages; Aggregation, Organization, Reduction and Transformation, Interpretation, and Synthesis. Methods such as this for data management and summarization have the potential to reduce the cognitive burden on clinicians and to improve safety. Figure 22.5 illustrates an automated clinical summary built through AORTIS concepts. Annotations seen here indicate information types and additional drill-downs into other aspects of the patient record. In this snapshot, clinicians are provided with a synthesized and aggregated overview of patients' problems, history, and health over time. Like the Twinlist interface above, human cognition's abilities as well as limitations have been taken into consideration in the design of this system. Relevant information is presented in a format that is easy to scan, color is used to increase recognition of abnormal values, and additional information is available with additional exploration of the system.

### 22.5.3 Visualization

At the heart of all these support tools is the need for information visualization. Better visualization is one way to improve the understanding of complex data, and consequently increase the value of electronically available medical data (Chittaro, 2001).

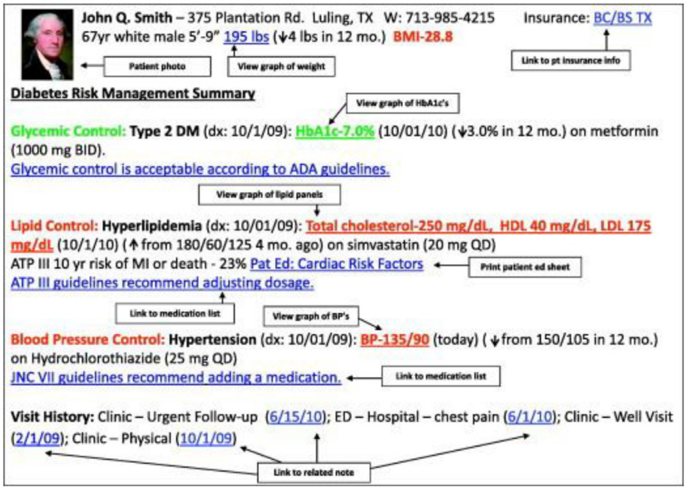


**FIGURE 22.5**

AORTIS automated clinical summary (Feblowitz et al., 2011).

The goal of visualization tools it to "provid[e] visual representations of datasets intended to help people carry out some task more effectively (Munzner, 2011)." This includes both the cognitive activity of building mental models through visualization (Spence, 2007) and visualization's ability to "amplify cognition" (Card et al., 1999). Rind et al. (Rind et al., 2010) provide an overview of the state of the art in information visualization systems for exploring and querying EHRs.

## 22.6 Summary

Many health care activities occur in collaborative team environments involving clinicians, patients, and a variety of groups. Health information technology has been developed at a rapid rate and implemented on a large scale. The integration of HIT into the collaborative health care team environment has been fundamentally changing the way health care is delivered. HIT has potential to improve the quality, efficiency, and safety of care in significant ways. However, in order to fully achieve these potentials, we need to address the new cognitive challenges brought by the introduction of HIT into the health care systems.

This chapter has discussed the cognitive and usability factors for such complex team environments by exploring the challenges brought about by human cognitive limitations and the unintended consequences of technology.

Next, we presented both the challenges and opportunities in a distributed cognition framework. Distributed cognition considers a HIT-enabled health team environment as a cognitive system that is distributed between people and technology, among individuals across space and time, and situated in social, physical, and organizational backgrounds. In order to fully understand the impact of HIT on such a distributed system, we need to understand not just the impact HIT has on the behaviors of individuals but also the behaviors of interactions between individuals and technology and among individuals, and the emergent behaviors of the system as a whole.

The TURF framework was introduced as a methodology to analyze the cognitive factors in distributed cognitive systems through analyses of the users, functions (ontology of work domain), representations (user interfaces), and tasks (task sequences or workflow across multiple individuals or between people and technology). Through the TURF-based cognitive analyses, information systems can be designed to address the cognitive challenges in such distributed systems.

Finally, the recent development and wide adoption of HIT, including EHR systems, health information exchange systems, and other systems, provides opportunities for tools that support cognition through the presentation and visualization of data in ways that support human processing, machine aggregation of information to not only manage the quantity of the data burden but also to provide cognitive support through pre-processing of information, and improvements of situation awareness for better decision making through dashboards and alert systems.

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