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Designing Human-Centered Distributed Information Systems

Jiajie Zhang, *University of Texas at Houston*
Vimla L. Patel, *Columbia University*
Kathy A. Johnson and Jack W. Smith, *University of Texas at Houston and NASA Johnson Space Center*
Jane Malin, *NASA Johnson Space Center*

Human-centered distributed information design methodology incorporates the theory of distributed cognition with the need for multiple levels of analyses in system design. This methodology provides systematic principles, guidelines, and procedures for designing human-centered computing systems.

Many computer systems are designed according to engineering and technology principles and are typically difficult to learn and use. The fields of human-computer interaction, interface design, and human factors have made significant contributions to ease of use and are primarily concerned with the interfaces between systems and users, not with the structures that are often more fundamental for designing truly human-centered systems. The emerging paradigm of human-centered computing (HCC)—which has taken many forms—offers a new look at system design.

HCC requires more than merely designing an artificial agent to supplement a human agent. The dynamic interactions in a distributed system composed of human and artificial agents—and the context in which the system is situated—are indispensable factors. While we have successfully applied our methodology in designing a prototype of a human-centered intelligent flight-surgeon console at NASA Johnson Space Center, this article presents a methodology for designing human-centered computing systems using electronic medical records (EMR) systems.

Distributed cognition

We base our human-centered computing perspective on the theory of distributed cognition.[1–9] According to this theory, people behave in information-rich environments filled with natural objects, artificial objects, and agents, whether human or nonhuman. This environment, according to the theory, is grounded in elaborate social and cultural structures. In everyday life, people must process information derived from human agents, artificial agents, and groups of agents. It is the interwoven processing of such information that generates intelligent behavior.

Distributed cognition considers human and artificial agents to be indispensable components of a single distributed system.[5] Human activities in concrete situations are guided, constrained, and even determined by the physical and social context in which they operate.[9,10] One study has argued that the properties of a distributed cognitive system consisting of a group of human agents interacting with complex systems—in an airplane cockpit or the control room of a ship—can differ radically from the properties of the components, and they cannot be inferred from the properties of the components alone, no matter how detailed the knowledge of the properties of those components might be.[1,11]

The theory of distributed cognition makes three major claims:

- The unit of analysis is the system composed of human and artificial agents.
- The pattern of information distribution among human and artificial agents can radically change the behavior of the distributed system.
- The behavior of a distributed system should be described by the information flow dynamics.

One research project described a similar system as *the triples rule*, which states that the unit of analysis for cognitive engineering and computer science is a triple composed of person, machine, and context.[12]

The goal of a traditional approach is to make user interfaces transparent so users can completely engage

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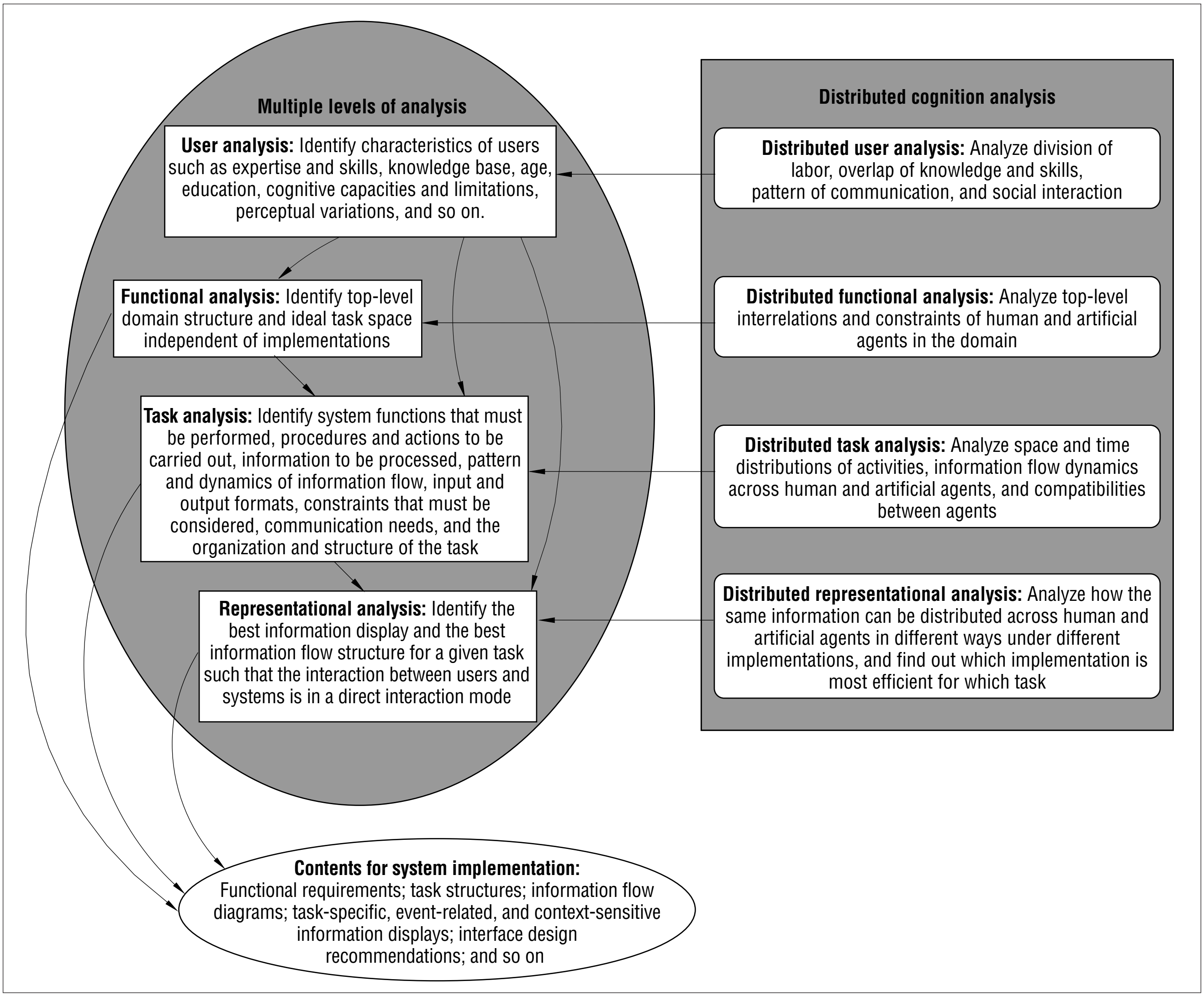

Figure 1. The methodology of human-centered distributed information design. Each of the four distributed analyses contributes to its corresponding analysis on the left. The component at the bottom represents the product of functional, task, and representational analyses. For each level of analysis, our general methodology lets us employ several alternative, specific methods.

in their primary tasks. With transparent interfaces, users directly interact with the system. However, user-friendly interfaces are far from sufficient as a design goal. In our methodology, user-friendly interfaces are only one of four levels of analysis. The three other levels—functions, tasks, and users—are just as important. For example, an excellent user-friendly interface might be irrelevant if the task the interface supports is not the task the user performs.

Design methodology

Our methodology, called human-centered distributed information design (HCDID), incorporates the theory of distributed cognition with the need for multiple levels of analyses in system design. We developed this methodology to provide systematic principles, guidelines, and procedures for designing HCC systems. We selected electronic medical records systems to demonstrate our methodology because HCC is almost nonexistent in EMR systems.

EMR systems are highly complex, distributed information systems that, with proper human-centered design, have the potential to improve the quality of health care dramatically. The lack of even minimum considerations of HCC design principles in most current EMR systems makes them very difficult to learn and use. In turn, this difficulty leads to strong resistance by physicians, and in some cases it leads to abandoning EMR systems altogether. The EMR system we discuss here is not a specific system. Rather, it is a collection of EMR systems that are currently on the market.

Figure 1 shows the HCDID methodology, which consists of three major components. The components on the left are multiple levels of analyses for single-user, human-centered design. The functional, task, and representational analysis levels have degrees of abstraction—with the level of functional analysis most abstract and the level of representational analysis most concrete. The user-analysis level contributes to each of the levels of functional, task, and representational analysis. The components on the right represent the additional analysis needed for designing distributed human-centered systems.

User analysis

User analysis provides user information to the functional, task, and representational analyses. User analysis is the process of identifying user characteristics, such as expertise, skill, knowledge, educational background, cognitive capacity, and so forth. User analy-

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sis is necessary for designing systems that have an information structure that must match user knowledge levels.

For an EMR system, different users operate different system components. These users include installers, maintainers, administrators, nurses, physicians, registration personnel, laboratory technicians, billing staff, and patients. Different users will have different levels of understanding when it comes to the same component of the system.

Researchers have written about the importance of technology in shaping cognitive activity and the impact of cognition on technology design.[13] These studies show that using EMR systems requires several changes in physicians' and trainees' information-gathering and reasoning strategies. For example, there are differences in the content and organization of information, with paper records organized according to a narrative structure and computer-based records organized according to discrete items of information. This difference in knowledge organization results in different data-gathering strategies, where the doctor-patient dialogue is cognitively influenced by the structure of the EMR system.

For distributed human–computer systems, it is critical to analyze users' group properties, such as division of cognition and activity, overlap of knowledge and skills, communication channels, social status, and so on. For example, whether two human agents are better than one human agent often depends on the overlap of knowledge and skills. The ways in which effort is distributed across a group of human agents can significantly affect the outcome of a task.

A recent study shows the importance of proper user analysis for EMR systems.[14] Nurses and physicians—who have partially overlapping knowledge bases, skills, experiences, and job responsibilities—rely on different patient strategies that can lead them to different understandings, diagnoses, and subsequent activities. Another study characterized the qualitative nature of team interaction and its relationship to training health professionals in a primary care unit in a Boston hospital.[15] This study showed that the demarcation of responsibilities and roles of personnel within the team can become fuzzy.

The nature of the individual expertise required was a function of the patient problem and the interaction goal. Team characteristics often contribute to reduction of unnecessary and redundant interactions. Distributed responsibilities let the team process massive amounts of patient information, which reduces individual cognitive loads. Individual expertise contributes to accomplishing team goals, although team performance shows a completely different structure.

You can obtain user information with indirect or direct methods. With direct methods, you would collect the information from the users with surveys, questionnaires, field visits, focus groups, interviews, or any of several ethnographic observation techniques. With indirect methods, you collect the information from other sources, such as textbooks, handbooks, protocols, procedures, job descriptions, operation rules, and other training and education materials.

One important function of task analysis is ensuring that the system implementation includes only the necessary and sufficient task features that match user capacity and are required by the task.

Functional analysis

Functional analysis is the process of identifying critical top-level domain structures—goals that can be largely independent of implementations. Functional analysis is more abstract than task and representational analyses because it does not involve details of task processes and representation. In other words, functional analysis is similar to traditional requirements analysis. Work domain analysis (which focuses on the structures of a work domain) and cognitive work analysis (which focuses on cognitive activities in the work domain) are two of the methodologies that can help in conducting functional analysis. For a distributed system, functional analysis also identifies a system's artificial and human agents, their interrelations and constraints, and their essential roles. For a knowledge-rich domain such as medicine or aviation, functional analysis requires the acquisition of detailed domain knowledge and a deep understanding of domain structures.

Consider one of the products of doing a functional analysis for an EMR system. An ideal EMR should be able to support the following functions: data, alerts, reminders, schedules, clinical decision support, medical knowledge, communication, and other aids. These functions should be complete, accurate, and timely. These functions should also be available for all types of health-care professionals. Furthermore, these functions should be available at all times and at all points of care. The ideal EMR should overcome the known problems associated with paper-based records but still provide that kind of functionality. Finally, and most importantly, an ideal EMR should be able to improve the quality of health care.

A distributed functional analysis of EMR can show the variety of artificial and human agents and their interrelations. Examples of artificial agents include various modules within EMR, such as patient record module, alert module, decision-support module, and communication module. Examples of human agents include physicians, nurses, laboratory technicians, and registration staff. An example of the interrelations between artificial and human agents is a mapping that shows which artificial agent supports which human agent, and to what degree.

Task analysis

Task analysis is more concrete than functional analysis because it involves specific task structures and procedures. However, it is still more abstract than representational analysis because it does not involve the details of how information is represented. Task analysis is a critical component in cognitive systems engineering and usability engineering. It consists of the process of identifying system functions, task procedures, input and output formats, constraints, communication needs, organization structures, information categories, and task information flow.

One important function of task analysis is ensuring that the system implementation includes only the necessary and sufficient task features that match user capacity and are required by the task. Fancy features—and features that do not match user capacity or are not required by the task—might only generate additional processing demands for the user, and thus make the system harder to use. But avoiding unnecessary features does not mean excluding adaptation mechanisms that dynam-

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ically adjust the interactions between users and tasks in changing contexts.

Hierarchical task analysis, which is the basic method for revealing the structure of any task that has goals and subgoals, describes a task in terms of a hierarchy of operations by using a graphical representation. Hierarchical task analysis decomposes a high-level task into its constituent subtasks and operations, and is essential for any system consisting of both human and artificial agents. This type of analysis typically shows the big picture of the task components and the relations among them. It also takes into account both physical and mental activities.

The theory of distributed representations is the foundation for the analysis of the distribution of information patterns among human and artificial agents.[5,6] Human agents interact with each other and with artificial agents synchronously and asynchronously—at one place and at different places. The analysis of locations and activities can reveal how tasks are distributed across space and over time.

One study demonstrated this type of analysis on more than 20 medical personnel, who interacted over the Internet and through conference calls over a period of two years. The purpose of the study was to develop software that could be used in any hospital system.[16] Information flow analysis can help analyze how the information gets propagated and transformed among human and artificial agents. Distributed task analysis, by the same token, can reveal critical task structures that cannot be identified by conventional task analysis, which focuses on a single individual's interaction with a system.

Task analysis can help identify task structures, interaction among procedures, and information flow. For example, task analysis can identify overlooked tasks, relative task importance, overlapping task information, function groups, relation to user analysis, and so on. It can also help pinpoint task bottlenecks where special design requirements come into play. Another product of task analysis is a taxonomy based on information-processing needs. For example, there are information tasks for retrieval, gathering, seeking, encoding, transformation, calculation, manipulation, comparison, organization, navigation, and so on. Identifying different information-processing needs is essential for the creation of task-specific, context-sensitive, and event-related information displays.

A systematic and comprehensive task analysis of an EMR system is out of reach for any individual or even a small research group. However, it is essential for designing a new EMR system or redesigning an existing EMR system to make it human-centered. Commitment from a large institution is essential for a comprehensive task analysis. We have carried out preliminary task analysis of several small components of EMR systems. For example, one analysis showed that writing a prescription using an EMR system requires more steps and much more time than writing a paper prescription, although the mental effort required is less for EMR than for paper prescription writing.

Additionally, performing a hierarchical task analysis to identify an EMR system's underlying data structure can help pinpoint some fundamental problems. For example, one study showed that current EMR systems use one of two data structures, neither of which is driven by human-centering.[13] One EMR data structure, for example, uses a hierarchical data model to capture information used by specific applications. It is primarily a patient-record system added onto a billing system. The other data structure makes extensive use of an event-based approach by recording information according to a time-oriented view to facilitate its reuse by multiple applications. Unfortunately, these two data structures do not support the daily tasks of health-care professionals, so they are not human-centered. A typical daily task, such as making a diagnosis, is better supported by an EMR system that organizes information around problems.

> Distributed task analysis can show crucial interactions among human and artificial agents and can provide an understanding of these interactions for designing according to human-centered principles.

Because EMR systems are used by many types of people—synchronously and asynchronously, and at the same or different locations—a distributed task analysis can show crucial interactions among human and artificial agents and can provide an understanding of these interactions for designing according to human-centered principles. To our knowledge, very little analysis of this type has been done for EMR systems.

Representational analysis

Functional analysis and task analysis deal with system functions, structures, and processes, whereas representational analysis deals with the interface between systems and users. Representational analysis is based on a robust phenomenon called *representational effect*,[5] in which different representations of a common abstract structure or process can generate dramatically different representational efficiencies, task difficulties, and behavioral outcomes.

The form of a representation can influence and sometimes determine what information can be easily perceived, what processes can be activated, and what information can be derived from the representation. For a complex or novel task, some portion of the task space might never be explored, and some structures of the task might never be discovered without a change in representation. Representational analysis can be performed on system properties that are identified through functional and task analysis. With direct-interaction interfaces, users can efficiently engage in the primary tasks they intend to perform. And they can avoid the interface housekeeping tasks that typically act as barriers between users and systems.

Representational analysis can help systematically generate innovative ideas for data displays and information for exploration, evaluation, and selection. This type of analysis works through developing a taxonomy of displays and tasks, and through mapping principles between displays and tasks. Researchers have applied representational analysis to relational information displays and even cockpit instrumentation. A representational taxonomy of relational information displays, when combined with a task taxonomy from task analysis, can systematically determine the best display format for a specific task.

Representational analysis can help identify alternative displays for each task in the taxonomy of information-processing needs and can also help determine the best match between a display and a task for each unique event under each unique situation. This type of analysis then determines the mapping between a display and a task with a mapping principle: the display should carry exact information for the task, no

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more and no less. The task-specific, context-sensitive, and event-related displays are basic elements for implementing HCC systems.

Medical records can be organized and displayed in different ways in EMR systems. Source-oriented displays present data organized by the data source, such as lab reports, radiology reports, or physical examinations. Concept-oriented displays group data according to clinical problems. For example, a concept-oriented display for abdominal pain might present history, radiology reports, blood tests, and assessments in a single display.

Medical data can also be organized and displayed along timelines and according to different processes. Several studies have found that different types of displays are good for different tasks and that no single type of display is good for all tasks for all users. This finding is the mapping principle between tasks and representations. Empirical findings are certainly important, but it is neither practical nor necessary to conduct empirical testing for every system component.

The representational analysis, which is based on established theories, principles, and generalizable empirical regularities, can offer more than the empirical studies. When combined with task, user, and functional analyses, representational analysis can systematically generate human-centered displays and tasks for several users, which is essential for designing human-centered EMR systems.

The products generated from our HCDID methodology are the contents for implementing human-centered distributed computing systems. Examples of these products are functional requirements, descriptions of task structures and procedures, specifications of information-flow dynamics, and ideas for task-specific, event-related, and context-sensitive information displays. Although other cognitive engineering methods might generate the same contents, HCDID offers unique perspective, principles, and procedures that are rooted in the theory of distributed cognition and an approach that requires multiple levels of analysis.

HCDID considers HCC not just at the levels of representations, but also at the levels of users, functions, and tasks. In many system designs thought to be human-centered, human-centered principles are mainly applied at the representation level. A poor display of a good task structure that has the same functions of the same domain might be much more efficient than an excellent display on a poor task structure of the same domain. Displays are also critically dependent on users. A good display for one user might be a poor display for a different user because of user variation. As a general principle in human-centered display design, there will be no ideal display for all users in every context.

We are in the process of evaluating our methodology. We plan to refine it to make designing any new distributed, human-computer system much easier.

The Authors

Jiajie Zhang is an associate professor at the University of Texas at Houston. His research interests include human-computer interaction, cognitive science and engineering, distributed cognition, and health informatics. He received a PhD in cognitive science from the University of California at San Diego. Contact him at the School of Health Information Sciences, Univ. of Texas, Houston, 7000 Fannin, Ste. 600, Houston, TX 77030; jiajie.zhang@uth.tmc.edu.

Vimla L. Patel is a professor of medical informatics and medical psychology at Columbia University. Her research interests include medical cognition, cognitive evaluation of human-computer interaction, collaborative health-care teams, and naturalistic decision making in critical-care environments. She received a PhD in educational psychology from McGill University in Montreal, Canada. Contact her at the Dept. of Medical Informatics, Columbia Presbyterian Medical Center, Vanderbilt Clinic 5, 622 West 168th St., New York, NY 10032-3720; patel@dmi.columbia.edu.

Kathy A. Johnson is an assistant professor at the University of Texas at Houston and the medical informatics lead at NASA Johnson Space Center. Her research interests include decision-support systems, intelligent tutoring systems, human-centered computing, and databases. She received a PhD in computer science from Ohio State University. Contact her at the School of Health Information Sciences, Univ. of Texas, Houston, 7000 Fannin, Ste. 600, Houston, TX 77030; kathy.a.johnson@uth.tmc.edu.

Jane Malin is the technical assistant to the branch chief in the Intelligent Systems Branch at NASA Johnson Space Center. Her research interests include human-centered computing, methods for engineering advanced support software, autonomous monitoring, control agents, and intelligent modeling and simulation. She received a PhD in experimental psychology from the University of Michigan. Contact her at Mail Code ER2, NASA Johnson Space Center, Houston, TX 77058-3696; jane.t.malin1@jsc.nasa.gov.

Jack W. Smith is a professor at the University of Texas at Houston, and the deputy director of medical informatics and health-care systems at NASA Johnson Space Center. His research interests include modeling problem-solving in health care, the representations of knowledge for automating these processes, and the application of cognitive science to the understanding of human–computer interaction. He received an MD in clinical pathology from West Virginia University Medical School and a PhD in computer science from Ohio State University. Contact him at the School of Health Information Sciences, Univ. of Texas, Houston, 7000 Fannin, Ste. 600, Houston, TX 77030; jack.w.smith@uth.tmc.edu.

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