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43

Cognitive Task Analysis

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CONTENTS

Introduction	578
Types of Cognitive Task Analysis Currently in Use	579
Cognitive Task Analysis Families	579
Varieties of CTA Methods and Their Applications	579
Collect Preliminary Knowledge	580
Document Analysis	580
Observations	580
Unstructured Interviews	580
Identify Knowledge Representations	580
Learning Hierarchy Analysis	581
Apply Focused Knowledge Elicitation Methods	581
Concepts, Processes, and Principles	581
Critical Decision Method	582
Analyze and Verify Data Acquired	582
Format Results for the Intended Application	582

Current Research Evidence for the Impact of Cognitive Task Analysis	583
Declarative Knowledge and CTA	583
Procedural Knowledge and CTA	584
Cues	584
Decision Points	585
Cognitive Skills	585
Instructional Evidence	586
Generalizability of CTA-Based Training Benefits	586
Cost–Benefit Studies of CTA	586
Integrating Cognitive Task Analysis and Training Design	587
Optimal Integration of CTA and Training Design	587
Learning Tasks	587
Supportive Information	587
Just-in-Time information	588
Part-Task Practice	588
Cognitive Task Analysis and 4C/ID Model	588
Decomposition of the Complex Skill	588
Sequencing Task Classes	588
Analyze the Nonrecurrent Aspects of the Complex Skill	588
Analyze the Recurrent Aspects of the Complex Skill	589
The Next Generation of Research on Cognitive Task Analysis	589
First Principles of Cognitive Task Analysis	589
Research on Automated, Unconscious Expert Knowledge	590
Cost Effectiveness and Cost–Benefit Research	590
Conclusion	591
References	591

ABSTRACT

This chapter presents an overview of the current state of cognitive task analysis (CTA) in research and practice. CTA uses a variety of interview and observation strategies to capture a description of the explicit and implicit knowledge that experts use to perform complex tasks. The captured knowledge is most often transferred to training or the development of expert systems. The first section presents descriptions of a variety of CTA techniques, their common characteristics, and the typical strategies used to elicit knowledge from experts and other sources. The second section describes research on the impact of CTA and synthesizes a number of studies and reviews pertinent to issues underlying knowledge elicitation. In the third section, we discuss the integration of CTA with training design. Finally, in the fourth section, we present a number of recommendations for future research and conclude with general comments.

KEYWORDS

Automated knowledge: About how to do something; with repetition, it operates outside of conscious awareness and executes much faster than conscious processes.

Cognitive task analysis: Interview and observation protocols for extracting implicit and explicit knowledge from experts for use in instruction and expert systems.

Complex tasks: Tasks where performance requires the integrated use of both controlled and automated knowledge to perform tasks that often extend over many hours or days.

Declarative knowledge: Knowledge about what or why; hierarchically structured; formatted as propositional, episodic, or visuospatial information that is accessible in long-term memory and consciously observable in working memory.

Subject-matter expert (SME): A person with extensive experience who is able to perform a class of tasks rapidly and successfully.

INTRODUCTION

Cognitive task analysis is the extension of traditional task analysis techniques to yield information about the knowledge, thought processes and goal structures that underlie observable task performance. [It captures information about both] ... overt observable behavior and the covert cognitive functions behind it [to] form an integrated whole. (Chipman et al., 2000, p. 3)

Cognitive task analysis (CTA) uses a variety of interview and observation strategies to capture a description of the knowledge that experts use to perform complex tasks. Complex tasks are defined as those for which their performance requires the integrated use of both controlled (conscious, conceptual) and automated (unconscious, procedural, or strategic) knowledge to perform tasks that often extend over many hours or days (van Merriënboer et al., 2002). CTA is often only one of the strategies used to describe the knowledge required for performance. It is a valuable approach when advanced experts are available who reliably achieve a desired performance standard on a target task and the goal is to capture the cognitive knowledge used by them (Clark and Estes, 1999). Analysts use CTA to capture accurate and complete descriptions of cognitive processes and decisions. The outcome is most often a description of the performance objectives, equipment, conceptual knowledge, procedural knowledge, and performance standards used by experts as they perform a task. The descriptions are formatted so they can be used as records of task performance and to inform novices in a way that helps them achieve the performance goals in any context. CTA is most often performed before (or as an integral part of) the design of instruction, work, job aids, or tests. The descriptions are then used to develop expert systems, tests to certify job or task competence, and training for acquiring new and complex knowledge for attainment of performance goals (Chipman et al., 2000; Jonassen et al., 1999).

TYPES OF COGNITIVE TASK ANALYSIS CURRENTLY IN USE

Researchers have identified over 100 types of CTA methods currently in use, which can make it difficult for the novice practitioner to choose the appropriate method (Cooke, 1994). The number and variety of CTA methods are due primarily to the diverse paths that the development of CTA has taken. It has origins in behavioral task analysis, early work in specifying computer system interfaces, and in military applications—each with its own demands, uses, and research base. Over the past 20 years, CTA has been increasingly informed by advances in cognitive science and has become an important component for the design of systems and training in many domains. The growing body of literature describing CTA methods, applications, and results mirrors the diverse application and development of CTA methods; however, reviews and classifications are available to guide those interested in exploring and applying CTA, including a comprehensive review of reviews provided by Schraagen et al. (2000).

Cognitive Task Analysis Families

Cooke (1994) conducted one of the more extensive reviews of CTA. She identified three broad families of techniques: (1) observation and interviews, (2) process tracing, and (3) conceptual techniques. Observations and interviews involve watching experts and talking with them. Process tracing techniques typically capture an expert's performance of a specific task via either a think-aloud protocol or subsequent recall. In contrast, conceptual techniques produce structured, interrelated representations of relevant concepts within a domain.

Cooke's (1994) three families of techniques differ in terms of their specificity and formality. Generally, observations and interviews are informal and allow knowledge elicitors much flexibility during elicitation. Process tracing methods have more structure and specificity, although some analysis decisions are left to the elicitor. Conceptual techniques are well specified and formal, with few judgments on the part of the elicitor. As a further comparison, more formal methods require greater training on the mechanisms and produce more quantitative data compared to the informal methods, which focus on interview skills and generate qualitative output. Because different techniques may result in different aspects of the domain knowledge, Cooke recommends the use of multiple methods, a recommendation often echoed throughout the CTA literature (Ericsson and Simon, 1993; Russo et al., 1989; Vosniadou, 1994).

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Wei and Salvendy's (2004) review of CTA methods introduced a fourth family—formal models—which uses simulations to model tasks in the cognitive domain. Their review further differs from others in that they provided practical guidelines on how to use the classifications of CTA methods to select appropriate techniques to accomplish various objectives. One guideline, for example, suggests that when tasks or jobs do not have a defined domain, observations and interviews are especially useful in the initial phase of CTA to generate a more explicit context and identify boundary conditions.

VARIETIES OF CTA METHODS AND THEIR APPLICATIONS

These reviews provide a starting point to explore the numerous varieties of CTA methods and their applications. We examine the overall CTA process and describe in depth some methods that have particular application to instructional design. Although there are many varieties of CTA methods, most knowledge analysts follow a

five-stage process (Chipman et al., 2000; Clark, 2006; Coffey and Hoffman, 2003; Cooke, 1994; Crandall et al., 2006; Hoffman et al., 1995; Jonassen et al., 1999). The five common steps in most of the dominant CTA methods are performed in the following sequence:

- Collect preliminary knowledge.
- Identify knowledge representations.
- Apply focused knowledge elicitation methods.
- Analyze and verify data acquired.
- Format results for the intended application.

The following sections contain descriptions of common CTA methods and brief explanations of each type as it is used during each stage of the general process.

Collect Preliminary Knowledge

In this initial stage, the analyst identifies the sequence of tasks that will become the focus of the CTA. Analysts attempt to become generally familiar with the knowledge domain and identify experts to participate in the knowledge elicitation process. Although knowledge analysts and instructional developers do not need to become subject-matter experts (SMEs) themselves, they should be generally familiar with the content, system, or procedures being analyzed. If possible, two or more subject-matter experts should be selected to participate in the process (Chao and Salvendy, 1994; Lee and Reigeluth, 2003). Although specific criteria for identifying experts may change depending on circumstances,* all SMEs must have a solid record of successful performance at the tasks being analyzed. Experts are most often interviewed separately to avoid premature consensus regarding the knowledge and skills necessary for effective performance. Techniques typically used during this phase include document analysis, observation, and interviews (structured or unstructured). The analyst uses the results of this stage to identify the knowledge types and structures involved in performing the tasks.

Document Analysis

Analysts often begin their reviews by collecting any available written resources describing the tasks and related subject matter. This can include a wide variety of documents, such as promotional literature, bro-

chures, manuals, employee handbooks, reports, glossaries, course texts, and existing training materials. These documents are analyzed for orientation on the tasks, preparation of the in-depth analysis, and confirmation of preliminary ideas (Jonassen et al., 1999). This orientation prepares analysts for subsequent task analysis activities; for example, the information elicited during structured interviews may be more robust when analysts are already familiar with experts' terminology. Documentation analysis also allows comparison of existing materials on a procedure with accounts of expert practitioners to identify any immediate discrepancies between doctrine and typical implementation.

Observations

Observation is one of the most frequently used and most powerful tools of knowledge elicitation. It can be used to identify the tasks involved, possible limitations and constraints for subsequent analysis, and available information necessary to perform the task. It also allows analysts to compare an expert's description of the task with actual events. In many CTA systems, analysts will unobtrusively observe experts while they are performing the tasks under examination to expand their understanding of the domain. Analysts observe and record the natural conditions and actions during events that occur in the setting (Cooke, 1994). Although definitive identification of an expert's mental operations cannot be accomplished through observation, analysts may note the occasions on which it seems that experts must make decisions, assess situations, or engage in analysis.

Unstructured Interviews

"The most direct way to find out what someone knows is to ask them" (Cooke, 1999, p. 487). In addition to observation, unstructured interviews are also common early in the CTA process to provide an overview of the domain and to raise issues and questions for exploration in subsequent structured interviews. In unstructured interviews, analysts may not dictate the content or sequence of conversation. In other instances, however, they may ask an expert to focus on a task, event, or case with instructions to "tell me everything you know about..."

Identify Knowledge Representations

Using the information collected during the preliminary stage, analysts examine each task to identify subtasks and types of knowledge required to perform the task. Most CTA approaches are organized around knowl-

* See extensive discussions of appropriate definitions of expertise and criteria for identifying experts in Cooke (1992), Dawes (1994), Ericsson and Smith (1991), Glaser and Chi (1988), Mullin (1989), and Sternberg and Horvath (1998).

edge representations appropriate for the task, such as concept maps, flow charts, semantic nets, and so forth. These representations provide direction and order to latter stages in the CTA process because knowledge elicitation methods map directly to knowledge types. Some are best used to elicit procedural knowledge, while others are more successful for capturing declarative knowledge (Chipman et al., 2000). A learning hierarchy is one example of a method to organize the types of knowledge required to perform a task.

Learning Hierarchy Analysis

A learning hierarchy analysis represents the content of skills ordered from more complex problem-solving skills at the top to simpler forms of learning (Gagné, 1962, 1968; Jonassen et al., 1999), so, for example, problem solving is followed by rule learning, which is followed by concepts. Thus, the basic idea is that people can only learn rules if they have already mastered the prerequisite concepts necessary to learn the rules. Analyzing a learning hierarchy begins by identifying the most complex (highest) learning outcome and then determining the underlying skills that must be mastered to achieve the target outcome. A hierarchy of skills is represented as a chart of tasks for each intellectual skill that is acquired to progress to increasingly complex skills. The learning hierarchy constructed at this stage of the CTA process provides the guide to structure the next stage of knowledge elicitation by identifying the information that must be captured from the SMEs. Thus, it reflects the reiterative nature of the CTA process, in which the details of the knowledge, skills, and cognitive strategies necessary for complex learning are revealed, refined, and confirmed.

Apply Focused Knowledge Elicitation Methods

During knowledge elicitation, the analyst applies various techniques to collect the knowledge identified in the prior stage. Past research indicates that different elicitation methods yield different types of knowledge and that knowledge is rarely articulated without being the focus of elicitation (Crandall et al., 2006; Hoffman et al., 1998). Analysts attempt to choose methods appropriate to the targeted knowledge type as determined by the knowledge representations identified for each task; consequently, most elicitation efforts entail multiple techniques. Among the many types of knowledge elicitation methods, variations of structured and semi-structured interviews are most commonly involved in CTA because they are relatively easy to use and require less training than more formal methods such as protocol analysis (Ericsson and Simon, 1993)

or the use of repertory grids (Bradshaw et al., 1993). It is the variation in these specific techniques that defines the major differences between specific CTA models. Although the methods may differ in focus, they share a common purpose in capturing the conditions and cognitive processes for necessary for complex problem solving. Following are descriptions of two CTA models that have been documented to effectively elicit experts' knowledge in a manner that is particularly effective for instruction (Crandall and Getchell-Reiter, 1993; Velmahos et al., 2004).

Concepts, Processes, and Principles

Gathering concepts, processes, and principles (CPPs) (Clark, 2004, 2006) involves a multi-stage interview technique that captures the automated and unconscious knowledge acquired by experts through experience and practice. Multiple SMEs describe the same procedure, followed by cycles of expert self-review and peer review. The initial, semi-structured interview begins with a description of the CTA process by the analyst. The SME is then asked to list or outline the performance sequence of all key subtasks necessary to perform the larger task being examined. SMEs are also asked to describe (or help the interviewer locate) at least five authentic problems that an expert should be able to solve if they have mastered the task. Problems should range from routine to highly complex whenever possible. The resulting sequence of tasks becomes the outline for the training to be designed or the job description produced after the CTA is completed. Starting with the first subtask in the sequence, the analyst asks a series of questions to collect:

- The sequence of actions (or steps) necessary to complete the subtask
- The decisions that have to be made to complete the subtask, when each must be made, the alternatives to consider, and the criteria used to decide among the alternatives
- All concepts, processes, and principles that are the conceptual basis for the experts' approach to the subtask
- The conditions or initiating events that must occur to start the correct procedure
- The equipment and materials required
- The sensory experiences required (e.g., the analyst asks if the expert must smell, taste, or touch something in addition to seeing or hearing cues in order to perform each subtask)
- The performance standards required, such as speed, accuracy, or quality indicators

The interview is repeated for each SME; each interview is recorded and transcribed verbatim for later analysis.

Critical Decision Method

The critical decision method (CDM) (Klein et al., 1989) is a semi-structured interview method that uses a set of cognitive probes to determine the bases for situation assessment and decision making during critical (nonroutine) incidents (for a full procedural description, see Hoffman et al., 1998). CDM is based on the concept of expert decision making as the recognition of cue patterns in the task environment without conscious evaluation of alternatives; thus, situational awareness plays a dominant role in experts' selection of courses of action. The speed with which such decisions are made suggests that experts unconsciously assess feasible goals, important cues, situational dynamics, courses of action, and expectancies. To elicit this knowledge, CDM uses a retrospective, case-based approach with elicitation occurring in multiple sweeps to gather information in progressively deepening levels of detail.

The technique begins by selecting a critical incident from the expert's task experience that was unusual in some way. The experts involved provide unstructured accounts of the incident, from which a timeline is created. Next, the analyst and the experts identify specific points in the chronology at which decisions were made. These decision points are defined as instances when other reasonable alternative courses of action were possible. The decision points are then probed further using questions that elicit: (1) the perceptual cues used in making the decision, (2) prior knowledge that was applied, (3) the goals considered, (4) decision alternatives, and (5) other situation assessment factors. The reports are recorded and transcribed verbatim.

Analyze and Verify Data Acquired

As noted above, CTA methods vary in structure, formality, and results. Because the knowledge elicitation techniques described here are less formal, they require that the analyst code and format the results for verification, validation, and applicability for use in their intended application. When conducting interviews with experts, practitioners recommend recording the interviews and transcribing them for review at a later time, rather than trying to take detailed notes during the interview, which may distract from the process. Transcripts may be coded to summarize, categorize, or synthesize the collected data.

Following coding, the formatted output is presented to the participating SMEs for verification, refinement, and revision to ensure that the representations of tasks and their underlying cognitive components are complete and accurate. Once the information in the formatted output has been verified or revised by the expert, the analyst should then compare it with the output of other experts to verify that the results accurately reflect the desired knowledge representation.

The analysis stage in CPP (Clark, 2004, 2006) begins with the analyst preparing a summary of the interview in a standard format that includes the task, a list of subtasks, and the conditions, standards, equipment, and materials required. For each subtask, the analyst then writes a procedure that includes each action step and decision step required to perform the task and gives the procedure to the SME to review. To verify the individual CTAs, the analyst gives each subject-matter expert's product to one of the other SMEs and asks that person to edit the document for accuracy and efficiency (that is, to determine the fewest steps necessary for a novice with appropriate prior knowledge to perform the task). In the final stage, the analyst edits the individual CTAs into one formatted description of how to accomplish all tasks. After final approval by the SMEs, this final, formatted document provides the information for the instructional design process. Clark (2006) provides the format of the protocol.

The critical decision method prescribes no single method for coding the transcripts that are transcribed verbatim from the recorded interviews, as each specific research question defines how the transcripts are coded (Klein et al., 1989). The coding scheme, however, should be domain relevant and have cognitive functionality; in other words, it should tag information that represents perceptual cues, decision points, and situational assessments. A sample of a coded protocol can be found in Hoffman and colleagues (1998).

Format Results for the Intended Application

The results of some highly structured CTA methods (e.g., cognitive modeling) are readily applied to expert systems or computer-assisted tutoring applications. For less formal CTA methods, such as those described here, the results must be translated into models that reveal the underlying skills, mental models, and problem-solving strategies used by experts when performing highly complex tasks. Further, these models inform the instructional design of curriculum, training and other performance applications. The concepts, processes, and principles (Clark, 2004, 2006) method generates a description of the conceptual knowledge, conditions, and a detailed list of the actions and decisions

necessary to perform a task. These products can be incorporated into an instructional design system. Similarly, products resulting from the application of the critical decision method have been used for a variety of instructional applications, including building and evaluating expert systems and identifying training requirements. CDM can provide case studies and information regarding which aspects of a task depend on explicit knowledge and which depend on tacit knowledge (Klein et al., 1989).

CURRENT RESEARCH EVIDENCE FOR THE IMPACT OF COGNITIVE TASK ANALYSIS

Modern CTA evolved from a behavioral approach to analyzing performance. As the understanding of occupational demands evolved from a focus on physical performance to a focus on cognitive performance, evidence suggested that key aspects of performance entailed knowledge that was not directly observable (Ryder and Redding, 1993; Schneider, 1985). Applications of behavioral task analysis to training resulted in incomplete descriptions that led to decision errors during job performance (Schraagen et al., 2000). Early versions of CTA were designed to capture the decisions and analyses that could not be directly observed as well as the deeper conceptual knowledge that served as the basis for analytical strategies and decisions (Clark and Estes, 1999). Thus, training shifted from the reinforcement of associations between perceptual stimuli and behaviors to the development of declarative and procedural knowledge.

Research evidence indicates that the accurate identification of experts' cognitive processes can be adapted into training materials that are substantially more effective than those developed through other means (Merrill, 2002; Schaafstal et al., 2000; Velmahos et al., 2004). When content is inaccurate or incomplete, any instruction based on that knowledge will be flawed (Clark and Estes, 1996; Jonassen et al., 1999). Such flaws interfere with performance and with the efficacy of future instruction (Lohman, 1986; Schwartz and Bransford, 1998). Resulting misconceptions resist correction, despite attempts at remediation (Bargh and Ferguson, 2000; Chinn and Brewer, 1993; Thorley and Stofflet, 1996).

Declarative Knowledge and CTA

Declarative knowledge is hierarchically structured, propositional, episodic, visuospatial information that is accessible in long-term memory and consciously

observable in working memory (Anderson, 1983; Anderson and Lebiere, 1998; Gagné et al., 1992). This type of knowledge supports performance through the conceptual understanding of processes and principles related to a task and the role that the task plays within its broader context (Gagné, 1982). SMEs possess extensive declarative knowledge of their domains in the form of principled frameworks of abstract, schema-based representations. These frameworks allow experts to analyze complex problems efficiently (Glaser and Chi, 1988; Zeitz, 1997). These elaborate schemas enable experts to retain and recall information, events, and problem states with a high degree of accuracy (Cooke et al., 1993; Dochy et al., 1999; Ericsson and Kintsch, 1995). Further, broad, principled understandings of their domains facilitate skill transfer to solve related novel and complex problems (Gagné and Medsker, 1996; Hall et al., 1995; van Merriënboer, 1997).

When communicated to novices, the organization of experts' knowledge also impacts training outcomes. In an examination of experts' instructions to novices, Hinds et al. (2001) found that trainees who received explanations from experts performed better on transfer tasks than trainees who received their explanations from non-experts. The experts provided explanations that were significantly more abstract and theoretically oriented than those of the non-experts, so learners in the expert-to-novice instructional condition were able to solve transfer problems more quickly and effectively than their counterparts in the non-expert-to-novice instructional condition.

Conceptual knowledge alone, however, is insufficient for generating effective performance. The non-expert instructors in the study provided more concrete, procedural explanations, which facilitated higher performance by trainees when they attempted to perform the original target task. The abstractions provided by the experts lacked key details and process information necessary for optimal performance. This finding is consistent with many others in the training literature, suggesting that the most effective learning occurs when all necessary information is available to the learner in the form of instruction and/or prior knowledge (for a review, see Kirschner et al., 2006).

Findings from a variety of studies indicate that without CTA to facilitate knowledge elicitation, experts in many fields unintentionally misrepresent the conceptual knowledge on which they base their performance. In a study by Cooke and Breedin (1994), for example, expert physicists attempted to predict the trajectories of various objects and provided written explanations of the methods by which they reached their conclusions; however, when the researchers

attempted to replicate the physicists' predictions on the basis of the explanations provided, they were unable to attain the same results. The calculated trajectories were significantly different from those provided by the experts.

In a similar study, expert neuropsychologists evaluated hypothetical patient profiles to determine their theoretical levels of intelligence (Kareken and Williams, 1994). Participants first articulated the relationships between various predictor variables (e.g., education, occupation, gender, and age) and intelligence. They then estimated IQ scores on the basis of values for the predictor variables they identified; however, their estimates differed significantly from the correlations they provided in their explanations of the relationships among predictor variables. Many were completely uncorrelated. Clearly, the experts' performance relied on processes that were very different from their declarative knowledge of their practice.

Procedural Knowledge and CTA

Procedural knowledge is required for all skilled performance. Skill acquisition often begins with learning declarative knowledge about discrete steps in a procedure; yet, the development of automaticity occurs as we practice those procedures. The automatization process involves learning to recognize important environmental cues that signal when the skill is to be applied and the association of the cues to the discrete covert (cognitive) and overt (action) steps required to attain a goal or subgoal (Neves and Anderson, 1981). Through practice, these associations and steps increase in reliability and speed of performance. Over time, the procedures require diminishing levels of mental effort or self-monitoring to perform until they utilize very few, if any, cognitive resources (Wheatley and Wegner, 2001). This consistent, repeated mapping of conditional cues and steps manifests as an integrated if-then decision rule between the cue (if) and the procedure (then) necessary to attain a goal from a particular problem state (Schneider and Shiffrin, 1977). This representation is a *production* within the ACT-R cognitive model of learning proposed by Anderson (Anderson, 1995; Anderson and Lebiere, 1998).

During complex tasks, multiple if-then productions are strung together to generate more sophisticated hierarchies of performances. Each individual production attains a subgoal that is a component of the overall goal. To move from one production to the next in a sequence, the new subgoal must be identified and an appropriate production selected. For novices, the identification and selection process for nearly every subgoal is a conscious, deliberate decision; however,

experts automate this process, so they cannot consciously identify many of these decision points (Blessing and Anderson, 1996).

Automaticity has two primary properties that limit the effectiveness of unassisted explanations by experts.* First, automated knowledge operates outside of conscious awareness, and executes much faster than conscious processes (Wheatley and Wegner, 2001). As such, it is not available for introspection or accurate self-monitoring. Second, automated processes are typically uninterrupted, so they cannot be effectively changed once they are acquired (Hermans et al., 2000); consequently, experts' unaided self-reports of their problem-solving processes are typically inaccurate or incomplete** (Chao and Salvendy, 1994; Feldon, 2004).

Cues

Each element of an if-then production has great importance for effective training. For learners to develop effective procedures, they must attend to relevant cues to determine correctly which subgoals and procedures are appropriate. Thus, incorporating experts' knowledge of these cues is important for optimal instruction (Fisk and Eggemeier, 1988; Klein and Calderwood, 1991). Crandall and Getchell-Reiter (1993), for example, investigated the procedural knowledge of expert nurses specializing in neonatal intensive care for newborn or premature babies. The participants were 17 registered nurses who averaged 13 years of overall experience and 8.1 years of specialization. Without a formal knowledge elicitation technique, they attempted to recall highly detailed accounts of critical incidents or measures they had implemented that they believed had positively influenced a baby's medical condition. After completing a free recall phase, the researchers used CTA to identify additional relevant information that the nurses did not articulate. Analysis of the transcripts revealed that the CTA probes elicited significantly more indicators of medical distress in the babies than were otherwise reported. Before CTA, the nurses' explanations of the cues they used were either

* The literature on expertise has not reached a consensus on the role of automaticity, however, much empirical evidence suggests that it plays a defining role. See Feldon (in press) for an extensive review. Until the article reaches publication, it can be found on the SpringerLink website under digital object identifier (DOI) 10.1007/s10648-006-9009-0. A prepublication draft can also be located at http://www.cogtech.usc.edu/recent_publications.php.

** When experts attempt to solve novel problems, the elements of their decision-making processes that are newly generated are less likely to be reported inaccurately; however, preexisting processes that were applied to those problems will continue to be subject to self-report errors (Betsch et al., 1998).

omitted or articulated vaguely as “highly generalized constellations of cues” (Crandall and Getchell-Reiter, 1993, p. 50).

Comparison of the elicited cues to those described in the available medical and nursing training literature of the time revealed that more than one third of the cues (25 out of 70) used by the expert nurses in the study to correctly diagnose infants were absent from that literature. These cues spanned seven previously unrecognized categories that were subsequently incorporated into standard training for novice nurses entering neonatal intensive care (Crandall and Gamblian, 1991).

Decision Points

In addition to knowing which cues are important for decision making, it is also necessary to correctly identify the points at which those decisions must be made. Much of the research on decision making suggests that many decisions are made prior to awareness of the need to make a decision (Bargh et al., 2001; Wegner, 2002). Abreu (1999) found that practicing psychotherapists evaluated fictitious case studies more negatively when they were primed with material about African-American stereotypes than when they rated the same information without priming. Similarly, when Bargh et al. (2001) subconsciously primed participants with goals of either cooperation or high performance, the actions of the participants in a variety of tasks typically conformed to the subliminal goal despite their being completely unaware of either the content of the prime or the fact that they held the goal itself.

In professions, automaticity presents significant problems for training if experts are relied upon to explain the points at which decisions must be made. In medicine, for example, studies of the reliability of diagnoses by expert physicians for identical symptoms presented at different times only correlated between .40 and .50 (Einhorn, 1974; Hoffman et al., 1968). Despite self-reports suggesting that the participants considered extended lists of symptoms, analysis of the symptoms in the cases presented indicated that only one to four symptoms actually influenced diagnosis decisions (Einhorn, 1974).

Some experts freely acknowledge that they are unable to accurately recall aspects of their problem-solving strategies. Johnson (1983) observed significant discrepancies between an expert physician's actual diagnostic technique and the technique that he articulated to medical students. Later, he discussed with the physician why his practice and his explanation differed. The physician's explanation for the contradiction was, “Oh, I know that, but you see, I don't know

how I do diagnosis, and yet I need things to teach students. I create what I think of as plausible means for doing tasks and hope students will be able to convert them into effective ones” (Johnson, 1983, p. 81).

Cognitive Skills

Correctly identifying and explaining the sequences of cognitive and psychomotor actions that are triggered by cues at decision points are likewise crucial to effective instruction. Although psychomotor aspects of a task are relatively simple for learners to observe, cognitive operations require articulation for a learner to successfully replicate an expert's performance; however, automaticity often impairs this process. As an example, a team of engineers and technicians with expertise in the assembly of sophisticated research equipment attempted unsuccessfully to generate a complete set of assembly instructions, despite extensive and repeated efforts to include every relevant fact, process, and heuristic (Collins et al., 1985). When scientists who purchased the equipment attempted to assemble it according to the instructions, the equipment did not function. After many discussions with the engineers, the scientists eventually discovered that the expert team had accidentally omitted a necessary step from the instructions. The step turned out to be a universally implemented practice among the engineers and technicians that they had failed to articulate.

Chao and Salvendy (1994) systematically documented the rates at which experts omit cognitive skills from self-reports. Six expert programmers were asked to complete a series of challenging troubleshooting tasks, and all of their actions were recorded. The programmers were then asked to explain their procedures using a variety of different knowledge elicitation methods. No single expert was able to report more than 41% of their diagnostic actions, 53% of their debugging actions, or 29% of their interpretations, regardless of the knowledge elicitation method used; however, when the researchers began compiling the elicited explanations from different experts, they found that the percentage of actions explained increased. When explanations from all six experts were aggregated, the percentages of verbalization for each category of actions increased to 87%, 88%, and 62%, respectively. The improvement in information elicited reflects the experts' individual differences in which subgoal productions had been automated to greater and lesser extents. Thus, one promising practice for instruction based on expert knowledge is to employ CTA methods with multiple experts prior to developing instruction.

Instructional Evidence

Several studies provide direct evidence for the efficacy of CTA-based instruction. In a study of medical school surgical instruction, an expert surgeon taught a procedure (central venous catheter placement and insertion) to first-year medical interns in a lecture/demonstration/practice sequence (Maupin, 2003; Velmahos et al., 2004). The treatment group's lecture was generated through a CTA of two experts in the procedure. The control group's lecture consisted of the expert instructor's explanation as a free recall, which is the traditional instructional practice in medical schools. Both conditions allotted equal time for questions, practice, and access to equipment. The students in each condition completed a written post-test and performed the procedure on multiple human patients during their internships. Students in the CTA condition showed significantly greater gains from pretest to post-test than those in the control condition. They also outperformed the control group when using the procedure on patients in every measure of performance, including an observational checklist of steps in the procedure, number of needle insertion attempts required to insert the catheter into patients' veins, frequency of required assistance from the attending physician, and time to completion for the procedure.

Similarly, Schaafstal et al. (2000) compared the effectiveness of a preexisting training course in radar system troubleshooting with a new version generated from cognitive task analyses. Participants in both versions of the course earned equivalent scores on knowledge pretests; however, after instruction, students in the CTA-based course solved more than twice as many malfunctions, in less time, as those in the traditional instruction group. In all subsequent implementations of the CTA-based training design, the performance of every student cohort replicated or exceeded the performance advantage over the scores of the original control group.

Merrill (2002) compared CTA-based direct instruction with a discovery learning (minimal guidance) format and a traditional direct instruction format in spreadsheet use. The CTA condition provided direct instruction based on strategies elicited from a spreadsheet expert. The discovery learning format provided authentic problems to be solved and made an instructor available to answer questions initiated by the learners. The traditional direct instruction format provided explicit information on skills and concepts and guided demonstrations taken from a commercially available spreadsheet training course. Scores on the post-test problems favored the CTA-based instruction group (89% vs. 64% for guided demonstration vs. 34% for the discovery condition). Further, the average times to

completion also favored the CTA group. Participants in the discovery condition required more than the allotted 60 minutes, the guided demonstration participants completed the problems in an average of 49 minutes, and the participants in the CTA-based condition required an average of only 29 minutes.

Generalizability of CTA-Based Training Benefits

Lee (2004) conducted a meta-analysis to determine how generalizable CTA methods are for improving training outcomes across a broad spectrum of disciplines. A search of the literature in ten major academic databases (Dissertation Abstracts International, Article First, ERIC, ED Index, APA/PsycInfo, Applied Science Technology, INSPEC, CTA Resource, IEEE, Elsevier/AP/Science Direct) using keywords such as "cognitive task analysis," "knowledge elicitation," and "task analysis" yielded 318 studies. Seven studies qualified, based on the qualifications of (1) training based on CTA methods with an analyst, (2) conducted between 1985 and 2003, and (3) reported pre- and post-test measures of training performance. A total of 39 comparisons of mean effect size for pre- and post-test differences were computed from the seven studies. Analysis of the studies found effect sizes between .91 and 2.45, which are considered to be large (Cohen, 1992). The mean effect size was $d = +1.72$, and the overall percentage of post-training performance gain was 75.2%. Results of a chi-square test of independence on the outcome measures of the pre- and post-tests ($\chi^2 = 6.50$, $p < 0.01$) indicated that CTA most likely contributed to the performance gain.

Cost-Benefit Studies of CTA

There are few published cost-effectiveness or cost-benefit studies that compare CTA with other task analysis approaches. One exception, reported by Clark and Estes (1996), described a field-based comparison of traditional task analysis and cognitive analysis by a large (10,000+ employees) European organization that redesigned a required training course in emergency and safety procedures for approximately 500 managers. The old and new versions of the course continued to be offered after the new version of the course was designed so the relative efficacy of the two approaches could be compared. All objectives and test items were similar in both the old and new versions. As Table 43.1 indicates, the use of CTA required a greater front-end investment of time (the organization refused to release salary data) both for the CTA itself and the training of instructors for the course (data on the time required to

TABLE 43.1
Cost Comparison of Behavioral and Cognitive Task Analysis

Comparison Activities	Behavioral Task Analysis and Design Days ^a	Cognitive Task Analysis and Design Days
Task analysis and design	7	38
Training of presenters	0	18
Delivery by trainers	80	34
Subtotal	87	90
Total time for 500 trainers	1000	500
Total training days ^b	1087	590

^a Day = person work day to design and present safety course.

^b Total savings with CTA: 1087 days—590 days = 497 days, or 2.5 person years.

Source: Clark, R.E. and Estes, F., *Int. J. Educ. Res.*, 25, 403–417, 1996. With permission.

train instructors for the old course were not available). Yet, even with the approximately 85% more front-end time invested in design, development, and instructor training, the new course resulted in 2.5 person-years of time savings, because it could be offered in 1 day (compared with 2 days for the previous course) with equal or greater scores on the performance posttest. Although these data are only suggestive, the time savings reported by Clark and Estes (1996) reflect similar time savings reported above by Velmahos et al. (2004) and Merrill (2002).

INTEGRATING COGNITIVE TASK ANALYSIS AND TRAINING DESIGN

Optimal Integration of CTA and Training Design

For optimal application to instruction, CTA methods should be fully integrated with a training design model to facilitate the alignment between learning objectives, knowledge (declarative and procedural) necessary for attaining the objectives, and instructional methods appropriate to the required knowledge. Currently, three major systems take this approach: the Integrated Task Analysis Model (ITAM) (Redding, 1995; Ryder and Redding, 1993), Guided Experiential Learning (GEL) (Clark, 2004, 2006), and the Four-Component Instructional Design (4C/ID) system (van Merriënboer, 1997; van Merriënboer and Kirschner, 2007; van Merriënboer et al., 2002). Of these, the 4C/ID model is the most extensively developed. It can be distinguished from other instructional design models in three ways. First, the emphasis of the model is on the integrated and coordinated performance of task-specific constituent skills rather than specific knowledge types or

sequenced performance of tasks. Second, a distinction is made between supportive information, which helps learners perform the nonrecurrent aspects of a complex skill, and procedural or just-in-time (JIT) information, which is presented to learners during practice and helps them to perform the recurrent aspects of a complex skill. Third, the 4C/ID model is based on learners performing increasingly complex skills as a whole task, with part-task practice only of the recurrent skills; in contrast, traditional design methods emphasize the deconstruction of a complex task into part tasks, which, once learned separately, are compiled as whole-task practice. The assumption of the 4C/ID model is that environments supporting complex skill learning can be described in terms of four interrelated components: learning tasks, supportive information, just-in-time information, and part-task practice.

Learning Tasks

Learning tasks are concrete, authentic, whole-task experiences that are organized sequentially from easy to difficult. Learning tasks at the same level of difficulty comprise a *task class*, or group of tasks that draw upon the same body of knowledge. Learning tasks within a class initially employ scaffolding that fades gradually over subsequent tasks within the class. Learning tasks foster schema development to support nonrecurrent aspects of a task. They also facilitate the development of automaticity for schemata used during recurrent aspects of a task.

Supportive Information

Supportive information assists the learner with interpreting, reasoning, and problem-solving activities that comprise the nonrecurrent aspects of learning tasks. It

includes mental models demonstrated through case studies, cognitive strategies modeled in examples, and cognitive feedback. Through elaboration, supportive information helps learners to apply their prior knowledge when learning new information they need to perform the task.

Just-in-Time information

Just-in-time information consists of rules, procedures, declarative knowledge, and corrective feedback required by learners to perform recurrent aspects of the task. JIT information is presented in small units as “how-to” instruction, with demonstrations of procedures and definitions of concepts illustrated with examples. As learners perform the recurrent aspects of a task and acquire automaticity, the amount of JIT information provided diminishes.

Part-Task Practice

Part-task practice opportunities are provided for repetitive performance of the recurrent aspects of a task when a high degree of automaticity is required. Part-task practice is repeated throughout instruction and mixed with other types of practice. Part-task practice includes items that vary from very familiar to completely novel.

COGNITIVE TASK ANALYSIS AND 4C/ID MODEL

The 4C/ID model utilizes CTA to accomplish four tasks: (1) decomposing complex skills into skill hierarchies, (2) sequencing the training program within task classes, (3) analyzing nonrecurrent aspects of complex skills to identify cognitive strategies and mental models, and (4) analyzing recurrent aspects of the complex skill to identify rules or procedures and their prerequisite knowledge that generate effective performance. In general, these activities occur within the framework of the five-stage CTA process; however, because this process is highly integrated with the 4C/ID model, the instructional design model guides the CTA activities. This integration with the instructional design process tends to highlight the reiterative nature of the CTA process.

Decomposition of the Complex Skill

In the first group of task analysis activities, complex skills are broken down into constituent skills, and their interrelationships are identified.* Performance objectives are specified** for all constituent skills, and the objectives are classified as recurrent or nonrecurrent.

Objectives are classified as nonrecurrent if the desired behavior varies from problem to problem and is guided by the use of cognitive strategies or mental models. Objectives are recurrent if the desired behavior is highly similar from problem to problem and is guided by rules or procedures. Sometimes recurrent constituent skills require a high degree of automaticity; these skills are identified for additional part-task practice.

Documentation analysis, observation, and unstructured interviews with SMEs provide the information for building a preliminary skills hierarchy to guide further knowledge elicitation efforts. Data collection, verification, and validation of the skills hierarchy require multiple iterations of knowledge elicitation using multiple SMEs. The verified skills hierarchy then serves as a guide for deeper CTA techniques, such as Clark’s concepts, principles, and processes (Clark, 2004, 2006). The CPP data identify constituent skills and their interrelationships, performance objectives for each constituent skill, and the classification of the skill as recurrent or nonrecurrent. The CPP method also identifies problems ranging from easy to difficult to assist in sequencing task classes.

Sequencing Task Classes

The second group of task analysis activities involves categorizing learning tasks into task classes. The skills hierarchy and classified performance objectives determine the sequence of training for individual constituent skills. The 4C/ID-model employs a whole-task approach, in which trainees learn all constituent skills at the same time. In the first task class, learners perform the simplest version of the whole task. As the conditions under which the task is performed become increasingly complex, the whole task scenarios become more authentic and reflective of those encountered by experts in the real world. CTA processes are used both to verify the skills hierarchy and to confirm the sequencing of task classes from simple to complex.

Analyze the Nonrecurrent Aspects of the Complex Skill

The third set of analytic activities identifies the supportive information necessary for each task class in the form of mental models (how is the problem domain

* The three categories of interrelationships are *coordinate* (performed in temporal order), *simultaneous* (performed concurrently), and *transferable* (performed in any order).

** Performance objectives reflect the performance as a result of learning and include an action verb, a description of tools used, conditions, and standards for performance.

organized?) and cognitive strategies (how to approach problems in the domain?). Knowledge elicitation methods commonly used with SMEs to capture data for nonrecurrent aspects of a complex skill include interviews and think-aloud protocols. The CTA methods are repeated for both simple versions and complex versions of the task to capture the knowledge required for performing the nonrecurrent aspects of the task.

Analyze the Recurrent Aspects of the Complex Skill

The final set of task analysis activities in the 4C/ID model is an in-depth analysis of the recurrent constituent skills. These are identified during the skill decomposition process to identify the JIT information required for the recurrent aspects of the learning tasks. Each constituent skill that enables the performance of another constituent skill is identified in a reiterative process, until the prerequisite knowledge already mastered by learners at the lowest level of ability is identified.

Analysts employ CTA techniques to identify task rules and generate highly specific, algorithmic descriptions of task performance. Next, the prerequisite knowledge required to apply the procedure is identified. The analysis of concepts occurs through the creation of feature lists that identify the characteristics of all instances of a concept. At a lower level, facts (which have no prerequisites) are identified. At a higher level, processes and principles are identified. When completed, the analyst incorporates these prerequisite knowledge components into the rules or procedures for performing the task.

In sum, the results of the four sets of CTA activities in the 4C/ID model provide detailed and in-depth information about the skills, sequence, cognitive strategies, mental models, rules, and prerequisite knowledge required for complex skill learning through the instructional design of its four interrelated components: (1) learning tasks, (2) supportive information, (3) JIT information, and (4) part-task practice. Combined, they form a fully integrated system for problem-based learning in complex domains. A complete description and procedure for implementing the 4C/ID model can be found in van Merriënboer and Kirschner (2007).

THE NEXT GENERATION OF RESEARCH ON COGNITIVE TASK ANALYSIS

Although CTA appears to have significant potential to improve various kinds of performance, it shares many of the challenges reported in studies of instructional

design theories and models (Glaser, 1976; Salas and Cannon-Bowers, 2001). We need many more well-designed studies that systematically compare the impact of different forms of CTA on similar outcome goals and measures. We also need to understand the efficacy of different CTA methods when used with different training design models and theories.

So many types of CTA have been used and reported, and variation in the application of methods is so overwhelming that it is doubtful that any generalization about CTA will satisfy basic standards of construct validity. Researchers are cautioned to look carefully at the description of the methods used to implement CTA to classify the family origin of the technique being replicated. We attempted to describe five common elements of most CTA methods in the first part of this chapter, but the specific strategies used to implement each of these elements varies across studies. The elements we described are focused on the common steps used to implement CTA. This is a *sequence model* and is similar to the Analysis, Design, Development, Implementation, and Evaluation (ADDIE) model for instructional design. Schraagen et al. (2000) and Cooke (1994) have discussed this problem in detail and have attempted to organize the various methods into families based on the type of outcome being pursued (e.g., training, job design, and assessment). Wei and Salvendy (2004) have suggested 11 very useful guidelines for selecting the best CTA method to achieve a goal (see Table 43.2).

First Principles of Cognitive Task Analysis

A different and equally valuable strategy for tackling the multiplicity of CTA methods would be to apply Merrill's (2002) first principles approach to a similar problem with instructional design models. Merrill classified what appeared to be the most psychologically active instructional methods in a group of popular, evidence-based instructional design models. One of the principles he suggested is that designs that help learners connect with prior knowledge are more successful. An attempt to identify first principles of CTA would be a benefit to researchers and practitioners by identifying the active ingredients in key CTA methods; for example, nearly all CTA methods seem to place a heavy premium on the identification of the environmental or contextual cues that indicate the need to implement a skill. The study of neonatal nurses by Crandall and Getchell-Reiter (1993) involved generating more accurate diagnostic symptoms (cues) expressed by very sick babies. Because the recognition of conditional cues may be automated and unconscious for many SMEs, the need for accurate and exhaustive

TABLE 43.2
Guidelines for Selecting CTA Methods

When To Use Various CTA Methods	Families of CTA Methods			
	Observations and Interviews	Process Tracing	Conceptual Techniques	Formal Models
Tasks and domain are not well defined in the initial stages.	X			
Procedures to perform a task are not well defined.	X			
Tasks are representative, and the process is clear.		X		
Task process and performance require tracking.		X		
Verbal data are easily captured without compromising performance.		X		
Domain knowledge and structures require defining.			X	
Multiple task analyzers are used, and task requires less verbalization.			X	
Task requires quantitative predication, and task models change little when the scenario changes.				X
Task performance is affected or distracted by interference.		X	X	X
Task analyzers lack significant knowledge and techniques.	X	X	X	
Tasks are:				
Skill-based	X	X		
Rule-based		X	X	
Knowledge-based			X	X

Source: Adapted from Wei, J. and Salvendy, G., *Behav. Inform. Technol.*, 23(4), 273–299, 2004.

identification of important cues may be one of the most important principles of CTA. In the case of the neonatal nursing studies, the cues captured during CTA have changed the textbook instructions for future neonatal nurses. Other principles may be associated with the identification of the sequence in which productions must be performed and the decisions that must be made (including the alternatives that must be considered and the criteria for selecting alternatives). Principles may also be related to the protocols that are used to observe and interview experts to capture the most accurate and exhaustive description of their task-based knowledge. It is also likely that a separate set of principles would be needed to characterize team or organizational CTAs (Schraagen et al., 2000).

Research on Automated, Unconscious Expert Knowledge

Concerns about experts’ awareness of their own expertise and the strategies used to capture unconscious knowledge are arguably the most important research issues associated with CTA. The body of research on unconscious, automated knowledge has yet to be widely integrated into instructional design or the practice of educational psychologists. Most of the research in this area has been conducted by those interested in psychotherapy and the dynamics of stereotypes and bias in decision making (Abreu, 1999; Bargh and Ferguson, 2000; Wheatley and Wegner, 2001) and motivation

(Clark et al., 2006). Yet, we have ample evidence of the importance of this issue in CTA and training from the results of current research by, for example, Velmahos et al. (2004) and Chao and Salvendy (1994). We need to know much more about how unconscious expertise influences the accuracy of task analysis. We also need to know much more about how to modify automated, unconscious knowledge when people must learn to modify skills. Clark and Elen (2006) have reviewed past research and made suggestions for further study.

Cost Effectiveness and Cost–Benefit Research

Another promising area of future research is cost-effectiveness and cost–benefit analysis (Levin and McEwan, 2000). Existing studies have not explored this issue systematically, but very promising preliminary analyses indicate significant learner time savings and decreases in significant performance errors (Clark and Estes, 1996; Merrill, 2002; Schaafstal et al., 2000; Velmahos et al., 2004). These data are important in part because many key decision makers have the impression that CTA is an overly complex process that requires a great deal of time to conduct and should be avoided due to its cost (Cooke, 1994, 1999). It is accurate to state that CTA increases the time and effort required for front-end design—particularly when a number of experts who share the same skill must be observed and interviewed; yet, it is also possible that these costs may be offset by delivery-end savings due

to increased learner accuracy and decreased learning time. People in formal school settings seldom consider decreased learning time as a benefit, but in business and government settings time is a valuable commodity. The conditions under which savings are, and are not, available would be a valuable adjunct to continued development of CTA. Many other suggestions are possible but are beyond the scope of this chapter.

CONCLUSION

Cognitive task analysis is one of the major contributions to instructional technology that have resulted from the cognitive revolution in psychology and education beginning in the 1970s. CTA does not seek to replace behavioral task analysis (or the analysis of documents and research to support training) but instead adds to existing methods that help capture the covert mental processes that experts use to accomplish complex skills. The importance of CTA is based on compelling evidence that experts are not fully aware of about 70% of their own decisions and mental analysis of tasks (Clark and Elen, 2006; Feldon and Clark, 2006) and so are unable to explain them fully even when they intend to support the design of training, assessment, job aids, or work. CTA methods attempt to overcome this problem by specifying observational and interview strategies that permit designers to capture more accurate and complete descriptions of how experts succeed at complex tasks. Research evidence described in this chapter strongly suggests huge potential benefits for designers and learners when CTA-based performance descriptions are used in training and job aids.

Many designers are apparently not aware of or are not using CTA. In January 2007, we searched Google™ Scholar for the terms “task analysis” or “task analysis models” and then “cognitive task analysis” or “cognitive task analysis models.” The former terms returned about nine to ten times more hits than the cognitive task analysis terms. We looked at a number of the texts used to teach instructional design and could not find any references to CTA.

Cognitive task analysis has been the subject of research more often than it has been applied in practice, so we suspect that few designers have been trained to conduct effective cognitive task analyses. It is also possible that the assumptions underlying CTA conflict with the assumptions that underlie some of the currently popular design theories such as constructivism and problem-based learning (Kirschner et al., 2006). Educators who avoid direct instruction in favor of expert-supported group problem solving or communities of practice would not be inclined to conduct CTA

to support a constructivist context for learning new skills or to teach CTA in graduate programs. Our review of the research evidence for CTA strongly indicates that if it is adopted it might make a huge contribution to learning and performance. It is also clear that many questions about CTA remain to be answered.

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* Indicates a core reference.

