Cognitive Task Analysis

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> *"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."* (p. 3, Chipman, Schraagen, & Shalin, 2000)

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 where 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 (see van Merriënboer, Clark, & de Croock, 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 & 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 that they can be used as records of task performance and/or to inform novices in a way that helps them achieve the performance goal(s) in any context. CTA is most often performed before (or as an integral part of) the design of instruction, work, job aids and/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, Schraagen, & Shalin, 2000; Jonassen, Tessmer, & Hannum, 1999).

This chapter presents an overview of the current state of CTA in research and practice. 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 discusses the integration of CTA with training design. The third section describes research on the impact of CTA and synthesizes a number of studies and reviews pertinent to issues underlying knowledge elicitation. In the fourth section, we present a number of recommendations for future research. The main conclusions are given in the final section.

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 is 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 twenty 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. There are, however, reviews and classifications to guide those interested in exploring and applying CTA, including a comprehensive "review of reviews" provided by Schraagen, Chipman, and Shute (2000).

Cooke (1994) conducted one of the more extensive reviews of CTA. She identified three broad families of techniques: (a) observation and interviews, (b) process tracing, and (c) 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 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 (see also Ericsson & Simon, 1993; Russo, Johnson, & Stephens, 1989; Vosniadou, 1994).

Wei and Salvendy's (2004) review of CTA methods introduces a fourth family—formal models—which use simulations to model tasks in the cognitive domain. Their review further differs from others by providing practical guidelines on how to use the classifications of CTA methods to select appropriate techniques to accomplish various objectives. For example, one guideline 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.

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 & Hoffman, 2003; Cooke, 1994; Hoffman, Shadbolt, Burton, & Klein, 1995; Jonassen et al., 1999). The five common steps in most of the dominant CTA methods are performed in the following sequence:

1) Collect preliminary knowledge
2) Identify knowledge representations
3) Apply focused knowledge elicitation methods
4) Analyze and verify data acquired
5) 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.

(1) 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 themselves, they should be generally familiar with the content, system, or procedures being analyzed.

If possible, two or more subject matter experts (SMEs) should be selected to participate in the process (Chao & Salvendy, 1994; Lee & Reigeluth, 2003). Although specific criteria for identifying experts may change depending on circumstances[1], all SMEs must have a solid record of successful performance at the task(s) 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/or related subject matter. This can include a wide variety of documents, including promotional literature, brochures, 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

[1] 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).

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…"

(2) Identify Knowledge Representations

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

(3) 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 (Hoffman, Crandall, & Shadbolt, 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 & Simon, 1993) or the use of repertory grids (e.g., Bradshaw, Ford, Adams-Webber, & Agnew, 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 & Gretchell-Leiter, 1993; Velmahos, Toutouzas, Sillin, Chan, Clark, Theodorou, & Maupin, 2004).

Concepts, Processes, and Principles (CPP; Clark, 2004, 2006). CPP involves a multi-stage interview technique that captures the automated and unconscious knowledge acquired by experts through experience and practice by using multiple SMEs to describe the same procedure, followed by cycles of expert self- 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 sub-tasks 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:

(a) the sequence of actions (or steps) necessary to complete the sub task;
(b) the decisions that have to be made to complete the sub task, when each must be made and, the alternatives to consider, and the criteria to decide between the alternatives;
(c) all concepts, processes and principles that are the conceptual basis for the experts' approach to the sub-task;
(d) the conditions or initiating events that must occur to start the correct procedure;
(e) the equipment and materials required;
(f) 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 sub task), and

(g) the performance standards required, such as speed, accuracy or quality indicators.

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

Critical Decision Method (CDM; Klein, Calderwood, & MacGregor, 1989). CDM 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: (a) the perceptual cues used in making the decision, (b) prior knowledge that was applied, (c) the goals considered, (d) decision alternatives, and (e) other situation assessment factors. The reports are recorded and transcribed verbatim.

(4) 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, and/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 validate 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 sub-tasks, and the conditions, standards, equipment and materials required. For each sub-task, 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 SME's product to one of the other SMEs and asks them 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 et al. (1998).

(5) 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 rgarding 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 & 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 analysis that could not be directly observed as well as the deeper conceptual knowledge that served as the basis for analytical strategies and decisions (Clark & 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 (e.g., Merrill, 2002; Schaafstal, Schraagen, & van Berlo, 2000; Velmahos et al., 2004). When content is inaccurate or incomplete, any instruction based on that knowledge will be flawed (Clark & Estes, 1996; Jonassen et al., 1999). Such flaws interfere with performance and with the efficacy of future instruction (Lohman, 1986; Schwartz & Bransford, 1998). Resulting misconceptions resist correction, despite attempts at remediation (Bargh & Ferguson, 2000; Chinn & Brewer, 1993; Thorley & 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 & Lebiere, 1998; Gagné, Briggs, & Wager, 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 & 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, Atlas, Lane, & Berger, 1993; Dochy, Segers, & Buehl, 1999; Ericsson & Kintsch, 1995). Further, broad, principled understandings of their domains facilitate skill transfer to solve related novel and complex problems (Gagné & Medsker, 1996; Hall, Gott, & Pokorny, 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, Patterson, and Pfeffer (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, Sweller, & Clark, 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 & Williams, 1994). Participants first articulated the relationships between various predictor variables (e.g., education, occupation, gender, and age) and intelligence. Then, they 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 sub-goal (Neves & 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 & 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 & Shiffrin, 1977). This representation is a *production* within the ACT-R cognitive model of learning proposed by Anderson (1995; Anderson & Lebiere, 1998).

During complex tasks, multiple IF-THEN productions are strung together to generate more sophisticated hierarchies of performances. Each individual production attains a sub-goal that is a component of the overall goal. To move from one production to the next in a sequence, the new sub-goal must be identified and an appropriate production selected. For novices, the identification and selection process for nearly every sub-goal is a conscious, deliberate decision. However, experts automate this process, so they cannot consciously identify many of these decision points (Blessing & Anderson, 1996).

Automaticity has two primary properties that limit the effectiveness of unassisted explanations by experts[2]. First, automated knowledge operates outside of conscious awareness, and executes much faster than conscious processes (Wheatley & Wegner, 2001). As such, it is not available for introspection or accurate self-monitoring. Second, automated processes are typically uninterruptible, so they cannot be effectively changed once they are acquired (Hermans, Crombez, & Eelen, 2000). Consequently, experts' unaided self-reports of their problem-solving processes are typically inaccurate or incomplete[3] (e.g., Chao & 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 sub-goals and procedures are appropriate. Thus, incorporating experts' knowledge of these cues is important for optimal instruction (Fisk & Eggemeier, 1988; Klein & Calderwood, 1991).

For example, Crandall and Getchell-Reiter (1993) 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 which they believed they had positively influenced a baby's medical condition. The researchers asked the nurses be as specific as possible about the assessment parameters, diagnostic cues, and clinical judgments that they used in the incident. However, after completing the 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 omitted or articulated vaguely as "highly generalized constellations of cues" (p. 50). In contrast, 25 of the 70 diagnostic cues identified through CTA that were important in the nurses' diagnosis of problems had not been reported during free recall.

Comparison of the elicited cues to those articulated in available medical and nursing training at the time revealed that more than one-third of the cues used by expert nurses to correctly diagnose infants were not included. These cues spanned seven previously unrecognized categories that were subsequently used to train novice nurses entering neonatal intensive care (Crandall & Gamblian, 1991).

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[2] The literature on expertise has not reached a consensus on the role of automaticity. However, much empirical evidence suggests it plays a defining role. See Feldon (in press) for an extensive review.

[3] 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, pre-existing processes that were applied to those problems will continue to be subject to self-report errors (Betsch, Fiedler, & Brinkmann, 1998).

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, Gollwitzer, Lee-Chai, Barndollar, & Trötschel, 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 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, Slovic, & Rorer, 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. For 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, Green, & Draper, 1985). When scientists who purchased the equipment attempted to assemble it to those 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 sub-goal 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 posttest and performed the procedure on multiple human patients during their internships. Students in the CTA condition showed significantly greater gains from pretest to posttest 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 needed 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 pre-existing 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 posttest 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, whereas 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 10 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: Training based on CTA methods with an analyst, conducted between 1985 and 2003, and reported pre and post test measures of training performance. A total of 39 comparisons of mean effect size for pre- and posttest 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 posttests ($\chi^2 = 6.50$, $p < 0.01$) indicated that CTA most likely contributed to the performance gain.

Cost-benefit studies of CTA. There are few published studies of cost-effectiveness or cost-benefit that compare CTA with other task analysis approaches. One exception, reported by Clark and Estes (1999), described a field-based comparison of traditional task analysis and cognitive analysis by a large (10,000+ employee) 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 in order to compare the relative efficacy of the two approaches. All objectives and test items were similar in both the old and new versions.

As Table 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 train instructors for the old course was not available). Yet even with the approximately 85 percent 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 one day (compared with two days for the previous course) with equal or greater scores on the performance posttest. While these data are only suggestive, the time savings reported by Clark and Estes (1999) reflect similar time savings reported above by Velmahos et al. (2004) and Merrill (2002).

INSERT TABLE 1 ABOUT HERE

Integrating Cognitive Task Analysis 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, there are three major systems that take this approach: Integrated Task Analysis Model (ITAM; Redding, 1995; Ryder & Redding, 1993), Guided Experiential Learning (GEL; Clark, 2004, 2006), and the Four Component Instructional Design system (4C/ID; van Merriënboer, 1997; van Merriënboer et al., 2002; van Merriënboer & Kirschner, in press). 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 model's emphasis 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, whereas traditional design methods give emphasis to 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 (JIT) information, and part-task practice.

Learning tasks are concrete, authentic whole task experiences, 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 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.

JIT information consists of rules, procedures, declarative knowledge, and corrective feedback required for 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 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.

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.

(1) 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[4]. Performance objectives are specified[5] 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 (2004, 2006) Concepts, Principles, and Processes. The CPP data identifies constituent skills and their interrelationships, performance objectives for each constituent skill, and 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.

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[4] There are three categories of interrelationships: coordinate (performed in temporal order), simultaneous (performed concurrently), and transposable (performed in any order).

[5] 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.

(2) 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.

(3) 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 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 in order to capture the knowledge required for performing the nonrecurrent aspects of the task.

(4) 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: (a) learning tasks, (b) supportive information, (c) JIT information, and (d) 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 is found in van Merriënboer and Kirschner (in press).

The Next Generation of Research on Cognitive Task Analysis

While 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 (e.g., Glaser, 1976; Salas & 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 in order to classify the family origin of the technique being replicated. While we attempted to describe five "common elements" of most CTA methods in the first part of this chapter, the specific strategies used to implement each of these elements varied 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 ADDIE model (Analysis, Design, Development, Implementation, and Evaluation) 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 2).

INSERT TABLE 2 ABOUT HERE

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 which 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. For example, the neonatal nurses in the Crandall and Getchell-Reiter (1993) study involved generating more accurate diagnostic symptoms (cues) expressed by very sick babies. Since the recognition of conditional cues may be automated and unconscious for many SMEs, the need for accurate and exhaustive 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 need to 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 CTA's (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 (e.g., Abreu, 1999; Bargh & Ferguson, 2000; Wheatley & Wegner, 2001) and motivation (e.g., Clark, Howard, & Early, 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) review past research and make suggestions for further study.

Cost Effectiveness and Cost Benefit Research

Another promising area of future research is cost-effectiveness and cost-benefit analysis (Levin & McEwan, 2000). Existing studies have not explored this issue systematically, but preliminary analyses indicating significant learner time savings and decreases in significant performance errors (e.g., Clark & Estes, 1999; Merrill, 2002; Schaafstal et al., 2000; Velmahos et al., 2004) are very promising.

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 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

CTA is one of the major contributions to instructional technology that have resulted from the "cognitive revolution" in psychology and education starting in the 1970's. 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 & Elen, 2006; Feldon & 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. As this chapter was going to press, we entered search terms in Google Scholar for "task analysis" or "task analysis models" and then for "cognitive task analysis" or "cognitive task analysis models". The former terms return 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.

CTA 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.

References

Abreu, J. M. (1999). Conscious and nonconscious African American stereotypes: Impact on first impression and diagnostic ratings by therapists. *Journal of Consulting and Clinical Psychology, 67*, 387-393.

Anderson, J. R. (1983). *The architecture of cognition*. Cambridge, MA: Harvard University Press.

Anderson, J. R. (1995) ACT: A simple theory of complex cognition. *American Psychologist*, *51*, 355-365.

Anderson, J. R., & Lebiere, C. (1998). *The atomic components of thought*. Mahwah, NJ: Lawrence Erlbaum Associates.

Bargh, J. A., & Ferguson, M. J. (2000). Beyond behaviorism: On the automaticity of higher mental processes. *Psychological Bulletin, 126*, 925-945.

Bargh, J. A., Gollwitzer, P. M., Lee-Chai, A., Barndollar, K., & Trötschel, R. (2001). The automated will: Activation and pursuit of behavioral goals. *Journal of Personality and Social Psychology, 81*, 1014-1027.

Betsch, T., Fiedler, K., & Brinkmann, J. (1998). Behavioral routines in decision making: The effects of novelty in task presentation and time pressure on routine maintenance and deviation. *European Journal of Social Psychology, 28*, 861-878.

Blessing, S. B., & Anderson, J. R. (1996). How people learn to skip steps. *Journal of Experimental Psychology: Learning, Memory, and Cognition, 22*, 576-598.

Bradshaw, J. M., Ford, K. M., Adams-Webber, J. R., & Agnew, N. M. (1993). Beyond the repertory grid: New approaches to constructivist knowledge acquisition tool development. In K. M. Ford & J. M. Bradshaw (Eds.), Knowledge acquisition as modelling (pp. 9-32). New York: John Wiley & Sons.

Chao, C.-J., & Salvendy, G. (1994). Percentage of procedural knowledge acquired as a function of the number of experts from whom knowledge is acquired for diagnosis, debugging and interpretation tasks. *International Journal of Human-Computer Interaction*, *6*, 221-233.

Chinn, C. A., & Brewer, W. F. (1993). The role of anomalous data in knowledge acquisition: A theoretical framework and implications for science education. *Review of Educational Research,* 63(1), 1-49.

Chipman, S. F., Schraagen, J. M., & Shalin, V. L. (2000) Introduction to cognitive task analysis. In J. M Schraagen, S. F. Chipman & V. J. Shute (Eds.), *Cognitive Task Analysis* (pp. 3-23). Mahwah, NJ: Lawrence Erlbaum Associates.

Clark, R. E. (2004). Design Document For A Guided Experiential Learning Course. Final report on contract DAAD 19-99-D-0046-0004 from TRADOC to the Institute for Creative Technology and the Rossier School of Education.

Clark, R. E. (2006). Training aid for cognitive task analysis. Technical report produced under contract *ICT 53-0821-0137—W911NF-04-D-0005* from the Institute for Creative Technologies to the Center for Cognitive Technology, University of Southern California.

Clark, R. E., & Elen, J. (2006). When less is more: Research and theory insights about instruction for complex learning. In J. Elen & R. E. Clark (Eds.), *Handling Complexity in Learning Environments: Research and Theory* (pp. 283-297). Oxford: Elsevier Science Limited.

Clark, R. E., & Estes, F. (1996) Cognitive task analysis, *International Journal of Educational Research*, *25*, 403-417.

Clark, R. E., Howard, K., & Early, S. (2006). Motivational challenges experienced in highly complex learning environments. In J. Elen & R. E. Clark (Eds.), *Handling complexity in learning environments: Research and Theory* (pp. 27-43). Oxford: Elsevier Science Limited.

Coffey, J. W., & Hoffman, R. R. (2003). Knowledge modeling for the preservation of institutional memory. *Journal of Knowledge Management, 7*(3), 38-52.

Cohen, J. (1992). A power primer. *Psychological Bulletin, 112,* 155-159.

Collins, H. M., Green, R. H., & Draper, R. C. (1985). Where's the expertise?: Expert systems as a medium of knowledge transfer. In M. Merry (Ed.), *Proceedings of the fifth technical conference of the British Computer Society Specialist Group on Expert Systems '85* (pp. 323-334). New York: Cambridge University Press.

Cooke, N. J. (1992). Modeling human expertise in expert systems. In R. R. Hoffman (Ed.), *The psychology of expertise: Cognitive research and empirical AI* (pp. 29-60). Mahwah, NJ: Lawrence Erlbaum Associates.

Cooke, N. J. (1994). Varieties of knowledge elicitation techniques. *International Journal of Human-Computer Studies, 41*, 801-849.

Cooke, N. J. (1999). Knowledge elicitation. In F. T. Durso (Ed.), *Handbook of applied cognition* (pp. 479-509). New York: Wiley.

Cooke, N. J., Atlas, R. S., Lane, D. M., & Berger, R. C. (1993). Role of high-level knowledge in memory for chess positions. *American Journal of Psychology, 106*, 321-351.

Cooke, N. J., & Breedin, S. D. (1994). Constructing naive theories of motion on-the-fly. *Memory and Cognition, 22,* 474-493.

Crandall, B., & Gretchell-Leiter, K. (1993). Critical decision method: A technique for eliciting concrete assessment indicators from the "intuition" of NICU nurses. *Advances in Nursing Science*, *16*(1), 42-51.

Crandall, B., & Gamblian, V. (1991). *Guide to Early Sepsis Assessment in the NICU.* Fairborn, OH: Klein Associates.

Dawes, R. M. (1994). *House of cards*. New York: Free Press.

Dochy, F., Segers, M., & Buehl, M. M. (1999). The relation between assessment practices and outcomes of studies: The case of research on prior knowledge. *Review of Educational Research, 69*(2), 145-186.

Einhorn, H. (1974). Expert judgment: Some necessary conditions and an example. *Journal of Applied Psychology, 59,* 562-571.

Ericsson, K. A., & Kintsch, W. (1995). Long-term working memory. *Psychological Review, 102*, 211-245.

Ericsson, K. A., & Simon, H. A. (1993). *Protocol analysis: Verbal reports as data (Rev. ed.).* Cambridge, MA: Bradford.

Ericsson, K. A., & Smith, J. (1991). *Towards a general theory of expertise: Prospects and limits.* New York: Cambridge University Press.

Feldon, D. F. (in press). Implications of research on expertise for curriculum and pedagogy. *Educational Psychology Review.*

Feldon, D. F. (2004) *Inaccuracies in expert self report: Errors in the description of strategies for designing psychology experiments*. Unpublished doctoral dissertation, Rossier School of Education, University of Southern California, USA.

Feldon, D. F., & Clark, R. E. (2006). *Instructional implications of cognitive task analysis as a method for improving the accuracy of experts' self-report.* In G. Clarebout & J. Elen (Eds.), *Avoiding simplicity, confronting complexity: Advances in studying and designing (computer-based) powerful learning environments* (pp. 109-116). Rotterdam, The Netherlands: Sense Publishers.

Fisk, A. D., & Eggemeier, R. T. (1988). Application of automatic/controlled processing theory to training of tactical command and control skills: I. Background and task analytic methodology. In *33rd Annual Proceedings of the Human Factors Society* (pp. 281-285). Santa Monica, CA: Human Factors Society.

Gagné, R. M. (1982). Developments in learning psychology: Implications for instructional design and effects of computer technology on instructional design and development. *Educational Technology, 22*(6), 11-15.

Gagné, R. M., Briggs, L. J., & Wager, W. W. (1992). *Principles of instructional design*. Fort Worth, TX: Harcourt Brace Jovanovich.

Gagné, R. M., & Medsker, K. L. (1996). *The conditions of learning: Training applications.* New York: Harcourt Brace.

Glaser, R. (1976). Components of a psychology of instruction: Toward a science of design. *Review of Educational Research*, *46*(1), 1-24.

Glaser, R., & Chi, M. T. H. (1988). Overview. In M. T. H. Chi, R. Glaser, & M. J. Farr (Eds.), *The nature of expertise* (pp. xv-xxviii). Mahwah, NJ: Lawrence Erlbaum Associates.

Hall, E. M., Gott, S. P., & Pokorny, R. A. (1995). *A procedural guide to cognitive task analysis: The PARI methodology.* Brooks Air Force Base, TX: Manpower and Personnel Division, U.S. Air Force.

Hermans, D., Crombez, G., & Eelen, P. (2000). Automatic attitude activation and efficiency: The fourth horseman of automaticity. *Psychologica Belgica, 40*(1), 3-22.

Hinds, P. J., Patterson, M., & Pfeffer, J. (2001). Bothered by abstraction: The effect of expertise on knowledge transfer and subsequent novice performance. *Journal of Applied Psychology, 86*, 1232-1243.

Hoffman, R. R., Crandall, B., & Shadbolt, N. (1998). Use of the critical decision method to elicit expert knowledge: A case study in the methodology of cognitive task analysis. *Human Factors, 40*, 254-277.

Hoffman, R. R., Shadbolt, N. R., Burton, A. M., & Klein, G. (1995). Eliciting knowledge from experts: A methodological analysis. *Organizational Behavior and Human Decision Processes, 62*(2), 129-158.

Hoffman, P., Slovic, P., & Rorer, L. (1968). An analysis of variance model for the assessment of configural cue utilization in clinical judgment. *Psychological Bulletin, 69,* 338-349.

Johnson, P. E. (1983). What kind of expert should a system be? *The Journal of Medicine and Philosophy, 8,* 77-97.

Jonassen, D. H., Tessmer, M., & Hannum, W. H. (1999). *Task analysis methods for instructional design.* Mahwah, NJ: Lawrence Erlbaum Associates.

Kareken, D. A., & Williams, J. M. (1994). Human judgment and estimation of premorbid intellectual function. *Psychological Assessment, 6*(2), 83-91.

Kirschner, P., Sweller, J., & Clark, R. E. (2006). Why minimally guided learning does not work: An analysis of the failure of discovery learning, problem-based learning, experiential learning and inquiry-based learning. *Educational Psychologist, 41*(2), 75-86.

Klein, G. A., & Calderwood, R. (1991). Decision models: Some lessons from the field. *IEEE Transactions on Systems, Man, and Cybernetics, 21*, 1018-1026.

Klein, G. A., Calderwood, R., & MacGregor, D. (1989). Critical decision method for eliciting knowledge. *IEEE Transactions on Systems, Man, and Cybernetics, 19*, 462-472.

Lee, R. L. (2004). *The impact of cognitive task analysis on performance: A meta analysis of comparative studies*. Unpublished Ed.D. dissertation, Rossier School of Education, University of Southern California, USA.

Lee, J.-Y., & Reigeluth, C. M. (2003). Formative research on the heuristic task analysis process. *Educational Technology, Research and Development, 51*(4), 5-24.

Levin, H. M., & McEwan, P. J. (2000). *Cost effectiveness analysis: Methods and applications, 2nd edition*. Beverly Hills, CA: SAGE Publications.

Lohman, D. F. (1986). Predicting mathemathantic effects in the teaching of higher-order thinking skills. *Educational Psychologist*, *21*(3), 191-208.

Maupin, F. (2003). *Comparing cognitive task analysis to behavior task analysis in training first year interns to place central venous catheters*. Unpublished doctoral dissertation, University of Southern California, Los Angeles, California.

Merrill, M. D. (2002). A pebble-in-the-pond model for instructional design. *Performance Improvement, 41*(7), 39-44.

Mullin, T. M. (1989). Experts estimation of uncertain quantities and its implications for knowledge acquisition. *IEEE Transactions on Systems, Man, and Cybernetics, 19,* 616-625.

Neves, D. M., & Anderson, J. R. (1981). Knowledge compilation: Mechanisms for the automatization of cognitive skills. In J. R. Anderson (Ed.), *Cognitive skills and their acquisition* (pp. 335-359). Hillsdale, NJ: Erlbaum.

Redding, R. E. (1995). Cognitive task analysis for instructional design: Applications in distance education. *Distance Education, 16*, 88-106.

Russo, J. E., Johnson, E. J., & Stephens, D. L. (1989). The validity of verbal protocols. *Memory & Cognition, 17*(6), 759-769.

Ryder, J. M., & Redding, R. E. (1993). Integrating cognitive task analysis into instructional systems development. *Educational Technology, Research and Development, 41*, 75-96.

Salas, E., & Cannon-Bowers, J. A. (2001). The science of training: A decade of progress. *Annual Review of Psychology, 52*, 471-497.

Schaafstal, A., Schraagen, J. M., & van Berlo, M. (2000). Cognitive task analysis and innovation of training: The case of the structured troubleshooting. *Human Factors 42*, 75-86.

Schneider, W. (1985). Training high-performance skills: Fallacies and guidelines. *Human Factors, 27,* 285-300.

Schneider, W., & Shiffrin, R. M. (1977). Controlled and automatic human information processing: 1. Detection, search, and attention. *Psychological Review*, *84*, 1-66.

Schraagen, J. M., Chipman, S. F., & Shute, V. J. (2000) State-of-the-art review of cognitive task analysis techniques. In J. M Schraagen, S. F. Chipman & V. J. Shute (Eds.), *Cognitive Task Analysis* (pp. 467-487). Mahwah, NJ: Lawrence Erlbaum Associates.

Schwartz, D., & Bransford, J. D. (1998). A time for telling. *Cognition and Instruction, 16*, 475-522.

Sternberg, R. J., & Horvath, J. A. (1998). Cognitive conceptions of expertise and their relations to giftedness. In R. C. Friedman & K. B. Rogers (Eds.), *Talent in Context* (pp. 177-191). Washington, DC: American Psychological Association.

Thorley, N., & Stofflet, R. (1996). Representation of the conceptual change model in science teacher education. *Science Education, 80,* 317-339.

van Merriënboer, J. J. G. (1997). *Training complex cognitive skills: A four-component instructional design model for technical training.* Englewood Cliffs, NJ: Educational Technology Publications.

van Merriënboer, J. J. G., Clark, R. E., & de Croock, M. B. M. (2002). Blueprints for complex learning: The 4C/ID*-model. *Educational Technology Research and Development, 50*(2), 39-64.

van Merriënboer, J. J. G., & Kirschner, P. A. (in press). *Ten steps to complex learning: A systematic approach to Four-Component Instructional Design*. Mahwah, NJ: Lawrence Erlbaum Associates.

Velmahos, G. C., Toutouzas, K. G., Sillin, L. F., Chan, L., Clark, R. E., Theodorou, D., & Maupin, F. (2004). Cognitive task analysis for teaching technical skills in an inanimate surgical skills laboratory. *The American Journal of Surgery*, *18*, 114-119.

Wegner, D. M. (2002). *The illusion of conscious will*. Cambridge, MA: MIT Press.

Wei, J., & Salvendy, G. (2004). The cognitive task analysis methods for job and task design: Review and reappraisal. *Behaviour & Information Technology, 23*(4), 273-299.

Wheatley, T., & Wegner, D. M. (2001). Automaticity of action, Psychology of. In N. J. Smelser & P. B. Baltes (Eds.), *International Encyclopedia of the Social and Behavioral Sciences* (pp. 991-993). Oxford, IK: Elsevier Science Limited.

Zeitz, C. M. (1997). Some concrete advantages of abstraction: How experts' representations facilitate reasoning. In P. J. Feltovich, K. M. Ford, & R. R. Hoffman (Eds.), *Expertise in context* (pp. 43-65). Menlo Park, CA: American Association for Artificial Intelligence.

Table 1

Cost Comparison of Behavioral and Cognitive Task Analysis (From Clark & Estes, 1999)

Comparison Activities	Behavioral Task Analysis & Design Days*	Cognitive Task Analysis & Design Days
Task Analysis & Design	7	38
Training of Presenters	0	18
Delivery by Trainers	80	34
Sub-total	87	90
Total time for 500 trainers	1,000	500
Total training days**	1,087	590

*Day = person work day to design and present safety course
**Total savings with CTA: 1,087 days – 590 days = 497 days or 2.5 person years

Table 2

Guidelines for Selecting CTA Methods (Following Wei & Salvendy, 2004)

	Families of CTA Methods			
When to use different CTA methods	Observations & Interviews	Process Tracing	Conceptual Techniques	Formal Models
1. In initial stages when tasks and domain are not well-defined	X			
2. Procedures to perform a task are not well defined	X			
3. Tasks are representative and process is clear		X		
4. Task process and performance need tracking		X		
5. Verbal data is easily captured without compromising performance		X		
6. Domain knowledge and structures need defining			X	
7. Multiple task analyzers are used, and task requires less verbalization			X	
8. Task needs quantitative predication, and task models change little when scenario changes				X
9. Task performance is affected or distracted by interference		X	X	X
10. Task analyzers lack significant knowledge and techniques	X	X	X	
11. Tasks are:				
(a) Skill-based	X	X		
(b) Rule-based		X	X	
(c) Knowledge-based			X	X