Cognitive Task Analysis for Training*

Richard E. Clark & Fred Estes
University of Southern California

Published as: Clark, R. E. and Estes, F. (1996)Cognitive task analysis, *International Journal of Educational Research.* 25(5). 403-417.

Abstract

Two factors have made behaviorally-based task analysis training systems obsolete: 1) these systems cannot describe the complex knowledge required of European and North American workers by recent changes in the global economy, and 2) recent research in cognition show that the cognitive processes and structures involved in complex work tasks serve as a more useful content for training and development. A description and a brief review of research on cognitive task analysis (CTA) systems is provided. Claims for the benefits of CTA will be discussed, including Means and Gott's (1988) suggestion that the equivalent of five years of advanced job knowledge can be transmitted in about 50 hours of training based on CTA. The article concludes with a call to include current knowledge of CTA in training design systems and for additional research directed to the development of CTA systems.

Introduction

One of the most important training innovations during the Industrial Revolution in the early part of this century was the development of task analysis in Europe and North America. Task analysis protocols allowed industrial managers to observe highly skilled workers and to describe the precise activities that were required to perform the variety of jobs that were required for manufacturing (Gael, 1988). Once a job and its component tasks had been analyzed and recorded, inexperienced workers could be more quickly trained to perform necessary jobs.

Prior to task analysis, job training was accomplished almost exclusively by observational learning on-the-job ("sit by Nelly") and formal apprenticeships. Both these methods required a great deal of time and produced variable results for a couple of reasons. First, the role model did not always know what behaviors to highlight for the learner, for reasons discussed later. Second, some very critical steps or decisions occur very rarely and so are inefficient to observe in real-time. Task analysis methods developed early in this century have been so successful that some form of them are still being used today in most training design systems. Task analysis laid the foundation for the development of training objectives (Mager, 1984). In addition to training, task analysis often forms the basis for job description schemes (Fine, 1988), hiring criteria and the performance appraisal systems adopted by larger business organizations and governments (Cooke, 1992a; Gael, 1988). Task analysis laid the foundation for the development of training objectives (Mager, 1984). In addition to training, task analysis often forms the basis for job description schemes (Fine, 1988), hiring criteria and the performance appraisal systems adopted by larger business organizations and governments (Cooke, 1992a; Gael, 1988).

Task analysis may be one of the most successful training inventions in the past century. Yet, there seem to be at least two recent developments that have made traditional task analysis systems inadequate to support the current demands on business trainers in the changing organizational environment of Europe and North America: a primarily behavioral focus and advances in research on cognitive processes and structures.

A Changing Organizational Climate for Training

In the first place, the task analysis systems utilized by most of the training design systems inuse today were developed during the era of behavioral psychology. Formal analysis of tasks and jobs in North America began with the work of Munsterberg, Taylor, and the Gilbreths (Primhoff & Fine, 1988). Munsterberg, a German student of Wundt, developed the first task analysis system to describe the emergency reactions of railroad workers and naval officers to facilitate their training (Clark, 1995). Fred Taylor advanced task analysis with a famous study of the use of different types of shovels. Frank and Lillian Gilbreth extended Munsterberg's task analysis system with a popular and influential study of bricklaying (Clark, 1995). All of these early systems, and their later extensions, focused on the description of overt behavior. Many manufacturing jobs continue to require a great number of overtly physical tasks, fine motor coordination, and relatively simple decisions; behavior task analysis, therefore, has been more or less adequate for those components of manufacturing training, although modern methods and equipment increasingly call for more knowledge and broader decision-making authority from workers.

Behavioral analysis, however, focuses directly on observable behavior and ignores the impact of cognitive processes and structures on complex job tasks, such as advanced problem solving and "trouble shooting" of intricate, extensive and integrated systems (Cooke, 1992a). More complex tasks used to be rare in business and were therefore the responsibility of highly paid expert managers. However, there is general agreement that the majority of jobs in European and North American organizations now require more complicated problem solving skill than in the past (Berryman, 1993). The increased use of teams requires explicit business process protocols as the basis for shared decision-making. Recent dramatic changes in the international economy and parallel changes in business organizations may have made behaviorally-based task analysis schemes more or less irrelevant for characterizing and training these more complex jobs and tasks.

Cascio (1995) summarizes the many forces that are changing business organizations and the challenge to industrial and organizational trainers. The dual trends toward global markets and increased competition within countries resulting from national privatization plans and deregulation are influencing most jobs. The impact of global competition has included many sweeping changes: 1) a trend toward smaller organizations that employ fewer people, 2) a shift from the manufacturing and distribution of products to services, 3) a gradual movement from vertically integrated management hierarchies in organizations to relatively flat networks of workers with multiple specialties, 4) the tying of pay to market value and not to a worker's position within the organization, and 5) the redefinition of work from executing a stable set of tasks to satisfying the dynamic and shifting requirements of the customer. An interesting example of training research that addresses some of these problems can be found in the study reported in this issue by Achtenhagen and Oldenbürger (1996). Their interest in training factors that influence the "client focus" of trainees and training programs is one of many lines of research that attempt to direct training programs to the rapid changes taking place in business. In this world, business as usual is a recipe for failure.

Adjusting business processes to accommodate the complex demands of global competition requires many innovations in business, including: a great amount of cross-training; the learning of a large number of complex analytical strategies; sophisticated problem solving ability; and the fostering of "self-regulated" learning on the part of all employees. The ISO 9000 standards developed in Europe are a major driver of these changes. A few large organizations are in the process of building "human performance technology" systems to aid in the development of these advanced skills (Means & Gott, 1988; Stolovitch & Keeps, 1992). The knowledge required to support the continued success of organizations will change quickly over short periods of time. These changes will continue to place complex demands on the organizational specialists charged with providing the training, development and performance of workers.

Research on the Cognitive Development of Expertise at Work

A second factor calling for advanced task analysis systems in place of behavior-only systems has been recent advances in our understanding of the cognitive processes and structures that support the development of advanced expertise at work (Anderson, 1993, 1995; Chase & Simon, 1973; Ericsson & Smith, 1991; Ericsson & Charness, 1994; Glaser, 1985, 1990). These advances are largely unknown in the business education community.

Berryman suggests that the reason for this gap between research and practice in business is due to the relative isolation of the industrial psychologists who work with industry to advance job and task analysis. Many of the experienced and successful industrial psychologists were trained during the behavioral era in universities. Berryman claims that "at present, there is virtually no bridge between industrial psychology and cognitive science . . ."(1993, p.350).

Cognitive psychology focuses on the knowledge content, structures, and contexts involved in perception, pattern recognition, attention, memory, decision making, reasoning, problem solving, and thinking (Cooke, 1992a). In the cognitive paradigm, experts and novices have developed qualitatively and quantitatively different knowledge structures and processes about tasks within their domain of expertise. Experts are capable of a great variety of advanced skills, including consistent, extremely rapid, accurate and effective diagnosis and solving of complex problems within their domain of expertise. While novices experience a severe limitation on conscious processing in the form of the "seven, plus or minus two" paradigm (Miller, 1956), there is recent evidence that experts may have direct access to much of the content of declarative memory in their domain of experience (Baddley, 1994). They also possess a series of rapid and highly efficient, domain-specific rules about the conditions that require the use of problem solving strategies and the expected consequence of each stage of the use of interventions (Means & Gott, 1988).

Cognitive differences between experts and novices who have similar general ability is largely influenced by a very long regimen of motivated, deliberate practice (Ericsson et al., 1993). When deliberate practice is characterized by gradual, but highly challenging increases in the demand and difficulty of tasks accompanied by constant corrective feedback extending over approximately a decade, it often results in the creation of cognitive structures responsible for exceptional performance. It is important to note that "job experience" does not necessarily qualify as deliberate practice, especially if it lacks progressive and varied challenge. A worker's five years of experience, for example, may actually represent one year of experience repeated five times.

Also important for business is the research evidence that many of the current job selection and hiring criteria may not be very reliable at identifying individuals with advanced problem solving expertise. Glaser, et al. (1985) have described the ineffectiveness of traditional hiring and promotion criteria such as educational level, understanding of basic principles (for example, scientific principles), and familiarity with technology (for example, the operation of test equipment) as indicators of advanced problem solving e expertise. They argue that differences between educated and experienced, but ineffective candidates on the one hand, and advanced and productive experts on the other hand, may be best identified during the solving of complex, job-specific problems. Many global companies including Novell and Microsoft now certify job competency for some technical positions through the simulation of authentic job tasks. While Glaser et al. (1985) describe the development of abbreviated versions of problems that can be used for selection and hiring, these tests require a firm basis in cognitive task analysis (Means & Gott, 1988). In describing the reconciliation of cognitive psychology and psychometrics, Anastasi (1988) discusses the importance of cognitive analysis in the construct validation of psychological testing. Embretson (1983, 1986) recognized two aspects of construct validation: 1) nomethic span or the traditional multitrait, multimethod correlational approach of tying validity to other measures of the same construct, and 2) construct representativeness or tying validity to the specific cognitive processes and structures needed for performance. Snow (1993) calls for task analytic research to guide test construction and validity.

Capturing the Cognitive Elements of Advanced Expertise At Work

Our understanding of expertise at work has been enhanced by research on different types of knowledge over the past three decades. There is general agreement in cognitive psychology that most human being are capable of acquiring declarative knowledge, production knowledge, or both about any task. Declarative knowledge is information about "why or that". Procedural or production knowledge is information about "how and when". Any given individual might have one kind of knowledge about any event, but lack the other. The individual may know why a chemical reaction occurs but not how to produce that reaction. Or through long practice, the individual might have learned how to diagnose and fix certain technical problems, but not understand the underlying scientific principles. Alternately, an expert might be unable to articulate why certain steps in a problem solving procedure are necessary because the procedure has become automated and no longer accessible to conscious processes. Declarative knowledge is characterized by its conscious quality and speed with which it can be learned and modified. One of the primary "purposes" of declarative knowledge seems to be the management and solving of novel problems (Anderson, 1983, 1995; Gagne et al., 1993) and the generation of procedures to handle those novel situations when they occur more frequently (Anderson, 1993).

A variety of cognitive formats of declarative knowledge are available to most individuals, including images, propositions, and linear orderings (Anderson, 1994; Gagne, Yekovitch, & Yekovitch, 1993). While there may be many different types of declarative knowledge, each of which can exist in a variety of formats, the most common types of declarative knowledge used at work may be concepts, principles, and processes (Clark, 1995, Cooke, 1992a). The cognitive mechanisms that acquire and modify the cognitive representations of knowledge, and the various structures that knowledge can take, will continue to be the focus of a large and growing body of research. Yet declarative knowledge can be inaccurate, as the literature of misconception indicates (Burton, 1982; Posner et al., 1982; VanLehn, 1990). Ohlsson (1996) describes some of this literature and demonstrates a way to use these mistakes and misconceptions during training.

Procedural or production knowledge is the second type and is characterized by its unconscious, automated quality that make it very rapid and efficient to express. The benefit of procedural knowledge is that it is very efficient and highly accurate in the context where it was developed. Yet the development, correction and automating of production knowledge is very slow and once automated, it cannot be changed, but must be "circumvented" (Anderson, 1983, 1995). This is part of the reason why the inefficient layout of keys on a computer keyboard has not changed despite research evidence that there is a much better configuration of keys available. Once the ingrained configuration changed, all of those who have automatic procedural knowledge about typing "lose" their expertise and their performance drops to a level little better than novices.

There is evidence (Anderson, 1983, 1993, 1995) that production knowledge results from the repeated use of declarative knowledge to accomplish a specific task context. While this phenomenon is not well researched, it appears that all types of declarative knowledge have automated, procedural counterparts. If we use a concept such as cost or value often, our production system automates what might be called a "classification production" that identifies examples of cost and value in our area of expertise without conscious deliberation. The purpose of this automation is to speed the use of the knowledge that we apply constantly and free up working memory for novel events. It might be said therefore, that whereas the purpose of declarative knowledge is to handle novelty, the purpose of procedural knowledge is to automate mental strategies and skills that are more routine.

One recent attempt to summarize research on these two types of knowledge and describe a practical system for instruction can be found in Gagne, Yekovitch, & Yekovitch (1993). They make the point that what makes expert knowledge difficult to access is the fact that even the most advanced experts are largely unaware of the automated strategies that guide most of their problem solving. This leads to the condition where highly competent experts believe they know how they perform, and yet a significant portion of their conscious awareness of their automated expertise is inaccurate. This fact challenges the common business practice of training advanced employees with mentoring, on-the-job tutoring, or apprenticeship programs. The implicit or unconscious nature of expert knowledge also challenges the reliance placed on job descriptions used by organizations and governments.

Current Use of Task Analysis by Government for Job Descriptions

The government of the United States invests heavily in describing thousands of jobs in order to facilitate federal funding, job development schemes, and government hiring. Job analysis is the responsibility of the Department of Labor. This department produces the Dictionary of Occupational Titles (DOT) which makes use of task analysis. However, the jobs and task described in the DOT are focused on behaviors and not on the many cognitive strategies necessary to perform jobs. For example, the DOT describes one of the tasks of "computer programmer" as preparing a flowchart to illustrate the sequence of steps in the program, but does not discuss the complex planning and reasoning involved in flowcharting that would distinguish it from other tasks such as listing the work breakdown structure for building a brick wall. Likewise, the DOT description of air-traffic controller makes no mention of the need to divide attention among several tasks simultaneously, although this is clearly one of the primary factors in the intense cognitive workload characterizing this job (Cooke, 1992b).

The Position Analysis Questionnaire (PAQ), one of the most common tools for traditional task analysis and the basis of the DOT, is a scale of 187 general questions divided into six sections, only one of which concern mental processes. Government rater who are conducting job analysis are asked to decide if a job requires a given activity, using a five-point scale from "very minor" to "extreme". An activity might be "combining information from various sources" and exemplars of this skill are "an economist using information form various sources to predict future economic conditions, a pilot flying an aircraft, a judge trying a case . . .". Clearly this level of generality captures the idea that the job requires complex thought, but would be useless from the standpoint of understanding the thought process itself. The amount of transfer between economic forecasting, flying an jet plane, and judging a legal case must be small indeed.

Business Barriers to Cognitive Task Analysis Evaluation

Complicating the development of newer cognitive methods of training for business is the competitive nature of information about jobs within business organizations. Businesses which attempt to capture advanced expertise through cognitive methods are not inclined to publish their results due to concerns that such data will benefit competing businesses (Berryman, 1993). Thus, much of the research and practice this is currently available to describe these new approaches is generated by military training research specialists (e.g., Gott, 1989; Hall, Gott & Pokorny, 1995), and those researchers who specialize in the learning of generic "tool" skills such as mathematics and computer programming (e.g., Anderson, 1983, 1995); reading (Bransford & Vie, 1989) and the training of physicians (e.g., Norman & Schmidt, 1992). Yet one of the most common conclusions from published research is that even exceptionally abstract and complex diagnostic and problem solving skills can be captured and recorded employing cognitive task analysis and subsequently applied as the basis for highly efficient business training systems (Cooke, 1992a).

Cognitive Task Analysis (CTA)

Cooke (1992a) defines CTA as the general term used to describe a set of methods and techniques that specify the cognitive structures and processes associated with task performance. The focal point is the underlying cognitive processes, rather than observable behaviors. Another defining characteristic of CTA is an attempt to describe the differences between novices and experts in the development of knowledge about tasks (Redding, 1989).

Related to this developmental emphasis, a major tenet of the cognitive approach to task analysis is that knowledge takes different forms. These different forms of knowledge enable different performances and individuals at different stages in the development of expertise are capable of very different types of performance (Black, 1992). Also, individuals at different levels of expertise require different types of knowledge and differing amounts and types of training methods (Clark, 1990, 1995).

While experts often possess an abundance of declarative knowledge about their specialty, the vast majority of their knowledge lies in their automated procedural knowledge. In fact, when the mental models used by experts can be elicited and represented by CTA, there is good evidence that it can be captured and taught to others, and that even a skilled performer can improve with an expert model (Staszewski, 1988). This is the rationale for expert systems, such as Anderson's Geometry Tutor and LISP Tutor (Anderson, 1995), and a variety of trouble shooting approaches for complex military systems (Means & Gott, 1988). The evidence seems to support the generalization that superior performance of the expert is highly domain specific (Ericsson & Charness, 1994).

In contrast with behavioral strategies, CTA examines knowledge in far greater depth. For example, a cognitive task analysis conducted for the U.S. Navy on an F-16 flight simulator (Levine & Baker, 1990) had one time "monitors radar in order to determine relative position of enemy aircraft" on a task list of 45 items that covered "controlling aircraft under standard flight conditions". Contrast this level of detail with the item "combines information from various sources" description mentioned earlier from the DOT. Also, the DOT notes that a radiologist makes diagnoses after correlating x-rays with other tests and examinations, but does not mention the expertise required to recognize patterns in x-rays and to correctly interpret their meaning, as documented by Lesgold et al. (1988). In addition to and because of a far higher degree of domain specificity, cognitive task analyses are customized for very narrow applications. The output of the PAQ is a printout profile of job requirements based on the task elements with the highest rating scores. The results of a cognitive task analysis, on the other hand, are generally reported containing quantitative data summarized form one or more scales and relatively long interpretive discussions of the data with advanced experts, along with environmental and contextual background.

Varieties of CTA Systems

Both behavioral and cognitive task analysis use a great variety of systems and approaches. Levine, Thomas, and Sistrunk (1988) list 11 general approaches to collecting task analysis data and many specific techniques fall under each method. Cooke (1992b) lists four general families of approaches to organize 112 different specific task analysis systems. However, there is a great deal of overlap in the many specific methods used to collect information for CTA. For example, both behavioral and cognitive task analysis use think-aloud verbal protocols. Behavioral approaches focus on what performers do, while cognitive analyses focus protocols on identifying what expert and novice performers think about before, during, and after each job task.

Differences between the various CTA approaches tend to be based more on the specific nature of the types of tasks being analyzed and the eventual use of the information being collected. For example, task analysis approaches that seek the development of computer-based "expert systems", designed to be direct aids to the performance of novice and intermediate performers, tend to focus exclusively on describing the decisions and actions of experts. Many of these approaches owe a great deal to the GOMS (Goals, Operators, Methods, Selections) task analysis system originally developed by Card, Moran and Newell (1983). Task analysts, using the GOMS approach have developed expert systems in such areas as medicine, engineering, manuscript editing, and oil and mineral exploration (Sternberg & Gitomer, 1992). The systems that result are not intended to train and therefore do not collect a great deal of information useful for training, such as common instances, decision rules for solving complex problems, alternative diagnostic hypotheses, and system process maps (Hall, Gott & Pokorny, 1995).

Evidence that the GOMS approach can be the basis for more elaborate cognitive task analysis systems for training can be found in the work of Sternberg & Gitomer (1992) who describe the development and testing of a system for training in the trouble shooting of complex aircraft hydraulic systems. In this instance, the GOMS approach was paired with another powerful CTA approach called the PARI method (Precursor or reason for action, Action, Result, Interpretation of result) described in some detail by Hall, Gott & Pokorny (1995).

The PARI method was designed by the United State Air Force to support the training of diagnostic skills useful for problem solving with highly complex technological systems. The emphasis in the training systems that employ the PARI method is "adaptive expertise", that is, training resulting in the ability to solve problems that were not specifically addressed in the training, but that might occur in the system being diagnosed. Another way to describe the goals of the PARI method is that it seeks to identify the procedural knowledge required for routine problems as well as the appropriate declarative knowledge about the system required to support the diagnosis and solving of novel problems that may occur in the future.

PARI task analysis procedures involve the selection and interviewing of advanced and intermediate experts. The dyadic interviews initially have the goal of identifying a representative sample of domain problems that need to be solved. Structured interviews are developed where one expert poses a problem to a second expert who then generates and describes a step-by-step solution to each problem. The problems all relate to a specific task or system domain. The first expert gives the second expert the result or consequence of steps or segment of the procedure being described. These results lead the second expert to adjust the hypotheses offered about the problem and gives information about branches in expert problem solving, based on system responses. Grounding knowledge in a specific and authentic domain is an important feature of the PARI approach.

A number of recent CTA approaches have features similar to the PARI method. Gott (1988) provides a review of three cognitive task analysis approaches in addition to PARI, including Anderson's LISP tutor, Soloway's PROUST de-bugging tutor, and the technique used by Morris and Rouse (1985) in their study of trouble shooting characteristics. She concludes that hierarchically organized, rule-based performance systems lead to better instruction for novel problem solving within a task domain by suggesting very efficient ways to chunk the action and decision procedural steps that need to be learned together. These "productions" are gradually perfected and automated with use over time.

This is similar to the conclusion reached by Anderson (1993) after the extensive research he has conducted on his ACT* (Adaptive Control of Thought) cognitive design system. In the introduction to his updated version of that system, called ACT-R (-Rational), Anderson states that he has "always thought that the data argued for production-rule theories more generally than for any specific production-rule theory" (1993, p.vii). This view implies that CTA systems will not be found to be specific to the type of job task being analyzed and that similar benefits might derive from CTA systems that, on the surface, at least, are dissimilar. The generalizability of CTA methods brings up the issue of CTA benefits.

Claims About the Cost-Benefit of Cognitive Task Analysis

There are few claims and very little research concerning the economic benefits of CTA. Indeed, many military training specialists suggest that CTA is the only strategy which has been found to work for training on, for example, the trouble shooting of complex technological systems (Means & Gott, 1988). One of the most dramatic claims was advanced by Means and Gott (1988) who speculate that the equivalent of five years of job knowledge can be transmitted in 50 hours of training based on CTA. What Means and Gott do not explain is the cost and amount of the effort required to conduct a task analysis that will result in the 50 hours of training.

The issue of cost-benefit analysis deserves much more attention from researchers. Informal estimates one hears from specialists in this area suggest that approximately 30 to 35 hours of CTA activities involving both a CTA specialist full time and at least two part time task experts are required to produce the knowledge content for one hour of training. However, if Means and Gott's estimate is accurate, one year of experience for many on-the-job apprentices would cost much more than the CTA and training design time required for all trainees plus 10 hours of training salary time required for each trainee.

The largest cost in the training program of large companies is to be found in the "delivery" cost. And the largest expense in delivery is the salary cost of the people who are involved in training. CTA will most likely cost more on the front-end and take longer during the analysis stage, but provide considerable savings in the cost of delivery and the speed with which trainees are able to use complex strategies on the job. This is similar to the front-end investment in the development of complex technical products, such as application-specific integrated circuits (ASIC's). In fact, the training needed to support the manufacture, marketing, or support of a product should be rightly be considered part of the "extended product". There are various estimates of the relative benefits of CTA over traditional task analysis methods used in training.

An Example of a Cost-Effectiveness Study of CTA and Traditional Methods

One of the authors of this article collected data during a CTA-based training project within a European organization. A comparison between traditional and CTA methods was obtained when an organization with approximately 10,000 employees decided to design a second version of an existing, legally mandated course for managers. The design of the new course for managers used a CTA approach. The original course continued to be offered during and after the design of the new course in order for comparisons to take place. The objectives of both courses was identical and was related to safety procedures mandated by law. All managers in the organization were required to periodically pass a performance-based examination based on the course. The old course required two training days for the managers to complete. The CTA designed course, including all content from the old course plus added material not available in the old course, required only one training day (see Table 1).

Insert Table 1 about here

The new course required over 30 times the effort for the design and training of the trainers (with most of the preparation effort invested in the cognitive task analysis and training of the presenters). This additional investment did not appear to reduce the overall savings by any appreciable amount because the new course resulted in a 50% savings in training time on the part of the trainee managers. The performance test results from the new course equaled or exceeded the old course. The overall financial benefit obtained from the CTA based course was estimated to be equivalent to 2.5 years of the average manager's salary, every time all managers were required to take the course. This type of financial leverage is again similar to technical products which require more time to design, but result in higher quality and added functionality which commands a premium price in the marketplace.

Research Issues

An important issue in the development of CTA for business applications is the great number of important research questions that remain unanswered. There are a variety of views about the impact of this lack of research. Ohlsson (1991) has described a number of important questions that he feels must be addressed in research. He suggests that until more research is conducted, CTA and the training design systems based on CTA must remain "an art".

Anderson (1993) is less pessimistic about the chances for immediate application of a comprehensive, research based system in the form of his ACT-R theory. A compromise view would suggest that while important research questions need to be answered, a number of CTA methods should be incorporated into business training design. This final section describes some of the more general questions that need to be addressed in research and in the application of CTA.

There are at least three different types of issues that need to be addressed in future research on CTA. One issue involves the types of knowledge that must be identified during CTA in order to adequately support the type of performance required at the conclusion of business training. Included in this first type of research issue is the complex issue of how different types of knowledge interact to produce complex performance. We know very little about the way that declarative and procedural knowledge work separately or together to produce the intricate performance that characterizes advanced performance or the solving of highly abstract business problems (Ohlsson, 1991).

A second research issue surrounds the selection of the most efficient and ecologically valid ways to conduct cognitive task analysis and identify knowledge types. Cooke (1992a) identifies validity as one of the central issues of CTA in developing information that is both meaningful and useful.

The third issue is the accurate measurement of the cost-effectiveness of CTA. This requires the collection of cost and benefit data for both CTA and traditional task analysis. Also, the various alternative CTA methods cataloged by Cooke (1992b) and others, should be compared.

Knowledge Types

How many and what types of declarative and procedural knowledge need to be included in CTA? Most training design systems provide a description of knowledge types that indiscriminately mix declarative and procedural knowledge, including the most successful systems, such as the ones proposed by Gagne and Briggs (1979), Gagne (1985), Gagne & Medsker (1996) and Merrill (1983). Some of these systems describe over 100 types of declarative knowledge which makes task analysis very complex.

Research on learning of these knowledge types extends over many decades. Space does not permit a review of this research , or its limitations for CTA methods, but the point here is that as few as these three types may permit training designers to characterize most of the conscious knowledge required to perform the declarative component of most job tasks. More recent attempts to describe knowledge types as part of CTA (Black, 1992; Cooke, 1992a; Ohlsson, 1991) focus on many fewer types. A few reviewers of studies in this area have tended to emphasize only three types of declarative knowledge: concepts, principles, and what might be called "processes". Much more research on this issue is required. A related research issue concerns the process by which declarative knowledge is transformed into automated procedural knowledge with use. Anderson's ACT* (1983) and ACT-R (1995) design system provide a detailed description of this process. However, very little effort has been invested in distinguishing the different types of procedural knowledge. Is it possible, for example, that all procedural knowledge is similar in structure but that we will find ways to catgegorize it usefully in terms of the cognitive functions served? For example, when we learn to correctly define a novel concept that becomes a routine element of a job, is the automated procedure that results a "classification" procedure that helps us identify job-relevant examples of the concept?

A more difficult research problem is to find a way to conceptualize the cognitive interactions between the different types of declarative knowledge on the one hand, and automated procedural knowledge on the other hand (Ohlsson, 1991). This interaction must take place constantly so that human beings can perform complex cognitive tasks. Yet we know very little about the form that this "cooperative" activity between the two knowledge types take when actual job tasks are performed.

What types of procedural or production knowledge needs to be included in CTA? Since only declarative knowledge is accessible to our conscious introspection, it has been the exclusive focus of nearly all business training. It is probably fair to say that one learned declarative knowledge at school and much of our procedural knowledge through job experience. Research is needed to clarify these procedural knowledge types.

Selection of CTA Method

Given the vast number of CTA methods how do we go about selecting the right analysis tools for a given job? This means knowing the types of knowledge involved in the given task, as well as knowing what tools elicit that type of knowledge. This also means understanding the organizational context well enough to use the skills of an ethnographer in eliciting the information without distorting it through the clumsiness of the analyst or the inappropriateness of the technique.

Validating a CTA method can be tricky. A CTA method can be viewed as a constructed response competency certification test for a given job where an examinee is asked to describe the declarative knowledge and demonstrate the procedural knowledge required on the job. The difference is that the purpose of the standard certifcation test is to determine if the examinee responds to the test items in accordance with the established answers. The key issue is to discriminate between those who have mastered a domain and those who have not. The purpose of the CTA method is examine presumed experts on the test items in order to establish the answers. The key issue is to discriminate between those pieces of knowledge that are components of the given domain and those that are not. All the issues of validating mental measures apply but must be inverted to find reliable and valid methods of eliciting correct knowledge from people, rather than assessing the correctness of people's knowledge.

There are also a number of questions around the interaction of declarative and procedural knowledge. What is the mechanism by which declarative knowledge becomes procedural? How do declarative and procedural knowledge work together in novel situations? How do we train for people for novel situations? Answering these questions will go a long way toward satisfying Ohlsson's requirements for a technology of CTA training design.

The Cost-Effectiveness of CTA

The cost-effectiveness of CTA is another very crucial area for training research. When the United States Department of Labor considered using CTA for an updated version of the DOT, a panel of the American Psychological Associate (APA) concluded that at present CTA was too costly for a full analysis of the approximately 20,000 jobs cataloged by the DOT (Camara, 1992). The factors that prevented the panel from recommending a massive use of CTA was the lack of agreement on a simple and manageable CTA method and the cost of training of those who would conduct CTA. Since very few people have experience with CTA methods, hundreds of specialists would have to be trained in order to conduct such a massive project. Given the necessity and large benefits of CTA, however, the the final report of the panel (Camara, 1992) called for more applied research on engineering a practical, cost-effective CTA method.

This raises some vexing but important issues for companies. If CTA methods are not yet ready for extensive field use by government training specialists, should business users wait until the cognitive scientists have developed a simplified, tested and generally accepted product? There seem to be a number of "beta versions" of CTA operating successfully (Cooke, 1994; Clark, 1995). If traditional task analysis methods truly fail to capture the essential elements of cognitively complex work, then many hours of productive work time and much money is being squandered on ineffective training, sub-optimal productivity on the job, poor quality, and missed opportunity.

These considerations raise a number of obvious and important questions: 1) what are the true costs of a CTA? 2) how do these costs differ by method? 3) what are the true costs of a traditional task analysis? 4) how can we measure the comparative efficacy of CTA and raditional task analysis methods? 5) how can we measure the true bottom line benefits of CTA and traditional task analysis? The APA panel is right that cost is always an issue, but business benefits must always be measured against the bigger picture is product quality, market share, and return on investment.

How is a practical engineering solution to emerge? Cooke (1992) proposes two solutions: 1) a focused CTA limited to the complex requirements of a job, and 2) the use of cognitive engineering methods, such as problem decision trees and structured walkthoughs. It also appears that we need to focus on fewer types of declarative knowledge in the first practical systems we explore. These ideas merit serious investigation. Even so, there are still the problems of funding this applied performance technology research. What are the high value applications that would merit some research and development funding? Will industrial alliances and professional associations find ways to share the costs of continued research and development for the common good, as Semantech has done for microchips in North America?

References

Achtenhagen, F. & Oldenbürger, H. A. (1996) Goals for vocational furthur education and training: The view of employees and the view of superiors. International Journal of Educational

Anastasi, A. (1988). Psychological testing, (6th ed.). New York, NY: Macmillan.

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

Anderson, J.R. (1995a). Cognitive psychology and its implications, (4th ed.). New York, NY: Freeman.

Anderson, J.R. (1995b). Learning and memory: An integrated approach. New York: Wiley

Anderson, J.R. (1993). Rules of the mind. Hillsdale, NJ: Lawrence Erlbaum.

Berryman, S.E. (1993). Learning in the workplace. In L. Darling-Hammond (Ed.), Review of Research in Education, vol. 19. Washington, D.C.: American Educational Research Association.

Black, J. B. (1992) Cognitive task analysis, In W. J. Camara (ed.) Implications of cognitive psychology and cognitive task analysis for the revision of the Dictionary of Occupational Titles. Washington D.C.: American Psychological Association.

Bransford, J. D. & Vye, N.J. (1989) A perspective on cognitive research and its implications for instruction. In L. B. Resnick U& Lee. Klopfer (Eds.) Toward the thinking curriculum: Current cognitive research (173-205). Alexandria, VA; Association for Supervision and curriculum Development.

Burton, R.R. (1982). Diagnosing bugs in a simple procedural skill. In D.H. Sleeman and J.S. Brown (Eds.), Intelligent tutoring systems. London, England: Academic Press.

Card, S., Moran, T. P., & Newell, A. (1983) The psychology of human-computer interaction. Hillsdale, NJ: Erlbaum Publishing

Camara, W.J. (1992). Introduction. In W.J. Camara (Ed.), Implications of cognitive psychology and cognitive task analysis for the revision of the Dictionary of Occupational Titles. Washington, D.C.: American Psychological Association.

Carlisle, K. E. (1986). Analyzing jobs and tasks. Englewood Cliffs, NJ: Educational Technology Publications.

Cascio, W. F. (1995) Whither industrial and organizational psychology in a changing world of work? American Psychologist, 50(11), 928-939.

Chase, W.G., and Simon, H.A. (1973). Perception in chess. Cognitive Psychology, 4, 55-81.

Clark, R. E. (1995) A history of instructional psychology. International Encyclopedia of Education, Second Edition. Oxford: Pergamon Press Ltd.

Cooke, N.J. (1992). The implications of cognitive task analyses for the revision of the Dictionary of Occupational Titles. In W. J. Camara (Ed.), Implications of Cognitive Psychology and Cognitive Task Analysis for the Revision of the Dictionary of Occupational Titles, Washington D.C.: American Psychological Association.

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

Davis, L. E., and Wacker, G. J. (1988). Job design. In S. Gael (Ed.), The Job Analysis Handbook for Business, Industry, and Government, Vol. I. New York, NY: John Wiley & Sons.

Embretson, S.E. (1983). Construct validity: Construct representation versus nomothetic span. Psychological Bulletin, 93, 179-197.

Embretson, S.E. (1986). Intelligence and its measurement: Extending contemporary theory to existing tests. In R.J. Sternberg (Ed.), Advances in the psychology of human intelligence, vol. 3. Hillsdale, NJ: Lawrence Erlbaum.

Ericsson, K A, and Charness, N. (1994). Expert performance: Its structure and acquisition. American Psychologist, 49(8), 725-747.

Ericsson, K.A., Krampe, R.T., and Tesch-Romer, C. (1993). The role of deliberate practice in the acquisition of expert performance. Psychological Review, 100(3), 363-406.

Ericsson, K.A., and Smith, J. (1991). Prospects and limits of the empirical study of expertise: An introduction. In K.A. Ericsson and J. Smith (Eds.), Toward a general theory of expertise: Prospects and limits. Cambridge, England: Cambridge University Press.

Fine, S.A. (1988). Functional job analysis. In S. Gael (Ed.), The Job Analysis Handbook for Business, Industry, and Government, Vol. II. New York, NY: John Wiley & Sons.

Gael, S. (1988). Job descriptions. In S. Gael, The job analysis handbook for business, industry, and government, vol. I. New York, NY: John Wiley.

Gael, S. (1988). Preface. In S. Gael, The job analysis handbook for business, industry, and government, vol. I. New York, NY: John Wiley.

Gagne, E.D., Yekovich, C.W., and Yekovich, F.R. (1993). The cognitive psychology of school learning. New York, NY: HarperCollins.

Gagne, R. M. (1985) The conditions of learning (4th Ed.), New York: Holt Reinhart and Winston.

Gagne, R. M. & Briggs, L. J. (1979) Principles of instructional design (2nd ed.). New York: Holt Reinhart and Winston.

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

Gitomer, D. H. (1992). Cognitive science implications for revising the Dictionary of Occupational Titles. In W. J. Camara (Ed.), Implications of Cognitive Psychology and Cognitive Task Analysis for the Revision of the Dictionary of Occupational Titles, Washington D.C.: American Psychological Association.

Glaser, R. (1990) The reemergence of learning theory within instructional research. American Psychologist. 45(1), 29-39.

Glaser, R., Lesgold, A., Lajoie, S., Eastman, R., Greenberg, L., Logan, D., Magone, M., Weiner, A., Wolf, R., Yengo, L. (1985). Cognitive task analysis to enhance technical skills training and assessment. (Final Report to the Air Force Human Resources Laboratory on Contract No. F41689-8v3-C-0029.) Pittsburgh, PA: Learning Research and Development Center, University of Pittsburgh.

Gott, S. (1989). Apprenticeship Instruction for Real-World Tasks: The Coordination of Procedures, Mental Models, and Strategies. Review of Research in Education, Volume 15. Washington D.C.: American Educational Research Association

Hall, E.M., Gott, S.P., and 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.

Koubek, R. (1993). Toward a Model of Expert Knowledge Structures and Their Role in Cognitive Task Performance. Washington D.C.: Office of Navel Research

Lesgold, A., Rubinson, H., Feltovich, P., Glaser, R., Klopfer, D., and Wang, Y (1988). Expertise in a complex skill: Diagnosing x-ray pictures. In M.T.H. Chi, R. Glaser, and M.J. Farr (Eds.), The nature of exertise. Hillsdale, NJ: Lawrence Erlbaum.

Levine, E.L., and Baker, C.V. (1990). Team task analysis for training design: A procedural guide to the multiphase analysis of performance (MAP) system and a tryout of the methodology. (Contract No. DAAL03-86-D-001, Delivery Order 1281.) Orlando, FL: Naval Training Systems Center.

Levine, E.L., Thomas, J.N., and Sistrunk, F. (1988). Selecting a job analysis approach. In S. Gael (Ed.), The job analysis handbook for business, industry, and government, vol.I. New York, NY: John Wiley.

Mager, R.F. (1984). Preparing instructional objectives, Second Edition. Belmont, CA: Lake Publishing.

Means, B. & Gott, S. (1988) Cognitive task analysis as a basis for tutor development: Articulating abstract knowledge representations. In J. Psotka, L. D. Massey, & S. A. Mutter, Intelligent tutoring systems: Lessons learned. Hillsdale, N.J. : Lawrence Earlbaum.

Merrill, M. D. (1983) Component display theory, In C. M. Reigeluth (Ed.) Instructional design theories and models: An overview of their current status. Hillsdale, N.J.: Lawrence Erlbaum Publishers.

Miller, G.A. (1956). The magical number seven, plus or minus two: Some limits on our capacity for processing information. Psychological Review, 63, 81-97.

Morris, N.M., and Rouse, W.B. (1985). Review and evaluation of empirical research on troubleshooting. Human Factors, 27(5), 503-530.

Norman, G. R. & Schmidt, H. G. (1992) the psychological basis of problem-based learning: A review of the evidence. Academic Medicine, 67(9), 557-565.

Ohlsson, S. (1991) Towards intelligent tutoring systems that teach knowledge rather than skills: Five research questions. In E. Scanlon, & T. O'Shea (Eds.) New Directions in Educational Technology, 71-96. New York: Springer-Verlag

Ohlsson, S. (1996) Learning from error and the design of task environments, International Journal of Educational Research, January 1966.

Posner, G.J., Strike, K.A., Hewson, P.W., and Gertzog, W.A. (1982). Accomodation of a scientific conception: Toward a theory of conceptual change. Science Education, 66, 211-227.

Primhoff, E. S., and Fine, S.A. (1988). A history of job analysis. In S. Gael (Ed.), The Job Analysis Handbook for Business, Industry, and Government, Vol. I. New York, NY: John Wiley & Sons.

Redding, R.E. (1989). Perspectives on cognitive task analysis: The state of the state of the art. Proceedings of the Human Factors Society 33rd Annual Meeting.

Steinberg, L.S., and Gitomer, D.H. (1992) Cognitive Task Analysis, Interface Design, and Technical Troubleshooting, Princeton, N.J.: Educational Testing Service

Snow, R.E. (1993). Construct validity and constructed-response tests. In R.E. Bennett and W.C. Ward (Eds.), Construction versus choice in cognitive measurement. Hillsdale, NJ: Lawrence Erlbaum.

Staszewski, J.J. (1988). Skilled memory and expert mental calculation. In M.T.H. Chi, R. Glaser, and M.J. Farr (Eds.), The nature of expertise. Hillsdale, NJ: Lawrence Erlbaum.

Stolovich, H.D., and Keeps, E.J. (1992). Handbook of human performance technology: A comprehensive guide for analyzing and solving performance problems in organizations. San Francisco, CA: Jossey-Bass.

Van Cott, H. P., and Paramore, B. (1988). Task analysis. In S. Gael (Ed.), The Job Analysis Handbook for Business, Industry, and Government, Vol. I. New York, NY: John Wiley & VanLehn, K. (1990). Mind bugs: The origins of procedural misconceptions. Cambridge, MA: MIT Press.

Table 1
Cost comparison of training course versions using traditional or cognitive task analysis

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

Day = person day
* total savings for organization with CTA: 1,087 days - 590 days = 497 days
or 2.5 person years