DOCUMENT RESUME

ED 383 294 IR 017 149

AUTHOR	Dehoney, Joanne
TITLE	Cognitive Task Analysis: Implications for the Theory and Practice of Instructional Design.
PUB DATE	95
NOTE	13p.; In: Proceedings of the 1995 Annual National Convention of the Association for Educational Communications and Technology (AECT), (17th, Anaheim, CA, 1995); see IR 017 139.
PUB TYPE	Reports - Evaluative/Feasibility (142) -- Speeches/Conference Papers (150)
EDRS PRICE	MF01/PC01 Plus Postage.
DESCRIPTORS	Academic Achievement; *Cognitive Measurement; Cognitive Psychology; *Instructional Design; Integrated Curriculum; Learning Laboratories; *Learning Theories; Models; *Problem Solving; *Task Analysis

ABSTRACT

Cognitive task analysis grew out of efforts by cognitive psychologists to understand problem-solving in a lab setting. It has proved a useful tool for describing expert performance in complex problem solving domains. This review considers two general models of cognitive task analysis and examines the procedures and results of analyses in three domains. From the standpoint of technique, cognitive task analysis can and should be integrated into systematic instructional design. True integration will require instructional designers to reexamine their theories of learning with an eye toward adopting the learning constructs developed by cognitive psychologists. (Contains 28 references.) (Author)

Title:

Cognitive Task Analysis: Implications for the Theory and Practice of Instructional Design

Author:

Joanne Dehoney
Department of Instructional Technology
University of Georgia
Athens, GA 30602

Abstract

Cognitive task analysis grew out of efforts by cognitive psychologists to understand problem-solving in a lab setting. It has proved a useful tool for describing expert performance in complex problem solving domains. This review considers two general models of cognitive task analysis and examines the procedures and results of analyses in three domains. From the standpoint of technique, cognitive task analysis can and should be integrated into systematic instructional design. However, true integration will require instructional designers to reexamination their theories of learning with an eye toward adopting the learning constructs developed by cognitive psychologists.

Cognitive Task Analysis: Implications for the Theory and Practice of Instructional Design

Introduction

Task analysis as practiced within the world of instructional design typically results in a linear description of the job process and/or hierarchical orderings of the intellectual skills required to achieve the task. These constructs are particularly useful for defining observable tasks easily subject to top down (or bottom up) analysis. When the object of training is to move people toward expert performance in a complex problem solving task, an instructional designer relying entirely on task analysis methodolcgies from the instructional design literature may be at a loss. However, useful task analysis models and techniques have been developed by cognitive scientists working in the areas of knowledge engineering, ergonomics, and cognitive measurement. These techniques generally focus on illuminating the "covert heuristic" (Wilson and Cole, 1990) used by experts to solve problems, and result in a description of an expert's mental model of the problem.

Cognitive task analysis (CTA) techniques were first used by cognitive scientists studying human cognition in a lab setting, typically by having subjects (college students) work through domain-free problems such as "The Tower of Hanoi" or "Missionaries and Cannibals". Of interest to instructional designers, however, is CTA's usefulness as a method for describing the performance of people who solve difficult problems for a living. Funke (1991) identified six features common to such problems:

1) Intransparency—only some aspects lend themselves to direct observation; often one must infer an underlying state from observational data. Alternatively, the problem can be fully assessed in principle, but it involves so many variables that by necessity a few relevant ones must be chosen;

2) Polytely—multiple goals;

3) Complexity of situation—the problem involves a large number of control processes and regulatory features;

4) Connectivity of variables—changes in one variable affects the status of other variables;

5) Dynamic developments—the problem situation may suddenly change for the worse, forcing a problem solver to act immediately under time pressure;

6) Time-delayed effects—not every action show immediate results.

Three occupations discussed extensively in the literature as subjects for CTA: air traffic controllers (Means, 1993), electronics specialists troubleshooting avionics equipment-testing workstations (Lajoie & Lesgold, 1992; Lesgold &Lajoie, 1991; Lesgold, Lajoie, Logan, & Eggan, 1990; and Means, 1993), and nuclear power plant operators (Roth & Woods, 1992; Roth, Woods, and Pople, 1992), reflect these qualities.

Given Funke's characterization, among the problem-solvers' most important skills will be metacognitive strategies for selecting relevant information, prioritizing and revising goals, and working between multiple versions of the problem representation. For example, a practitioner may keep current and projected models in mind. A CTA approach provides a framework for identifying and integrating skills such as these into the overall task description.

This review of the literature considers the roots and practice of CTA, with the general goal of elucidating and perhaps expanding the notion of task analysis in instructional design. The first section of the paper summarizes the underlying theory of CTA, focusing on research in problem-solving and expertise. The following sections review the literature on CTA models and techniques and examine weaknesses of CTA. Finally, implications of the technique for the theory and practice of instructional design are considered.

Underlying theory

Problem-solving

Problem-solving theory developed within the information-processing view of cognition (see, Reimann & Chi, 1989 for a review). The terminology from this strand of the literature is also widely used in describing CTA. Initially the solver internally represents the problem in terms of its objects, actions that can be taken on objects, strategies that can be used to work on the problem, and constraints on objects, actions, and strategies. This original representation of the problem as given is called the initial state, which evolves into subsequent problem states as operators are applied by the solver until the goal state is reached. The set of all possible problem states and all possible combinations of operators is the problem space. By definition, problem solving is the process of picking a path through the problem space from the initial state to the goal state.

Expertise

When conducting a task analysis, the problem representation of an expert (or a novice-expert comparison) is of particular interest. But in complex domains expert problem-solving becomes inextricably linked with domain knowledge (Reimann & Chi, 1989, Bedard & Chi, 1992). The problem representations and operators used by experts are specific to their domain, and cannot be easily identified outside the domain. Expert performance is characterized by other consistent features. Experts' domain knowledge is broader, more interconnected, and better organized. They learn to quickly recognize recurring patterns in their domains (Bedard & Chi, 1992). As expertise grows, procedural knowledge becomes more comprehensive and automatic, freeing up processing capacity. (Means, 1988) This process can lead to a dissociation between verbal knowledge and performance as experts may not be able to easily describe what they do (Sanderson, 1989). Another component of experts' problem-solving capacity is increased memory for information in their problem domain (Anderson, 1993). Experts tend to view problems by focusing on underlying principles instead of surface features and, as opposed to novices, will impose structure on ill-defined problems. Finally, when following a means-end problem solving strategy (the process of iteratively setting and revising intermediate goals to reach a targeted end-goal), experts follow more efficient paths (Bedard & Chi, 1992).

Implications

The implications for cognitive task analysis are important. The primary goal of CTA is to reveal the problem representations and operators of the solver (operations include actions and strategies). But because domain knowledge and expert performance are linked, the analyst must acquire enough domain expertise to ask the right questions. The finding that experts manipulate domain data in higher-level "chunked" form is particularly important because people may be unable to access subordinate elements of chunked information easily from memory. In the same vein, cognitive strategies are generally not accessible to domain practitioners in the abstract, instead tending to be buried features of particular situations that are automatically applied when appropriate. Finally, experts' domain-specific patterns are another potential subject of inquiry for CTA.

Models of Cognitive Task Analysis

Most practitioners treat CTA as a fluid concept with the general practical goal of identifying an expert's metacognitive domain-organizing structures, and in particular his problem representation, whether it be propositional or an internal visual representation. (Wilson, 1989; Nelson, 1990). The actual procedure may in some cases focus on deriving the implicit rule base used to solve a problem (Ohlosson, 1990). The main focus may also be on determining the way the expert organizes domain knowledge, resulting in representations of his schemata, semantic webs, or mental representations of the problem state (Means, 1993; Lesgold et al., 1990; Nelson, 1990). However, at least two researchers have proposed formal models of cognitive task analysis.

Gardner (1985) defines the purpose of CTA as identifying the performance components, knowledge structures, and metacognitive knowledge underlying a task. Performance components are the automatic mental processes underlying all cognition, such as encoding, inference, response, and performing operations on internal representations. Knowledge structures are the network of propositions and rules that form domain knowledge. Metacognitive knowledge, in Gardner's view, is the collection of overt mental strategies people apply to a task to control higher-order planning, such as breaking the problem into parts.

Roth and Woods (1989) define cognitive task analysis as a two part process. The goal of the first stage is to define competent performance of the task, or to create a model of the problem-solving environment. The resulting *competence model* specifies "what people must be able to do to accomplish the task: what kinds of problems they must solve, what must they know and how must they use this knowledge to solve problems; what knowledge must be accessed to select goals, form intentions to act, to monitor and adapt plans" (p. 246). The competence model defines the parameters of the rest of the CTA, pointing the analyst toward the areas of the task that require study. Roth and Woods also believe that by first defining a competence model, the analyst is more likely to correctly identify sources of poor performance. The second stage of analysis derives a *performance model* which specifies how practitioners actually perform the task. It is in this phase that domain specific knowledge is elicited through a variety of interviewing and observational techniques.

These two models describe CTA at completely different, but compatible levels, which can be described in Roth's and Woods' own terms. Gardner's conception can be seen as part of a performance model of CTA, for which Roth's and Wood's conception serves as the broader competency model.

Cognitive Task Analysis Procedures

While investigators have pursued a rich and varied group of strategies to perform CTA's, the procedures can generally be grouped into three categories. These are: 1) methods for using domain knowledge to structure the analysis, 2) focus problem development, and 3) knowledge elicitation.

Acquiring domain knowledge

Before analysts can get very far, they must learn enough about the domain to be able to ask the right questions about how people do the task and to be able to understand the answers. The objective is to get a preliminary sense of "the basic concepts, procedures, range of problems and sources of complexity in the task" (Roth &Woods, p.250) — to develop a competency model that serves to structure the rest of the analysis.

As in any task analysis, one starts with the "official" version of the task by reviewing any existing materials that describe it. Beyond examining documentation, a typical approach at this stage is to interview several people who perform it. However, these discussions can tend to focus on isolated details of the task, often producing several unrelated versions or a skewed picture of its true dimensions. Roth and Woods recommend having a domain expert prepare and deliver an overview presentation first, then moving into structured interviews to add detail. A second approach is to leverage expert knowledge to define the task without specifically attempting to bring the task analyst up to speed. Means, for example, used panels of experts who checked each others' versions of domain problems so that consensus could be reached on which sorts problems were useful for study. Lesgold included on his analysis team an expert with extensive experience training novices (Lesgold & Lajoie, 1991).

Developing focus problems

After defining the range of problems, the analyst needs a forum for examining which cognitive skills are brought to bear on the problems. Rather than analyze a live task in an "online" work setting, a typical technique is to design focus problems that contain critical features of the kinds of problems faced by people performing the task. Such problems may be critical incidents, or they may be generally representative of the job task, but they must be entirely domain specific in order to stimulate the metacognitive skills and representations of the domain that are the focus of the task analysis. By studying the practitioner's approach to solving these problems, the analyst gathers information about the key skills generally required to carry out the task.

Roth and his colleagues (Roth & Woods, 1989; Roth, Woods & Pople, 1992; Moray &Rotenburg, 1989) convened panels of experts to construct the focus problem, an approach similar to the one described by Means. After convening her experts to define typical problem types, Means (1993) had her experts construct problem examples. In their work on avionics troubleshooting systems, Lesgold and his colleagues relied on their expert to define the focus problem, but his decision was informed by protocol data (see below) from previous observations of airmen working in the problem area (Lesgold et al., 1990). [1]

Knowledge elicitation techniques

Performance components. With the focus task in place, the analyst collects observational and interview data concerning task performance. The data of interest may occur at the performance component level as described by Gardner. For example, Lesgold and Lajoie (1991) measured semantic retrieval efficiency on a subtask in an effort to determine whether there were differences in the accessibility and organization of key concepts between effective and less effective beginning troubleshooters. Moray and Rotenberg (1989) collected eye-movement data as experts and novices worked on a computer simulation of a temperature control problem with relevance to power stations. From this data they formed hypotheses about the processing requirements of subsets of the task. The data allowed them to identify points at which "cognitive lockup" occurred. In this condition practitioners fixate on one aspect of the problem to the exclusion of other cues suggesting alternative solutions.

Conceptual knowledge. An inevitable goal of any task analysis is defining pertinent domain knowledge (Gardner's knowledge structures), particularly in areas where procedures have become automatic. This is largely accomplished through interviews. Although there are numerous ways to help people retrieve information from memory, only the most basic and important technique, prompting and probing, will be mentioned here by way of example. See Table 1 for a summary of many elicitation techniques.

Table 1
Cordingley's Knowledge Elicitation Techniques

Technique	Comments
Interview	All knowledge types will emerge
LaFrance questions	Reveal schemata w/6 levels of question
Laddering	Generate hierarchies of concepts
Focused Discussion	All knowledge types will emerge
Retrospective cases	Focus on procedural knowledge
Forward scenario	"
Critical incident	Often vividly remembered
Interesting cases	Reveal extremes of domain problems
Distinguishing goals	I.D. minimum features that define goal
Goal Decomposition	Means-end analysis
Decision Analysis	Assign value to each decision path
Teachback	Doublecheck gathered material
Construct Elicitation	Focus on schemata
Kelly's diads/triads	Software automates elicitation
Sorting	Forced conceptual categories
Protocol Analysis	Focus on cognitive strategies
Think aloud	Reports all thoughts during task
Eidetic Reduction	Critical self-evaluation of task
Retrospective report	Memory of thinking process--can be compared with real-time version
Simulations	Esp. useful if acquiring information about system requirements

Note. Table compiled from Cordingley, (1989).

Probes are content-free comments by the interviewer which are meant to encourage the expert to elaborate further, for example, "Can you tell me a bit more about that?" Prompts address specific aspects of the content, for example, "Who would you send that to?" Means and Loftus (1991) demonstrated that prompts which provide contextual cues are useful for decomposing molar (composite) memories for episodic events. For example, if the expert were being asked to recall a specific case of an activity performed periodically, the analyst would prompt by asking the expert to recall other activities that occurred in the same time period. Hinkle's laddering technique, described by Cordingley (1989), prescribes a prompting method for developing concept hierarchies. The interviewer prompts with "why" questions to elicit superordinate concepts, "how" questions to elicit subordinate concepts, and "other example" questions to move laterally at the same conceptual level in the domain.

Lesgold took a semi-structured interview approach to analyze avionics troubleshooters (Lesgold et al., 1990). He and his colleagues used a means-end analysis to define the problem space for a focus system fault problem. Then, based on the knowledge of the expert, they defined on paper an "effective problem space" which consisted only of those steps an expert would take plus the likely steps novices would take to move through the problem space. They developed a set of probe questions in advance for each step (or node) in the effective problem space, then presented the problem and effective problem space on paper to novices. Lesgold recorded the order in which novices worked through nodes of the problem space, asking the probe questions for each node as the novice chose that decision path. From the information he gathered, he was able to categorize deficits in novices' knowledge base. He also derived problem-solving strategies and mental models of the problem.

Metacognitive skills. To focus the analysis on metacognitive skills, one of the basic elicitation techniques is protocol analysis (Ericsson &Simon, 1985). In protocol analysis, the researcher records all the actions and verbalizations of the expert as he performs the task. From this data the analyst infers the expert's mental model of the task. In verbal protocol analysis, the analyst typically asks the problem solver to "think aloud" as they complete a task. They may audio or video tape the task and have the problem solver retroactively describe what he was thinking or doing at each step as they review the tape together. Means used this method widely to identify the skills and knowledge of troubleshooters and air traffic controllers. In the weakest version of the method, the analyst simply asks the practitioner to describe post hoc what the he was thinking as he completed the task. Other metacognitive elicitation techniques include reconstruction and asking practitioners to literally reproduce their mental representations by drawing them.

The reconstruction technique (Roth &Woods, 1989) externalizes practitioners' conceptual frameworks. The analyst briefly presents a picture or description of a domain situation to the practitioner. The practitioner is then asked to reconstruct the situation from memory. Memory distortions indicate the nature of the practitioner's schemata.

Examples of eliciting mental representations are provided by Means (1993). She asked avionics electronics technicians to draw their mental representations of a test station as they tried to diagnose a fault. This information helped her identify salient features of a complex problem representation. She drew conclusions about air traffic controllers' problem representations and planning strategies by having them draw the airspace post hoc as it looked when they completed the problem. Woods and Hollnagel (1988) also used drawings of experts' functional representations of their equipment as part of a CTA of nuclear power plant operators.

Computers as a tool for knowledge elicitation. As a final note about elicitation techniques, comparing human and computer problem-solving performance can sometimes reveal human strategies. Roth, Woods, and Pople (1992) compared human performance in a simulation of an emergency situation at a nuclear power plant to computer performance in the same situation. Two teams of experts worked the problem while the researchers collected protocol and observational data. By comparing the experts strategies to the computer's superior problem solution, Roth and his team were able to pinpoint the areas of the problem space where the experts' schemata interfered with optimal problem solution.

Results of CTA

Having performed a CTA, how can one organize the data in a useful form? The task analyses performed by Means, Lesgold, and Woods and their colleagues each resulted in a wealth of data organized in different forms.

From her protocol analyses Means (1993) created tables which related steps in the problem solution both to the specific knowledge which supported each step and to more general categories which describe the overall knowledge base required to do the job. Organized one way the data show the specific knowledge needed to do a task. Organized another way the data show which knowledge is common to various tasks. Means also tried to examine the working mental representations of her two groups of practitioners. Although she never specifies how she uses the troubleshooter's mental representations in her analysis, she used the air traffic controllers' representations to draw conclusions about using radar during training.

Woods' project comparing nuclear power plant operators' problem-solving to an expert system solution of the same problem was an interesting sidelight which arose after the expert system was well developed. Woods and his colleagues performed many CTA's during the development of the system, collecting a large body of declarative and procedural knowledge as well as experts' schematic representations of the physical systems with which they work. To define competency models of task performance, they combined these schematic images with text describing the knowledge base. Thus experts' pictorial representation of their mental models were used as an anchor to define the important goal states within the task. Performance models were then derived by posing problems that could arise within the competency model and documenting practitioners' means-end solutions.

In his CTAs of avionics troubleshooters Lesgold and his colleagues categorized the resulting protocol and interview data in primarily two ways. They identified six knowledge areas (see, Table 2) which listed all the metacognitive, declarative, and procedural knowledge required to solve the focus problems.

Table 2
One of Lesgold's Data Organizers

Information Type	Examples
Plans	Extend and test a card; trace through schematic of card.
Hypotheses	Short is caused by broken wire; ground missing from relay.
Device and system understanding	Understanding and use of external control panel; understanding of grounds and voltage
Errors	Getting pin numbers for a test wrong.
Methods and skills	Ability to run confidence check programs; ability to interpret diagrams of relays, contacts, coils.
Systematicity	Returns to point where he knew what was going on when a dead end was encountered; check path from power source.

Note. Adapted from Lesgold, et al., 1990.

They then used this framework as a diagnostic scale to compare the strengths and weaknesses of less and more proficient troubleshooters. They also superimposed novice solution paths through the problem space onto expert solution paths to simplify the process of identifying salient differences in the means-end solutions.

CTA Caveats

The benefit of CTA is clearly its rich and thorough description of task performance. However it is not without its drawbacks. The biggest problem is resource intensity. Gathering the data for a CTA will take hours of the practitioner's and analyst's time--far more than a traditional task analysis--and will generate huge quantities of data, only some of which will have broad applicability to the problem. Analyzing the data is then another time-consuming effort. As Means (1993) points out, the process of codifying and categorizing the data is highly iterative, with new conceptual categories emerging as you proceed that may require reviewing previously analyzed material.

The CTA process is fertile ground for bias and error. Roth and Woods (1989) list three dimensions that will determine the validity of CTA results:
"1) the specificity of the information being elicited, 2) . . . the fidelity or realism of the retrieval context, 3) the length of time between when the information was attended to by the expert and the time he is asked to report it" (p. 255). If the CTA lacks in any of these areas tremendous amounts of effort may be uselessly expended. In addition, complex problems will inevitably have a variety of good solution paths, and for any one path, a variety of explanations (Means, 1993). Therefore the choice of experts and solutions studied is another potential area of bias.

Finally, there is the question of how to best use the important cognitive and metacognitive data arising from a CTA, an area researchers are only beginning to understand.

By very definition, experts' mental models and strategies have been developed through the slow process of accumulating experience in their domain areas. It is completely unclear to what extent this process can be circumvented. Strategies, schemata, and organizational webs that emerge directly from domain knowledge--the powerful tools of expertise which are least subject to articulation and conscious manipulation by the expert--even if identified, may not be transferable. And if they are imposed on learners, they may interfere in as yet unknown ways with the process of acquiring expertise.

On the positive side, some lower-level cognitive strategies can be taught. For example, experts' domain specific strategies for planning and reflecting on the problem solving process will emerge from a CTA. These can be taught to novices through modelling (Brown, Collins, & Dugiud, 1989; Collins, Brown and Newman, 1990). Conceptual models such as a picture of an avionics test-station focusing only on certain pieces of equipment are another CTA result. Similar models which highlight the key features of a domain area have also been shown to aid learning (Mayer, 1989) for lower ability students. Although in Mayer's work the conceptual models used were not explicitly the working models of experts, it seems plausible that in some cases experts' models could be used productively in instruction.

Implications of CTA for Instructional Design

Similarities

A difficulty for instructional designers is that CTA procedures were developed by cognitive psychologists without reference to task analysis as described in the instructional design (ID) literature. The many similarities between the two approaches are obscured by differences in terminology and emphasis.

To note the most important similarity first, both approaches result in a hierarchical or proceduralized description of task. None of the articles reviewed here clearly laid out the proceduralized version of the knowledge uncovered by CTA. However, all of the CTA's were undertaken in the service of either expert system or intelligent tutor design. Therefore to be useful, the knowledge ultimately had to be put in a rule-based form manipulable by a computer program.

None of the knowledge uncovered by CTA is outside the range of knowledge types described by Gagne (cf. Gagne, Briggs, and Wager, 1992), whose instructional theory is perhaps the most influential outside the ID literature (Kyllonen & Shute, 1989). Because cognitive psychologists tend to work from the perspective of Anderson's ACT* theory (Anderson, 1987), they use fewer terms to describe the same knowledge types. But an instructional designer could carry out a CTA and describe the results in Gagne's terms--verbal information, discriminations, defined and concrete concepts, rules, and cognitive strategies. For example, Means' instantiated skill of avionics troubleshooters: "Knowing how P/S regulator is related to power fail indicator lights," (Means, 1993) can be recast as a defined concept: "Identify characteristics of faulty P/S regulator." Paths through a problem space, including planning and reflective steps, can easily be recast as a set of rules.

A final similarity worth considering is that between Gagne's learning hierarchies and Wood's competency model. A learning hierarchy, with its emphasis on what is to be achieved, not how, is conceptually similar to a competency model. However, where Gagne's hierarchy lists all the actions that lead to the desired goal-state, Wood's competency model lists each object that can be acted on and the actions that can be performed on that object in the service of the desired goal-state.

Barriers to Integrated Models

Given the above discussion, a question that must then be asked is, "Should cognitive psychologists conducting CTAs as part of an instructional design process be referring to the ID literature?" The answer, unfortunately, appears to be "Why bother?"

Perhaps most damaging, the ID literature is weak when it comes to addressing the importance of metacognitive skills in problem solving. Despite uncertainty about how to incorporate such skills in instruction, they have emerged as crucial factors in expert performance and are some of the richest data obtainable through a CTA. While the importance of domain-specific metacognitive skills is acknowledged by Gagne et al. (1992), they also believe that on a cost-benefit basis, ID resources are better focussed on the verbal information and intellectual skills (rules and concepts) within a domain (see, Gagne et al., 1992, p. 72). A look at Dick and Cary (1985) reveals no mention of metacognition or cognitive strategies in any form.

Secondly, cognitive psychologists have designed instruction, based on the results of CTA's, in which they provide successful remediation defined only in terms of declarative and procedural knowledge. Most notable is Lesgold's intelligent tutor, Sherlock (see, Lesgold & Lajoie, 1992, for an overview). Sherlock simultaneously addresses gaps in novices domain knowledge, domain-specific problem-solving cognitive strategies, and generic problem-solving skills in a contextualized form.

Finally, cognitive psychologists have defined a taxonomy of learning outcomes which better reflects the knowledge structures that have emerged from cognitive psychological research (Kyllonen & Shute, 1989). This taxonomy defines propositions as the simplest knowledge structure and mental models as the most complicated. The same research effort which applied CTA's to avionics troubleshooters and air traffic controllers is now poised to test this taxonomy and to systematically investigate instructional strategies based on it.

The opposite question might well be asked: "Could instructional designers benefit from a CTA approach to task analysis?" Here an affirmative answer seems appropriate. Most examples of task analysis in ID how-to texts are of tasks where the designer qualifies as an expert: introspection, simple research, or naturalistic observation are all that are required for the analysis. However, in the real world instructional designers frequently rely on subject-matter experts for task descriptions. Merely viewed at the most technical level as a collection of methods for working with subject-matter experts, CTA still adds a valuable dimension of specificity to ID's usually vague prescriptions for task analysis

Conclusion

Having traced the roots of CTA, reviewed its methods, and examined some examples in practice, it is obvious that researchers outside the field of ID are making major strides in the important area of analyzing real-world problem solving tasks. If ID is to grow, or even survive, as an interesting academic pursuit, it must find some way to incorporate and make use of this and other contributions from outside disciplines. At the very least, ID texts could incorporate CTA into the systematic design of instruction. It could be cast as a task analysis subroutine to be followed in the case of problems meeting the criteria by Funke which were presented at the beginning of this paper. Gagne et al. (1992) already differentiate the design procedure for intellectual skills from those for motor or affective skills.

However this solution begs the question to some extent. At issue are fundamental theoretical principles of learning. Cognitive task analysis and traditional task analysis, with their emphases on the practitioner and the task respectively, reflect the theoretical divergence between behaviorism and constructivism. As cognitive psychologists focus their research efforts on identifying and instructionally manipulating complex mental models, they will continue to make headway in defining instructional techniques for teaching in complex problem-solving domains. Unless ID also finds a way to capitalize on the importance of cognition in mediating task performance, it will not have the theoretical power to handle such tasks.

Footnotes

1. In general, it is a poor strategy to accept the task descriptions and solutions of one expert as a basis for examining the cognitive skills applied by others on the task, as Lesgold and Lajoie (1991) acknowledge. In doing so the analyst runs the risk of missing critical aspects of the task not articulated by their particular expert.

References

Anderson, J. R., (1987). Skill acquisition: Compilation of weak-method problem solutions. *Psychological Review, 94*, 192-209.

Anderson, J. R., (1993). Problem solving and learning. *American Psychologist, 48*, 35-93.

Bedard, J., and Chi, M. T. H., (1992). Expertise. *Current Directions in Psychological Science, 1*, 135-139.

Brown, J. S., Collins, A., and Duguid, P. (1989). Situated cognition and the culture of learning. *Educational Researcher*, 32-42.

Cordingley, E. S. (1989). Knowledge elicitation techniques for knowledge-based systems. In Diaper, D., (Ed), *Knowledge Elicitation: Principles, techniques and applications*. New York: Halsted Press.

Dick, W., and Carey, L., (1985). *The systematic design of instruction*. Glenview, IL: Scott, Foreman, and Company.

Ericsson, K. A., and Simon, H. A. (1985). *Protocol analysis: verbal reports as data.*. London: MIT Press.

Funke, J. (1991) Solving complex problems: Explorations and control of complex social systems. In Sternberg, R., and Frensch, P. A. (Eds.), *Complex problem solving*. Hillsdale: Lawrence Erlbaum Associates.

Gagne, R. M., Briggs, L. J., Wager, W. W., (1992). *Principles of instructional design (4th ed.)*. New York: Holt, Rinehart and Winston.

Gardner, M. K., (1985). Cognitive psychological approaches to instructional task analysis. In Gordon, E. W., (Ed.), *Review of research in education 12*. Washington, D. C.: American Educational Research Association.

Kyllonen, P.C., and Shute, V. J., (1989). A taxonomy of learning skills. In Ackerman, P. L., Sternberg, R. J., and Glaser, R., (Eds.), *Learning and individual differences: Advances in theory and research*. New York: Freeman and Co.

Lajoie, S. P., and Lesgold, A. M., (1992). Dynamic assessment of proficiency for solving procedural knowledge tasks. *Educational Psychologist, 27*(3), 365-384.

Lesgold, A. M., and Lajoie, S. P., (1991). Complex problem solving in electronics. In Sternberg, R., and Frensch, P. A. (Eds.), *Complex problem solving*. Hillsdale: Lawrence Erlbaum Associates.

Lesgold, A. M., Lajoie, S. P., Logan, D., and Eggan, G. (1990). Applying cognitive task analysis and research methods to assessment. In Fredriksen, N., Glaser, R., Lesgold, A., and Shafto, M., (Eds.), *Diagnostic monitoring of skill and knowledge assessment.* Hillsdale: Lawrence Erlbaum Associates.

Mayer, R. E., (1989). Models for understanding. *Review of Educational Research 59*, 43-64.

Means, B. (1993). Cognitive task analysis as a basis for instructional design. In Rabinowitz, M., (Ed.), *Cognitive science foundations of instruction.* Hillsdale: Lawrence Erlbaum Associates.

Means, B., and Loftus, E. F., (1991). When personal history repeats itself: Decomposing memories for recurring events. *Applied Cognitive Psychology, 5*, 297-318.

Moray, N. and Rotenberg, I., (1989). Fault management in process control. *Ergonomics, 32,* 1319-1342.

Nelson, W. A., (1989). Artificial intelligence knowledge acquisition techniques for instructional development. *ETR&D, 37*, 81-94.

Newell, A., and Simon, H. A., (1972) *Human problem solving.* Englewood Cliffs, NJ: Prentice Hall.

Ohlosson, S. (1990). Trace Analysis and spatial reasoning: An example of cognitive diagnosis and its implications for testing. In Fredriksen, N., Glaser, R., Lesgold, A., and Shafto, M., (Eds.), *Diagnostic monitoring of skill and knowledge assessment.* Hillsdale: Lawrence Erlbaum Associates.

Riemann, P. and Chi, M. T. H., (1989). Human expertise. In Kilhooly, K. J., (Ed.) *Human and machine problem solving.* New York: Plenum Press

Roth, E. M., Woods, D. D., and Pople, H. E., (1992) Cognitive simulation as a tool for task analysis. *Ergonomics, vol. 35*, 1163-1198.

Roth, E. M., and Woods, D. D., (1989). Cognitive task analysis: An approach to knowledge acquisition for intelligent system design. In Guida, G., and Tasso, C., (Eds.), *Topics in expert system design.* New York: Elsevier Publishers.

Rothkopf E. Z., Cognitive science applications to human resources problems. In Sticht, T. G., Chang, F. R. and Wood, S. (Eds.), *Advances in reading/language Research, 4.* Greenwich, CT: Jai Press.

Sanderson, P., (1989). Verbalizable knowledge and skilled task performance: association, dissociation, and mental models. *Journal of Experimental Psychology: Learning, Memory and Cognition, 15*(4), 729-747.

Wilson, B. and Cole, P., (1990). A review of cognitive teaching models. *ETR&D, Vol. 39*(4), 47-64.

Woods, D. D. and Hollnagel, E., (1988). Mapping cognitive demands in complex problem-solving worlds. In Gaines, B., and Boose, J. (Eds.), *Knowledge-based systems Vol 1.* San Diego, CA: Academic Press Limited.