TOWARDS A TAXONOMY OF COGNITIVE TASK ANALYSIS METHODS:

A SEARCH FOR COGNITION AND TASK ANALYSIS INTERACTIONS

by

Kenneth Anthony Yates

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DEDICATION

This work is a capstone of a program of study that I could not have completed without the love and support of two very special women.

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ABSTRACT

Experts are often called upon to provide their knowledge and skills for curriculum and materials development, teaching, and training. Experts also provide information to develop knowledge-based expert computer systems that facilitate problem-solving tasks in a wide range of fields. Cognitive task analysis (CTA) is a family of knowledge elicitation techniques that have been shown to effectively capture the unobservable cognitive processes, decisions, and judgments involved in expert performance. Over 100 types of CTA methods have been identified and classified. However, existing classification schemes primarily sort CTA techniques by process rather than desired outcome or application. Consequently, it is difficult for practitioners to choose an optimal method for their purposes. A more effective and efficient method to elicit, analyze, and represent expert knowledge would be to apply CTA methods known to be appropriate to the desired knowledge outcome. However, no taxonomy of CTA methods and knowledge types currently exists. The purpose of this study is to identify the most frequently used CTA techniques in the literature and identify which knowledge types are associated with their methods and outcomes. The results indicate that (a) the most frequently used CTA methods include both standardized and informal methods, (b) pairings of CTA methods are used in practice rather an individual methods, and (c) CTA methods have been associated more with declarative knowledge than procedural knowledge. Implications for future CTA research and instructional design are discussed.

CHAPTER 1: REVIEW OF THE LITERATURE

Statement of the Problem

> Unless one can decompose the particular task, in terms of desired learning outcomes and cognitive-process elements, there is almost no point to understanding knowledge structures, and unless one can gain access to those knowledge structures, in both the particular and the generic learners (expert, novice, or whatever), there is no dependable way to translate theory into practice. In short, one must know not only what learning operations the task requires, but also what operations the learner is and should be executing at each stage of the learning process. (Howell & Cooke, 1989, p. 160)

This claim provides a succinct argument for the benefits of utilizing cognitive task analysis (CTA) methods to capture accurate and complete descriptions of the performance objectives, equipment, conceptual and procedural knowledge, and performance standards that experts use to perform complex tasks (Clark, Feldon, Van Merriënboer, Yates, & Early, in press). Experts are often called upon to provide their knowledge and skills for curriculum and materials development, teaching, and training. They also provide information for the development of knowledge-based computer systems that attempt to address undefined and ill-structured problems (McTear & Anderson, 1990).

Historically, behavioral task analysis methods have served as the primary approach to capturing experts' observable actions for these purposes. However, replicating expert performance originating from behavioral analysis is problematic. Expertise, by its nature, is acquired as a result of continuous and deliberate practice in solving problems in a domain (Ericsson, Krampe, & Tesch-Römer, 1993). As new knowledge is acquired and practiced, it becomes automated and unconscious

(Anderson & Lebiere, 1998). Thus, when called upon, experts are often unable to completely and accurately recall the knowledge and skills that comprise their expertise, resulting in significant omissions that can negatively impact in instructional efficacy and lead to subsequent difficulties for learners (Chao & Salvendy, 1994; Feldon, in press; Hinds, 1999).

During the past 25 years, advances in human performance technology have resulted in the development of cognitive task analysis (CTA) as a group of knowledge elicitation methods, which capture the unobserved knowledge, cognitive processes, and goal structures that underlie human behavior (Chipman, Schraagen, & Shalin, 2000; Cooke, 1992). By capturing the decision steps and other cognitive processes, in addition to the action steps experts use in problem solving, instruction and expert systems can be developed that have the potential of replicating expert performance (Clark, 1999).

Evidence for the Impact of CTA on Learning and Performance

A number of studies reveal the effectiveness of CTA methods to improve the accuracy and completeness of information elicited from experts. They also demonstrate that learners' performance improves, as a result of training based on CTA methods.

For example, knowledge elicited by CTA methods improves performance in medical procedures, for which the consequences of incorrect or inaccurate training are potentially life threatening. Maupin (2003) and Velmahos et al. (2004)

documented higher levels of competence for medical interns who received training based on expert information elicited using cognitive task analysis methods. The study compared the skills of 24 surgical interns on the placement of the central venous catheter between training based on knowledge elicited using CTA methods and traditional instruction. Interns in the control group received instruction using the traditional Halsteadian (i.e., "see one, do one, teach one") method, in which a trainee watches a senior resident perform the procedure, performs the procedure under supervision himself, and lastly, instructs another trainee. Interns assigned to the experimental condition received training based on knowledge elicited from individual cognitive task analyses conducted with two senior surgeons that were combined and converted into a training program. Analyses of the results showed that the experimental group had higher mean scores on a post-training declarative knowledge test, required fewer attempts to insert the catheter into the vein successfully, and made fewer mistakes when performing the procedure. Qualitative analysis of the types of errors made by interns indicated that those tasks requiring non-observable decision making, such as selection of the appropriate type of catheter and the placement location, were more likely to be made by participants in the control group.

The accuracy and completeness of medical textbooks is critical in training nurses and other health care professionals; however, textbooks may not contain essential practical knowledge that is learned by on-the-job experience. Hoffman, Crandall, and Shadbolt (1998) reported studies that compared the tacit knowledge of

nurses working in a neonatal intensive care unit with information found in textbooks and found that the indicators detailed in the literature were not a good reflection of realistic clinical practice in the unit. The researchers conducted CTA interviews with 22 highly experienced neonatal nurses who gave accounts of critical case incidents, such as preparatory failure and cardiac arrest. An analysis of the interviews resulted in a number of diagnostic indicators. Compared with the text and manuals, the indicators elicited from the nurses was more elaborate and related more to perceptual judgments and alertness of shifts in the patients' conditions.

Similar to the health care domain, diagnosing or troubleshooting complex computer systems, such as those found in military applications, has high stake consequences, and often must be performed under severe time constraints in operational conditions. Consequently, training for troubleshooting in these contexts must achieve a high degree of speed and accuracy. Schaafstal, Schraagen and van Berlo (2000) conducted a series of cognitive task analyses to develop and test a structured troubleshooting training method consisting of teaching (a) a system independent strategy for troubleshooting, (b) functional models of the system, (c) and system specific domain knowledge. An experimental evaluation was conducted with 21 officers. Ten assigned to a control group received the regular course, and the remaining participants received the training in structured troubleshooting (ST). The variables measured were scores on the knowledge test, and blind ratings of the subjects' verbal protocols on solution accuracy, systematic reasoning, and functional understanding of the system. Although not a statistically reliable difference, the ST

group outscored the controls on the knowledge test (63% versus 55%). However, statistical analysis confirmed a significant effect in favor of the ST group on all verbal protocol ratings for percentage of problems solved (86% versus 40%), systematic reasoning (4.64 versus 2.60, scale = 1-5), and functional understanding (4.59 versus 2.87, scale = 1-5). Moreover, the results showed that the ST group solved the problems in at least 50% less time, providing an additional operational advantage.

Lee (2004) conducted a meta-analysis to determine the generalizability of CTA methods to improve training performance across a broad spectrum of disciplines. Meta-analysis is a technique of quantitative research synthesis incorporating the findings of different research studies that can be meaningfully compared using the size of the statistical effect. The use of effect size standardizes the studies' findings as to make them interpretable and consistent across all variables and measures (Lipsey & Wilson, 2001). A search of the literature in 10 major databases in a variety of domains (Dissertation Abstracts International, Article First, ERIC, ED Index, APA/PsycInfo, Applied Science Technology, INSPEC, CTA Resource, IEEE, Elsevier/AP/Science Direct), using keywords such as "cognitive task analysis," knowledge elicitation," and "task analysis," yielded 318 studies. Seven studies qualified, based on the qualifications of: training based on CTA methods with an analyst, conducted between 1985 and 2003, and reported pre- and post-test measures of training performance. A total of 39 comparisons of mean effect sizes for pre- and posttest differences were computed from the seven studies.

Analysis of the studies resulted in effect sizes of between .91 and 1.45, all considered "large" (Cohen, 1992), and an mean effect size of d=+1.72 and an overall percentage of post-training performance gain of 75.2%. Results of a chi-square test of independence on the outcome measures of the pre- and posttests (χ^2=6.50, p<0.01) indicated that CTA was most likely the cause of the performance gain.

Taxonomies

Taxonomies are classifications systems that organize objects or phenomena into categories (Jonassen, Tessmer, & Hannum, 1999). Although taxonomies are often hierarchical, they can also be a simple organization of objects or phenomena into groups or categories. Taxonomies represent a classificatory perspective. For example, a customer, dealer, or repair shop might classify automobiles differently.

Chulef, Read, and Walsh (2001) suggest that taxonomies play three fundamental roles in a domain of study in that they (a) provide a common vocabulary and language system to aid communication among researchers, (b) support the integration and systemization of findings and theories, and (c) facilitate theory development. For the practitioner in a domain, taxonomies and classifications are indispensable guides to identify appropriate methods, outcomes, and other relationships among the members of the system.

The Current Study

CTA methods have evolved through specific knowledge elicitation applications, mostly in the development of expert systems and in laboratory and military settings. As a result, over 100 variations of CTA methods have been identified (Cooke, 1994). Numerous classifications of CTA methods exist that categorize methods by technique and analytic focus. Technique classifications are those that concern mechanisms for eliciting, analyzing, and representing knowledge. Classifications by analytic focus categorize methods by the domain in which tasks are performed and the social and organizational context of practice in that domain (e.g., CTA Resource, 2006). Classifications of CTA methods by the type of knowledge to be elicited have also been developed (Essens, Fallesen, McCann, Cannon-Bowers, & Dorfel, 1995). Although they differ in overall theoretical approach, these classifications are similar, in that they assign classifications based on the process of conducting CTA and the mechanisms of the individual methods. As a result, there remain no clear guidelines for the practitioner to choose the appropriate combination of methods to apply to a specific task or intended results, "nor is it clear that an orderly relation exists between knowledge elicitation techniques and the type of knowledge that results" (Cooke, 1994, p. 804).

In real world applications, CTA is a toolkit consisting of multiple techniques that elicit knowledge, facilitate data analysis, and those that represent the content and structure of knowledge. This present study requires that these terms be clearly defined.

Crandall, Klein, and Hoffman (2006) describe CTA as encompassing three sets of activities: knowledge elicitation, data analysis, and knowledge representation. Knowledge elicitation methods are defined as those used to collect information about "what people know and how they know it: the judgments, strategies, knowledge, and skills that underlie performance" (p. 10). Data analysis is "the process of structuring data, identifying findings, and discovering meaning. Knowledge representation includes the critical tasks of displaying data, presenting findings, and communicating meaning" (p. 21). Although data analysis and knowledge representation are two distinct aspects of CTA, they are often linked with elicitation methods (e.g., concept maps, repertory grid). Furthermore, analysis and representation tools often share common characteristics so that they are frequently combined into a single category in classification schemes, as found, for example, on the CTA Resource (2006) Web site. As reflected in actual practice, then, it would appear more appropriate to examine CTA as a *pairing* of knowledge elicitation and analysis/representation techniques.

Maximally effective approaches to CTA tend to be those that are organized around and guided by the desired knowledge results (Chipman et al., 2000), and, as such, it would be helpful "to define a taxonomy of tasks, that, in effect, would classify tasks into types for which the same abstract knowledge representation and the same associated knowledge-elicitation methods are appropriate" (p. 7).

Therefore, in contrast with previous classifications of methods that focus on the CTA process, the current study incorporates a product approach that explores the

association between knowledge types as outcomes of the CTA process and the pairing of CTA methods.

Purpose of the Study

The purpose of this exploratory study is to examine the interactions between cognition and task analysis activities. The following research questions frame the study:

- What are the most frequently used pairings of knowledge elicitation and analysis/representation methods found in the CTA literature?
- To what extent do the pairings of these knowledge elicitation and analysis/representation methods match with formal CTA methods found in the literature?
- What knowledge types are associated with these knowledge elicitation and analysis/representation pairings? How consistent are the associations?
- To what extent do publications containing pairings of CTA methods include a statement that the methods incorporate activities addressing automated, tacit, or implicit knowledge?
- How can the applications of the most frequently used pairings of CTA methods be categorized?

Review of the Literature

Among the various definitions found in the literature, knowledge elicitation has been characterized as the process of acquiring knowledge from an expert within a particular problem domain (McTear & Anderson, 1990), and the process of explicating domain-specific knowledge underlying human performance (Cooke, 1999). Representing a wide range of applications, CTA has broadened the focus of knowledge elicitation to include other aspects of cognition, including perception, planning, and decision-making processes. Chipman et al. (2000) define CTA as an "extension of traditional task analysis techniques to yield information about the knowledge, thought processes, and goal structures that underlie observable task performance" (p. 3).

CTA methods are often referred to as a "practitioner's tool kit" (Cooke, 1999, p. 4). Included in this tool kit are techniques that elicit knowledge, facilitate data analysis, and those that represent the content and structure of knowledge (Crandall et al., 2006). Knowledge elicitation methods are defined as those used to collect information about "what people know and how they know it: the judgments, strategies, knowledge, and skills that underlie performance" (p. 10). Data analysis is "the process of structuring data, identifying findings, and discovering meaning. Knowledge representation includes the critical tasks of displaying data, presenting findings, and communicating meaning" (p. 21). Although data analysis and knowledge representation are two distinct aspects of CTA, they are sometimes

integrated with elicitation, for example, creating a concept map or constructing a repertory grid.

As with any took kit, the achievement of the desired outcome depends on the practitioner's understanding of what each tool accomplishes. To assist the practitioner in choosing the appropriate method for the desired outcome, numerous classification schemes have been developed. A review of these classifications and their limitations provide the context for the current study.

Knowledge, in its broadest form, is the raw material that the CTA practitioner extracts, analyzes, and formats, and as such, provides the fundamental reason for conducting CTA. The representation or output of CTA gives a view of expertise in the performance of a task in context that can be used for the design of instruction, expert systems, and other applications (Militello, 2001). Although classifications by knowledge representation offer a level of understanding of the application of CTA methods, empirical research in cognitive science has resulted in a more fundamental and useful method to comprehend and classify the content, structure and application of knowledge. This cognitive view of knowledge types and uses provides the framework for the current study.

Classifications of CTA Methods

During the 1980s, CTA and other labels for knowledge elicitation emerged as a result of a convergence of an emphasis on the study of cognition, the computerization of work, and the shift to more cognitive tasks in the workplace.

There was a tendency to conduct CTA studies in context to examine the interactions of cognition, work environments, and complex communication; however, this resulted in fragmented, single-purpose studies from which various cognitive task analysis methodological approaches and labels emerged (Hoffman & Woods, 2000).

One of the first classification systems was developed by Bainbridge (1979) who, responding to the criticism of self-report and "awareness" studies, examined the conditions in which verbal reports could be used as evidence, namely, when it is determined that verbal reports are sufficiently correlated with observable behavior. She proposed a classification matrix of types of desired information versus elicitation techniques. Bainbridge classified desired information into seven categories: (a) general information on the effects of variables, (b) general information on control strategy, (c) numerical information on control strategy, (d) technical aspects of process, (e) decision sequences, (f) general types of cognitive processes, and (g) full range of behaviors. The elicitation techniques in the matrix included the questionnaire, interview, static simulation, on-line interview, verbal protocol, and observation. Bainbridge cautioned that the appropriate technique depends on the task being performed. Additionally, although verbal reports can be inaccurate, verbal data can be both interesting and useful. Bainbridge was one of the first of many researchers who have recommended using a combination of techniques, as different types of cognitive processing are most likely reported in different ways, and "we are far from being clear about either the different types of cognitive process which exist or the best methods to use" (p. 432).

Researchers have since identified over 100 types of CTA methods due primarily to the diverse paths that the development of CTA has taken (Cooke, 1994). With origins in behavioral task analysis, early work in specifying computer system interfaces, and in military applications – each with its own demands, uses, and research base – the growing body of CTA literature continues to reflect the diverse application of CTA methods. This has resulted in a growing interest to categorize CTA methods in an attempt to understand what methods are appropriate under specific conditions. However, many of these categorizations have focused on the mechanics, such as the elicitation method used and the training required (Militello, 2001), while others have organized the various methods according to the type of outcome and application of the results (Schraagen, Chipman, & Shute, 2000).

Schraagen et al. (2000) conducted a "review of reviews" in which they briefly described 20 reviews of CTA methods published from 1990 through 2000. When the reviews are compared (see Table 1, as cited in Schraagen et al., 2000), they reveal, as expected, the predominate focus of CTA on the development of expert systems and instructional design. Also, it is not surprising that the typical review is intended to guide the practice of conducting CTA, given the number and diversity of methods available to the practitioner. The description of the classification scheme presented in the review, on the other hand, further demonstrates the challenge of not only choosing the appropriate individual method, but also choosing classification system to guide the choice of a method.

Table 1.
Comparison of Reviews of CTA Techniques

Reference	Focus	Classification	Type
Grant and Mayes (1991)	Expert systems	Task analysis relating to human cognition Theories and models Observations	Theory Development
Olson and Biolsi (1991)	Elicitation, analysis, and representation	Direct (e.g., interview, think aloud) Indirect (e.g., repertory grid, judgments of similarity or relatedness)	Practice
Wilson and Cole (1991)	Instructional design	Cognitive apprenticeship framework	Practice
Alm (1992)	Meta-analysis	Context, tasks, structure, mental representations	Practice
Kirwan and Ainsworth (1992)	Organizations	Behavioral task analysis CTA	Practice
Redding (1992)	Instructional design	CTA process and deliverables	Practice
Benysh, Koubek, and Calvez (1993)	Expert systems	Verbal reports Clustering techniques Scaling methods	Practice
Means (1993)	Instructional design	Case studies	Practice
Williams and Kotnur (1993)	Expert systems	Manual, machine-aided, machine-learning	Practice

Table 1, Continued

Cooke (1994)	Elicitation process	Observations and interviews Process tracing Conceptual techniques	Practice
John and Kieras (1994)	Expert systems	GOMS	Practice
Essens, Fallesen, McCann, Cannon-Bowers and Dorfel (1994)	Human-computer interaction	Declarative Procedural Strategic	Practice
Merkelbach and Schraagen (1994)	None specified	Task modeling Knowledge modeling Cognitive modeling	Theory Development
Whitefield and Hill (1994)	Expert systems	Hierarchical task analysis Task knowledge structures GOMS Cognitive task analysis	Practice
Dehoney (1995)	Instructional design	Domain knowledge Focus problems Knowledge elicitation	Practice
DuBois and Shalin (1995)	Assessment	None specified	Practice
Hall, Gott and Pokorny (1995)	Instructional Design	PARI	Practice
Hoffman, Shadbolt, Burton and Klein (1995)	Instructional design Expert systems	Familiar tasks Interviews Contrived techniques	Practice
Crandall, Klein, Militello and Wolf (1997)	Instructional design	ACTA	Practice

Table 1, Continued

Gordon and Gill (1997)	Instructional design Expert systems	None specified	Practice

As seen in Table 1, classification systems for CTA methods range from those that focus on the "front end" elicitation process (e.g., Cooke, 1994) to those that provide guidelines based on desired knowledge outcomes (e.g., Essens et al., 1994). More recently, Militello (2001) classified CTA using types of expertise represented as a framework. In addition, Wei and Salvendy (2004) offered a classification that moved the discussion forward by providing specific guidelines and procedures for choosing an appropriate method. To provide a more complete understanding of the development of current classification systems, each is described briefly.

Examples of CTA Classifications

Mechanism approach. Cooke (1994, 1999) provided one of the most frequently cited and comprehensive reviews of elicitation methods in which she identified three broad families of techniques: (a) observation and interviews, (b) process tracing, and (c) conceptual techniques[1]. Observations and interviews involve watching experts and talking with them. The knowledge elicitation process often begins with watching people perform a task in a natural setting, or when impractical, in a simulated or contrived context, to obtain a global impression of the domain, to generate a general conceptualization, and to identify any constraints that must be

[1] Cooke (1999) divides observation and interviews into two distinct categories making a total of four categories of CTA methods.

accommodated during later stages in the CTA process. Cooke (1999) characterizes interviews as "the most direct way to find out what someone knows" (p. 487). Types of interviews vary from open-ended to constrained and elicit a wide range of knowledge types depending on the questions asked and the specific task.

Process tracing techniques are used to collect sequential behavioral events which are documented as protocols and analyzed to capture underlying cognitive processes (Cooke, 1999). Verbal reports, eye movements, gestures, and other nonverbal behaviors may also be captured and analyzed to provide additional insight into the cognitive processing during the performance of a task.

Conceptual techniques produce structured, interrelated representations of relevant concepts within a domain. Different conceptual elicitation methods produce different quantities and types of concepts (Cooke, 1999)

Cooke's (1994, 1999) three families differ in terms of their specificity and formality, as well as their procedures and emphasis on a particular knowledge type. Generally, observations and interviews are less formal in structure and specificity than process tracing methods, which, in turn, are less formal than conceptual methods. Similarly, less formal methods produce more qualitative data, and the more formal techniques quantitative output. Because different techniques may result in different aspects of the domain knowledge, Cooke recommends the use of multiple methods, a recommendation often echoed throughout the CTA literature (see also Crandall et al., 2006; Ericsson & Simon, 1993; Hoffman, Shadbolt, Burton,

& Klein, 1995; Jonassen et al., 1999; Russo, Johnson, & Stephens, 1989; Schraagen, Chipman, & Shalin, 2000).

It is important to note that Cooke (1994) makes the distinction among knowledge elicitation, knowledge acquisition, and knowledge engineering. Elicitation is the "process of collecting from a human source of knowledge, information that is thought to be relevant to that knowledge" (p. 802). Elicitation is part of acquisition, which is defined as the "explication and formalization of that knowledge," and has, as its goal, "to externalize knowledge in a form that can be implemented in a computer" (p. 802). Both are part of knowledge engineering, which refers to building an expert system or a knowledge base system. Analysis techniques are included in Cooke's classification, thus placing them on the same level as elicitation techniques. Knowledge representation, as defined by Crandall et al. (2006), would appear to fall more within the Cooke's definition of acquisition, rather than elicitation. Thus, it could be that the specificity of terms used in individual studies has been compromised by the general reference to "CTA methods" in the literature.

Cooke, Roth and Freeman (CTA Resource, 2006) expanded on Cooke's (1994) classifications by categorizing techniques primarily associated with knowledge elicitation and knowledge analysis and representation. As defined in the CTA Methods Summary Table (see Appendix A), elicitation methods are used to acquire data, while analysis/representation refers to methods that produce an analytic product or representation. Their classification scheme also evaluates methods

against various attributes according to the strength of the association (high or low). Attributes of elicitation include observation, text analysis, interview, and psychometrics. Attributes of analysis/representation include descriptive, tables/graphs, qualitative models, simulation and numeric models, in addition to the focus of the analysis as domain, operations, cognition, and social/organizational.

Knowledge type approach. Essens et al. (1994) define CTA as seeking to describe, in cognitive terms, how goals and tasks are accomplished. Accordingly, they approached classifying CTA methods from the perspective of capturing the cognitive requirements of task performance. CTA plays a critical role in providing information to decide which aspects of task performance need to be supported. For example, to support a decision-making process, knowing *that* a decision has to be made is less important then knowing *how* that decision is made. The authors refer to knowledge elicitation as techniques that tap an expert's knowledge and differentiate these techniques by the type of knowledge that defines the decision-maker's performance. Thus, they distinguish three classifications; those that elicit declarative, procedural, and strategic knowledge.

According to Essens et al. (1994), declarative knowledge describes facts, rules, concepts, and attributes of a domain. Procedural knowledge pertains to the steps, transformations, and operations applied to knowledge in reaching a decision, such as rules, actions, heuristics, strategies, and processes. Strategic knowledge is closely associated with meta-cognitive processes, such as external monitoring of demands, internal monitoring of capabilities, and control of cognitive processes.

Although the focus of Essens et al.'s (1994) classification is on desired outcomes, it is interesting to note that they recognize the variety of approaches found in the literature "reflect different views of cognition and the lack of firmly established theoretical principles for analysis" (p. 114).

Representation approach. As many CTA methods link elicitation with analysis/representation techniques, only a few studies are found in the literature that focuses specifically on analysis/representation (Crandall, et al., 2006). Recently, Militello (2001) suggested that the representation or output of CTA is a view of expertise in the context of a specific task. Accordingly, she proposed a categorization scheme centered around the types of expertise elicited and represented by various CTA methods that includes four categories: expertise in context, conceptual links, operation sequences, and simulations of expert performance.

Methods that elicit expertise on context (e.g., Critical Decision Method) capture cues, judgments, and problem-solving strategies in a dynamic setting. Conceptual links (e.g., concept maps) provide a static representation of the abstract mental models of how the expert organizes information. Methods that capture operation sequences, such as goals, timelines, and interactions, include hierarchical task analysis, timeline analysis, and workflow analysis. Simulations of expert performance use computer models to represent human performance of a task in a software environment.

Because each representation of expertise captures different aspects of the behavior and cognition, Militello (2001) recommends a combination of methods that

result in two dimensions of expertise (a) that relate to the level of contextual detail (rich versus abstract) and (b) that concern the view of expertise in time (static versus dynamic).

Guidelines approach. Wei and Salvendy (2004) extended the classification of CTA methods based on the mechanisms of the techniques – observations and interviews, process tracing, and conceptual techniques – by the addition of a fourth family – formal models. The authors also classified each family according to the degree to which the technique is formally specified, with observations and interviews being less formal and specified and formal models more formal and well specified. Methods are also compared based on appropriate application characteristics, inputs, outputs, and processes, which are then summarized as general weaknesses and advantages for each method. Wei and Salvendy's review differs from other classifications in that it provides guidelines to select CTA methods in practical applications.

Wei and Salvendy (2004) further analyzed CTA methods in the context of task and job design, and concluded that "based on the summarized literature reviews …the current methods are only found to capture part of the human performance aspect in the cognitive domain" (p. 289). They based their analysis on a human-centered information-processing (HCIP) model designed to capture the cognitive attributes of tasks and their influence on task performance. Cognitive attributes of task performance are classified within 11 modules that fall in three broad categories: functional, resource, and affect, and are claimed to be "the most complete cognitive

capability requirements for job design" (p. 293). Using the HCIP model as the standard, they evaluated 26 task analysis methods to determine whether the methods (a) generally covered, (b) somewhat covered, or (c) extensively captured and represented the cognitive attributes within the 11 modules. Wei and Salvendy found that the attributes, such as generate ideas, intervene, human learning, cognitive attention, sensory memory, ability and skills, and social environment, are not, or are rarely, addressed by the 26 methods reviewed.

Wei and Salvendy's (2004) review and analysis of CTA methods using the HCIP model is important for two reasons. First, it validates the suggestion made by Hoffman et al. (1995) that two or more CTA methods should be combined to ensure complete and accurate results. Known as the "differential access hypothesis," Hoffman et al. proposed that different elicitation techniques capture different types of knowledge, and that the characteristics of the domain and task should be considered when choosing a technique. To compensate for the differential access effect, Wei and Salvendy recommend either combining CTA methods with traditional task analysis, or combining CTA methods from the same or different CTA family to capture all the cognitive attributes of task performance. Wei and Salvendy's study also demonstrates how a cognitive model can be used to systematically evaluate the characteristics CTA methods based on an objective standard, in this case the HPIC model, to identify commonalities and differences among the methods.

In sum, existing classification systems examine CTA through unique lenses representing diverse theoretical and application approaches. Although generally helpful for the practitioner, the narrow focus of these systems, as shown in the next section, limits research in and progress toward a unified theory of CTA and a simplified taxonomy that can apply over a wide range of domains.

Limitations of Existing Classification Systems

The diverse development and application of CTA has led to many conflicting and confusing definitions. The term "cognitive task analysis," for example, refers to both the general process of conducting CTA (Chipman et al., 2000) and an explicit set of knowledge elicitation techniques to identify the knowledge, goals, strategies, and decisions that underlie observable task performance (CTA Resource, 2006). Crandall et al. (2006) describe three critical components of CTA: knowledge elicitation, data analysis, and knowledge representation. They note, however, that many knowledge elicitation methods have analytical processes and representational formats embedded within the method. Such vague distinctions within the process of CTA make classification and comparisons of methods difficult.

The absence of clear definitions among individual methods also makes classification difficult. As an example, interviews are commonly used for knowledge elicitation, because they are easy to conduct. However, the CTA literature refers to three types of interviews: unstructured, semi-structured, and structured. Based on actual usage, there is no clear distinction between them. The

characteristics and uses of interviews for knowledge elicitation appear to fall along a continuum of three attributes of (a) formality from "structured" (predetermined, often closed questions with no follow up questions) to "semi-structured" predetermined outline of questions and opportunistic follow up questions to "unstructured" (free flowing, uninterrupted request to the expert to "tell me everything you know about...."), (b) content ranging from a broad domain to a specific situation, incident, or task, and (c) knowledge type desired, whether declarative, procedural, or both. However, the outcomes of some types of structured interviews, such as those that involve functional diagrams, charts, and the generation of if-then rules, are more characteristic of knowledge representation. As in this case with interviews, classifications of the full range of elicitation methods are difficult and of limited use when they focus solely on descriptive features.

Cooke (1994, 1999), for example, classified knowledge elicitation methods along one or more dimensions by focusing on the description of the mechanics of the techniques. One dimension centered on verbal reports and the conditions that determine their accuracy and completeness. Another dimension Cooke incorporated characterized elicitation methods as direct or indirect. Direct methods include those in which knowledge can be verbalized, such as interviews, questionnaires, and observations. Indirect methods, on the other hand, rely more on knowledge inferred from other behavior and include methods such as hierarchical clustering and repertory analysis. Using these underlying dimensions, Cooke (1994) initially classified knowledge elicitation methods into three families: observation and

interviews, process tracing, and conceptual techniques, and subsequently (1999) divided observations and interviews into separate categories.

Given the different research and development paths CTA methods have taken within expert systems, human factors, and cognitive science, it is difficult to consolidate the literature around one methodological theme. To date, the classification of CTA methods has been largely dependent on the theoretical approaches taken and the goals and purposes of the classification system (Hoffman et al., 1995). For example, in expert systems, emphasis is placed on generating knowledge representations that can be easily formatted for computer systems, whereas human factors applications call for more ecologically valid methods appropriate for elicitation in naturalistic settings.

Typically, classification systems focus either on the processes and mechanisms of knowledge elicitation or on knowledge representations as the product of analyzing elicited information (Cooke, 1994). A cursory review of classification schemes from either method clearly indicates that there are many differently labeled CTA methods that are similar in both their elicitation technique and their analysis/representation of data. Therefore, current classification systems appear to have characteristics more associated with *typologies*, than with true *taxonomies*. According to Patton (2002) typologies classify some aspect of the world into parts along a continuum. In contrast, taxonomies classify items into mutually exclusive and exhaustive categories.

Well-developed and widely accepted taxonomies have conceptual and theoretical benefits that play a significant role in the development of a domain (Chulef et al., 2001). They provide a common vocabulary and language among researchers, which enables studies to utilize shared conceptual meanings. Taxonomies also afford the integration and systemization of findings and theories in a domain. When phenomena appear to be related, they can then be studied in the context of a taxonomy to determine if they are, in fact, related and which characteristics might be expected of that relationship. Through this facilitation of comparative analysis, taxonomies enhance the development of theoretical and causal models within a domain (e.g., the periodic table of elements, Bloom's taxonomy, the Linnean system of biological classification, etc.).

Hempel (1965) analyzed the logical and methodological aspects of classifications and the progress of science as background for the development of the taxonomy of mental disorders. Hempel defined a classification system as a division of a set or class of objects into subclasses or members of a given set. Each subclass is an extension of an underlying concept. Scientific concepts have two functions: First, they describe things and events within the domain of investigation. They also enable the establishment of general theories to predict and understand observable phenomena. As advances are made in a field of study, scientific concepts (a) give way to the formulation and systemization of principles that refer to unobservable entities, (b) are expressed in theoretical terms, and (c) explain observable phenomena. According to Hempel, scientific progress is made when a broader

spectrum of observable phenomena in a domain can be explained and predicted by increasingly generalized covering laws, and, in turn, when this theoretical development results in a reduction of taxonomic categories.

The issues involved in advancing classification systems toward the development of theory can be exemplified by the controversy surrounding the Diagnostic and Statistical Manual of Mental Disorders (DSM; American Psychiatric Association, 1994). In their critique, Follette and Houts (1996) argue that the DSM is a flawed classification system, because it neither demonstrates taxonomic progress nor facilitates the development of theory within the domain of clinical psychiatry. Although the DSM claims to be atheoretical to promote widespread adoption in the medical community, it is, in reality, based on a weakly stated medical model easily deducible from the content. Follette and Houts argue that this claim of atheoreticality is not only an illusion, but it also impedes the progress of research in mental disorders. Moreover, as judged by the principles of Hempel (1965), the history of the DSM does not meet the standards of scientific progress. As evidence, they offer, one only needs to observe the proliferation of diagnostic categories in subsequent editions of the DSM.

Follett and Houts (1996) argue that the proliferation of DSM categories demonstrates that “the taxonomy is not flourishing but foundering, because a system that merely enumerates symptoms and then syndromes cannot exhibit simplification by the application of an organizing theory” (p. 1126); as a result, there is no possibility of collapsing categories. According to the Hempel (1965) model,

categories are instances of theoretical generalizations, rather than socially consensual labels. Thus, the addition of categories represents a slippage in taxonomic stability, whereas a reduction in categories represents the development of an organizing theory and scientific progress.

There are strikingly similarities between the developmental history of the DSM and the challenges CTA researchers face to move current CTA classification systems toward theoretically driven taxonomies. As the review of the CTA literature in the previous section illustrates, the number of CTA methods has proliferated dramatically. Although there are now many different CTA classification schemes, in contrast to the overarching DSM, these classifications have remained mostly at the descriptive stage, supported by broad theoretical and methodological approaches to knowledge elicitation, analysis, and representation. Moreover, research in and application of CTA methods traverse a variety of domains, mainly within expert systems, human factors, and training design. Consequently, CTA lacks a common vocabulary and language making systematic taxonomic research difficult. Thus, it is unlikely that an organizing theory that facilitates a reduction in categories will emerge, unless common definitions and measures of probative data for specific goals of CTA are found.

Cooke's (1994, 1999) classification system of knowledge elicitation methods is widely accepted and represents one of the seminal works most frequently cited in the CTA literature. However, in the context of this discussion, it would appear to have two limitations. First, the methods classified within the system represent

techniques associated not only with knowledge elicitation, but also with data analysis and knowledge representation. For example, protocol analysis, as defined by Ericsson and Simon (1993) incorporates both elicitation (primarily think aloud) and data analysis techniques (coding verbatim statements in specific categories). Repertory grid (as a matrix of constructs ranked in importance by the informant), as another example, integrates all three components of CTA: elicitation, analysis, and knowledge representation methods. In this respect, the three families of methods Cooke proposed represent a collection of methods according to methodological similarities, rather than of a well-developed taxonomy in which theoretical development leads to increasingly generalized covering laws and a reduction of taxonomic categories, in accordance with Hempelian ideals.

This leads to the second limitation of Cooke's classification system that concerns the lack of a central organizing theory. By choosing to focus on the mechanics or "how" elicitation is conducted as the organization of the classification, Cooke limits the exploration of relationships between the methods and their outcomes, or the "why" component that promotes the development of theory.

The point here is not to disparage Cooke's or any other classification scheme. These systems have provided a useful means to compare and contrast techniques to better understand the appropriate conditions and expectations for their results. In short, current classifications have helped to organize and otherwise make sense out of the number and diversity of knowledge elicitation, analysis, and representation methods, as well as providing helpful guidelines for practitioners. The issue in

question is whether existing CTA classifications are attenuating or augmenting scientific progress according to Hempelian ideals. For progress to be made, the theories underlying current classifications need to be further developed and articulated. Before this can happen, however, researchers, as previously stated, need to agree on common definitions, goals, and measures to conduct their research.

Toward that end, it has been noted that the common objective among all CTA methods is to reveal the knowledge, cognitive processes, and goal structures that underlie observable behavior (Chipman et al., 2000). Regardless of the application, the requirements for knowledge outcomes of CTA most often include a model of expertise for problem solving within a domain. There is an overwhelming body of empirical research identifying the cognitive properties of expertise that cross a wide range of domains (see Feldon, in press, for an extensive review). These properties center on experts' broad conceptual and strategic knowledge that facilitates the evaluation of problem states and alternative solutions, combined with automated procedures for effective and efficient decision-making. Thus, if the common goal among CTA methods is to capture the cognitive properties of expertise at varying levels, a potentially productive line of taxonomic research and theory development should focus on common measures and methods to identify the types and functions of knowledge that ultimately produce models of expertise. Based on existing theories of cognition that are well-developed and articulated, a taxonomy of CTA methods and cognition could possibly achieve the desired reduction in taxonomic

categories, while providing clearly explicated guidelines for conducting the CTA enterprise.

To summarize, there are numerous classifications of CTA methods in the literature that, for the most part, classify methods based on an methodological or theoretical approach. However, Cooke (1994) noted that it is not clear that an orderly relation exists between knowledge elicitation techniques and the type of knowledge that results. According to Hoffman et al. (1995), a classification scheme for analyzing and comparing various methods needs to reflect cognitive functionality, that is, tasks that are good for eliciting tacit knowledge and perceptual judgments, and tasks that are good for eliciting procedural knowledge.

Knowledge Taxonomies

Declarative and Procedural Knowledge

Anderson (1983; Anderson et al., 2004; Anderson & Lebiere, 1998) made the distinction between declarative knowledge, which refers to what we know, and procedural knowledge, which refers to skills we know how to perform. This distinction became the foundation for his original theory of cognitive architecture and knowledge called Adaptive Control of Thought (ACT*), and subsequent iterations, including the most recent ACT-R 5.0. The foundation for this distinction lies in defining the critical "atomic" components of the system – chunks and productions. Anderson (1996) claims the following:

> All that there is to intelligence is the simple accrual and tuning of many small units of knowledge that in total produce complex cognition. The whole is no more than the sum of its parts, but it has a lot of parts. (p. 356)

Declarative knowledge. Declarative knowledge consists as a hierarchy of cognitive units, with each unit comprised of no more than five cognitive elements, or chunks (Miller, 1956) that encode elements in a particular relationship.[2] Cognitive units are propositions, temporal strings, or spatial images (Anderson, 1983). In the information processing system, the basic unit of information is the proposition (E. D. Gagné, 1985), and corresponds basically to an idea containing two elements: a relation and a set of arguments. The arguments are the subject of the proposition and normally consist of nouns and pronouns; the relation of a proposition is a verb, adjective, or adverb that constrains the relationship. Thus, in the example, "John is a graduate student," John is unconstrained (There are many things we can know about John); graduate student is unconstrained (There are many things we can know about graduate students); however, with the addition of "is" the proposition is constrained to only one meaning about John being a graduate student. Declarative knowledge, then, corresponds to things we are aware we know and can usually describe to others (Anderson & Lebiere, 1998).

Other cognitive psychologists have defined declarative knowledge in a variety of ways. For example, Ormrod (2004) describes declarative knowledge acquired through textbooks and teachers, experience and about the world around us, and how things were or are. Schunk (2000) states that declarative knowledge refers

[2] Cowan (2000) argues that working memory is limited to three (plus or minus one) cognitive elements.

to “knowing that,” or facts, subjective beliefs, scripts (events), and organized passages. Finally, declarative knowledge is factual knowledge; it is “knowing what” (Bruning, Schraw, Norby, & Ronning, 2004).

Procedural knowledge. Procedural knowledge consists of condition-action (IF-THEN) pairs called productions which are activated according to rules relating to a goal structure (Anderson, 1983). Within the ACT framework, all knowledge is initially declarative and is interpreted by general procedures. Productions, then, connect declarative knowledge with behavior. Procedural knowledge represents “how to do things.” It is knowledge that is displayed in our behavior, but that we do not hold consciously (Anderson & Lebiere, 1998).

As a task is performed, interpretive applications are gradually replaced with productions that perform the task directly, a process called *proceduralization.* For example, rehearsing how to manually shift gears in a car is gradually replaced by a production that recognizes and executes the production. In other words, explicit declarative knowledge is replaced by direct application of procedural knowledge (Anderson, 2005). Sequences of productions may be combined into a single production, a process called *composition*. Together, proceduralization and composition are called *knowledge compilation*, which creates task-specific productions during practice. The process of proceduralization affects working memory by reducing the load resulting from information being retrieved from long-term memory.

Gagné (1985) makes two distinctions between declarative knowledge and procedural knowledge. Although declarative knowledge varies tremendously in topic and scope, it is relatively static, whereas procedural knowledge is dynamic. Procedural knowledge is transformational, in that the output is quite different than the input. Second, the activation of declarative knowledge is slower and more conscious, whereas the activation of procedural knowledge increases with practice, until it becomes fast and automatic.

Component Display Theory

Merrill (1983; 1994) defined Component Display Theory (CDT) as a set of prescriptive relationships that can be used to guide the design and development of learning activities. According to CDT, the degree to which these relationships are included is directly correlated to the achievement of the learning objectives. Objectives are categorized using a two-dimensional classification system, with performance as one dimension and content type as the other dimension. CDT is strongly influenced by Gagné's (1965) conditions of learning which describes the conditions necessary for the acquisition of specific outcome categories. Both CDT and Gagné's conditions of learning assume that different categories of outcomes require a different means of promoting and assessing achievement of the outcome. However, CDT extends Gagné one-dimensional classification to a two-dimensional performance-content matrix. For the purposes of this study, the performance-content matrix of knowledge types and uses is further described, as it will be used to classify

CTA methods. The instructional design component of CDT is excluded from the study and therefore, is not considered.

Figure 1.
Performance-Content Matrix

FIND				
USE				
REMEMBER				
	FACT	CONCEPT	PROCEDURE	PRINCIPLE

The performance-content matrix classification system is illustrated in Figure 1 (Merrill, 1983). In the performance dimension, there are three levels: remember, use, and find. The five content dimensions are fact, concept, process, principle, and procedure.

Performance categories. Remember requires a person to search memory to reproduce or recognize some item of previously stored information. *Use* requires a person to apply some abstraction to a specific case. *Find* requires that a person derive or invent a new abstraction.

Merrill (1983) derived the categories of the performance dimension of the performance-content matrix, based upon assumptions about the nature of human memory, that is, there is more than one kind of learning and more than one kind of memory structure. There are two kinds of memory structures relevant to CDT – associative memory and algorithmic memory.

Associative memory consists of a hierarchical network structure, which is accessed for information storage and retrieval. Associative memory is used in knowledge stating. According to CDT, when a person stores information in associative memory and then retrieves it in the same form, there is minimal structural change. In recalling the information, then, there should be no error, as no derivative or thought processes are involved. In CDT, the performance of literal storing and retrieving information is called *remember-verbatim*. Associative memory is also used when information is integrated and stored with other information in memory. However, recall of this information may lead to error, as other non-relevant information may be retrieved along with the target information. In CDT, the performance level for the integration of information into associative memory is called *remember-paraphrase.* Although Merrill combines both forms of associative memory performance under the level remember, the distinction between verbatim and paraphrase may become important in this study to distinguish between CTA methods that are intended to elicit one or the other of these knowledge uses.

Algorithmic memory is involved when information, in the form of processing strategies or schemas, is modified, as it is integrated and stored with existing processing structures. Merrill (1983) distinguishes between two ways that information can be incorporated in algorithmic memory. The first is called *integration*, which occurs when schema is retrieved to accommodate the new information. When a possible schema is identified, an attempt is made to instantiate the variables of the schemas. When information is retrieved, it is the product of the

integration. This is an active process that often takes some time and is prone to error. Although a person may have a correct schema, there may be error in recognizing an instance of that schema. Or, in the case of a procedure, a correct knowledge schema may not guarantee the correct application of that schema. In CDT, integrative processing is called *use* and refers to a general rule to process specific information, whether concepts, principles, or procedures.

Merrill (1983) describes a second way to use algorithmic memory by reorganizing information. *Reorganization* is an inductive process of examining phenomena and creating new schema internally, rather than reacting to external stimuli. This type of processing is called *find*, which refers to finding new generalities or higher-level processes. Merrill characterizes find as an iterative process involving trial and error, that is, creating and testing schemas, often resulting in following wrong paths. In CDT, find has similar applications, as does use. For example, concept use involves identifying an instance of the concept, whereas finding a concept requires that a person choose a beginning schema to make the first, albeit possibly incorrect or incomplete, classification. As such, for the purposes of classifying CTA methods by use, the find performance level is subsumed into the use level.

Content categories. *Facts* are described as arbitrarily associated pieces of information, such as names, dates, and events. *Concepts* are objects, events, or symbols that share common attributes and that are identified by the same name. *Process* is a series of events (Merrill, 1994). *Principles* are cause and effect or

correlational relationships that are used to interpret events or circumstances. *Procedures* are an ordered sequence of steps necessary to accomplish a goal, solve a problem, or produce a product.

Merrill (1983) suggested that the content categories are based on an assumption that humans impose an organization on their world by classifying things by subject matter. Concepts, then, are formed when things are grouped together into classes that share common attributes. Subject matter emerges when a relationship between two or more concepts is discovered.

Reigeluth (1983) describes several distinguishing features of CDT over previous taxonomies. First, CDT is highly integrative, in that it builds on well-researched components and models developed by other researchers and theorists. Second, CDT classifies objectives on two dimensions, by the type of content and the desired level of performance, and thus, builds on and extends Gagné's (1965) one-dimensional classification. Finally, Reigeluth states that CDT has an extensive base of empirical support, in both formal research and real-world field-testing.

During the last decade, conceptions of Merrill's (1983) system have been adjusted to further distinguish nature and function of declarative and procedural knowledge (R. Clark, personal communication, July 24, 2006). The adjustment centers on the question: How do you apply a concept, process, or principle, other than with a procedure? In adapting Merrill's system to accommodate this question, knowledge types are associated with two activities: remember/say and use/apply. For example, a person is able to recall and say concepts, processes, principles, and

procedures. However, when applied as procedures, concepts are used to classify, processes to debug or troubleshoot, principles to create a new instance of something, and procedures to perform the steps in a task. Figure 2 summarizes the two uses of the four knowledge types within this cognitive framework.

Figure 2.
Knowledge Types and Activities

Type	Remember/Say	Use/Apply
Concept	Define an object, event, or symbol	Classify objects, events, or symbols
Process	Describe the stages	Troubleshoot a system
Principle	Identify cause and effect	Create a new instance
Procedure	List steps	Perform steps

In sum, declarative and procedural knowledge work together to solve problems. As declarative knowledge is applied to task performance, it becomes procedural. The nature of procedural knowledge is that it becomes automated and unconscious. Merrill's CDT is a method to classify knowledge according to type and application, and, as such, provides guidance for the elicitation of knowledge, thought processes, and goal structures that underlie observable task performance.

CHAPTER 2: METHOD

The research questions posed in this study represent a multi-dimensional review of the existing research to explore interactions between CTA activities, knowledge types, and knowledge applications. As such, this study represents the first step in an ongoing series of studies to establish generalized causal inference among the variables. Shadish, Cook, and Campbell (2002) suggest that generalized causal inference is established through two tasks: (a) identifying construct labels for persons, settings, treatments, and outcomes, and (b) exploring the extent to which a causal relationship generalizes over variations in persons, settings, treatments, and outcomes. Generalizable studies, they posit, result from scientists applying five principles:

1. Assess surface similarity between study operations and target generalization.
2. Rule out irrelevancies that do not change a generalization.
3. Make discriminations that limit generalizations.
4. Interpolate within samples and extrapolate beyond samples
5. Develop and test causal theories about the target of generalization.

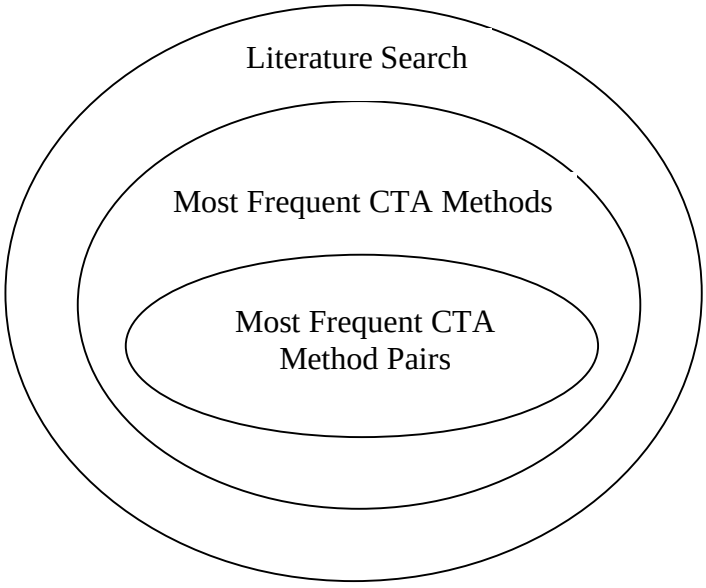
Although no one principle, alone, is sufficient, knowledge of generalized causal inference is not complete unless all five components are addressed.

"Qualitative methods provide an important avenue for discovering and exploring causal explanations" (Shadish et al., 2002, p. 389). In the form of descriptive reviews, qualitative methods are useful to find clues about generalized

causal factors and potential moderators of intervention effects, and are common as an initial phase of a strategy to conduct increasingly generalizable studies. The strength of descriptive review lies in its ability to generate hypotheses, provide dense accounts of the literature, and develop theories with qualitative categories and relationships among the variables. The disadvantages are the difficulty of tracking these relationships and analyzing the complexity of the moderators and outcomes, as the number of studies under examination increases.

In this study, the five research questions provided the framework for determining the methods for data collection. Figure 3 shows an overview of the process. A search of the literature provided the initial sample of studies. The CTA methods in the sample were classified by name and type (elicitation, analysis/representation, or both) and ranked by frequency. A sample representing the most frequently cited CTA methods was selected and the studies in this sample were reviewed further to identify and classify all CTA methods reported within each study. Statistical analysis was then used to find the most frequent pairings of CTA methods. Studies in which these pairings occurred were then examined to identify and classify the results as to the type and subtypes of knowledge outcomes. The studies were also reviewed to categorize how the results were applied, and whether statements pertaining to methods sensitive to eliciting automated knowledge were included. A detailed description of the methods to collect data for each research question is provided in the sections that follow.

Figure 3.
Study Sample Methodology



Research Question 1:

What are the most frequently used pairings of knowledge elicitation and analysis/representation methods found in the CTA literature?

As shown in Figure 3 and in the previous overview, an iterative process was used to supply the data for this question. In this section, the operational definitions for CTA methods and CTA method pairings used in the study are provided. The classification scheme and method for classifying the CTA methods identified in the literature search is described next, followed by a detailed description of the two-stage process to determine the most frequent CTA method pairs.

Operational Definitions

CTA is often referred to as a "toolkit," a term that reflects the number and variety of methods available to the practitioner. Included in this toolkit are techniques that elicit knowledge, facilitate data analysis, and those that represent the content and structure of knowledge. This present study requires that these terms be clearly defined.

CTA methods. Crandall et al. (2006) describe CTA as encompassing three sets of activities: knowledge elicitation, data analysis, and knowledge representation. Knowledge elicitation methods are defined as those used to collect information about "what people know and how they know it: the judgments, strategies, knowledge, and skills that underlie performance" (p. 10). Data analysis is "the process of structuring data, identifying findings, and discovering meaning. Knowledge representation includes the critical tasks of displaying data, presenting findings, and communicating meaning" (p. 21). Although data analysis and knowledge representation are two distinct aspects of CTA, they are often linked with elicitation methods (e.g. concept maps, repertory grid). Furthermore, analysis and representation tools often share common characteristics, so that they are frequently combined into a single category in classification schemes. Therefore, as an operational definition for this study, CTA methods refer to *individual* knowledge elicitation methods and individual analysis/representation methods.

CTA method pairings. In practice, many CTA studies incorporate multiple elicitation and analysis/representation methods, as often recommended in the

literature. However, components of both knowledge elicitation and analysis/representation must be present for a successful CTA study (Crandall et al., 2006). For the purposes of this study, then, the operational definition of CTA method *pairings* refers to a pairing of an individual elicitation method with an individual analysis/representation method.

Classification Scheme

The CTA Methods Summary Table based on Cooke's (1994) extensive review can be found at the CTA Resource (2006) Web site and is attached as Appendix A. This table describes over 100 methods and classifies the methods as elicitation (E), analysis/representation (A), or both elicitation and analysis/representation (E & A). The methods listed in the CTA Methods Summary Table were adapted and used as the primary resource for classifying the publications in this study. When knowledge elicitation and analysis/representation methods not listed in CTA Methods Summary were encountered during the classification process, they were added. Table 2 contains a list of the methods and their corresponding classifications that were added to the classification scheme in this study.

Table 2.
Additional CTA Methods for the Classification of Studies

Name and Description	Elicitation	Analysis/ Representation
Document Analysis - The analyst seeks out information from texts based on *a priori* types of information.	E	A

Table 2, Continued

Card Sorting – The analyst has the informant sort cards containing information into different categories. In studies, where a specific card sorting techniques is not specified, the generic Card Sort was used as a classification.	E	A
Concept Map – The analyst has the informant write information as a graph of nodes and the relations that connect them.	E	A
Structured Interview – The analyst asks the informant pre-determined questions requiring closed responses.	E	
Semi-structured Interview – The analyst uses an outline of questions to ask the informant leaving opportunity for follow up and branching questions.	E	

The coding form, attached as Appendix B, was developed to record the classification of the studies, according to CTA method, knowledge types and subtypes, sensitivity to automated knowledge, and application of the final results.

Two-Stage Process To Determine The Most Frequent CTA Method Pairings

The selection of the study sample was an iterative process of first "casting a wide net," and then applying increasingly constraining selection criteria. The process consisted of the two stages. In the first stage, a literature search was conducted and abstracts of studies meeting the search criteria were collected. The abstracts were reviewed for inclusion or exclusion from the sample, based on pre-established criteria. CTA methods cited in the abstracts of the included studies were recorded and ranked by frequency. In the second stage, based on availability, the

complete text of each study in the "most frequent" sample was reviewed, and all CTA methods used in the study were classified. In addition, the studies were coded as to knowledge types represented in the results, and whether the study addressed issues relating to automated knowledge. Based on analysis of the collected data, the most frequent pairings of CTA methods were identified as the final study sample. The method and results for each stage are described in the next section.

Stage One. Using keywords "knowledge elicitation" and "cognitive task analysis," a search was conducted in seven publication databases: ArticleFirst, Engineering Village (INSPEC/Compendex), ERIC, IEEE, ISI Web of Science, PsycINFO, and Elsevier ScienceDirect. Knowledge elicitation was included as a keyword, because it is a term generally associated with the knowledge acquisition process, appears early in the literature, and, in the early literature, refers to both observable behaviors and cognitive processes. No constraints were placed on the date of publication in the search criteria, which provided an additional advantage for using both terms as keywords. The search returned a total of 1065 studies after duplicate studies were removed. The number of unduplicated studies in the search results for each database is listed in Table 3.

Table 3.
Studies in Phase One

Database	Search Results	Excluded	Remaining
ArticleFirst	34	8	26
Engineering Village (INSPEC/Compendex)	728	181	547
ERIC	31	27	4

Table 3, Continued

IEEE	17	6	11
ISI Web of Science	104	36	68
PsycINFO	120	41	79
ScienceDirect	31	16	15
Total	1065	315	750

The abstracts of each study were obtained and reviewed to determine whether the study met one or more criteria of (a) describing a technique for knowledge elicitation and/or knowledge analysis/representation, and/or (b) reporting the results of applying knowledge elicitation and/or analysis/representation. If the abstract provided insufficient information to apply the criteria, an attempt was made to find the complete study for further analysis. A total of 315 studies were excluded during this phase, leaving 750 studies for further consideration (see Table 3). Studies excluded during this initial review were: (a) general reviews of methods, classifications, or ontologies; (b) theoretical or conceptual approaches; (c) descriptions of computer authoring tools or software design of knowledge based systems; and (d) other applications that did not include knowledge elicitation or an attempt to capture cognitive processes.

Each abstract was reviewed and a record was made of any knowledge elicitation or analysis/representation method stated in the abstract. A total of 901 methods were identified, which were then grouped and ranked in descending order. A complete list is of methods and their frequency is found in Appendix C. Within

the ranked frequency groups, the eleven methods listed in Table 4 represented approximately 60% of the 901 methods identified in the abstracts.

Table 4.
Most Frequently Cited Methods

Method	Number	Percentage
Structured Interview	135	14.98
Concept Map	79	8.77
Verbal Think-aloud	65	7.21
Process Tracing	54	5.99
Repertory Grid/laddered grid	50	5.55
Observation	33	3.66
Hierarchical analysis	28	3.11
Card Sorting	27	3.00
Document analysis	26	2.89
CDM/CIM	25	2.77
Unstructured Interview	24	2.66

Stage Two. An attempt was made to locate each study that utilized the methods listed in Table 4. A total of 154 studies were located and reviewed to classify all the knowledge elicitation and analysis/representation methods utilized in each study, according to the CTA Methods Summary Table (Appendix A) supplemented by the methods in Table 2. Statistical analysis was then applied to determine the CTA method pairings represented within the study sample. The CTA method pairings were ranked by frequency, and those that were clustered within the highest frequency were selected. The studies that utilized the most frequent CTA method pairings were identified as the final study sample, and included 154 studies.

Research Question 2:

To what extent do the most frequent CTA method pairings of knowledge elicitation and analysis/representation methods match with formal CTA methods found in the literature?

The most frequent CTA method pairings were examined and categorized as either formal or informal based on Cooke's (1994, 1999) general description of the three families of CTA methods. The mechanisms of formal CTA methods are well specified, standardized, and intended to be applied systematically. In contrast, informal techniques are less structured and more adaptable to meet the constraints of the task and domain. As an example, observations and interviews are less formal in structure and specificity than protocol analysis and conceptual methods, such as repertory grid and card sorting. CTA method pairings were considered formal, when a formal elicitation method was paired with a formal analysis/representation method, for example, the pairing of protocol analysis – protocol analysis, or card sort – card sort. Conversely, an example of an informal paring would that of semi-structured interview with diagram drawing.

Research Question 3:

What knowledge types are associated with the most frequent CTA method pairings of knowledge elicitation and analysis/representation methods? How consistent are the associations?

Each study in the final study sample was reviewed to identify the types of knowledge outcomes that resulted from the application of CTA methods. The criteria for classifying the outcomes of the 154 studies identified in Stage Two of the study sample selection process are described next.

Declarative and procedural knowledge. The results identified in each study were classified as declarative knowledge and procedural knowledge and recorded on the coding form. For the purposes of this study, declarative knowledge was defined as knowledge about some thing, event, or symbol, commonly described as "knowing that." Procedural knowledge was defined as knowledge about how to do something (to use or apply), or an ordered sequence of steps necessary to accomplish a goal, solve a problem, or produce a product, commonly described as "knowing how," and often represented as "If-THEN" statements.

Declarative knowledge subtypes. When sufficient data was available in the studies, the results were further classified according to knowledge subtypes according to pre-determined definitions. For declarative knowledge subtypes, *concepts* were defined as objects, events, or symbols that shared common attributes and that were identified by the same name. *Processes* were defined as a sequence of stages that describe how something works or a series of events. *Principles* were defined as cause and effect or correlational relationships that are used to create a new instance or interpretation of events or circumstances.

Procedural knowledge subtypes. When sufficient information was available, the results were also classified as to procedural subtypes. *Classify* procedures were

defined as the grouping of things, events, or symbols according to attributes. *Change* procedures were associated with an ordered sequence of steps necessary to accomplish a goal, solve a problem, or produce a product.

Research Question 4:

To what extent do studies containing the most frequent CTA method pairings include a statement that the methods incorporate activities addressing automated, tacit, or implicit knowledge?

For each publication, an analysis was made as to whether the methods used were sensitive to eliciting automated knowledge. To be classified as sensitive to automated knowledge, the method must have met at least one of the following criteria: (a) recommended or used method(s) with more than one subject matter expert; (b) called for an iterative approach, in which the subject matter expert had the opportunity to correct and supplement previous results; or (c) recommended or used multiple methods.

Research Question 5:

How can the applications of the most frequent CTA method pairings be categorized?

The final application of the CTA outcomes in each study was identified and recorded. The criteria outline by Patton (2002) of internal homogeneity, or the extent that data can be grouped meaningfully, and external heterogeneity, or the

extent to which differences among categories are bold and clear (p. 465), were applied to determine the final categories.

CHAPTER 3: RESULTS

Co-coding and Inter-coder Reliability

A random sample of approximately 17% of the publications (26 publications) was selected from the 154 studies in the sample. A doctoral student in education with knowledge and experience in knowledge types and CTA methods independently coded the random sample with respect to CTA methods, knowledge types and subtypes, and sensitivity to automated knowledge. The CTA Methods Summary Table, supplemented by Table 2, and a Coding Guide was provided to the co-coder. Upon completion of the co-coding, a meeting was held to discuss the discrepancies.

Co-coding of CTA methods resulted in an inter-coder reliability of 68%. Co-coding for declarative knowledge resulted in an inter-coder reliability of 88%, and for procedural knowledge a reliability of 94%. Reliabilities for declarative knowledge subtypes were 86% for concepts, 70% for processes, and 33% for principles. Reliabilities for procedural knowledge subtypes were 71% for classify and 45% for change procedures. Coding for sensitivity to automated knowledge resulted in an inter-coder reliability of 92%.

Results for Coding of CTA Methods

The review and coding of each of the 154 studies identified in Stage Two of the study sample selection yielded the knowledge elicitation and analysis/representation methods and frequencies listed in Table 5.

Table 5.
Frequency of Individual Methods

Method	Type	Frequency
20 Questions	E	2
Card Sort	E & A	13
Clustering Routines	A	8
COGNET	A	2
Cognitive Function Model	E & A	2
Cognitive Task Analysis	E	22
Cognitive Work Analysis	A	1
Comparing Two or More Representations	A	1
Concept Listing	E	5
Concept Map	E & A	20
Conceptual Graph Analysis	A	8
Content Analysis	A	37
Correlation/covariance	A	3
Critical Decision	E	9
Critical retrospective	E	2
Design Storyboarding	E	1
Diagram Drawing	A	47
Document Analysis	E & A	32
Eliciting Estimations of Probability	E	1
Event Co-occurrence	E	1
Event Trees	A	1
Failure Models and Effects Analysis	A	1
Fault Trees	A	2
Field Observations/Ethnography	E	13
Focused Observation	E	9
Free association	E & A	1
Functional Abstraction Hierarchy	A	2
GOMS	A	1
Graph Construction	E & A	4
Grounded Theory	A	5
Group Discussion	E	2
Group Interview	E	17
Hierarchical Sort	A	3
Hierarchical Task Analysis	A	11
Identifying Aspects of the Representation	E & A	7
Influence Diagrams	A	3
Information Flow Analysis	A	9
Interaction Analysis	A	1

Table 5, Continued

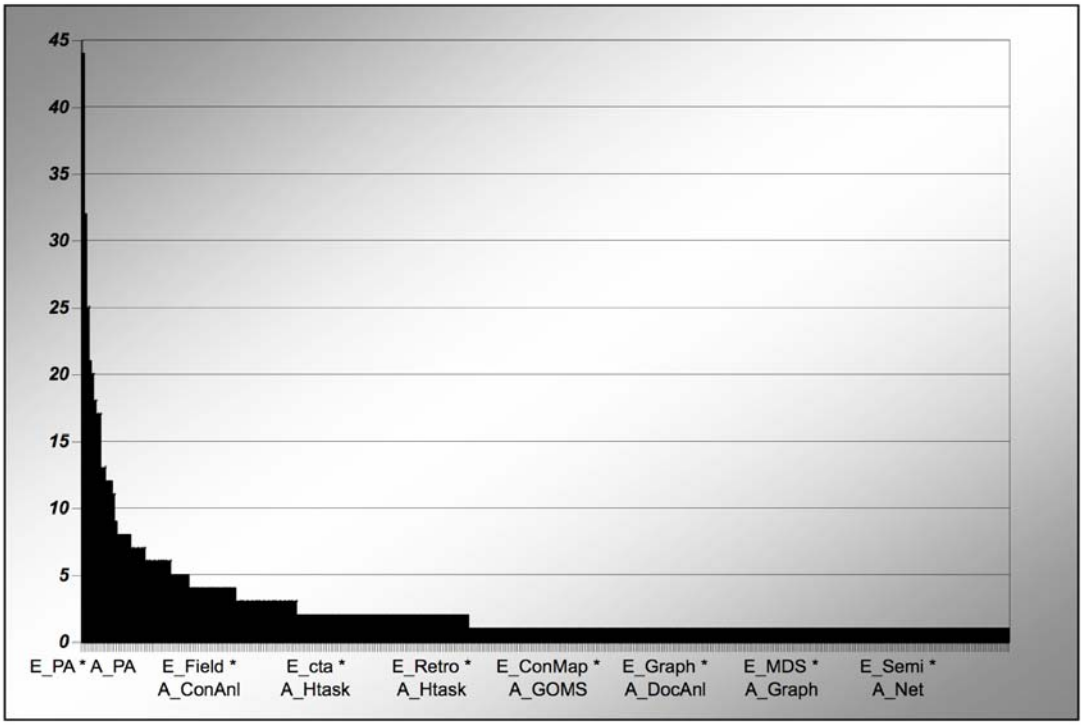
Interruption Analysis	E	3
Job Analysis	A	1
Laddering	E & A	6
Likert Scale Items	E	8
Multidimensional Card Sorting	E & A	4
Multidimensional Scaling	E & A	5
Network Scaling	A	4
Nonverbal Reports	E	2
Operational Sequence Analysis	A	2
Operator Function Model	E & A	1
Paired Comparison	E & A	4
PARI	E	1
Process Tracing/Protocol Analysis	E & A	44
Q Sort	E	2
Questionnaires	E	9
Repeated Sort	E & A	2
Repertory Grid	E &A	18
Retrospective/Aided Recall	E	14
Semi-structured Interview	E	45
Simulators/Mockups	E	7
SOAR	A	1
Statistical Modeling/Policy Capturing	A	12
Strategies Analysis	A	3
Structural Analysis Techniques	A	6
Structured Interview	E	24
Structured Observation	E	1
Table-top Analysis	E	1
Task analysis	E	1
Teach-back	E	2
Think-aloud	E	33
Timeline Analysis	A	1
Triad Comparison	E	1
Unstructured Interview	E	13
Work Domain Analysis	A	1
Workflow Model	A	4

E = Knowledge Elicitation A = Analysis/Representation

Analysis for CTA Method Pairings

Crosstabulation analysis of the methods identified in Table 5 resulted in 1010 coded *pairings* of elicitation and analysis/representation methods identified in the 154 publications. The summary list of CTA method pairing frequency results and the complete results of the Crosstabulation analysis is found in Appendix D and E respectively. Figure 4 represents the frequency distribution of the CTA method pairings, and shows a cluster of high frequency of CTA method pairings.

Figure 4.
Frequency of CTA Method Pairings



A review of the frequency distribution data revealed that 276 (27%) CTA method pairings were clustered around 15 elicitation and analysis/representation

method pairs. Thus, for the purposes of this study, the pairings listed in Table 6 were considered as consisting the final study sample for further analysis by knowledge type and subtype.

Table 6.
Most Frequent CTA Method Pairings

Elicitation	Analysis/Representation	Number
Process Tracing/ Protocol Analysis	Process Tracing/ Protocol Analysis	44
Document Analysis	Document Analysis	32
Think Aloud	Process Tracing/ Protocol Analysis	25
Semi-structured Interview	Diagram Drawing	21
Concept Mapping	Concept Mapping	20
Repertory Grid	Repertory Grid	18
Semi-structured Interview	Content Analysis	17
Document Analysis	Diagram Drawing	17
Semi-structured Interview	Process Tracing/ Protocol Analysis	13
Card Sort	Card Sort	13
Structured Interview	Diagram Drawing	12
Semi-structured Interview	Document Analysis	12
Group Interview	Diagram Drawing	12
Process Tracing/ Protocol Analysis	Diagram Drawing	11
Document Analysis	Content Analysis	9

Results of Matching CTA Method Pairings with Formal Methods

Applying the criteria set forth previously to match CTA method pairings with formal CTA methods to the results in Table 6, resulted in the identification of four formal methods: (a) Process Tracing/Protocol Analysis, (b) Concept Mapping, (c) Repertory Grid, and (d) Card Sort.

Analysis for Declarative and Procedural Knowledge Types

Crosstabulation analysis of the 276 method pairings in Table 6 with the coding results for declarative and procedural knowledge resulted in 89 (32.25%) associations with declarative knowledge, 17 (6.16%) with procedural knowledge, and 170 (61.59%) associations with both declarative and procedural knowledge. Table 7 lists the number of associations among declarative and procedural knowledge types and CTA method pairs.

Table 7.
Method Pairings by Declarative and Procedural Knowledge

Elicitation	Analysis/ Representation	Decl	Proc	Decl & Proc.
Process Tracing/ Protocol Analysis	Process Tracing/ Protocol Analysis	7	3	34
Document Analysis	Document Analysis	14	2	16
Think Aloud	Process Tracing/ Protocol Analysis	2	2	21
Semi-structured Interview	Diagram Drawing	4	2	15
Concept Mapping	Concept Mapping	14	0	6
Repertory Grid	Repertory Grid	7	2	9

Table 7, Continued

Semi-structured Interview	Content Analysis	6	1	10
Document Analysis	Diagram Drawing	5	1	11
Semi-structured Interview	Process Tracing/ Protocol Analysis	2	1	10
Card Sort	Card Sort	7	1	5
Structured Interview	Diagram Drawing	8	0	4
Semi-structured Interview	Document Analysis	2	1	9
Group Interview	Diagram Drawing	5	0	7
Process Tracing/ Protocol Analysis	Diagram Drawing	3	0	8
Document Analysis	Content Analysis	3	1	5

Decl = Declarative Proc = Procedural

Analysis for Declarative and Procedural Knowledge Subtypes

For each CTA method pairing in Table 6, the results of frequency counts for declarative knowledge subtypes (concept, process, principle) and procedural subtypes (classify, change) are listed in Table 8.

Table 8.
CTA Method Pairings by Knowledge Subtypes

Elicitation	Analysis/ Representation	Con	Pro	Prin	Class	Chan
Process Tracing/ Protocol Analysis	Process Tracing/ Protocol Analysis	35	20	4	16	14
Document Analysis	Document Analysis	24	15	1	9	10

Table 8, Continued

Think Aloud	Process Tracing/ Protocol Analysis	19	11	3	10	7
Semi-structured Interview	Diagram Drawing	18	12	1	6	5
Concept Mapping	Concept Mapping	18	5	1	0	1
Repertory Grid	Repertory Grid	13	3	1	6	2
Semi-structured Interview	Content Analysis	14	6	1	3	3
Document Analysis	Diagram Drawing	14	10	1	6	7
Semi-structured Interview	Process Tracing/ Protocol Analysis	10	7	2	5	5
Card Sort	Card Sort	8	2	0	2	1
Structured Interview	Diagram Drawing	11	8	0	1	0
Semi-structured Interview	Document Analysis	7	7	0	6	5
Group Interview	Diagram Drawing	9	7	1	1	0
Process Tracing/ Protocol Analysis	Diagram Drawing	11	7	2	3	4
Document Analysis	Content Analysis	7	3	1	3	3

Con = Concept; Pro = Process; Prin = Principle; Class = Classify; Chan = Change

Results for Sensitivity to Automated Knowledge

Table 9 lists the CTA method pairings in Table 6, and the results for applying the criteria for sensitivity to eliciting automated knowledge to the studies from which the CTA method pairings were derived.

Table 9.
Method Pairings associated with Automated Knowledge

Elicitation	Analysis/ Representation	Number	Sensitive to Automated Knowledge	
			Yes	No
Process Tracing/ Protocol Analysis	Process Tracing/ Protocol Analysis	44	40	4
Document Analysis	Document Analysis	32	27	5
Think Aloud	Process Tracing/ Protocol Analysis	25	22	3
Semi-structured Interview	Diagram Drawing	21	19	2
Concept Mapping	Concept Mapping	20	18	2
Repertory Grid	Repertory Grid	18	14	4
Semi-structured Interview	Content Analysis	17	15	2
Document Analysis	Diagram Drawing	17	14	3
Semi-structured Interview	Process Tracing/ Protocol Analysis	13	12	1
Card Sort	Card Sort	13	11	2
Structured Interview	Diagram Drawing	12	12	0
Semi-structured Interview	Document Analysis	12	11	1
Group Interview	Diagram Drawing	12	12	0
Process Tracing/ Protocol Analysis	Diagram Drawing	11	9	2
Document Analysis	Content Analysis	9	7	2

Results for the Classification of Method Pairings by Application

The 154 studies from which the CTA method pairings in Table 6 were derived were classified according to the application of the results. Four application categories emerged: (a) human factors (23, 14.94%), (b) expert systems (75, 48.70%), (c) theoretical and experimental (30, 19.48%), and (d) instructional design and training (26, 16.88%). The number of studies that were classified in each application category for the most frequent CTA method pairings is listed in Table 10.

Table 10.
Classification of CTA Method Pairings by Application

Elicitation	Analysis/ Representation	HF	ES	T/E	ID/T
Process Tracing/ Protocol Analysis	Process Tracing/ Protocol Analysis	1	17	11	17
Document Analysis	Document Analysis	4	20	5	3
Think Aloud	Process Tracing/ Protocol Analysis	0	11	7	7
Semi-structured Interview	Diagram Drawing	2	14	2	3
Concept Mapping	Concept Mapping	4	7	4	5
Repertory Grid	Repertory Grid	2	10	5	1
Semi-structured Interview	Content Analysis	1	7	5	4
Document Analysis	Diagram Drawing	2	12	1	2
Semi-structured Interview	Process Tracing/ Protocol Analysis	1	4	3	5
Card Sort	Card Sort	3	7	2	1
Structured Interview	Diagram Drawing	4	7	1	0
Semi-structured Interview	Document Analysis	1	8	2	1

Table 10, Continued

Group Interview	Diagram Drawing	5	7	0	0
Process Tracing/ Protocol Analysis	Diagram Drawing	1	7	1	2
Document Analysis	Content Analysis	0	5	2	2

HF = Human Factors; ES = Expert Systems; T/E = Theoretical Experimental; ID/T = Instructional Design & Training

The four application categories derived in the previous analysis were further analyzed to identify the knowledge type classifications associated with each category. The results of this analysis are listed in Table 11 and provided additional data to examine the interactions among the CTA applications, knowledge outcomes, and methods. The results show, for example, that the proportion of declarative knowledge to procedural knowledge outcomes is about 55% for both expert systems and ID/training, whereas the proportion in human factors and theoretical experimental are 79% and 67%, respectively.

Table 11.
Knowledge Types Associated with CTA Applications

	HF	ES	T/E	ID/T
Declarative	22	62	29	24
Concept	16	51	22	23
Process	8	23	10	14
Principle	1	1	1	4
Procedural	6	50	14	20
Classify	0	16	3	10
Change	0	13	4	10

HF = Human Factors; ES = Expert Systems; T/E = Theoretical Experimental; ID/T = Instructional Design & Training

CHAPTER 4: CONCLUSIONS

The purpose of this study was to explore the interactions between cognition and task analysis methods. Specifically, it first sought to identify, without regard to the date of publication, studies that utilized knowledge elicitation and cognitive task analysis methods, and then to examine and classify a sample of these studies by applying various criteria. Although, as an exploratory study, no formal hypotheses were stated, five research questions guided the study. As the initial search of the literature returned a large number of knowledge elicitation and CTA studies, the first part of the study concerned the selection of a study sample of the most frequently used individual elicitation and analysis/representation methods. The second part of the selection process identified the most frequent pairings of knowledge elicitation and analysis/representation methods, as reflected in the actual practice of CTA.

A review of the description of the CTA methods that were used to classify the sample studies revealed that the mechanisms of some methods could be categorized as well specified, formal, and intended to be applied systematically, while others were less structured, and able to be adapted to meet the constraints of the task and domain. Therefore, the study sought to determine whether the formal methods were applied consistently and produced consistent knowledge outcomes.

Contrasted with previous CTA classification schemes that assigned labels to CTA methods, based on their process, technique or theoretical approach, this current study sought, as the third research question, to determine whether the product or outcomes of the application of CTA methods could be classified as either declarative

or procedural knowledge, and, if sufficient data were available, further classified as to declarative knowledge subtypes (concept, process, principle) and procedural knowledge subtypes (classify, change). It was thought that such a classification might lead to additional studies toward creating an evidence-based taxonomy of CTA methods based on desired knowledge outcomes.

The fourth research question concerned whether the studies in the sample included statements that addressed the elicitation of automated knowledge.

Because the literature often refers to the context and intended application of the output of CTA as factors for choosing CTA methods, the last research question concerned the categorization of the sample studies according to the intended application of the results to provide additional interpretive data.

Research Questions

Research Question 1:

What are the most frequently used pairings of knowledge elicitation and analysis/representation methods found in the CTA literature?

Consistent with the recommendation found frequently in the literature, the initial data gathered for this study confirmed that, in practice, CTA studies often incorporated more than one individual knowledge elicitation and analysis/representation method. However, because the success of the CTA enterprise depends upon the effective use of both elicitation and analysis/representation methods, this study sought to identify and examine the

pairing of these methods within each study and their associations with knowledge type outcomes.

The findings of this study indicate that there are 15 most frequently used pairings of elicitation and analysis/representation techniques, and that the characteristics of the pairings are similar in several aspects.

Four methods - Process Tracing/Protocol Analysis, Concept Mapping, Repertory Grid, and Card Sort – are relatively formalized and specific in their methodology. The methods integrate the components of knowledge elicitation and analysis/representation. Further, the techniques are well documented, and there is a considerable body of literature for each method.

Document Analysis was not listed in the CTA Methods Summary Table; however, it was encountered early in the coding process and added to the coding form. Document Analysis was labeled as both an elicitation and analysis/representation technique, which reflected the actual use of the technique in the studies.

Process Tracing/Protocol Analysis was also paired with other individual methods. As an elicitation method, it was paired with Diagram Drawing, which was frequently used to represent results in tables, flow charts, and system state diagrams. As a technique to analyze and represent results, Process Tracing/Protocol Analysis was paired with Think Aloud and Semi-structured Interview, two elicitation methods. The pairing with Think Aloud is expected, as it is a technique in which a person verbalizes perceptions, decisions, and actions while performing a task, and an

essential element of both the theory and technique of Process Tracing/Protocol Analysis. Semi-structured Interview was also paired with Process Tracing/Protocol Analysis. This was an unexpected result, as interviewing is not a component of this formal and standardized method, and raises the question whether formal CTA methods are being applied systematically and consistently.

In addition to being paired with Process Tracing/Protocol Analysis, the Semi-structured Interview was paired with Diagram Drawing, Content Analysis, and Document Analysis. The pervasive use of the Semi-structured interview demonstrates the relative ease with which this elicitation method can be applied, and its results analyzed and represented by tables, diagram, or in the case of Content Analysis, a priori or emergent categories. The pairing of Semi-structured Interview with Document Analysis demonstrates that multiple methods were frequently used in the study sample, and that Document Analysis is often a preliminary step to familiarize the analyst with the domain and/or task under investigation and to design the remaining knowledge elicitation and analysis/representation process.

It was also found that Diagram Drawing, in which the analyst represents processes in or states of an informant's domain by charts and diagrams, for example, was paired with five elicitation methods, thus demonstrating the critical task of displaying data and presenting findings when conducting CTA.

Research Question 2:

To what extent do pairings of knowledge elicitation and analysis/representation methods match with formal CTA methods found in the literature?

The current study's method of pairing individual knowledge elicitation and analysis/representation methods provided the opportunity to examine whether the individual method pairings match the standardized methods and systematic procedures established for formal CTA methods described in the literature.

For the most part, CTA method pairings of elicitation and analysis/representation techniques in the final study sample were matched with the formal CTA methods, as in the case of Concept Mapping – Concept Mapping, Repertory Grid – Repertory Grid, and Card Sort – Card Sort.

Process Tracing/Protocol Analysis, however, was paired not only with itself, as expected, but also with Think Aloud, Semi-structured Interview, and Diagram Drawing. Think Aloud, or verbalizing one's thoughts while performing a task, is a major component of Process Tracing/Protocol Analysis. A Semi-structured interview, however, involves a dialog between the informant and the analyst. Fundamental to Process Tracing/Protocol Analysis is the theory that a person can only verbalize that which is attended to in working memory. Thus, it would seem that interrupting the informant during task performance with questions would diminish or modify the results of the elicitation process and the precise application of the Process Tracing/Protocol Analysis techniques that follow.

Additional review of the studies corresponding to these method pairings may reveal a trend toward the adaptation or generalization of Process Tracing/Protocol Analysis as a generic process of recording, transcribing, and categorizing informants' verbal interviews as they describe how they performed a task. In the event that such a trend exists with this or other more formal methods, important questions arise concerning the consistency and validity of the results from their use, and whether the formal names and descriptions of the protocols have relevant meaning. In other words, the more that the practice of these methods departs from the formal protocols, which have empirically supported theoretical foundations, the less likely the results will be valid and reliable.

Research Question 3:

What knowledge types are associated with the knowledge elicitation and analysis/representation pairings? How consistent are these associations?

Declarative and Procedural Knowledge

The findings of the current study show that the most frequent elicitation and analysis/representation method pairings associated with declarative knowledge only are (a) Document Analysis-Document Analysis (14), (b) Concept Mapping-Concept Mapping (14), (c) Structured Interview-Diagram Drawing (8), (d) Card Sort-Card Sort (7), (e) Repertory Grid-Repertory Grid (7), and (f) Process Tracing/Protocol Analysis - Process Tracing/Protocol Analysis (7). Overall, these results were expected and consistent with the intended use of the methods found in the literature.

The literature indicates that Document Analysis has been widely used for "bootstrapping" early in the CTA process, and also has been the focus of knowledge-based systems, intended to apply data elicited from printed format. Concept Mapping, Card Sort, and Repertory Grid are formal methods that have been strongly and consistently associated in the literature with eliciting and representing conceptual knowledge. Similarly, the constraining nature of the Structured Interview facilitates elicitation of specific information. The results for Process Tracing/Protocol Analysis may be attributed to techniques of this methodology to aggregate solution steps and processes by comparing and summarizing task sequences between subjects with process knowledge as the outcome.

The most frequent method pairings associated with procedural knowledge only are (a) Process Tracing/Protocol Analysis – Process Tracing/Protocol Analysis (3), Document Analysis – Document Analysis (2), (c) Think Aloud – Process Tracing/Protocol Analysis (2), Semi-Structured Interview – Diagram Drawing (2), and (d) Repertory Grid – Repertory Grid (2). Repertory Grid would appear to be an outlier within this group; however, in the studies, this method was occasionally used in the development of expert systems, in which concepts are represented as IF-THEN statements, and thus, coded as procedures.

The most frequent method pairings that were coded as resulting in both declarative and procedural knowledge include: (a) Process Tracing/Protocol Analysis – Process Tracing/Protocol Analysis (34), (b) Think Aloud – Process Tracing/Protocol Analysis (21), (c) Document Analysis – Document Analysis (16),

(d) Semi-Structured Interview - Diagram Drawing (15), and (e) Document Analysis – Diagram Drawing (11). These were expected results for three reasons: (1) Think Aloud or Retrospective Recall, essential components of Process Tracing/Protocol Analysis, are most often used to capture actions during or after the performance of a task; (2) Process Tracing/Protocol Analysis techniques not only capture actions, but also goals, plans, states, and other kinds of information; and (3) Although Process Tracing/Protocol Analysis consists of a specified set of techniques, the studies indicate that some of these techniques , such as the coding and categorizing of verbal transcripts, have been broadly interpreted and applied. Other frequent method pairings that resulted in both declarative and procedural knowledge are Semi-Structured Interview, Diagram Drawing, and Document Analysis. These are also broadly interpreted and widely utilized methods, as their methods are less specified, and often determined by the desired outcomes.

Declarative and Procedural Knowledge Subtypes

Within the 154 documents in the final study sample, declarative knowledge subtype associations were: 218 method pairings associated with concepts, 123 pairings with processes, and 19 with principles. The associations with procedural knowledge subtypes consisted of 77 associated with classify and 46 with change functions. In general, the results show a substantial weighting of declarative knowledge outcomes (75%) over procedural knowledge outcomes (25%).

As expected from the results already reported, Process Tracing/Protocol Analysis, alone and paired with other methods, represented the most frequent

association with declarative concepts (75), processes (45), and principles (11), and with classify (34) and change (30) procedures. In particular, this method accounted for 11 out of 19 total method pairings for principles. Also as anticipated, methods normally associated with conceptual knowledge (i.e., Concept Mapping, Repertory Grid, Card Sort) were less represented in the procedural subtype classifications, although Repertory Grid had a greater frequency in the classify category, due to its use for knowledge base systems. Whereas, the knowledge subtype outcomes for Document Analysis, Semi-structured Interview, Diagram Drawing, and Content Analysis, as highly adaptable and less structured methods, extended over concepts, processes, classify, and change. However, the Semi-structured Interview method accounted for 38 associations with classify and change procedures, second only to Process Tracing/Protocol Analysis.

These findings suggest that although less formal methods provide the advantage of flexibility and ease of use, their inconsistency with respect to knowledge results suggests that an in depth analysis of their actual use may reveal mechanisms that are consistency associated with specific knowledge types. An examination of studies using semi-structured interviews, for example, may show that the structure and content of the questions posed in these interviews consistency elicit specific types of knowledge and that this knowledge might be easily analyzed and best represented in a particular manner. Such data might lead to establishing new standardized protocols, which, in turn, could be subject to further research to establish their validity and reliability.

Research Question 4:

To what extent do publications containing pairings of CTA methods include a statement that the methods incorporate activities addressing automated, tacit, or implicit knowledge?

To be classified as sensitive to automated knowledge, the study must have met at least one of the following criteria: (a) Recommended or used method(s) with more than one subject matter expert; (b) Called for an iterative approach, in which the subject matter expert had the opportunity to correct and supplement previous results; or (c) Recommended or used multiple methods.

A review of the studies resulted in 132 studies that met the criteria and 22 studies that did not. This was an unexpected result, as it was generally thought that efforts to capture automated knowledge have been applied relatively recently. It may be that this data is associated with the substantial weighting of declarative knowledge outcomes (75%) over procedural knowledge outcomes (25%).

The literature reviewed for this study revealed other interesting trends. During the 1979s and 1980s, expert systems sometimes relied on a single expert for the knowledge required to design and develop the system, because only one expert was available or "easier to work with" than multiple experts. Considerations for the use of multiple experts included availability, degree of cooperation between experts and developers, and mechanisms to resolve ideological and factual conflicts among the experts. In the 1990s the use of multiple experts and a more iterative approach increased in parallel with research in cognition and CTA methods.

The recommendation to use multiple methods to capture different aspects of knowledge appeared early and consistently throughout the literature.

Research Question 5:

How can the applications of the most frequently used pairings of CTA methods be categorized?

The studies in the final sample were categorized as to the application of the outcomes. As reflected in the literature, it was expected that a large number of applications of knowledge acquisition techniques would be for the development of expert systems. The results indicated that 75 (48.70%) of 154 studies reviewed applied the results to expert systems. Since the early 1980s, computer applications have been developed to replicate the knowledge and skills that experts use in problem solving. However, as reported throughout the literature reviewed for this study, the initial stage of knowledge acquisition has been the most difficult in the development process for expert systems.

There were 30 studies in the theoretical and experimental category. The diversity of the subject domains and applications of CTA methods found in the literature account for this number, as well as the relatively recent advances in cognitive science, the origins of CTA in behavioral task analysis, and interest in applying CTA methods to areas beyond expert systems.

Instructional Design and Training was the next emergent category with 26 studies. A significant number of these studies were funded and conducted in military

settings to report the effectiveness of using CTA methods for developing training systems for troubleshooting, situation awareness, and weapons. In addition, a large number of studies applied to training medical diagnosis and procedure skills.

The human factors category consisted of 23 studies and included those that researched human-computer interaction, manufacturing processes, organizational performance, and team CTA.

Representation Bias

An examination of the interactions among applications, methods, and knowledge type outcomes in the CTA process is complicated by the possible effect of representation bias in knowledge acquisition for expert systems, in which the analyst's choice of elicitation methods is influenced by the final representation and use of the results (Cooke, 1992; Cooke & McDonald, 1986). The development of expert systems requires that knowledge be represented as condition-action pairs. This requirement influences the choice of CTA methods and the final representation of expertise, including declarative knowledge (concepts, processes, principles), as procedural IF-THEN rules.

Because the development of expert systems accounts for about 49% of the applications of CTA in the study sample, the influences of a representation-driven knowledge acquisition would be expected, for example, in the greater use of formal conceptual elicitation and analysis/representation pairings, which results can be more easily converted to production rules. The data in Table 5 provides some evidence for

this, in that, when sorted by frequency, the cluster of the most frequently cited individual CTA methods includes Concept Map, Repertory Grid, Cord Sort, and Process Tracing/Protocol Analysis, all of which are classified as both elicitation and analysis/representation methods. Another indication of representation bias at work may be, as previously noted, the unexpected association between the Repertory Grid method, typically associated with conceptual knowledge elicitation, and procedural knowledge outcomes.

In addition, the data in Table 11, which shows associations in the study sample between the applications of CTA and knowledge type outcomes, approaches the issue differently. The data in the table shows that the percentage of general declarative and procedural knowledge outcomes, 55% and 45% respectively, are identical for both expert systems and instructional design/training. This result would be expected, as declarative and procedural knowledge are required for both applications. However, the CTA process may be different. Knowledge acquisition for expert systems appears to assume that expertise can be represented by conditional rules and seeks to capture declarative knowledge as an intermediate step. Development of training and other instructional programs, on the other hand, require the representation of both declarative and procedural knowledge that underlie expert performance of a task.

Summary

This study examined the interactions among cognitive task analysis methods and cognition identified in a sample of studies (n=154) chosen through an iterative review process. Individual CTA methods found in the studies were classified as either elicitation or analysis/representation using a system adapted from CTA Resources (2006). The results showed that, in practice, pairings of elicitation and analysis/representation methods are used, rather than individual methods. Because the success of CTA relies upon the effective use of both elicitation and analysis/representation methods, the remainder of the study then focused on examining the most frequent pairings of these methods and their knowledge outcomes. The results demonstrate that (a) The most frequently used CTA method pairings include both standardized methods and informal methods, (b) the application of the methods have been associated more with declarative knowledge than procedural knowledge, (c) standardized methods appear to provide greater consistency in the results than informal models, (d) through a variety of techniques, most studies have addressed issues concerning automated knowledge, and (e) the analysis of interactions among applications, methods, and knowledge types is influenced by possible effects of representation bias.

Implications

The implications of this study apply to two areas of research. The first relates to research in cognitive task analysis, and the second pertains to research in instructional design.

Cognitive Task Analysis

It is not difficult to acquire a basic theoretical understanding of cognitive task analysis, as there are many definitions in the literature, each providing a different perspective. For example, Crandall et al. (2006) recently unpacked CTA as: (a) cognitive, in that it seeks to capture the reasoning and knowledge required for complex problem solving; (b) task, referring to the outcomes people are trying to achieve; and (c) analysis, as breaking something down into its parts, understanding each part, and the relation each part has to the whole task.

On the other hand, the practice of CTA continues to present challenges even for the experienced user, primarily centered on choosing the appropriate CTA method for the domain and intended application. As shown in this current study, a number of classification systems are available to guide the practitioner; however, each has its own theoretical and methodological approach, which also must be taken into consideration. In addition, the findings show that only four of the top 15 CTA method pairings are formal methods supported by empirical evidence and standardized procedures that, if followed, predict knowledge outcomes. The remaining method pairings lack this specificity, and are, therefore, less predictable.

For the moment, it appears, CTA exists in an area of tension between basic research in psychology and cognitive science and the applied purposes and needs that drive it (Chipman et al., 2000). While some research focuses on the appropriate application and sequencing of individual CTA methods, there are calls for alternative approaches.

Clark et al. (in press) suggest applying Merrill's (2002) "first principles" approach to CTA research. Merrill examined the key cognitive components of well-known research-based instructional design methods and identified their similarities, which he compiled as "first principles." For example, Merrill suggested that the most effective learning models are problem centered, and demonstrate what is to be learned, rather than telling information about what is to be learned. The goal of a "first principles" approach to CTA methods would be to identify the active ingredients in key CTA methods.

How might a "first principles" research approach be pursued? Clark et al. (in press) recommend more studies that systematically compare different CTA methods on similar outcome goals and measures. Previous comparison studies have provided valuable insights in this area. For example, Chao and Salvendy (1994) conducted a study to determine the optimum number of experts for acquiring procedural knowledge using different CTA methods and tasks. They found that the percentage of strategies and sequential operations used by a single expert for a diagnosis task were approximately equal for protocol analysis (41%), interview (40%), induction (40%), and repertory grid (40%). For the debugging task, the interview and

induction were higher (53%, 50% respectively) than protocol and repertory grid (37% each). For the interpretation task, the percentage of procedures were, again, about equal, albeit lower, ranging from 21% -29%. The overall finding and primary purpose of the study demonstrated significant increases in the percentage of procedures as a result of using multiple experts, with three experts as their final recommendation; however, the study also provided insights about the impact of different CTA methods for different tasks.

As another example, Hodgkinson, Maule, and Bown (2004) compared two causal mapping techniques, pairwise comparisons and freehand drawings, designed to systematically elicit and represent a person's causal beliefs concerning an issue or event. The pairwise technique resulted in much greater complexity than the freehand method, although participants found pairwise comparisons more difficult and less engaging.

Hoffman, Coffey, Carnot, and Novalk (2002), on the other hand, find empirical comparisons of CTA methods problematic for several reasons. First, some studies have used college age participants and assessments of familiar topics. The generalizability of these finding may not transfer to genuine experts in domains of significant interest. Second, the dependant variables have not been carefully selected and clearly defined in that established metrics for one domain or application may not be suitable for another. Another factor that clouds results is that procedures and qualities that define a specific method are not followed in some studies. Those who are unpracticed and not complete familiar with the underlying theory and constructs

of a method sometimes fail to avoid common pitfalls than undermine a method's validity. As a final factor, Hoffman et al. suggest that some studies compare "apples and oranges" that result in findings that are difficult to interpret. When comparing methods, they must all be suited for a specific purpose. In short, a comparison of methods must involve a level playing field.

The evidence from this current study would seem to support this analysis. With exception of the formal methods, the findings indicate numerous haphazard pairings of methods that are ill-defined and result in the same knowledge type outcomes. Further research that examines the activities and their respective knowledge outcomes of these methods in depth may reveal method pairings that could be tested for validity and reliability, and thus become new standard elicitation/analysis/representation methods.

Another major area of CTA research is expertise. Eliciting and representing expert knowledge is the primary purpose of CTA, yet "the state of the art is lacking specification of just those kinds of knowledge [that are] most characteristic of expertise" (Chipman et al., 2000).

More or less reflecting the classification by technique approach, Hoffman et al. (1995) proposed a methodology for revealing, representing, preserving, and disseminating expert knowledge based three categories CTA methods: (a) analysis of tasks that experts perform, (b) various types of interviews, and (c) contrived techniques. They paraphrase the categories as: What do experts usually do? What

do experts say they do? And what do they do when they are constrained in some new way?

In a review of the literature on expertise, Feldon (in press) presents a four-part framework to examine the process elements that shape expertise through: (a) the role of knowledge, (b) the role of strategy, (c) the role of working memory, and (d) the role of skill automaticity. The overwhelming evidence is that experts and novices differ considerably, when viewed within the framework. However, the characteristics of expertise that provide the advantages experts demonstrate in task performance also present the challenge to the accuracy and validity of CTA methods. Further research on CTA methods within this framework might be paraphrased as: What do experts know, what type of knowledge is it, and how is it organized? And how do experts apply their knowledge, how does declarative and procedural knowledge work together, and what procedures do experts use to make decisions?

The findings of this current study contain apparent inconsistencies that warrant further investigation. Although the most of the applications described in the studies reviewed were categorized as expert systems, which rely on procedural rules for programming, the study shows that declarative knowledge was the dominant knowledge type associated with the methods used in the studies. Moreover, 85% of the studies were coded as being sensitive to automated knowledge. Clearly, further research is needed to sort out the working relationship between declarative and procedural knowledge.

Instructional Design

The implications of the study for research in instructional design can be viewed from two perspectives. The first concerns an understanding of the risks involved when task analysis is not considered the most important component of instructional design. Poorly executed task analysis leads to gaps that often are not obvious, until learners are asked to perform the tasks, and they cannot (Jonassen et al., 1999). The second perspective is the growing body of evidence demonstrating the benefits of CTA to improve learning and performance.

The job of the instructional designer is to analyze the knowledge that is required to perform a task. Most instructional design models advocate a mix of declarative and procedural knowledge, but the process of classifying and inventorying tasks can be challenging, given the numerous choice within some systems. The framework of the current study includes only three types of declarative knowledge: concepts, processes, and principles, and two types of procedural knowledge: classify and change. Further research is needed to generalize whether this classification system is adequate to define expert declarative and procedural knowledge across domains and applications.

Another area of research pertains to the integration of CTA methods and instructional design models into one system. Optimal instructional results are achieved when there is an alignment of learning objectives, types of knowledge required to achieve the objectives, and appropriate methods to acquire that knowledge (Clark et al., in press) . Only three examples of this model exist: the

Integrated Task Analysis Model (Ryder & Redding, 1993); Guided Experiential Learning (Clark, 2004; Clark & Elen, 2006), and the Four Component Instructional Design System (van Merriënboer, 1997; van Merriënboer, Clark, & de Croock, 2002). Additional research is needed to demonstrate the effectiveness of these systems, the sufficiency of the CTA methods, and the interaction among the components.

Conclusion

In conclusion, the current study is only a fist step in exploring the interactions between cognition and task analysis activities. Further studies will continue to investigate the "first principles" approach to cognitive task analysis. Based on existing theories of cognition that are well-developed and articulated, a taxonomy of CTA methods and cognition could possibly achieve the desired reduction in taxonomic categories, while providing clearly explicated guidelines for conducting the CTA enterprise.

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APPENDIX A: CTA METHODS SUMMARY TABLE

Name and Description	Elicitation	Analysis/ Representation
20 Questions - The analyst provides the informant with a situation, problem or solution. The informant determines the concept that the analyst has in mind by asking yes/no questions. The analyst derives information about the informant's problem solving process by noting the questions asked.	E	
ACTA - Applied Cognitive Task Analysis method uses task diagrams, knowledge audits, and simulated interviews to elicit and represent the cognitive aspects of a task. Computer-based training software is available from Klein Associates, Inc.	E	A
Active Participation - The informant performs a task or solves a problem in the domain. The analyst collaborates with the informant while observing and recording the informant's actions and environment.	E	
Activity Sampling - The analyst observes and records samples of the informants? actions at predetermined intervals.	E	
ACT-R - Hybrid architecture for modeling human cognitive tasks with considerable learning strengths and a large user community.		A
Barrier and Work Safety Analysis - The analyst identifies what hazards in the domain could lead to an accident. For each hazard, barriers are identified to prevent potential accidents.		A
Close Experimental/Minimal Scenario Technique - The analyst presents the informant with a scenario missing essential information. The informant the fills in the gaps in the scenario.	E	
Clustering Routines - A mathematical technique in which domain concepts are grouped based on ratings of similarity or conceptual distance.		A

COGNET - COGnition as a NETwork of Tasks is a theoretically based set of tools and techniques for performing cognitive task analyses and building models of human-computer interaction in real-time, multitasking environments. It provides an integrated representation of the knowledge, behavioral actions, strategies and problem solving skills used in a domain or task situation.		A
Cognitive Function Model - CFM combines the hierarchical graph structure of the Operator Function Model with a technique to assess the cognitive complexity of nodes to capture operations and cognitive challenges within complex systems. Software application developed by Klein Associates and Aptima, Inc.	E	A
Cognitive Task Analysis - The analyst explicitly identifies the knowledge, goals, strategies, and decisions that underlie observable task performance.	E	
Cognitive Work Analysis - The analyst employs five different frameworks (control tasks, work domain, social organization, strategies, and worker competencies) to characterize the demands of the domain and the knowledge, skills, strategies, and control actions required to operate effectively in the domain. It is used to define requirements for new support systems.		A
Comparing Two or More Representations - The analyst compares structural aspects of domain representations, aspects such as number of clusters and connectivity of graphs. INDSCAL is an available software tool.		A
Concept Listing - In a structured interview, the informant lists the key concepts of his or her domain.	E	
Conceptual Graph Analysis - The analyst represents the informant's domain knowledge by graphically representing domain concepts using a pre-defined syntax.		A
Content Analysis - The analyst organizes the informant's verbal report into a priori or emergent categories of interest.		A

Control Task Analysis - The analyst identifies the control tasks that need to be performed to achieve system goals, independent of how they are to be performed or by whom.		A
Controlled Association - The analyst presents the informant with a concept. The informant indicates all related concepts and assigns relatedness values.	E	
Controlled Simulated Observations - The analyst presents the informant with a concept to which the informant indicates all other related concepts. Each selected pair is then assigned a relatedness value.	E	
Correlation/Covariance - Informants? ratings of different concepts are correlated to estimate the similarity of the concepts.		A
Critical Decision - The informant recalls a challenging past experience and describes the decisions made and actions taken. The analyst elicits a timeline, background knowledge, environmental cues, decision options, novice errors, and other factors.	E	
Critical Incident - The informant recalls a challenging past experience and describes the actions taken. The analyst's probes (questions) and line of questioning are pre-planned.	E	
Critical Retrospective - The informant provides a verbal report regarding another informant's prior performance of a task.	E	
Crystal Ball/Stumbling Block - The informant describes a challenging assessment or decision. The analyst insists that the assessment is wrong, and that there are alternative interpretations of events, missing information, or assumptions. The informant generates these.	E	
Design Storyboarding - The analyst or the informant generates a sequence of sketches or graphics that represent candidate design concepts and how they would operate in a simulated scenario. It enables system developers to receive user input and feedback early in the concept development phase.	E	

Diagram Drawing - The analyst draws a diagram representing processes in or states of the informant's-9 domain. Possible formats include flow charts, activity charts, and system state/action state diagrams.		A
Discourse/Conversation/Interaction Analysis - The interaction between the informant and the analyst is parsed into statements and categorized.		A
Discrete Event Simulation - A simulation technique in which system state changes occur only at event nodes (not continuously). Toolkits may support network diagramming, programming, and data analysis. It is often used to model human tasks. MicroSaint and IPME are available software tools for this method.		A
Distinguishing Goals - The analyst presents all pairwise combinations of domain goals to the informant. The informant lists the characteristics that distinguish every two goals. The analyst derives a list of the minimal distinguishing features of each goal.	E	A
Dividing the Domain - The informant describes evidence or symptoms used in reasoning over domain problems. The analyst helps group these to define goals.	E	
Drawing Closed Curves - The informant diagrams the domain by circling concepts to group them together.	E	
Eliciting Estimations of Probability and Utility - The analyst derives the expected worth of a decision from the informant's definition of the possible consequences of a decision, the value of the consequences, and the probability of their occurrence. Bayesian techniques can be applied to model decision making using these data.	E	
EPIC-Executive Process - Interactive Control is a cognitive architecture for modeling human performance. Its focus is to improve man-machine systems by accounting for the timing of human perceptual, motor, and cognitive activity.		A

Event Co-Occurrence/Transition Probabilities - The analyst estimates the relatedness of events by examining the frequency with which events co-occur.	E	
Event Trees - The analyst graphs the chain of events in the informant? s domain. Events can involve either hardware or humans actions.		A
Exploratory Sequential Data Analysis - ESDA uses a variety of data analysis techniques for the empirical analysis of recorded observational data. The method is focused on research where the sequence of the informant's actions is of primary importance. MacShapa is an available software tool.		A
Failure Modes and Effects Analysis - The analyst determines what errors might occur in the informant's domain and what the consequences of such errors would be to the system.		A
Fault Trees - The analyst develops a fault tree that decomposes an undesired event into causal events and errors.		A
Field Observations/Ethnographic Methods - Practitioners are observed and interviewed in the actual work environment as they perform their regular work activities.	E	
Focus Groups/Joint Application Development - The analyst acts as a facilitator bringing experts and end users together in a workshop focused on solving a given problem. This is conducted in five phases; project definition, research, workshop preparation, the workshop, and final documentation.	E	
Focused Observation - The informant performs a task or solves a problem in the domain. The analyst observes and documents a specific aspect of the behavior and environment.	E	
Free Association - The informant free-associates to concepts presented by the analyst. The analyst groups concepts based on patterns of recall.	E	A

Functional Abstraction Hierarchy Approach - The analyst develops a representation of the domain in terms of goals-means relationships using an abstraction hierarchy of, for example, functional purpose, abstract function, generalized function, physical function, and physical form. This is a type of work domain analysis		A
Functional Flow Analysis - The informant and the analyst jointly create diagrams of relations between a system's functions.		A
GOMS - The analyst decomposes task performance into Goals, Operators, Methods, and Selection rules. It is a family of symbolic models of human performance with extensive application to human-to-computer interaction.		A
Graph Construction - The analyst has the informant draw a network of linked nodes that represent the informant's knowledge. SemNet Program is an available software tool.	E	A
Grounded Theory - The analyst organizes the informant's verbal report into categories of interest. Unlike content analysis the categories are not predetermined.		A
Group Discussion - A group of informants discusses their performance after completing a task.	E	
Group Interview - The analyst interviews multiple informants at one time. Techniques used include brainstorming and consensus decision making.	E	
Hazard and Operability Analysis - The analyst runs a structured focus group to systematically determine potential system design errors.		A
Hierarchical Sort - The analyst has the informant sort concepts in an increasing number of piles on each sort.		A
Hierarchical Task Analysis - The analyst decomposes tasks performed by the informant into a hierarchy of actions, goals, and sub-goals.		A

Identifying Aspects of the Representation - The analyst generates a structural model. The informant helps to interpret it by labeling dimensions, identifying useful levels of hierarchical cluster diagrams, etc.	E	A
Influence Diagrams - The analyst maps the informant's domain knowledge as a node-link graph with concepts on nodes and inter-node influence on links. Available software tools are Analytica and DEMOS.		A
Information Flow Analysis - The analyst develops a flow chart of the information and decisions required to carry out the system's functions. The informant reviews and corrects the diagram.		A
Interaction Analysis - The informant and analyst identify the interactions between tasks or events that impose a constraint on a system		A
Interruption Analysis - The informant thinks aloud while performing a task. The analyst interrupts the informant for clarification as needed. Job Analysis - The analyst identifies the tasks associated with a specific job.	E	A
Laddering - The analyst asks the informant questions to systematically build a taxonomy of domain concepts. Likert Scale Items - The analyst presents the informant with statements about a task. The informant then rates the statements on a semantically anchored scale.	E	A
Link Analysis - The analyst defines the relationships or links within and between informants and system components. The method is used to optimize these relationships.		A
Magnitude Estimation - The analyst presents the informant with pairs of concepts. The informant rates the relatedness of the pair with respect to a standard reference pair.	E	A
Management Oversight Risk Tree Technique - The analyst uses fault tree diagrams and a structured accident investigation auditing system to assess the adequacy of safety management structures.		A

MIDAS - The Man-machine Integration Design and Analysis System is a computer simulation of human cognitive and perceptual processes for modeling human performance and interactions with systems.		A
Minimal Scenario Technique - The analyst provides minimal (e.g. a few sentences) about a scenario or mission and then the informant requests the information needed to fully understand the situation.	E	
Multidimensional Card Sorting - The analyst has the informant sort concepts into piles and assign attributes and labels to each pile.	E	A
Multidimensional Scaling - The analyst presents all combinations of concept pairs for the informant to rate in terms of proximity. Using this data the analyst computes a multi-dimensional spatial layout of the presented concepts.	E	A
Network Scaling - The analyst computationally generates a graph representing proximities between concepts. Pathfinder is an available software tool.		A
Nonverbal Reports - The analyst collects data concerning an informant's nonverbal actions (eye movement, facial expressions, and gestures) during the performance of a task.	E	
OMAR - The Operator Model Architecture is a set of software tools used to model human performance and team performance. It has an agent-based architecture with extensive toolkit for model creation.		A
Operational Sequence Analysis - The informant creates diagrams of the system's functions at a level of detail that includes decisions and actions.		A
Operational Sequence Diagrams - The analyst represents the informant's domain as a flow chart that links operations in the order that they are carried out. The diagram is also supported by a text description.		A

Operator Function Model - OFM describes and/or prescribes the role of the operator in a complex system by building a hierarchical and dynamic visual representation (graph network) of operator activities and triggering events. OFMSpert is an executable version of the OFM. CFM has an OFMBuild component for static graphs.	E	A
P Sort - The analyst has the informant sort concepts into a fixed number of categories with limitations on the number of concepts per category.	E	A
Paired Comparison - The informant rates pairs of concepts with respect to their relatedness or similarity.	E	A
PARI - Informants present problem solving scenarios to one another. The analyst identifies the knowledge, information acquisition strategies and decision-making process that underlie performance using Precursors, Actions, Results, and Interpretations to structure observations.	E	
Process Tracing/Protocol Analysis - A set of techniques that attempt to trace the cognitive and decision-making process of an individual or team as they work through a problem or scenario.	E	A
Q Sort - The analyst presents the informant with concepts. The informant sorts them into piles based on relatedness.	E	
Questionnaires - The analyst provides the informant with a list of open-ended questions regarding concepts, attributes, and relations in the domain.	E	
Reclassification/ Goal Decomposition - The informant describes goals or outcomes in the domain. The analyst and informant work backward to define the events, evidence, or symptoms that lead to each goal or outcome.	E	A
Repeated Sort - The analyst performs a Q sort multiple times with the requirement that one or more piles differ from the previous sort	E	A

Repertory Grid - The informant generates domain constructs and rates them with respect to elements of those constructs. Data are typically used to cluster constructs or elements.	E	A
Retrospective/Aided Recall - The informant reports his or her thoughts on a task after it has been performed. The analyst may ask the informant follow-up questions after the report.	E	
Role Play - The analyst provides the informant with a role to play in a scenario. The informant then acts out the scenario, often with other informants, while the analyst documents behaviors.	E	
Self-Critiquing/Eidectic Reduction - The informant verbalizes observations about his or her own behavior while working on a task. The analyst records these comments.	E	
Shadowing Another - The informant provides real-time commentary as another expert solves a problem.	E	
Simulators/Mockups - Analyst uses simulators and mockups to observe informant behavior under conditions intended to simulate real-world conditions.	E	
Soar - A symbolic cognitive architecture with focus on goal description and execution monitoring, designed to implement intelligent agents. Soar version 8.4 software is available as well as several soar research groups.		A
Social Organization and Cooperation Analysis - The analyst focuses on the relationships between the actors within the domain.		A
Statistical Modeling/Policy Capturing - The analyst models the informant's decision policies using statistical techniques (e.g., regression) to estimate the weight the informant places or should place on decision variables.		A
Step Listing - In a structured interview, the informant lists the steps involved in performing a specific task in his or her domain.	E	

Strategies Analysis - The analyst focuses on the strategies used to achieve goals in the domain. These strategies are independent of individual actors.		A
Structural Analysis Techniques - he analyst uses a mathematical algorithm to transform the informant's concept relatedness measures into a graphical representation of the domain.(Knowledge Network Organizing Tool , KNOT)		A
Structured Observation - The informant performs a task or solves a problem in the domain. The analyst interprets the actions using a taxonomy or classification scheme developed a priori.	E	
Table-Top Analysis - The analyst presents a group of informants with a scenario to play out or discuss. The team derives a solution to the problem presented.	E	
Task Analysis - The analyst breaks tasks down into a series of external, observable behaviors.	E	
Teachback - The informant explains a concept to the analyst. The analyst then explains the concept back to the informant. This continues until the informant is satisfied with the analyst's understanding of the concept.	E	
Think-Aloud - The informant introspects about perceptions, decisions, and actions while performing a task. The analyst records these statements.	E	
Time Line Analysis - The analyst determines time critical sequences of tasks using the informant's definition of the temporal relationships of tasks.		A
Triad Comparison - The analyst elicits domain constructs by presenting the informant with three concepts to be compared. The informant selects the concept most unlike the other two and states a construct that characterizes the two similar concepts.	E	

Unstructured Interview - The informant is interviewed, typically concerning a given scenario or personal past experience. The analyst? s questions are ad hoc and lines of questioning are opportunistic.	E	
Walk-Throughs and Talk-Throughs - The informant demonstrates a task in situ or in a realistic mock-up for the analyst. When performing a talk-through the informant is removed from realistic surroundings and merely verbalizes the demonstration.	E	
Work Domain Analysis - The analyst examines the system controlled by the informant to understand the work domain (independent of the worker and any events, tasks, goals, or interfaces).		A
Worker Competency Analysis - The analyst focuses on the knowledge and skills required of an individual to act effectively within the domain.		A
Workflow Model - The analyst sets up a scenario and the informant works or talks it through to completion. The analyst elicits terms, processes, and concepts.		A

APPENDIX B: CODING FORM

METHOD	TYPE
20 Questions	E
ACTA	E & A
Active Participation	E
Activity Sampling	E
ACT-R	A
Barrier & work safety analysis	A
Card Sort	E & A
Close Experimental/Minimal scenario	E
Clustering routines	A
COGNET	A
Cognitive function model	E & A
Cognitive Task Analysis	E
Cognitive work analysis	A
Comparing two or more representations	A
Concept Listing	E
Concept Map	E & A
Conceptual graph analysis	A
Content analysis	A
Control task analysis	A
Controlled Association	E
Controlled Simulated observations	E
Correlation/covariance	A
Critical Decision	E
Critical Incident	E
Critical retrospective	E
Crystal ball/stumbling block	E
Design storyboarding	E
Diagram drawing	A
Discourse/Conversation/Interaction Analysis	A
Discrete event simulation	A
Distinguishing goals	E & A
Dividing the domain	E
Document Analysis	E & A
Drawing closed curves	E
Eliciting estimations of probability/utility	E
EPIC - Executive Process	A
Event co-occurrence/transition probabilities	E
Event trees	A
Exploratory sequential data analysis	A
Failure models and effects analysis	A
Fault trees	A

Field observation/ethnography	E
Focus group/joint application development	E
Focused observation	E
Free association	E & A
Functional abstraction hierarchy	A
functional flow analysis	A
GOMS	A
Graph construction	E & A
Grounded theory	A
Group Discussion	E
Group interview	E
Hazard and operability analysis	A
Hierarchical sort	A
Hierarchical Task analysis	A
Identifying aspects of the representation	E & A
Influence diagrams	A
Information flow analysis	A
Interaction analysis	A
Interruption analysis	E
Job analysis	A
Laddering	E & A
Likert scale items	E
Link analysis	A
Magnitude estimation	E & A
Management oversight risk tree	A
MIDAS - Man-machine integration	A
Minimal scenario technique	E
Multidimensional card sorting	E & A
Multidimensional scaling	E & A
Network scaling	A
Nonverbal reports	E
OMAR -Operator model architecture	A
Operational sequence analysis	A
Operational Sequence Diagrams	A
Operator function model	E & A
P sort	E & A
Paired comparison	E & A
PARI	E
Process tracing/protocol analysis	E & A
Q Sort	E
Questionnaires	E
Reclassification/goal decomposition	E & A
Repeated Sort	E & A
Repertory Grid	E & A
Retrospective/aided recall	E

Role play	E
Self-critiquing	E
Semi-structured Interview	E
Shadowing another	E
Simulators/Mockups	E
SOAR	A
Social organization	A
Statistical modeling/policy capturing	A
Step listing	E
Strategies analysis	A
Structural analysis techniques	A
Structured Interview	**E**
Structured observation	E
Table-top analysis	E
Task analysis	E
Teach back	E
Think-aloud	E
Time line analysis	A
Triad comparison	E
Unstructured interview	E
Walk-throughs/talk-throughs	E
Work domain analysis	A
Worker competency analysis	A
Workflow model	A

Declarative Knowledge (X)
- Concept (X)
- Process (X)
- Principle (X)

Procedural Knowledge (X)
- Classify (X)
- Change (X)

Sensitivity to Automated knowledge (Y or N)

Application of final results:

APPENDIX C: FEQUENCY RANKINGS OF CTA METHODS

Method	Frequency	%	Cum %
Structured interview	135	14.98%	14.98%
Concept map	79	8.77%	23.75%
Verbal Think-aloud	65	7.21%	30.97%
Process tracing	54	5.99%	36.96%
Repertory/laddered Grid	50	5.55%	42.51%
Observation	33	3.66%	46.17%
Hierarchical analysis	28	3.11%	49.28%
Card sorting	27	3.00%	52.28%
Document analysis	26	2.89%	55.16%
Cdm/cim	25	2.77%	57.94%
Unstructured interview	24	2.66%	60.60%
Case based scenarios	21	2.33%	
Kads/kat	21	2.33%	
Neural network	17	1.89%	
Model-based approaches	16	1.78%	
Fuzzy logic/cognitive map/rule analysis	15	1.66%	
Machine induction/learning	14	1.55%	
Simulation	14	1.55%	
Prototype analysis	11	1.22%	
Questionnaire	11	1.22%	
Goms	10	1.11%	
Workshop/group collaboration	10	1.11%	
Induction	9	1.00%	
Structural analysis	9	1.00%	
Acta	7	0.78%	
Computer modeling	7	0.78%	
Content analysis	7	0.78%	
Linguistic analysis	7	0.78%	
Simulation	6	0.67%	
Hypermedia/hypertext	5	0.55%	
Information processing cognitive modeling based	4	0.44%	
Mapping - causal or other	4	0.44%	
Pathfinder	4	0.44%	
Process tracing with eye movements	4	0.44%	
COGENT; macshapa; cognitive models	3	0.33%	
Computer learning	3	0.33%	
Decision table/trees	3	0.33%	
Grounded theory	3	0.33%	

Semantic networks;	3	0.33%
20 questions	2	0.22%
Artificial intelligence methods	2	0.22%
Exception graphs/to rules	2	0.22%
Itam	2	0.22%
Matrices	2	0.22%
Natural language processing	2	0.22%
Pairwise comparisons	2	0.22%
Rating and sorting	2	0.22%
Teachback	2	0.22%
Ternary grid	2	0.22%
Abstract object types	1	0.11%
Active software	1	0.11%
Agent ontology	1	0.11%
AI techniques; data mining	1	0.11%
Anthropological interview	1	0.11%
Appreciative inquiry method (aim)	1	0.11%
Apt	1	0.11%
Artefact ananlysis	1	0.11%
Automated graphical knowledge acquisition tool	1	0.11%
Automatic rule induction	1	0.11%
Checking software using different data	1	0.11%
C-KAT; self-administered	1	0.11%
Cognitive mapping	1	0.11%
Coherence method	1	0.11%
Computer aided knowledge elicitation (CAKE)	1	0.11%
Computer assisted failure gathering data	1	0.11%
Computer-aided software engineering (CASE)	1	0.11%
Computer-assisted (EID) ecological interface design	1	0.11%
Computer-assisted expert systems	1	0.11%
Computer-based knowledge acquisition	1	0.11%
Computer-expert interaction	1	0.11%
Concurrent conceptual design (CCD)	1	0.11%
Consultation reviews	1	0.11%
Core	1	0.11%
Critiquing novices processes	1	0.11%
CTAT (cognitive tutor authoring tools);	1	0.11%
Data mining	1	0.11%
Decision support system (dss)	1	0.11%

Distributed knowledge elicitation	1	0.11%
DKA; diagrammatic knowledge acquisition	1	0.11%
DNA; computer-assisted semi-structured dialog	1	0.11%
Ellipsoids	1	0.11%
Enterprise model	1	0.11%
Ethnography	1	0.11%
Expert critiquing	1	0.11%
Expert-machine interaction	1	0.11%
FMS status data	1	0.11%
Genetic algorithm generates the rules,	1	0.11%
Graphical knowledge editing.	1	0.11%
Graphs for statistical object models	1	0.11%
HAZOP, CCA and FMEA techniques	1	0.11%
ID3 rule generation system; decision tree	1	0.11%
Interactive argument	1	0.11%
Interactive computer for constructs	1	0.11%
Interactive computer graphics	1	0.11%
Interactive computer-based aid for knowledge elicitation	1	0.11%
Journal entries	1	0.11%
KAVE: computer-assisted interactive rule acquisition	1	0.11%
Kept	1	0.11%
Knowledge importance evaluation	1	0.11%
KSM (knowledge specification modeller); linguistic engineering	1	0.11%
Language modeling and simulation	1	0.11%
Learner-machine-expert interaction	1	0.11%
Logical spreadsheet	1	0.11%
Logs;	1	0.11%
Madam;	1	0.11%
Maps of spatial hypertext; reconfigurable information spaces	1	0.11%
Matching scores of templates created	1	0.11%
Mathematical simulation and inductive machine learning	1	0.11%
Mental models	1	0.11%
Multi-attribute decision-making; DECMAK	1	0.11%
Naturalistic decision making	1	0.11%
Naturalistic decision making (NDM)	1	0.11%
Notation in AI	1	0.11%
Object-oriented framework	1	0.11%

Ordered beliefs	1	0.11%
Pattern recognition	1	0.11%
PCS, participant construct system	1	0.11%
Perceptual control theory (pct)	1	0.11%
Peski	1	0.11%
Point estimation, interval estimation	1	0.11%
Position analysis questionnaire (paq)	1	0.11%
Purdue; questionnaire; PAQ	1	0.11%
RAKES using artificial intelligence	1	0.11%
Reciprocal knowledge exchange through structured argumentative discourses	1	0.11%
RPD- Recognition Primed Decision-making	1	0.11%
Sakas	1	0.11%
Schema-based hierarchy of templates	1	0.11%
Self-report paired comparison response latency	1	0.11%
Service constraints in telecommunications services	1	0.11%
Skill-based CTA	1	0.11%
TACOS; tactics acquisition and operationalization system	1	0.11%
Tagging images; classifying	1	0.11%
Time-scale oriented approach	1	0.11%
TMS; truth maintenance system	1	0.11%
VEGAN a form of associated networks	1	0.11%
Visual knowledge elicitation technique	1	0.11%
Total	901	

APPENDIX D: SUMMARY OF CTA METHOD PAIRINGS

Method Pairing	Frequency	Cum Freq	Percentage
E_PA * A_PA	44	44	4.4%
E_DocAnl * A_DocAnl	32	76	7.5%
E_Think * A_PA	25	101	10.0%
E_Semi * A_Diag	21	122	12.1%
E_ConMap * A_ConMap	20	142	14.1%
E_RpGrid * A_RpGrid	18	160	15.8%
E_DocAnl * A_Diag	17	177	17.5%
E_Semi * A_ConAnl	17	194	19.2%
E_Card * A_Card	13	207	20.5%
E_Semi * A_PA	13	220	21.8%
E_GrpInt * A_Diag	12	232	23.0%
E_Semi * A_DocAnl	12	244	24.2%
E_Struct * A_Diag	12	256	25.3%
E_PA * A_Diag	11	267	26.4%
E_DocAnl * A_ConAnl	9	276	27.3%
E_CDM * A_PA	8	284	28.1%
E_DocAnl * A_PA	8	292	28.9%
E_PA * A_ConAnl	8	300	29.7%
E_PA * A_DocAnl	8	308	30.5%
E_Think * A_ConAnl	8	316	31.3%
E_Think * A_DocAnl	8	324	32.1%
E_cta * A_ConAnl	7	331	32.8%
E_Ident * A_Ident	7	338	33.5%
E_PA * A_Htask	7	345	34.2%
E_Retro * A_PA	7	352	34.9%
E_Semi * A_InfFlo	7	359	35.5%
E_Struct * A_ConAnl	7	366	36.2%
E_cta * A_DocAnl	6	372	36.8%
E_cta * A_PA	6	378	37.4%
E_Field * A_DocAnl	6	384	38.0%
E_GrpInt * A_ConAnl	6	390	38.6%
E_Ladd * A_Ladd	6	396	39.2%
E_Quest * A_Diag	6	402	39.8%
E_Retro * A_Diag	6	408	40.4%
E_Struct * A_PA	6	414	41.0%
E_Think * A_Diag	6	420	41.6%
E_UnIntv * A_Diag	6	426	42.2%
E_UnIntv * A_DocAnl	6	432	42.8%
E_cta * A_Diag	5	437	43.3%

E_Field * A_PA	5	442	43.8%
E_GrpInt * A_DocAnl	5	447	44.3%
E_MDS * A_MDS	5	452	44.8%
E_Semi * A_ConMap	5	457	45.2%
E_Semi * A_Htask	5	462	45.7%
E_Struct * A_Ident	5	467	46.2%
E_Struct * A_RpGrid	5	472	46.7%
E_Card * A_MCS	4	476	47.1%
E_ConLis * A_Diag	4	480	47.5%
E_ConMap * A_Diag	4	484	47.9%
E_DocAnl * A_ConGra	4	488	48.3%
E_Field * A_ConAnl	4	492	48.7%
E_Focus * A_DocAnl	4	496	49.1%
E_Graph * A_Graph	4	500	49.5%
E_GrpInt * A_PA	4	504	49.9%
E_Likert * A_Diag	4	508	50.3%
E_MCS * A_Card	4	512	50.7%
E_MCS * A_MCS	4	516	51.1%
E_Pair * A_Pair	4	520	51.5%
E_PA * A_RpGrid	4	524	51.9%
E_Quest * A_ConAnl	4	528	52.3%
E_RpGrid * A_PA	4	532	52.7%
E_Retro * A_ConAnl	4	536	53.1%
E_Semi * A_Card	4	540	53.5%
E_Struct * A_DocAnl	4	544	53.9%
E_Think * A_Htask	4	548	54.3%
E_UnIntv * A_PA	4	552	54.7%
E_Card * A_Clust	3	555	55.0%
E_Card * A_DocAnl	3	558	55.2%
E_Card * A_RpGrid	3	561	55.5%
E_cta * A_InfFlo	3	564	55.8%
E_ConLis * A_ConGra	3	567	56.1%
E_ConMap * A_ConAnl	3	570	56.4%
E_ConMap * A_DocAnl	3	573	56.7%
E_DocAnl * A_Card	3	576	57.0%
E_DocAnl * A_ConMap	3	579	57.3%
E_DocAnl * A_WkFlow	3	582	57.6%
E_Field * A_Diag	3	585	57.9%
E_Focus * A_ConAnl	3	588	58.2%
E_GrpInt * A_WkFlow	3	591	58.5%
E_Ident * A_Diag	3	594	58.8%
E_Ladd * A_RpGrid	3	597	59.1%
E_Likert * A_ConAnl	3	600	59.4%

E_Likert * A_Net	3	603	59.7%
E_PA * A_ConGra	3	606	60.0%
E_RpGrid * A_Card	3	609	60.3%
E_RpGrid * A_Ladd	3	612	60.6%
E_Semi * A_RpGrid	3	615	60.9%
E_Semi * A_Stat	3	618	61.2%
E_Simul * A_Diag	3	621	61.5%
E_Struct * A_ConMap	3	624	61.8%
E_Struct * A_WkFlow	3	627	62.1%
E_Think * A_RpGrid	3	630	62.4%
E_20Q * A_ConAnl	2	632	62.6%
E_Card * A_ConAnl	2	634	62.8%
E_Card * A_Graph	2	636	63.0%
E_Card * A_Ladd	2	638	63.2%
E_Card * A_MDS	2	640	63.4%
E_Card * A_Repeat	2	642	63.6%
E_Card * A_Stat	2	644	63.8%
E_cogfn * A_cogfn	2	646	64.0%
E_cta * A_Htask	2	648	64.2%
E_cta * A_Ident	2	650	64.4%
E_ConLis * A_ConAnl	2	652	64.6%
E_ConMap * A_Clust	2	654	64.8%
E_ConMap * A_Stat	2	656	65.0%
E_ConMap * A_StruAn	2	658	65.1%
E_CDM * A_DocAnl	2	660	65.3%
E_DocAnl * A_Clust	2	662	65.5%
E_DocAnl * A_Ground	2	664	65.7%
E_DocAnl * A_Htask	2	666	65.9%
E_DocAnl * A_InfFlo	2	668	66.1%
E_DocAnl * A_MDS	2	670	66.3%
E_DocAnl * A_StruAn	2	672	66.5%
E_Field * A_ConMap	2	674	66.7%
E_Focus * A_Diag	2	676	66.9%
E_Focus * A_Ident	2	678	67.1%
E_Graph * A_Card	2	680	67.3%
E_GrpInt * A_ConMap	2	682	67.5%
E_GrpInt * A_Ident	2	684	67.7%
E_GrpInt * A_StruAn	2	686	67.9%
E_Ident * A_WkFlow	2	688	68.1%
E_Interp * A_PA	2	690	68.3%
E_Ladd * A_Card	2	692	68.5%
E_Ladd * A_cor	2	694	68.7%
E_Ladd * A_Diag	2	696	68.9%

E_Ladd * A_PA	2	698	69.1%
E_Likert * A_ConMap	2	700	69.3%
E_Likert * A_InfFlo	2	702	69.5%
E_Likert * A_PA	2	704	69.7%
E_MCS * A_MDS	2	706	69.9%
E_MDS * A_Card	2	708	70.1%
E_MDS * A_DocAnl	2	710	70.3%
E_MDS * A_MCS	2	712	70.5%
E_PA * A_COGNE	2	714	70.7%
E_PA * A_Ground	2	716	70.9%
E_PA * A_InfFlo	2	718	71.1%
E_PA * A_Ladd	2	720	71.3%
E_PA * A_WkFlow	2	722	71.5%
E_Qsort * A_ConAnl	2	724	71.7%
E_Qsort * A_Diag	2	726	71.9%
E_Quest * A_ConMap	2	728	72.1%
E_Quest * A_InfFlo	2	730	72.3%
E_Quest * A_Stat	2	732	72.5%
E_Repeat * A_Card	2	734	72.7%
E_Repeat * A_Repeat	2	736	72.9%
E_RpGrid * A_Diag	2	738	73.1%
E_RpGrid * A_InfFlo	2	740	73.3%
E_RpGrid * A_Stat	2	742	73.5%
E_RpGrid * A_StruAn	2	744	73.7%
E_Retro * A_ConMap	2	746	73.9%
E_Retro * A_Htask	2	748	74.1%
E_Semi * A_Clust	2	750	74.3%
E_Semi * A_ConGra	2	752	74.5%
E_Semi * A_Ground	2	754	74.7%
E_Semi * A_Ladd	2	756	74.9%
E_Simul * A_ConAnl	2	758	75.0%
E_Simul * A_InfFlo	2	760	75.2%
E_Struct * A_Card	2	762	75.4%
E_Struct * A_Clust	2	764	75.6%
E_Struct * A_Ground	2	766	75.8%
E_Teach * A_ConAnl	2	768	76.0%
E_Teach * A_Diag	2	770	76.2%
E_UnIntv * A_Card	2	772	76.4%
E_UnIntv * A_ConAnl	2	774	76.6%
E_UnIntv * A_Ident	2	776	76.8%
E_UnIntv * A_WkFlow	2	778	77.0%
E_20Q * A_Card	1	779	77.1%
E_20Q * A_Diag	1	780	77.2%

E_20Q * A_PA	1	781	77.3%
E_Card * A_Diag	1	782	77.4%
E_Card * A_Ground	1	783	77.5%
E_Card * A_Hsort	1	784	77.6%
E_Card * A_Htask	1	785	77.7%
E_Card * A_InfFlo	1	786	77.8%
E_Card * A_PA	1	787	77.9%
E_cogfn * A_cwa	1	788	78.0%
E_cogfn * A_ConMap	1	789	78.1%
E_cogfn * A_ConAnl	1	790	78.2%
E_cogfn * A_Diag	1	791	78.3%
E_cogfn * A_DocAnl	1	792	78.4%
E_cogfn * A_Funct	1	793	78.5%
E_cta * A_Card	1	794	78.6%
E_cta * A_ConMap	1	795	78.7%
E_cta * A_Ground	1	796	78.8%
E_cta * A_Pair	1	797	78.9%
E_cta * A_Stat	1	798	79.0%
E_cta * A_StraAn	1	799	79.1%
E_ConLis * A_cor	1	800	79.2%
E_ConLis * A_DocAnl	1	801	79.3%
E_ConLis * A_EvTree	1	802	79.4%
E_ConLis * A_Ground	1	803	79.5%
E_ConLis * A_InfDia	1	804	79.6%
E_ConLis * A_IntAna	1	805	79.7%
E_ConLis * A_Ladd	1	806	79.8%
E_ConLis * A_PA	1	807	79.9%
E_ConLis * A_StruAn	1	808	80.0%
E_ConMap * A_cogfn	1	809	80.1%
E_ConMap * A_ConGra	1	810	80.2%
E_ConMap * A_Fault	1	811	80.3%
E_ConMap * A_Funct	1	812	80.4%
E_ConMap * A_GOMS	1	813	80.5%
E_ConMap * A_Hsort	1	814	80.6%
E_ConMap * A_Ident	1	815	80.7%
E_ConMap * A_InfDia	1	816	80.8%
E_ConMap * A_Net	1	817	80.9%
E_ConMap * A_PA	1	818	81.0%
E_ConMap * A_WkFlow	1	819	81.1%
E_CDM * A_Card	1	820	81.2%
E_CDM * A_ConMap	1	821	81.3%
E_CDM * A_ConGra	1	822	81.4%
E_CDM * A_Diag	1	823	81.5%

E_CDM * A_Ground	1	824	81.6%
E_CDM * A_Htask	1	825	81.7%
E_crit * A_ConAnl	1	826	81.8%
E_crit * A_PA	1	827	81.9%
E_design * A_cogfn	1	828	82.0%
E_design * A_ConMap	1	829	82.1%
E_DocAnl * A_cogfn	1	830	82.2%
E_DocAnl * A_cwa	1	831	82.3%
E_DocAnl * A_cor	1	832	82.4%
E_DocAnl * A_Funct	1	833	82.5%
E_DocAnl * A_Graph	1	834	82.6%
E_DocAnl * A_Ident	1	835	82.7%
E_DocAnl * A_MCS	1	836	82.8%
E_DocAnl * A_OpSqAn	1	837	82.9%
E_DocAnl * A_OFM	1	838	83.0%
E_DocAnl * A_RpGrid	1	839	83.1%
E_DocAnl * A_Stat	1	840	83.2%
E_DocAnl * A_StraAn	1	841	83.3%
E_Elict * A_ConAnl	1	842	83.4%
E_Elict * A_Diag	1	843	83.5%
E_Event * A_ConMap	1	844	83.6%
E_Event * A_Stat	1	845	83.7%
E_Event * A_StruAn	1	846	83.8%
E_Field * A_Ground	1	847	83.9%
E_Field * A_Htask	1	848	84.0%
E_Field * A_MDS	1	849	84.1%
E_Field * A_Net	1	850	84.2%
E_Field * A_OpSqAn	1	851	84.3%
E_Field * A_SOAR	1	852	84.4%
E_Field * A_StraAn	1	853	84.5%
E_Field * A_WkFlow	1	854	84.6%
E_Focus * A_ConMap	1	855	84.7%
E_Focus * A_InfFlo	1	856	84.8%
E_Focus * A_OFM	1	857	84.9%
E_Focus * A_WkDoAn	1	858	85.0%
E_Focus * A_WkFlow	1	859	85.0%
E_Free * A_Free	1	860	85.1%
E_Free * A_InfDia	1	861	85.2%
E_Free * A_Pair	1	862	85.3%
E_Graph * A_DocAnl	1	863	85.4%
E_Graph * A_Hsort	1	864	85.5%
E_Graph * A_Htask	1	865	85.6%
E_Graph * A_MCS	1	866	85.7%

E_Graph * A_MDS	1	867	85.8%
E_Graph * A_Stat	1	868	85.9%
E_GrpDis * A_ConMap	1	869	86.0%
E_GrpDis * A_ConAnl	1	870	86.1%
E_GrpDis * A_Diag	1	871	86.2%
E_GrpDis * A_DocAnl	1	872	86.3%
E_GrpDis * A_PA	1	873	86.4%
E_GrpInt * A_Ground	1	874	86.5%
E_GrpInt * A_Htask	1	875	86.6%
E_GrpInt * A_InfDia	1	876	86.7%
E_GrpInt * A_InfFlo	1	877	86.8%
E_GrpInt * A_RpGrid	1	878	86.9%
E_GrpInt * A_Stat	1	879	87.0%
E_GrpInt * A_TimeLn	1	880	87.1%
E_Ident * A_Clust	1	881	87.2%
E_Ident * A_ConMap	1	882	87.3%
E_Ident * A_ConAnl	1	883	87.4%
E_Ident * A_DocAnl	1	884	87.5%
E_Ident * A_Htask	1	885	87.6%
E_Ident * A_MDS	1	886	87.7%
E_Ident * A_RpGrid	1	887	87.8%
E_Interp * A_ConAnl	1	888	87.9%
E_Interp * A_Diag	1	889	88.0%
E_Interp * A_DocAnl	1	890	88.1%
E_Interp * A_Ground	1	891	88.2%
E_Interp * A_StraAn	1	892	88.3%
E_Ladd * A_ConGra	1	893	88.4%
E_Ladd * A_ConAnl	1	894	88.5%
E_Ladd * A_Ground	1	895	88.6%
E_Ladd * A_Stat	1	896	88.7%
E_Likert * A_Card	1	897	88.8%
E_Likert * A_cor	1	898	88.9%
E_Likert * A_DocAnl	1	899	89.0%
E_Likert * A_Htask	1	900	89.1%
E_Likert * A_Ident	1	901	89.2%
E_Likert * A_Ladd	1	902	89.3%
E_Likert * A_MDS	1	903	89.4%
E_Likert * A_RpGrid	1	904	89.5%
E_Likert * A_Stat	1	905	89.6%
E_Likert * A_WkFlow	1	906	89.7%
E_MCS * A_Clust	1	907	89.8%
E_MCS * A_ConAnl	1	908	89.9%
E_MCS * A_DocAnl	1	909	90.0%

E_MCS * A_Graph	1	910	90.1%
E_MCS * A_Repeat	1	911	90.2%
E_MDS * A_Clust	1	912	90.3%
E_MDS * A_Graph	1	913	90.4%
E_MDS * A_Htask	1	914	90.5%
E_MDS * A_Ident	1	915	90.6%
E_MDS * A_Net	1	916	90.7%
E_MDS * A_OpSqAn	1	917	90.8%
E_MDS * A_RpGrid	1	918	90.9%
E_Nonver * A_PA	1	919	91.0%
E_OFM * A_DocAnl	1	920	91.1%
E_OFM * A_OFM	1	921	91.2%
E_Pair * A_ConAnl	1	922	91.3%
E_Pair * A_Free	1	923	91.4%
E_Pair * A_Hsort	1	924	91.5%
E_Pair * A_InfDia	1	925	91.6%
E_Pair * A_RpGrid	1	926	91.7%
E_PARI * A_COGNE	1	927	91.8%
E_PARI * A_PA	1	928	91.9%
E_PA * A_Card	1	929	92.0%
E_PA * A_ConMap	1	930	92.1%
E_PA * A_cor	1	931	92.2%
E_PA * A_Stat	1	932	92.3%
E_Qsort * A_ConGra	1	933	92.4%
E_Qsort * A_Ground	1	934	92.5%
E_Qsort * A_Ladd	1	935	92.6%
E_Qsort * A_PA	1	936	92.7%
E_Quest * A_Fail	1	937	92.8%
E_Quest * A_Fault	1	938	92.9%
E_Quest * A_Ident	1	939	93.0%
E_Quest * A_Net	1	940	93.1%
E_Quest * A_OpSqAn	1	941	93.2%
E_Quest * A_WkFlow	1	942	93.3%
E_Repeat * A_Clust	1	943	93.4%
E_Repeat * A_MCS	1	944	93.5%
E_RpGrid * A_cor	1	945	93.6%
E_RpGrid * A_DocAnl	1	946	93.7%
E_RpGrid * A_Htask	1	947	93.8%
E_RpGrid * A_Ident	1	948	93.9%
E_RpGrid * A_MDS	1	949	94.0%
E_RpGrid * A_Net	1	950	94.1%
E_RpGrid * A_Pair	1	951	94.2%
E_Retro * A_DocAnl	1	952	94.3%

E_Retro * A_Ground	1	953	94.4%
E_Retro * A_InfFlo	1	954	94.5%
E_Retro * A_Stat	1	955	94.6%
E_Semi * A_cogfn	1	956	94.7%
E_Semi * A_cwa	1	957	94.8%
E_Semi * A_comp2	1	958	94.9%
E_Semi * A_Funct	1	959	95.0%
E_Semi * A_Hsort	1	960	95.0%
E_Semi * A_Ident	1	961	95.1%
E_Semi * A_Job	1	962	95.2%
E_Semi * A_Net	1	963	95.3%
E_Semi * A_OFM	1	964	95.4%
E_Semi * A_Pair	1	965	95.5%
E_Semi * A_StraAn	1	966	95.6%
E_Semi * A_TimeLn	1	967	95.7%
E_Simul * A_Card	1	968	95.8%
E_Simul * A_DocAnl	1	969	95.9%
E_Simul * A_Ground	1	970	96.0%
E_Simul * A_MDS	1	971	96.1%
E_Simul * A_Net	1	972	96.2%
E_Struct * A_cor	1	973	96.3%
E_Struct * A_Fault	1	974	96.4%
E_Struct * A_GOMS	1	975	96.5%
E_Struct * A_Htask	1	976	96.6%
E_Struct * A_InfFlo	1	977	96.7%
E_Struct * A_Ladd	1	978	96.8%
E_Struct * A_MDS	1	979	96.9%
E_Struct * A_Net	1	980	97.0%
E_Struct * A_StraAn	1	981	97.1%
E_StObvs * A_ConAnl	1	982	97.2%
E_Table * A_Diag	1	983	97.3%
E_Table * A_InfDia	1	984	97.4%
E_TaskAn * A_Diag	1	985	97.5%
E_TaskAn * A_Ground	1	986	97.6%
E_Teach * A_comp2	1	987	97.7%
E_Teach * A_Stat	1	988	97.8%
E_Think * A_Card	1	989	97.9%
E_Think * A_COGNE	1	990	98.0%
E_Think * A_ConGra	1	991	98.1%
E_Think * A_cor	1	992	98.2%
E_Think * A_Graph	1	993	98.3%
E_Think * A_Ground	1	994	98.4%
E_Think * A_Ladd	1	995	98.5%

E_Think * A_MCS	1	996	98.6%
E_Think * A_MDS	1	997	98.7%
E_Think * A_Net	1	998	98.8%
E_Think * A_Stat	1	999	98.9%
E_Think * A_WkDoAn	1	1000	99.0%
E_Think * A_WkFlow	1	1001	99.1%
E_Traid * A_RpGrid	1	1002	99.2%
E_Traid * A_StruAn	1	1003	99.3%
E_UnIntv * A_ConMap	1	1004	99.4%
E_UnIntv * A_Graph	1	1005	99.5%
E_UnIntv * A_Ground	1	1006	99.6%
E_UnIntv * A_InfFlo	1	1007	99.7%
E_UnIntv * A_MCS	1	1008	99.8%
E_UnIntv * A_MDS	1	1009	99.9%
E_UnIntv * A_WkDoAn	1	1010	100.0%
E_20Q * A_Clust	0		
E_20Q * A_COGNE	0		
E_20Q * A_cogfn	0		
E_20Q * A_cwa	0		
E_20Q * A_comp2	0		
E_20Q * A_ConMap	0		
E_20Q * A_ConGra	0		
E_20Q * A_cor	0		
E_20Q * A_DocAnl	0		
E_20Q * A_EvTree	0		
E_20Q * A_Fail	0		
E_20Q * A_Fault	0		
E_20Q * A_Free	0		
E_20Q * A_Funct	0		
E_20Q * A_GOMS	0		
E_20Q * A_Graph	0		
E_20Q * A_Ground	0		
E_20Q * A_Hsort	0		
E_20Q * A_Htask	0		
E_20Q * A_Ident	0		
E_20Q * A_InfDia	0		
E_20Q * A_InfFlo	0		
E_20Q * A_IntAna	0		
E_20Q * A_Job	0		
E_20Q * A_Ladd	0		
E_20Q * A_MCS	0		
E_20Q * A_MDS	0		
E_20Q * A_Net	0		

E_20Q * A_OpSqAn	0
E_20Q * A_OFM	0
E_20Q * A_Pair	0
E_20Q * A_Repeat	0
E_20Q * A_RpGrid	0
E_20Q * A_SOAR	0
E_20Q * A_Stat	0
E_20Q * A_StraAn	0
E_20Q * A_StruAn	0
E_20Q * A_TimeLn	0
E_20Q * A_WkDoAn	0
E_20Q * A_WkFlow	0
E_Card * A_COGNE	0
E_Card * A_cogfn	0
E_Card * A_cwa	0
E_Card * A_comp2	0
E_Card * A_ConMap	0
E_Card * A_ConGra	0
E_Card * A_cor	0
E_Card * A_EvTree	0
E_Card * A_Fail	0
E_Card * A_Fault	0
E_Card * A_Free	0
E_Card * A_Funct	0
E_Card * A_GOMS	0
E_Card * A_Ident	0
E_Card * A_InfDia	0
E_Card * A_IntAna	0
E_Card * A_Job	0
E_Card * A_Net	0
E_Card * A_OpSqAn	0
E_Card * A_OFM	0
E_Card * A_Pair	0
E_Card * A_SOAR	0
E_Card * A_StraAn	0
E_Card * A_StruAn	0
E_Card * A_TimeLn	0
E_Card * A_WkDoAn	0
E_Card * A_WkFlow	0
E_cogfn * A_Card	0
E_cogfn * A_Clust	0
E_cogfn * A_COGNE	0
E_cogfn * A_comp2	0

E_cogfn * A_ConGra	0
E_cogfn * A_cor	0
E_cogfn * A_EvTree	0
E_cogfn * A_Fail	0
E_cogfn * A_Fault	0
E_cogfn * A_Free	0
E_cogfn * A_GOMS	0
E_cogfn * A_Graph	0
E_cogfn * A_Ground	0
E_cogfn * A_Hsort	0
E_cogfn * A_Htask	0
E_cogfn * A_Ident	0
E_cogfn * A_InfDia	0
E_cogfn * A_InfFlo	0
E_cogfn * A_IntAna	0
E_cogfn * A_Job	0
E_cogfn * A_Ladd	0
E_cogfn * A_MCS	0
E_cogfn * A_MDS	0
E_cogfn * A_Net	0
E_cogfn * A_OpSqAn	0
E_cogfn * A_OFM	0
E_cogfn * A_Pair	0
E_cogfn * A_PA	0
E_cogfn * A_Repeat	0
E_cogfn * A_RpGrid	0
E_cogfn * A_SOAR	0
E_cogfn * A_Stat	0
E_cogfn * A_StraAn	0
E_cogfn * A_StruAn	0
E_cogfn * A_TimeLn	0
E_cogfn * A_WkDoAn	0
E_cogfn * A_WkFlow	0
E_cta * A_Clust	0
E_cta * A_COGNE	0
E_cta * A_cogfn	0
E_cta * A_cwa	0
E_cta * A_comp2	0
E_cta * A_ConGra	0
E_cta * A_cor	0
E_cta * A_EvTree	0
E_cta * A_Fail	0
E_cta * A_Fault	0

E_cta * A_Free	0
E_cta * A_Funct	0
E_cta * A_GOMS	0
E_cta * A_Graph	0
E_cta * A_Hsort	0
E_cta * A_InfDia	0
E_cta * A_IntAna	0
E_cta * A_Job	0
E_cta * A_Ladd	0
E_cta * A_MCS	0
E_cta * A_MDS	0
E_cta * A_Net	0
E_cta * A_OpSqAn	0
E_cta * A_OFM	0
E_cta * A_Repeat	0
E_cta * A_RpGrid	0
E_cta * A_SOAR	0
E_cta * A_StruAn	0
E_cta * A_TimeLn	0
E_cta * A_WkDoAn	0
E_cta * A_WkFlow	0
E_ConLis * A_Card	0
E_ConLis * A_Clust	0
E_ConLis * A_COGNE	0
E_ConLis * A_cogfn	0
E_ConLis * A_cwa	0
E_ConLis * A_comp2	0
E_ConLis * A_ConMap	0
E_ConLis * A_Fail	0
E_ConLis * A_Fault	0
E_ConLis * A_Free	0
E_ConLis * A_Funct	0
E_ConLis * A_GOMS	0
E_ConLis * A_Graph	0
E_ConLis * A_Hsort	0
E_ConLis * A_Htask	0
E_ConLis * A_Ident	0
E_ConLis * A_InfFlo	0
E_ConLis * A_Job	0
E_ConLis * A_MCS	0
E_ConLis * A_MDS	0
E_ConLis * A_Net	0
E_ConLis * A_OpSqAn	0

E_ConLis * A_OFM	0
E_ConLis * A_Pair	0
E_ConLis * A_Repeat	0
E_ConLis * A_RpGrid	0
E_ConLis * A_SOAR	0
E_ConLis * A_Stat	0
E_ConLis * A_StraAn	0
E_ConLis * A_TimeLn	0
E_ConLis * A_WkDoAn	0
E_ConLis * A_WkFlow	0
E_ConMap * A_Card	0
E_ConMap * A_COGNE	0
E_ConMap * A_cwa	0
E_ConMap * A_comp2	0
E_ConMap * A_cor	0
E_ConMap * A_EvTree	0
E_ConMap * A_Fail	0
E_ConMap * A_Free	0
E_ConMap * A_Graph	0
E_ConMap * A_Ground	0
E_ConMap * A_Htask	0
E_ConMap * A_InfFlo	0
E_ConMap * A_IntAna	0
E_ConMap * A_Job	0
E_ConMap * A_Ladd	0
E_ConMap * A_MCS	0
E_ConMap * A_MDS	0
E_ConMap * A_OpSqAn	0
E_ConMap * A_OFM	0
E_ConMap * A_Pair	0
E_ConMap * A_Repeat	0
E_ConMap * A_RpGrid	0
E_ConMap * A_SOAR	0
E_ConMap * A_StraAn	0
E_ConMap * A_TimeLn	0
E_ConMap * A_WkDoAn	0
E_CDM * A_Clust	0
E_CDM * A_COGNE	0
E_CDM * A_cogfn	0
E_CDM * A_cwa	0
E_CDM * A_comp2	0
E_CDM * A_ConAnl	0

E_CDM * A_cor	0
E_CDM * A_EvTree	0
E_CDM * A_Fail	0
E_CDM * A_Fault	0
E_CDM * A_Free	0
E_CDM * A_Funct	0
E_CDM * A_GOMS	0
E_CDM * A_Graph	0
E_CDM * A_Hsort	0
E_CDM * A_Ident	0
E_CDM * A_InfDia	0
E_CDM * A_InfFlo	0
E_CDM * A_IntAna	0
E_CDM * A_Job	0
E_CDM * A_Ladd	0
E_CDM * A_MCS	0
E_CDM * A_MDS	0
E_CDM * A_Net	0
E_CDM * A_OpSqAn	0
E_CDM * A_OFM	0
E_CDM * A_Pair	0
E_CDM * A_Repeat	0
E_CDM * A_RpGrid	0
E_CDM * A_SOAR	0
E_CDM * A_Stat	0
E_CDM * A_StraAn	0
E_CDM * A_StruAn	0
E_CDM * A_TimeLn	0
E_CDM * A_WkDoAn	0
E_CDM * A_WkFlow	0
E_crit * A_Card	0
E_crit * A_Clust	0
E_crit * A_COGNE	0
E_crit * A_cogfn	0
E_crit * A_cwa	0
E_crit * A_comp2	0
E_crit * A_ConMap	0
E_crit * A_ConGra	0
E_crit * A_cor	0
E_crit * A_Diag	0
E_crit * A_DocAnl	0
E_crit * A_EvTree	0
E_crit * A_Fail	0

E_crit * A_Fault	0
E_crit * A_Free	0
E_crit * A_Funct	0
E_crit * A_GOMS	0
E_crit * A_Graph	0
E_crit * A_Ground	0
E_crit * A_Hsort	0
E_crit * A_Htask	0
E_crit * A_Ident	0
E_crit * A_InfDia	0
E_crit * A_InfFlo	0
E_crit * A_IntAna	0
E_crit * A_Job	0
E_crit * A_Ladd	0
E_crit * A_MCS	0
E_crit * A_MDS	0
E_crit * A_Net	0
E_crit * A_OpSqAn	0
E_crit * A_OFM	0
E_crit * A_Pair	0
E_crit * A_Repeat	0
E_crit * A_RpGrid	0
E_crit * A_SOAR	0
E_crit * A_Stat	0
E_crit * A_StraAn	0
E_crit * A_StruAn	0
E_crit * A_TimeLn	0
E_crit * A_WkDoAn	0
E_crit * A_WkFlow	0
E_design * A_Card	0
E_design * A_Clust	0
E_design * A_COGNE	0
E_design * A_cwa	0
E_design * A_comp2	0
E_design * A_ConGra	0
E_design * A_ConAnl	0
E_design * A_cor	0
E_design * A_Diag	0
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